Karlsruher Institut für Technologie

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End-to-end Modelling and Optimization of Optical Communication Systems using Deep Learning

Laurent Schmalen, Boris Karanov, Vincent Lauinger

Overview

- Introduction
- Application 1: Waveform Optimization for Short-Reach Optical Communications
  - Simple Transmitter Using Feed-Forward Neural Networks
  - Improved Transceivers Using Reccurent Neural Networks
- Application 2: Distance-agnostic Transceivers
- Application 3: In-Situ Optimization of Transmitters
- Application 4: Blind Equalization Using Variational Autoencoders
- Conclusions and Outlook

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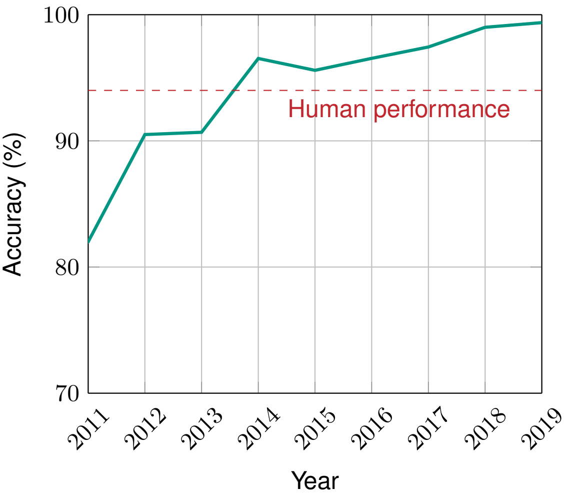
Machine Learning Success: Handwritten Digit Recognition

- **The MNIST database**[1] [2]

- **Error rates of 0.23%** can be achieved today

[1] Available online at: `http://yann.lecun.com/exdb/mnist/`
[2] Image source: `https://upload.wikimedia.org/wikipedia/commons/2/27/MnistExamples.png`

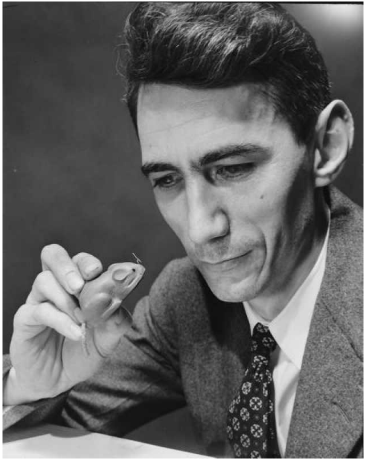
Machine Learning Success: Image Recognition



- Image recognition accuracy on CIFAR-10 dataset[3]
- In less than 10 years, advances in machine learning and in particular **neural networks** and **deep learning** yield systems that surpass human capabilities
- Almost perfect recognition accuracy

[3] Accuracy data from `https://benchmarks.ai/cifar-10`

Machine Learning for Communications

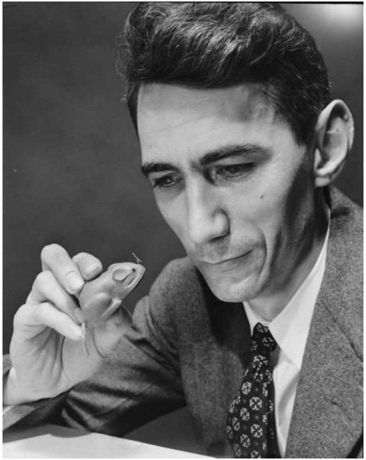


- 70 years of communications engineering have brought us close to the Shannon limit[4] (Shannon capacity)

- **But:** this applies only to a sub-class of all communication problems
- We don't know neither good nor optimal transceivers for many communication systems

[4] Image source: `https://commons.wikimedia.org/wiki/File:Claude_Shannon_1776.jpg`

Machine Learning for Communications



- 70 years of communications engineering have brought us close to the Shannon limit[4] (Shannon capacity)
- **But:** this applies only to a sub-class of all communication problems
- We don't know neither good nor optimal transceivers for many communication systems
- **Machine learning** can help us identify novel transceivers
- **This talk:**
  - Concept of using neural networks for optimizing of optical communication systems
  - Use of neural networks to learn parameters of the communication system

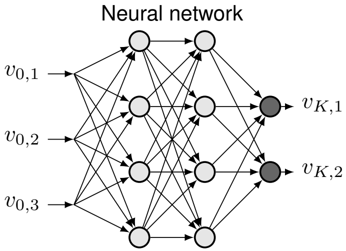
[4] Image source: `https://commons.wikimedia.org/wiki/File:Claude_Shannon_1776.jpg`

Neural Networks: A Whirlwind Tour

Feed-Forward Neural Networks (FFNN)

- Maps an input vector $\mathbf{v}_0 = \begin{pmatrix} v_{0,1} & \dots & v_{0,M} \end{pmatrix}$ to an output vector $\mathbf{v}_K = \begin{pmatrix} v_{K,1} & \dots & v_{K,n} \end{pmatrix} = f_{\text{NN}}(\mathbf{v}_0)$
- The neural network (NN) is a composed function consisting of layers, where each layer computes

$$\mathbf{v}_k = g_{\text{NL},k}(\mathbf{W}_k \mathbf{v}_{k-1} + \mathbf{b}_k), \qquad k = 1, \dots, K$$



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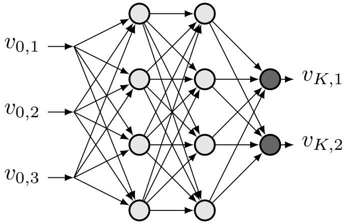
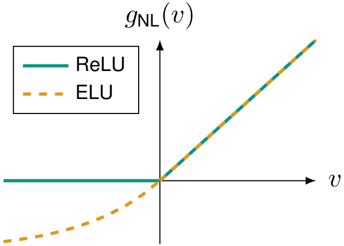
$$\mathbf{v}_k = g_{\text{NL},k}(\mathbf{W}_k \mathbf{v}_{k-1} + \mathbf{b}_k), \qquad k = 1, \dots, K$$

- Activation function g_{NL} introduces **nonlinear** relation between layers
- A popular choice for g_{NL} is the ReLU activation function (or one of its variants, e.g. the ELU function)

$$\mathbf{x} = g_{\text{NL}}(\mathbf{v}) = g_{\text{ReLU}}(\mathbf{v}) \qquad \text{with } x_i = \max(0, v_i)$$

Neural network





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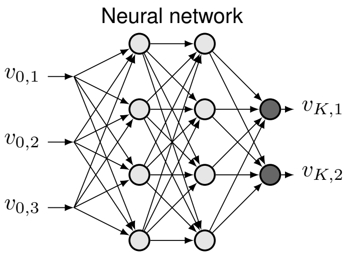
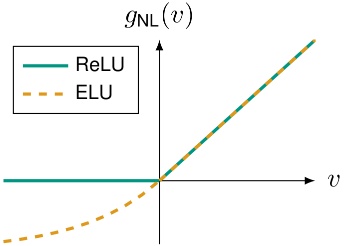
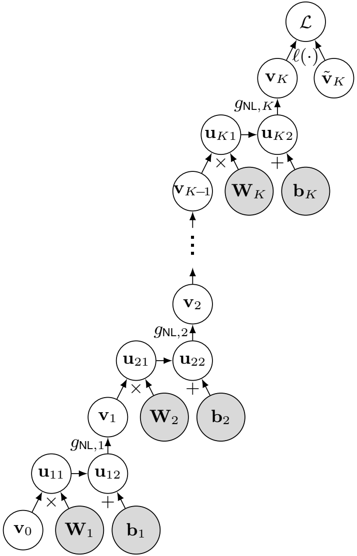
- **Objective of learning:** Find parameters $\mathbf{W}_k$ and $\mathbf{b}_k$ such that $f_{\text{NN}}(\mathbf{v}_0)$ approximates an (unknown) function whose inputs and outputs can be observed and fed to a training algorithm





Neural Networks: Computational Graph



Deep Learning

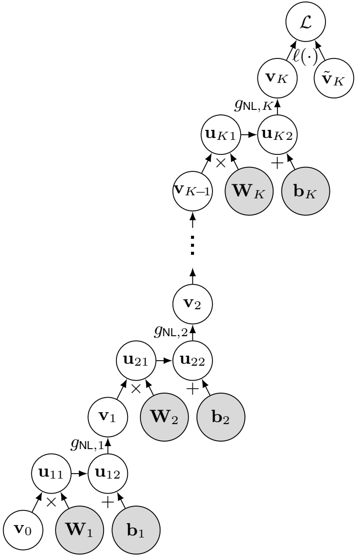
- Objective is to find NN parameters $\{\mathbf{W}_k, \mathbf{b}_k\}$ that minimize a **loss function**

$$\mathcal{L}\left(\{\mathbf{W}_k, \mathbf{b}_k\}_K\right) = \frac{1}{|\mathcal{S}|} \sum_{(\mathbf{v}_{0,i}, \tilde{\mathbf{v}}_{K,i}) \in \mathcal{S}} L\left(f_{\text{NN}}\left(\mathbf{v}_{0,i}\right), \tilde{\mathbf{v}}_{K,i}\right)$$

  where $(\mathbf{v}_{0,i}, \tilde{\mathbf{v}}_{K,i})$ are **examples** of inputs $(\mathbf{v}_{0,i})$ and observed outputs $(\tilde{\mathbf{v}}_{K,i})$ of the system we like to approximate

- **Training data set** $\mathcal{S}$ contains these examples

Neural Networks: Computational Graph



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- **Training data set** $\mathcal{S}$ contains these examples
- Parameters $\{\mathbf{W}_k, \mathbf{b}_k\}$ are optimized using **gradient descent**

$$\mathbf{W}_k \leftarrow \mathbf{W}_k - \epsilon \nabla_{\mathbf{W}_k} \mathcal{L}\left(\{\mathbf{W}_k, \mathbf{b}_k\}_K\right)$$
$$\mathbf{b}_k \leftarrow \mathbf{b}_k - \epsilon \nabla_{\mathbf{b}_k} \mathcal{L}\left(\{\mathbf{W}_k, \mathbf{b}_k\}_K\right)$$

- Efficient computation of gradient using a **computational graph**

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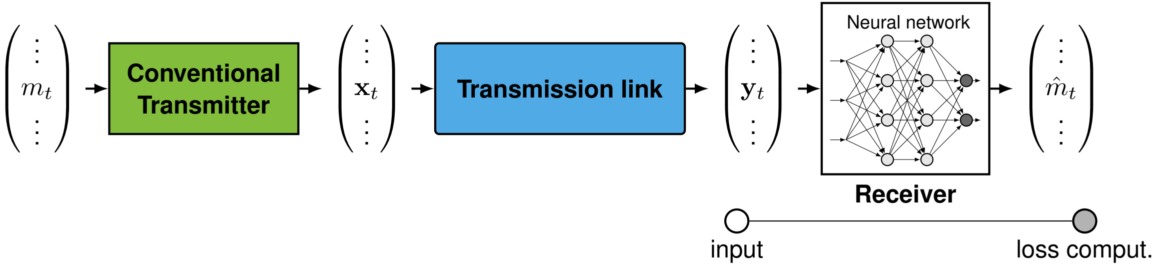
Receiver Processing Using Neural Networks



- Transmission of known sequence of messages (e.g., pilot) m_t
- Based on received data ($\mathbf{y}_t$), try to recover m_t as closely as possible
- Training dataset is database of received signals and associated symbols $\mathcal{S} = \{(\mathbf{y}_t, m_t) : t = 1, \ldots N\}$
- Proposed for optical communications [Lyu15] and used for example as receivers in PON systems [HCvV19]

[Lyu15] I. Lyubomirsky, "Machine learning equalization techniques for high speed PAM4 fiber optic communication systems," *CS229 Final Project Report*, Stanford University, 2015

[HCvV19] V. Houtsma, E. Chou, and D. van Veen, "92 and 50 Gbps TDM-PON using neural network enabled receiver equalization specialized for PON," in *Proc. Optical Fiber Communications Conference (OFC)*, 2019

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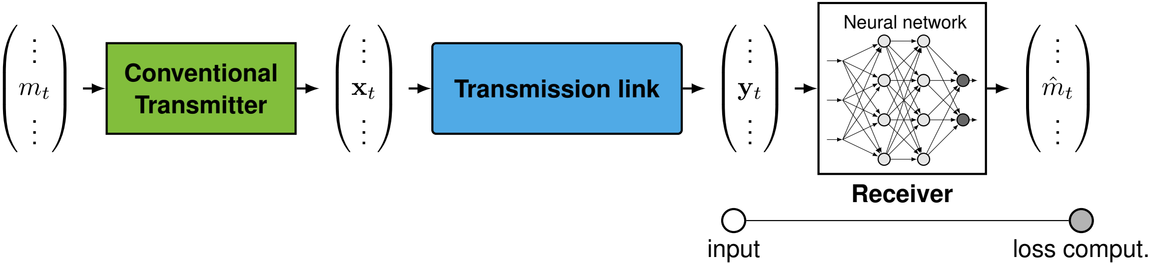

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- Proposed for optical communications **[Lyu15]** and used for example as receivers in PON systems **[HCvV19]**
- **Example:** AWGN channel

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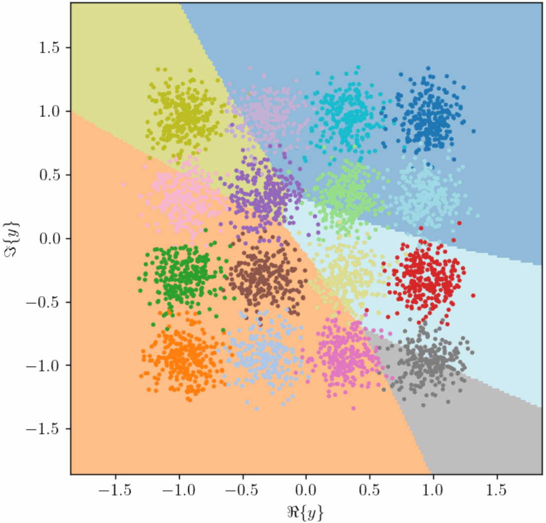
[HCvV19] V. Houtsma, E. Chou, and D. van Veen, "92 and 50 Gbps TDM-PON using neural network enabled receiver equalization specialized for PON," in *Proc. Optical Fiber Communications Conference (OFC)*, 2019

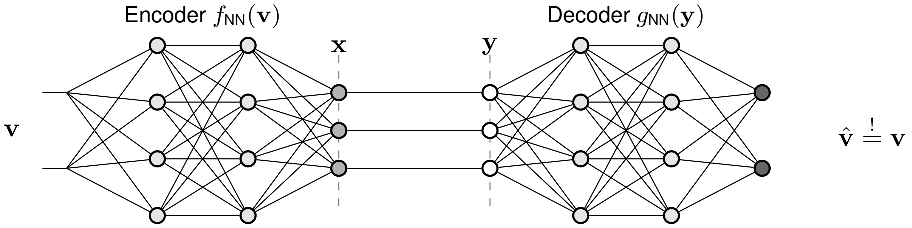
Example: Deep NN Detection in AWGN Channel



- Implementation using PyTorch[a]
- Source code available online[b]

[a] http://pytorch.org
[b] https://github.com/kit-cel/HHI_SummerSchool_2021

Auto-encoders – Basic Concept



- Consists of an **encoder** $f_{\text{NN}}(\mathbf{v})$ and a **decoder** $g_{\text{NN}}(\mathbf{y})$
- **Goal:** Try to reproduce $\mathbf{v}$ by $\hat{\mathbf{v}}$ as close as possible

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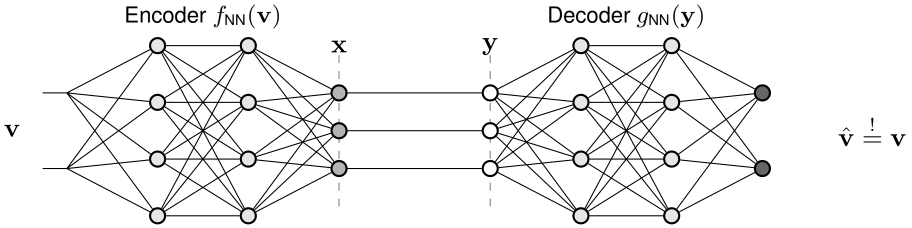

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- **Goal:** Try to reproduce $\mathbf{v}$ by $\hat{\mathbf{v}}$ as close as possible

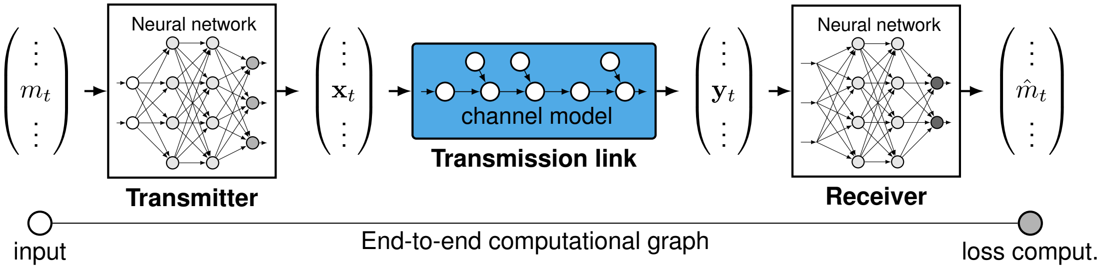
- Resembles a communication system (Goal: reproduce information as close as possible)
- Can we use auto-encoders to design communication systems? **[OKC16]**, **[OH17]**

[OKC16] T. O'Shea, K. Karra and T. C. Clancy, "Learning to Communicate: Channel Auto-encoders, Domain Specific Regularizers, and Attention," *2016 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT)*, 2016

[OH17] T. O'Shea and J. Hoydis, "An introduction to deep learning for the physical layer," *IEEE Trans. Cogn. Commun. Netw.*, vol. 3, no. 4, pp. 563-575, 2017.

[CAD+20] S. Cammerer, F. Ait Aoudia, S. Dörner, M. Stark, J. Hoydis, S. ten Brink, "Trainable communication systems: Concepts and prototype," *IEEE Trans. on Commun.*, 2020

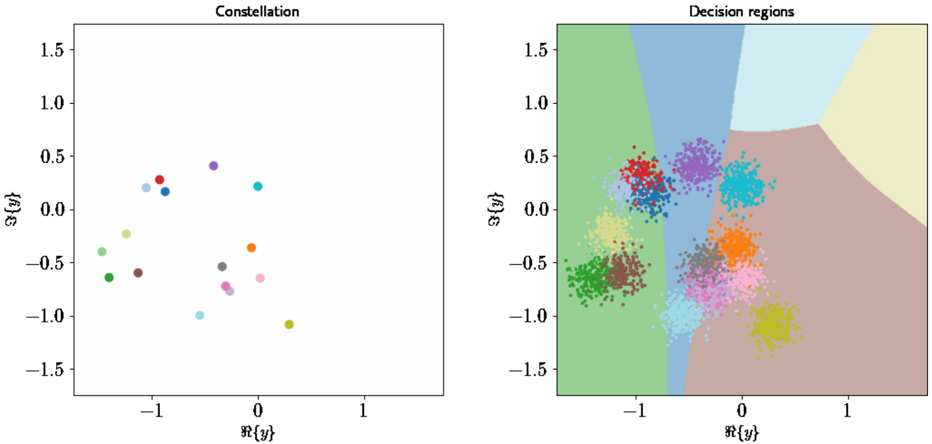
Communication System as Auto-Encoder



- Replacing (parts of) transmitter by neural network
- Transmission link needs to be modeled by an adequate, **differentiable** channel model that can be part of the computational graph

- **Example:** AWGN channel $\mathbf{y}_t = \mathbf{x}_t + \mathbf{n}_t$ with $\nabla_{\mathbf{W}} \mathbf{y}_t = \nabla_{\mathbf{W}} \mathbf{x}_t$

Example: Auto-Encoder in AWGN Channel



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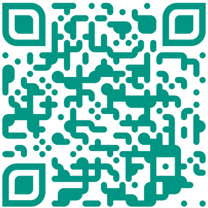

[5] https://github.com/kit-cel/HHI_SummerSchool_2021

Example: Zero-Dispersion Optical Fiber

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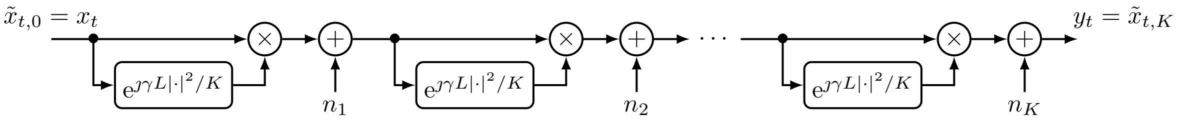
- A more complicated model is the zero-dispersion optical fiber model used in **[LHG+18]**
- Transmission over an optical fiber of length L having nonlinearity parameter γ and zero dispersion ($\beta_i = 0$)



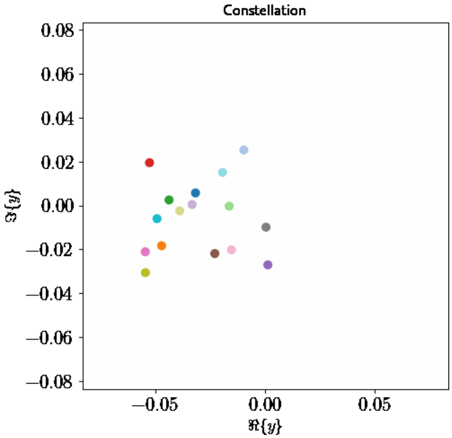
- Let $\tilde{x}_{x,0} = x_t$ and recursively compute

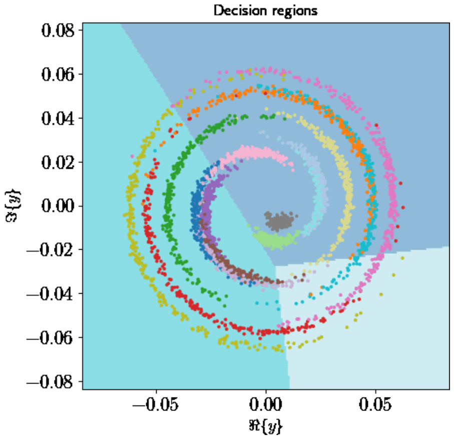
$$\tilde{x}_{t,i+1} = \tilde{x}_{t,i} \cdot \mathrm{e}^{\jmath L\gamma|\tilde{x}_{t,i}|^2/K} + n_{i+1}, \quad 0 \leq i < K$$

  where $n_{i+1} \sim \mathcal{CN}(0, P_N/K)$ is complex, circularly symmetric Gaussian noise (assuming ideal distributed amplification) and K the number of steps (ideally, $K \to \infty$)
- Computation graph is fully **differentiable**

[LHG+18] S. Li, C. Häger, N. Garcia, and H. Wymeersch, "Achievable Information Rates for Nonlinear Fiber Communication via End-to-end Autoencoder Learning," *Proc. ECOC*, Rome, Sep. 2018

Example: Zero-Dispersion Optical Fiber





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Auto-Encoders in Optical Communications

- End-to-end learning applied to optimize multidimensional constellations for IM/DD links [KCT+18], [CBS18]
- End-to-end learning of transceivers for the nonlinear Fourier transform [GJD+20]
- Constellation optimization for the zero-dispersion channel [LHG+18]
- Constellation optimization for geometric shaping [JEY+18], [JYZ19], [GAC+20]
- Differentiable channel models and nonlinearity compensation for coherent systems [HP20]

[KCT+18] B. Karanov, M. Chagnon, F. Thouin, T. A. Eriksson, H. Bülow, D. Lavery, P. Bayvel, and L. Schmalen, "End-to-end deep learning of optical fiber communications," *Journal of Lightwave Technology*, vol. 36, no. 20, pp. 4843–4855, 2018

[CBS18] M. Chagnon, B. Karanov, and L. Schmalen, "Experimental demonstration of a dispersion tolerant end-to-end deep learning-based IM-DD transmission system," *Proc. European Conference on Optical Communication (ECOC)*, 2018

[GJD+20] S. Gaiarin, R. T. Jones, F. Da Ros, and D. Zibar, "End-to-end optimized nonlinear Fourier transform-based coherent communications," *Proc. CLEO: Science and Innovations*, May 2020

[LHG+18] S. Li, C. Häger, N. Garcia, and H. Wymeersch, "Achievable Information Rates for Nonlinear Fiber Communication via End-to-end Autoencoder Learning," *Proc. European Conference on Optical Communication (ECOC)*, Sep. 2018

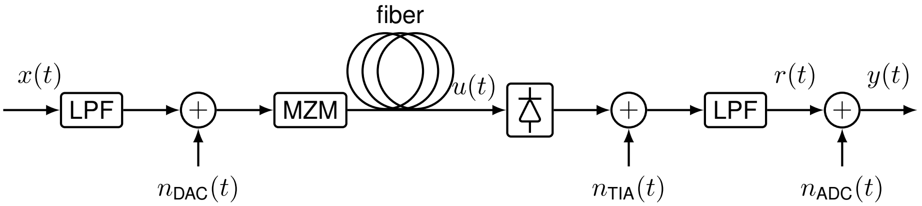
[JEY+18] R. T. Jones, T. A. Eriksson, M. P. Yankov, and D. Zibar, "Deep learning of geometric constellation shaping including fiber nonlinearities,", *Proc. European Conference on Optical Communication (ECOC)*, 2018

[JYZ19] R. T. Jones, M. Yankov, and D. Zibar, "End-to-end learning for GMI optimized geometric constellation shape," arXiv:1907.08535, 2019

[GAC+20] K. Gümüş, A. Alvarado, B. Chen, C. Häger, and E. Agrell, "End-to-End Learning of Geometrical Shaping Maximizing Generalized Mutual Information," *Proc. Optical Fiber Communications Conference (OFC)*, Mar. 2020

[HP20] C. Häger and H. D. Pfister, "Physics-Based Deep Learning for Fiber-Optic Communication Systems," *Journal of Selected Areas in Communications*, 2021

End-to-end Learning for IM/DD



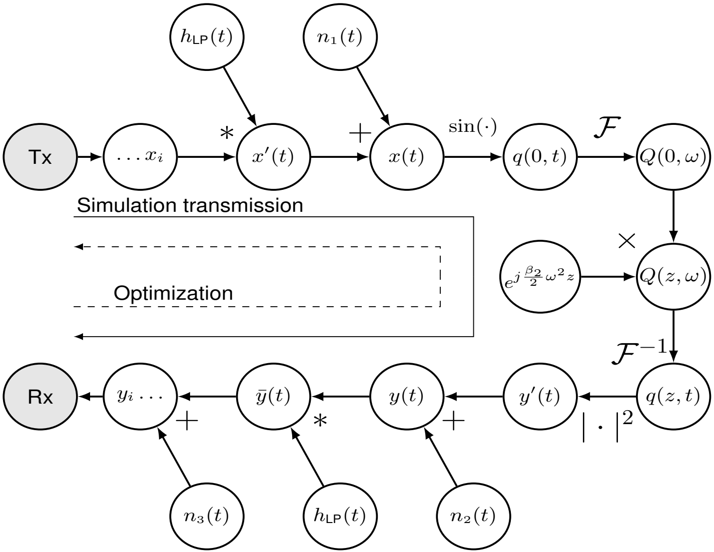
- IM/DD (intensity modul., direct detect.) ubiquitous in access networks and data center interconnects

$$y(t) = \left|\hat{h}_{\text{Fiber}}\left(\hat{h}_{\text{MZM}}\left(x(t) + n_{\text{DAC}}(t)\right)\right)\right|^2 + n_{\text{TIA}}(t) + n_{\text{ADC}}(t)$$

- Fiber adds only chromatic dispersion (no nonlinearities) with $H(\omega, z) = \exp\left(\jmath\frac{\beta_2}{2}z\omega^2\right)$
- Nonlinear channel with memory, *however*, optimal **computationally feasible algorithms absent**
- Model is fully **differentiable**

- Contrary to previous examples, channel input is **waveform**, not modulation symbols
- We need to **learn optimal waveforms**

Computational Graph of Channel Model



- Chromatic dispersion is added in frequency domain
- Fourier transform is linear and differentiable
- Channel model can be directly implemented in machine learning software

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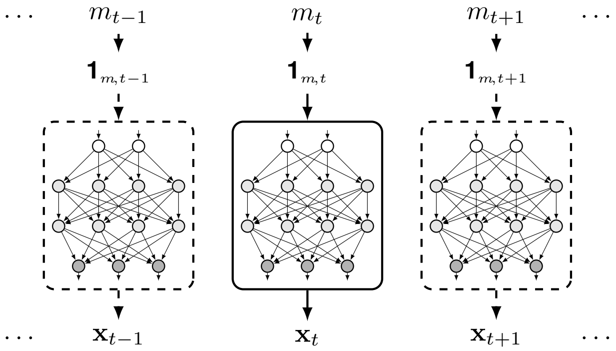
First Transmitter Attempt Using FFNN

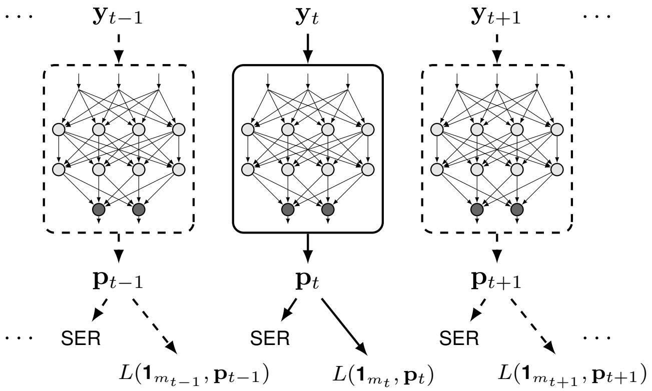


- Transform message m_t (from an alphabet containing M messages (e.g., a modulation alphabet)) into **one-hot**[7] vector $1_{m,t}$
- FNN encodes $1_{m,t}$ into n **oversampled waveform samples** $\mathbf{x}_t$
- Apply low-pass-filter (LPF, part of the channel model) to **smear** the waveforms

[KCT+18] B. Karanov, M. Chagnon, F. Thouin, T. Eriksson, H. Bülow, D. Lavery, P. Bayvel, L. S., "End-to-end Deep Learning of Optical Fiber Communications," *Journal of Lightwave Technology*, Oct. 2018

[7] A one-hot vector $\mathbf{1}_{m,t}$ of length M contains only zeros except a single "1" at position m_t

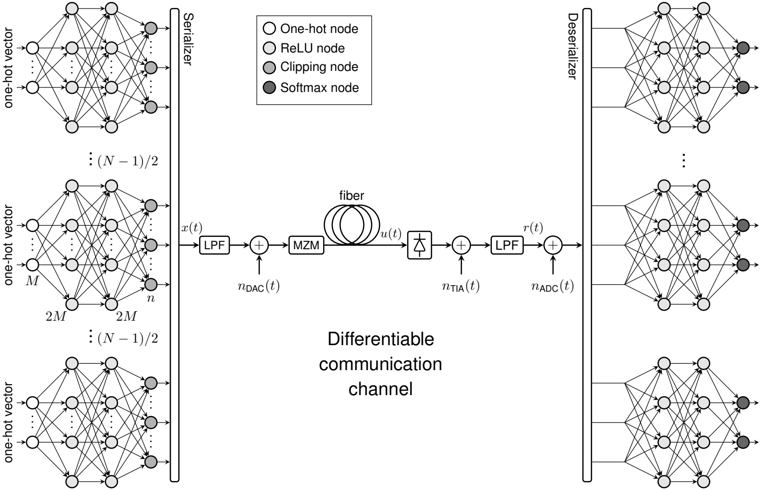
First Receiver Attempt Using FFNN



- Receiver input is chopped into blocks $\mathbf{y}_t$ of n received **samples**
- Samples are processed by an FFNN with a **softmax** output activation function (" ● ")
- Softmax output function generates a probability vector $\mathbf{p}_t$
- Decision according to most probable symbol
- Training using cross-entropy loss function

$$L(\mathbf{1}_{m_t}, \mathbf{p}_t) = -\log(p_{t,m_t})$$

Putting Everything Together



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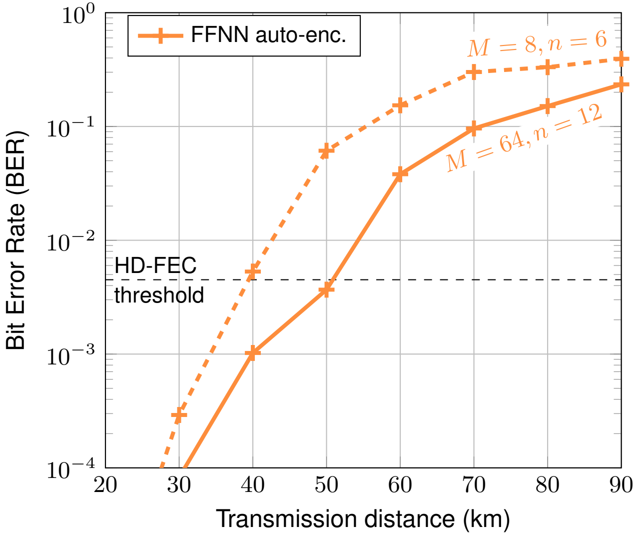
Simulation Results



- State-of-the-art IM/DD system with 42 Gb/s net rate
- For small alphabets (M small) and neural networks, reach is limited
- Increasing the alphabet and the neural networks enables extra reach (multidimensional constellations) as more dispersion can be compensated for
- Increasing the the NN size (i.e., M and thus n) leads to unfeasibly large networks

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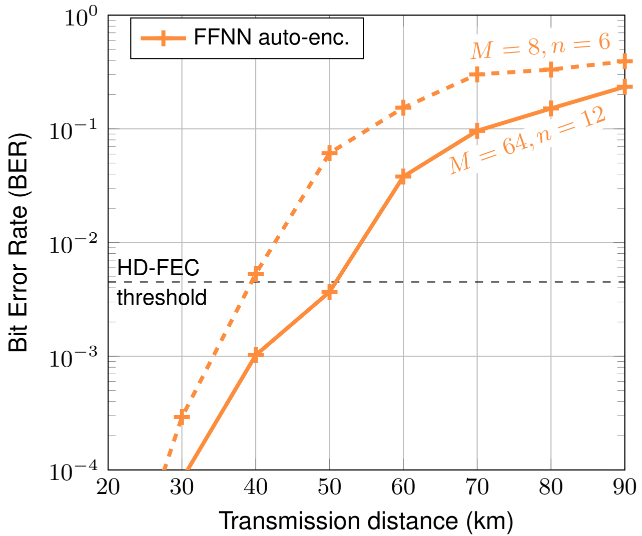

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- For small alphabets (M small) and neural networks, reach is limited
- Increasing the alphabet and the neural networks enables extra reach (multidimensional constellations) as more dispersion can be compensated for
- Increasing the the NN size (i.e., M and thus n) leads to unfeasibly large networks
- **New approach tailored to dispersive nature of channel needed**

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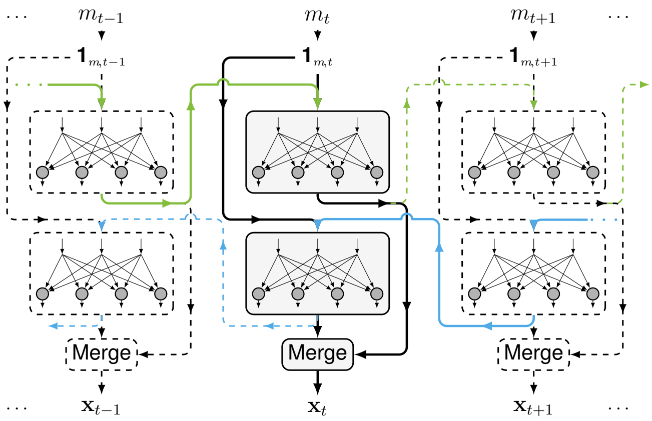
- Application 4: Blind Equalization Using Variational Autoencoders
- Conclusions and Outlook

Bidirectional Recurrent NN Based Transmitter

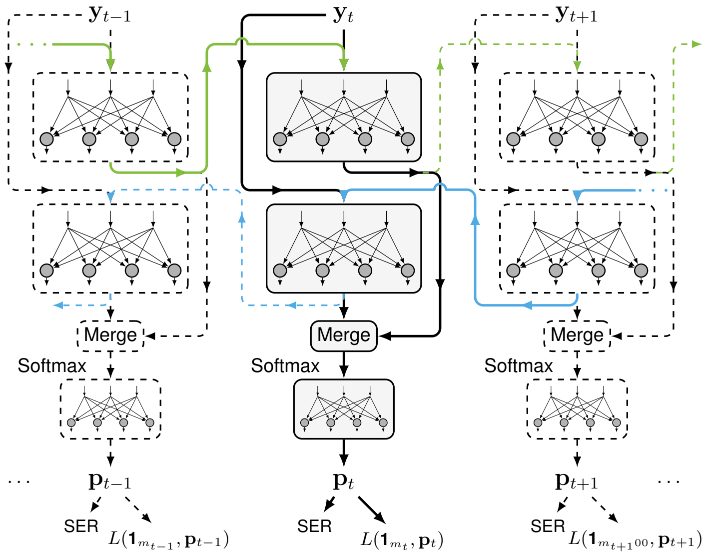


- Transmitter based on **bidirectional recurrent neural networks (BRNN)** [FG18] to account for memory due to chromatic dispersion
- Current message m_t jointly processed with previous and future messages vie **bidirectional recurrent neural network (BRNN)**
- Complexity gain using **small** networks inside RNN cells

[KLB+19] B. Karanov, D. Lavery, P. Bayvel, L. Schmalen, "End-to-end optimized transmission over dispersive intensity modulated channels using bidirectional recurrent neural networks," *Optics Express*, Jul. 2019

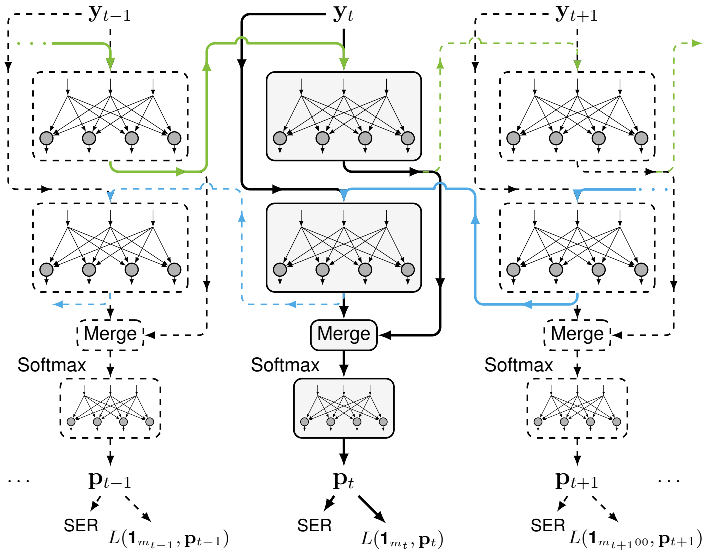
[FG18] N. Farsad, A. Goldsmith, "Neural network detection of data sequences in communication systems," *IEEE Trans. Signal Process*, 2018

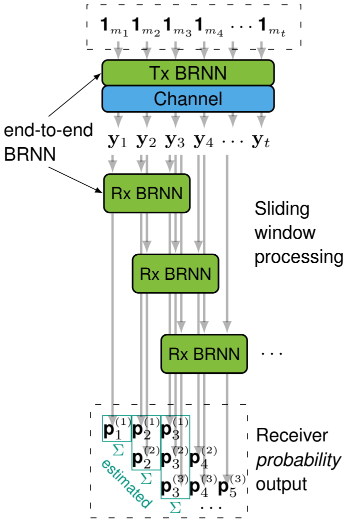
Bidirectional Recurrent NN Based Receiver



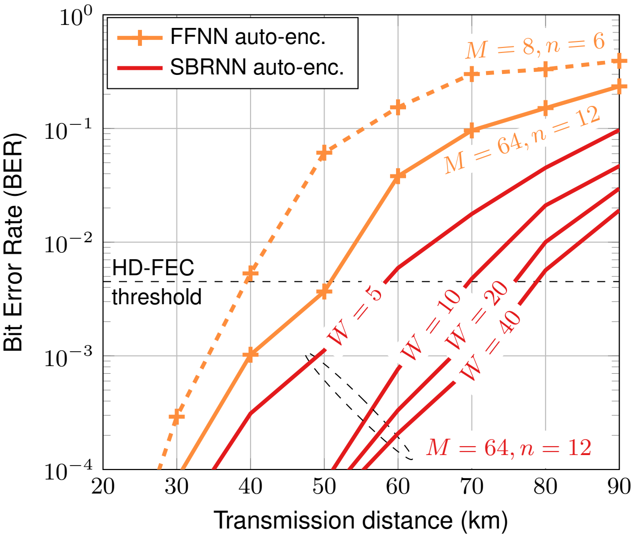
- Receiver structure similar to transmitter
- Additional **softmax** layer to generate probability vectors
- We use **sliding window** processing at the receiver to trade complexity and latency with performance
- A **window** of W stages is jointly processed at the receiver [FG18]

Bidrectional Recurrent NN Based Receiver





Simulation Results

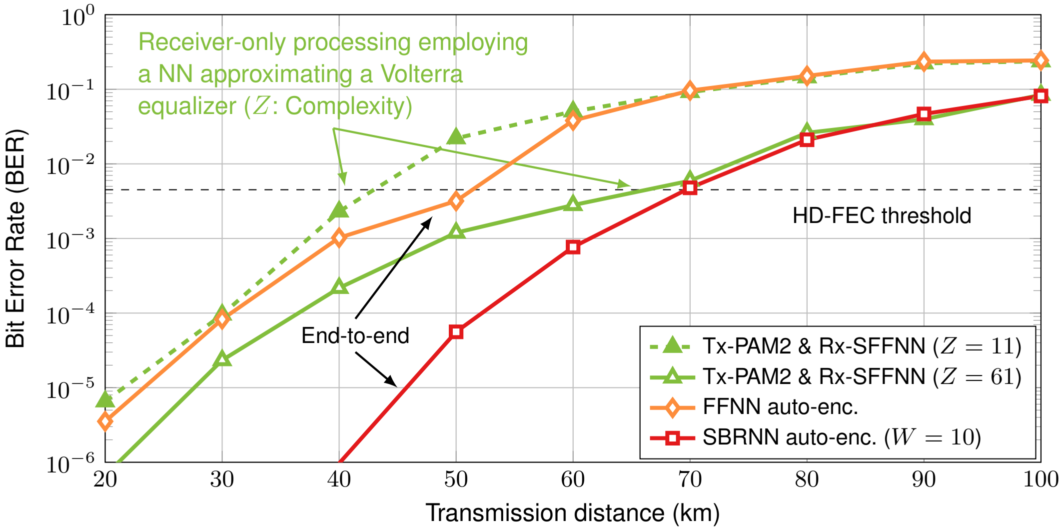


- SBRNN outperforms simple FFNN implementation at significantly **lower complexity**
- 20 km distance gain for $W = 10$
- SBRNN can **outperform** MLSD if complexity is constrained **[KLA+19]**
- Now: Comparison with pure receiver NN processing approximating a Volterra equalizer **[Lyu15]**

[KLA+19] B. Karanov, G. Liga, V. Aref, D. Lavery, P. Bayvel, and L. Schmalen, “Deep learning for communication over dispersive nonlinear channels: Performance and comparison with classical digital signal processing”, *Proc. Allerton Conf. on Commun., Control, and Computing*, 2019

[Lyu15] I. Lyubomirsky, “Machine learning equalization techniques for high speed PAM4 fiber optic communication systems,” *CS229 Final Project Report*, Stanford University, 2015

Simulation Results (2)



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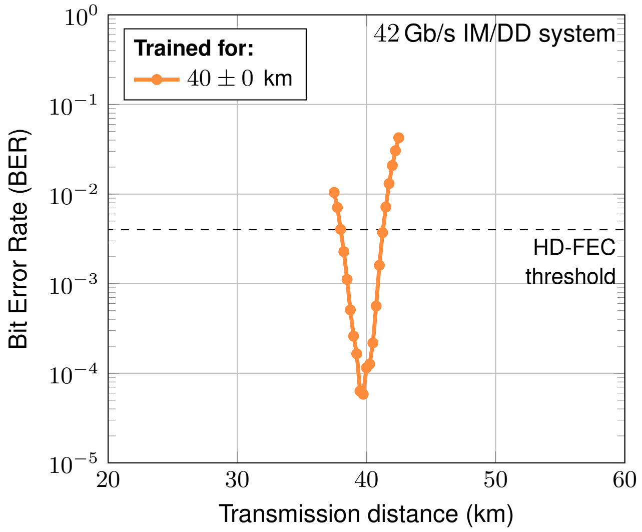
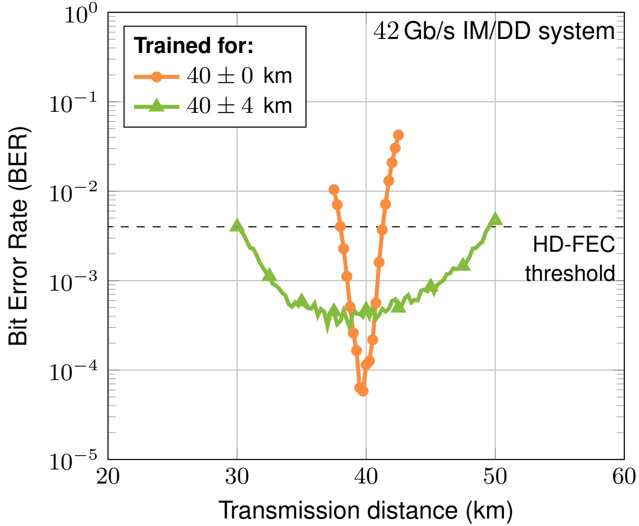
Training Generalization: Simulation Results



- **How well does the training generalize?**
- If no precautions are taken, not too well

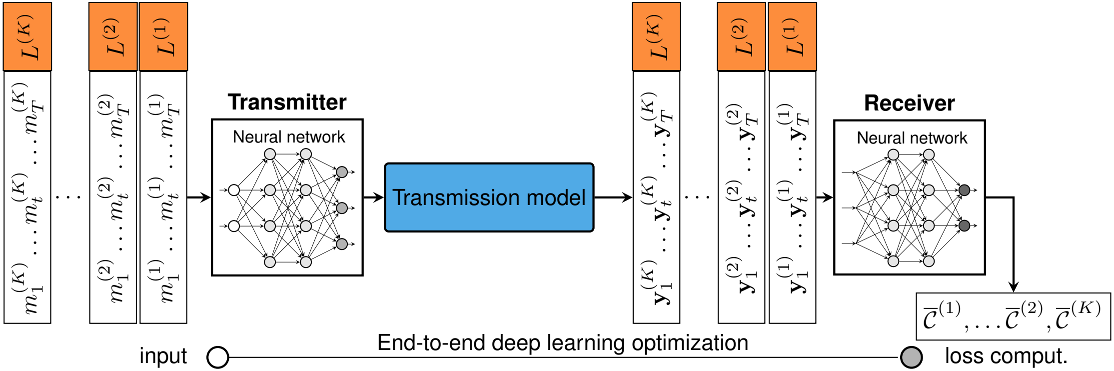
Training Generalization: Simulation Results



- **How well does the training generalize?**
- If no precautions are taken, not too well
- **Multi-task learning** enables transceivers that operate on a range of distances **without reconfiguration** [KCT+18]
- Big step towards **distance agnostic** transceivers

[KCT+18] B. Karanov, M. Chagnon, F. Thouin, T. Eriksson, H. Bülow, D. Lavery, P. Bayvel, L. S., "End-to-end Deep Learning of Optical Fiber Communications," *Journal of Lightwave Technology*, Oct. 2018

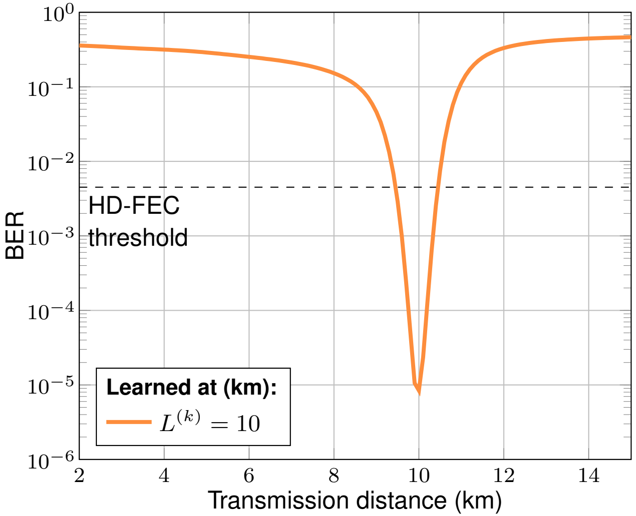
Strategies for Distance-Agnostic Transceiver

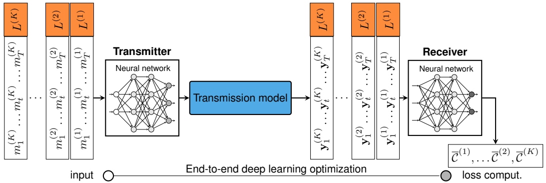


- Loss function

$$\overline{\mathcal{C}}^{(k)}(\boldsymbol{\theta}) = \frac{1}{T}\sum_{t=1}^{T} \ell\left(m_t^{(k)}, f_{\mathrm{Rx}}\left(\mathcal{H}_{\mathrm{ch}}\left\{\dots, f_{\mathrm{Tx}}\left(m_t^{(k)}\right), \dots\right\}_{L^{(k)}}\right)\right) = \frac{1}{T}\sum_{t=1}^{T} \ell\left(m_t^{(k)}, f_{\mathrm{Rx}}\left(\mathrm{y}_t^{(k)}\right)\right)$$

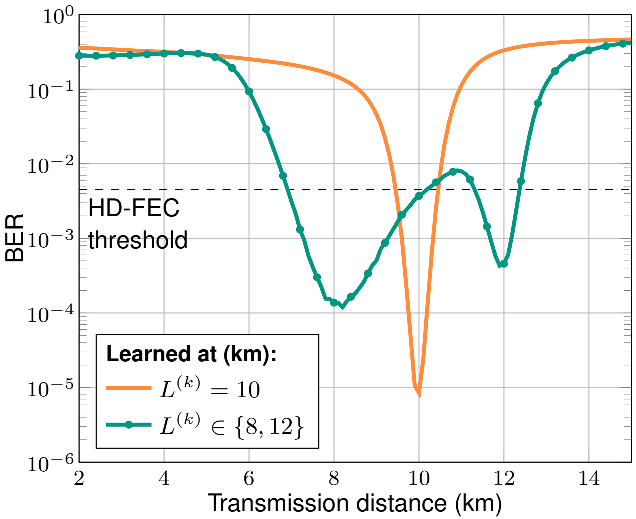
Strategies for Distance-agnostic Transceiver

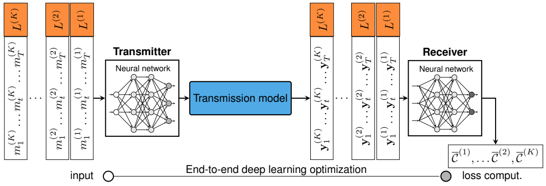




- 100 Gb/s IM/DD system
- Transmitter optimized at fixed distance
- Rapid performance degradation as distance changes

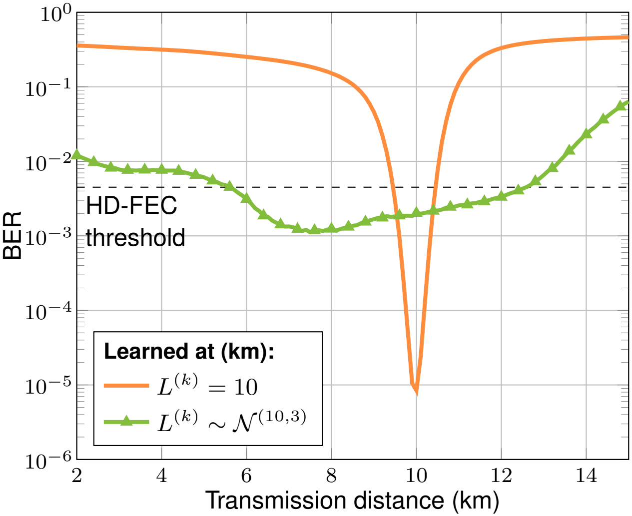
Strategies for Distance-agnostic Transceiver

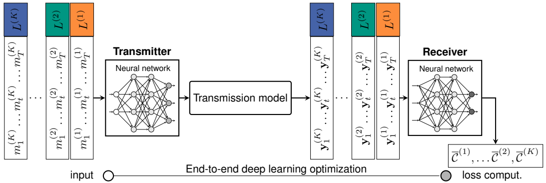




- 100 Gb/s IM/DD system
- Transmitter optimized at two distances $L^{(k)} \in \{8\,\text{km}, 12\,\text{km}\}$
- Strong BER variation but wider allowed range of operation

Strategies for Distance-agnostic Transceiver



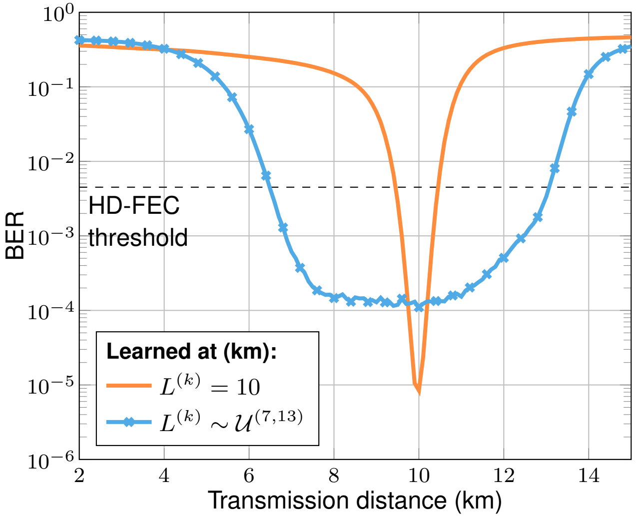


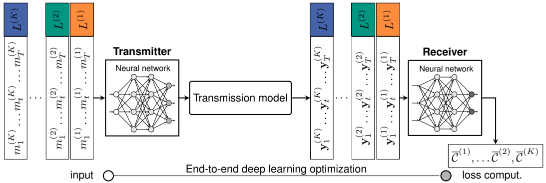
- 100 Gb/s IM/DD system
- Training examples with different accumulated link dispersions
- Gaussian distribution

[CKS18] M. Chagnon, B. Karanov, L. S., "Experimental demonstration of dispersion tolerant end-to-end deep learning-based IM-DD transmission system," *Proc. ECOC*, 2018

[KLA21] B. Karanov, L. S., A. Alvarado, "Distance-Agnostic Auto-Encoders for Short Reach Fiber Communications," *Proc. OFC*, 2021

Strategies for Distance-agnostic Transceiver



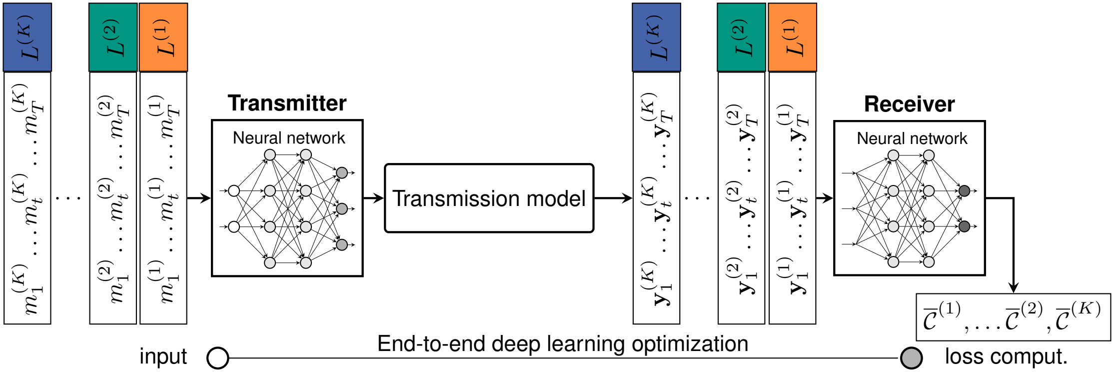


- 100 Gb/s IM/DD system
- Training examples with different accumulated link dispersions
- Uniform distribution

[CKS18] M. Chagnon, B. Karanov, L. S., "Experimental demonstration of dispersion tolerant end-to-end deep learning-based IM-DD transmission system," *Proc. ECOC*, 2018

[KLA21] B. Karanov, L. S., A. Alvarado, "Distance-Agnostic Auto-Encoders for Short Reach Fiber Communications," *Proc. OFC*, 2021

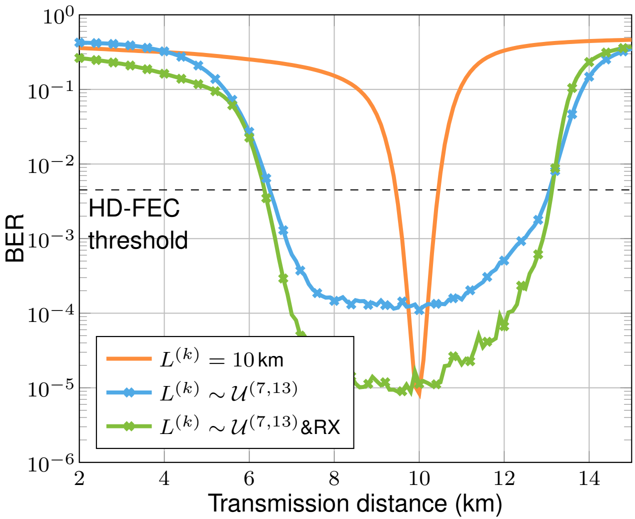
Enhanced Distance-agnostic Transceiver

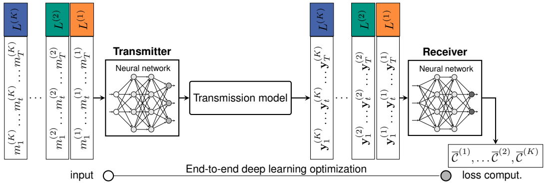


- Receiver has access to length $L^{(k)}$
- Loss function

$$\overline{\mathcal{C}}^{(k)}(\boldsymbol{\theta}) = \frac{1}{T}\sum_{t=1}^{T} \ell\left(m_t^{(k)}, f_{\mathrm{Rx}}\left(\mathcal{H}_{\mathrm{ch}}\left\{\ldots, f_{\mathrm{Tx}}\left(m_t^{(k)}\right), \ldots\right\}_{L^{(k)}}, L^{(k)}\right)\right) = \frac{1}{T}\sum_{t=1}^{T} \ell\left(m_t^{(k)}, f_{\mathrm{Rx}}\left(\mathrm{y}_t^{(k)}, L^{(k)}\right)\right)$$

Enhanced Distance-agnostic Transceiver





- 100 Gb/s IM/DD system
- Training examples with different accumulated link dispersions
- Receiver has knowledge of link distance (or coarse estimate thereof)
- Significant BER reduction

[KLA21] B. Karanov, L. S., A. Alvarado, "Distance-Agnostic Auto-Encoders for Short Reach Fiber Communications," *Proc. OFC*, 2021

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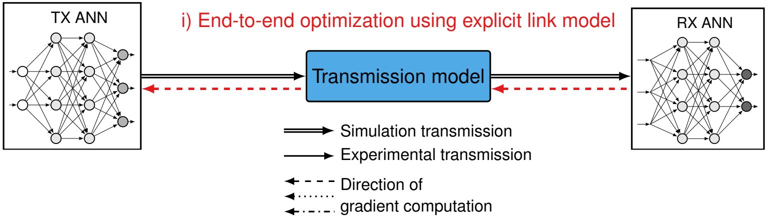
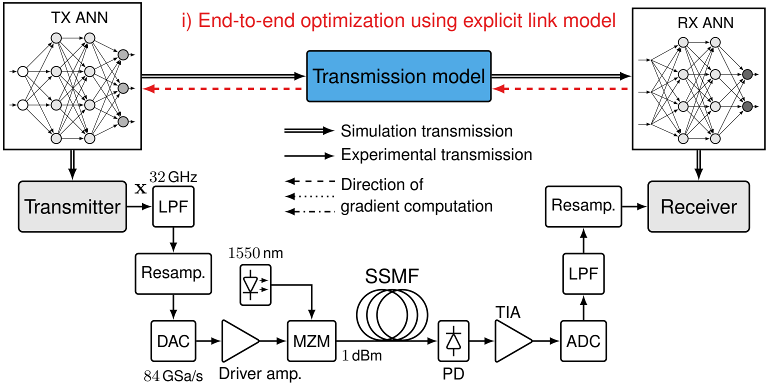
Experimental Demonstration



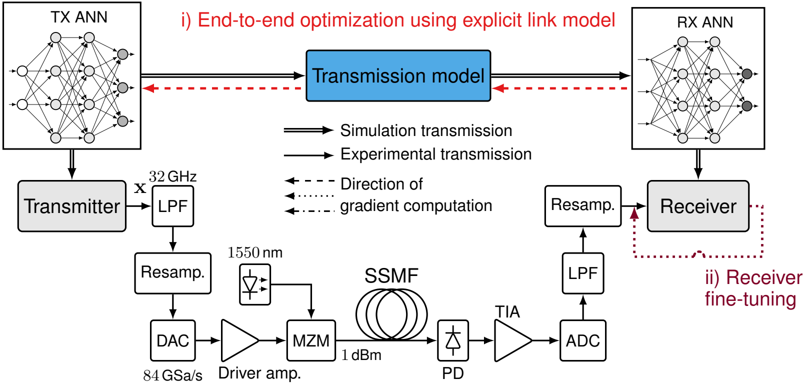
- Optimazion of transmitter and receiver using differentiable model

Experimental Demonstration



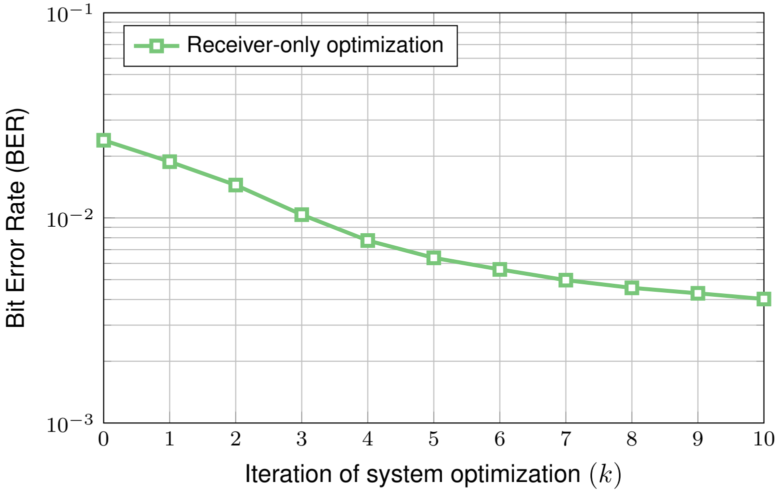
- Optimazion of transmitter and receiver using differentiable model
- Mismatch between model and experiment

Experimental Demonstration



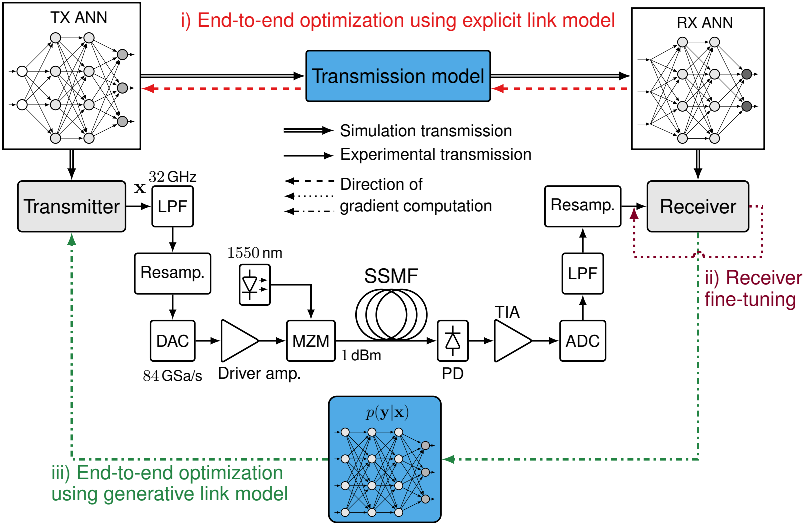
- Optimazion of transmitter and receiver using differentiable model
- Mismatch between model and experiment
- Receiver fine-tuning via supervised learning

Experimental Results: Receiver Fine-tuning



- Improvement of symbol and bit error probabilities
- Saturation after a few iterations
- (Had to stop iterating due to unavailability of experimental setup)

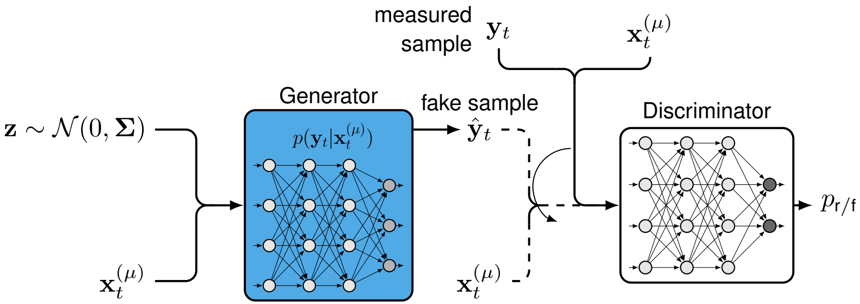
Experimental Demonstration



- Optimazion of transmitter and receiver using differentiable model
- Mismatch between model and experiment
- Receiver fine-tuning via supervised learning
- Transmitter fine-tuning via model of experimental testbed

Channel Modelling Using a Conditional GAN

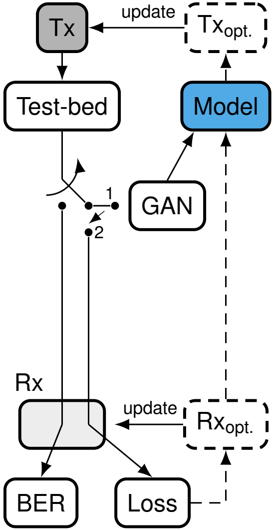
- Neural network that behaves like a random number generator with the same properties as the channel
- Combining $\mathbf{z} \sim \mathcal{N}(0, \mathbf{\Sigma})$ and the channel input $\mathbf{x}_t$, the generator generates a channel output distributed according to $p(\mathbf{y}|\vec{\mathbf{x}}_t)$



[GPM+14] I. Goodfellow *et al.*, "Generative adversarial nets," in *Proc. NeurIPS*, 2014

[KCA+20] B. Karanov, M. Chagnon, V. Aref, D. Lavery, P. Bayvel, L. S., "Concept and Experimental Demonstration of Optical IM/DD End-to-End System Optimization using a Generative Model," *Proc. OFC*, 2020

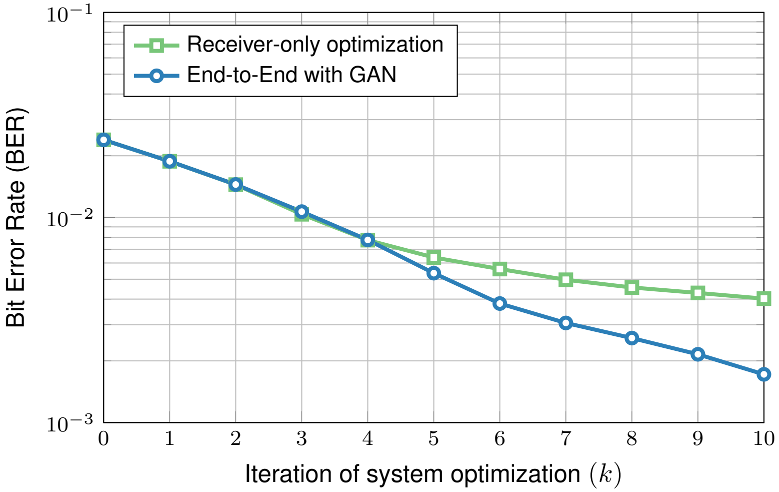
Channel Modelling Using a Conditional GAN



Training procedure:

1. Use testbed to generate input-output samples
2. Apply GAN training to get a channel model
3. Use this model to update and optimize the transmitter
4. With the new transmitter, use the test-bed to get input-output samples and optimize the receiver using supervised learning
5. Evaluate the system and re-iterate if not converged

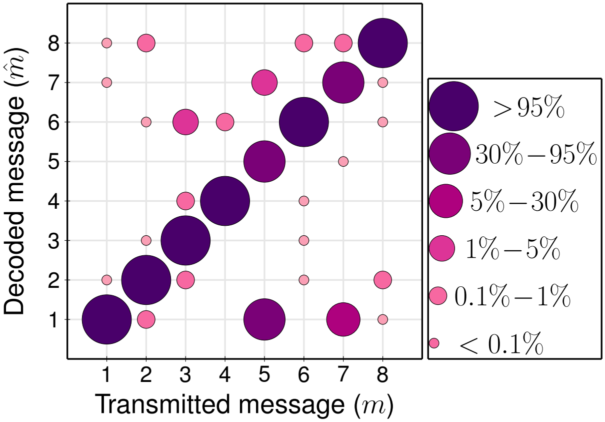
Experimental Results



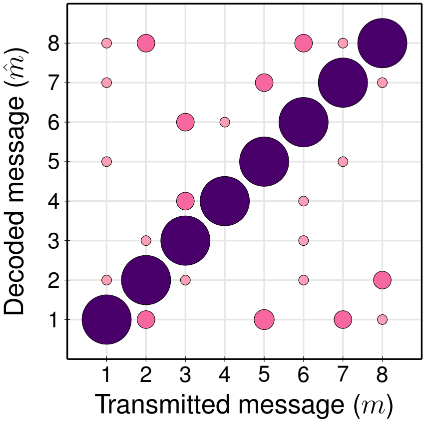
- Improvement of symbol and bit error probabilities
- More iterations will even be more beneficial
- (Had to stop iterating due to unavailability of experimental setup)

Experimental Results (2)

- End-to-end cross-over probabilities
- Initial cross-over probabilities



- After $k = 10$ iterations



In-Situ Transmitter Optimization Approaches

Approach 1: Generative adverserial nets (GANs)

- Demonstrated often ([YLJ+18], [ORW19], [SD19], [KCA+20], [DHC+20]), however, GAN training tends to be difficult, requiring careful hyperparameter tuning

Approach 2: Policy gradient methods

- Approach from reinforcement learning to estimate gradient [AH19], [GAH19]. Potentially slow convergence and requiring careful hyperparameter tuning

Approach 3: Bayesian filtering

- Recent approach [JYdR+], still many open questions

[YLJ+18] H. Ye, G. Y. Li, B. F. Juang and K. Sivanesan, "Channel agnostic end-to-end learning based communication systems with conditional GAN," in *Proc. GLOBECOM*, 2018

[ORW19] T. O'Shea, T. Roy and N. West, "Approximating the void: Learning stochastic channel models from observation with variational generative adversarial networks," in *Proc. of 2019 International Conference on Computing, Networking and Communications*, 2019

[SD19] A. Smith and J. Downey, "A communication channel density estimating generative adversarial network," *NASA Technical Reports* 2019

[KCA+20] B. Karanov, M. Chagnon, V. Aref, D. Lavery, P. Bayvel, L. S., "Concept and Experimental Demonstration of Optical IM/DD End-to-End System Optimization using a Generative Model," *Proc. OFC*, 2020

[DHC+20] S. Dörner, M. Henninger, S. Cammerer, S. ten Brink, "WGAN-based Autoencoder Training Over-the-air," *Proc. SPAWC*, 2020

[AH19] F. Ait Aoudia, J. Hoydis, "Model-free training of end-to-end communication systems," *IEEE J. Selected Areas in Communications*, 2019

[GAH19] M. Goutay, F. Ait Aoudia, J. Hoydis, "Deep reinforcement learning autoencoder with noisy feedback," *Proc. WiOPT*, 2019

[JYdR+] O. Jovanovic, M. Yankov, F. da Ros, D. Zibar, "Gradient-free training of autoencoders for non-differentiable communication channels," *Journal of Lightwave Technology*, 2021

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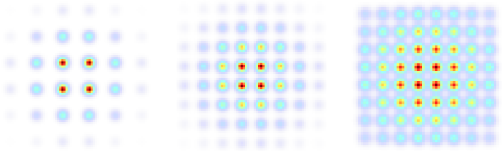
Motivation

- Great demand for **blind** equalizers
  - \+ saved data rate can increase FEC overhead or data throughput
  - ϟ have to be flexible and adaptive
  - ϟ must support higher-order modulation formats and probabilistic constellation shaping (PCS)



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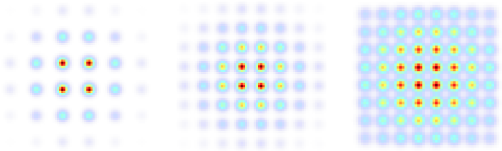

- **State-of-the-art**: Constant modulus algorithm (CMA) / multi modulus algorithm (MMA) **[Yan02]**
  - CMA: ill-matched for higher-order modulation formats and probabilistic shaping
  - MMA: high implementation complexity and low convergence rate

[Yan02] J. Yang *et al.*, "The multimodulus blind equalization and its generalized algorithms," *IEEE J. Sel. Areas. Commun.* **20**(5), pp. 997ff (2002).
[GW92] M. Ghosh and C. L. Weber, "Maximum-likelihood blind equalization," *Optical Engineering* **31**(6), pp. 1224–1229 (1992).

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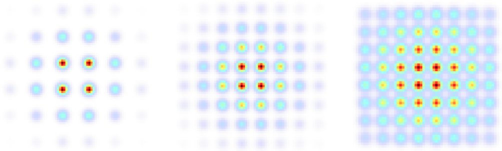

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  - CMA: ill-matched for higher-order modulation formats and probabilistic shaping
  - MMA: high implementation complexity and low convergence rate
- **Ideally**: Maximum likelihood detector, e.g. **[GW92]**

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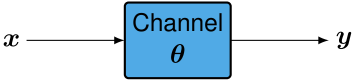
[GW92] M. Ghosh and C. L. Weber, "Maximum-likelihood blind equalization," *Optical Engineering* **31**(6), pp. 1224–1229 (1992).

System and Problem Description



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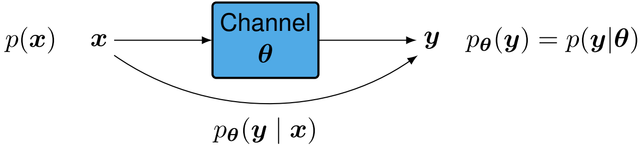

Goal: $$\hat{\boldsymbol{\theta}}_{\mathrm{ML}} = \arg\max_{\boldsymbol{\theta}} \; p_{\boldsymbol{\theta}}(\boldsymbol{y})$$

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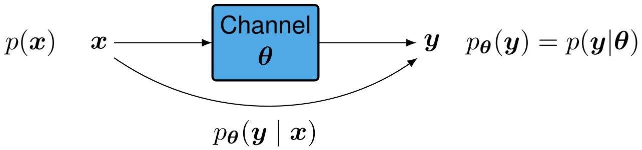
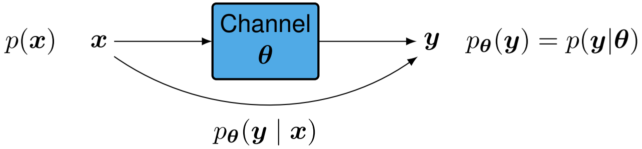


Goal: $\hat{\boldsymbol{\theta}}_{\mathrm{ML}} = \arg\max_{\boldsymbol{\theta}} \; p_{\boldsymbol{\theta}}(\boldsymbol{y})$

Given: $p(\boldsymbol{x})$, $\quad p_{\boldsymbol{\theta}}(\boldsymbol{y} \mid \boldsymbol{x}) = \mathcal{CN}\left(\boldsymbol{h} * \boldsymbol{x},\, \sigma_{\mathrm{w}}^2 \boldsymbol{I}_N\right)$

System and Problem Description



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Problem: $p_{\boldsymbol{\theta}}(\boldsymbol{y}) = \sum_{\boldsymbol{x}} p(\boldsymbol{x})\, p_{\boldsymbol{\theta}}(\boldsymbol{y} \mid \boldsymbol{x})$ $\rightarrow$ intractable

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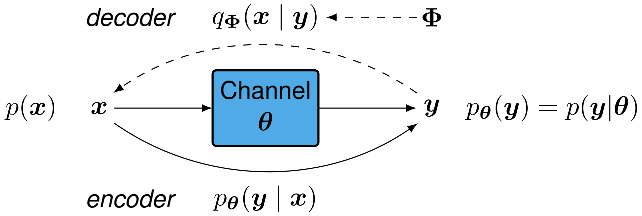

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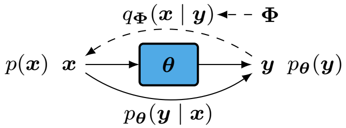
Problem: $p_{\boldsymbol{\theta}}(\boldsymbol{y}) = \sum_{\boldsymbol{x}} p(\boldsymbol{x})\, p_{\boldsymbol{\theta}}(\boldsymbol{y} \mid \boldsymbol{x}) \quad \rightarrow$ intractable

- **Idea**: use variational inference to approximate (intractable) ML problem **[CB18]**

[CB18] A. Caciularu and D. Burshtein, “Blind channel equalization using variational autoencoders,” *Proc. IEEE ICC*, Kansas City, USA, 2018.

Variational Inference via VAE Paradigm (1)



- **ML criterion**: $\hat{\theta} = \arg\max_{\boldsymbol{\theta}} \ p_{\theta}(\boldsymbol{y}) = \arg\max_{\boldsymbol{\theta}} \ \ln p_{\theta}(\boldsymbol{y})$

$$\ln p_{\boldsymbol{\theta}}(\boldsymbol{y}) = \ldots = \underbrace{\sum_{\boldsymbol{x}} q_{\boldsymbol{\Phi}}(\boldsymbol{x} \mid \boldsymbol{y}) \cdot \ln \frac{p_{\boldsymbol{\theta}}(\boldsymbol{x}, \boldsymbol{y})}{q_{\boldsymbol{\Phi}}(\boldsymbol{x} \mid \boldsymbol{y})}}_{=:\mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\Phi}, \boldsymbol{y})} + \underbrace{\sum_{\boldsymbol{x}} q_{\boldsymbol{\Phi}}(\boldsymbol{x} \mid \boldsymbol{y}) \cdot \ln \frac{q_{\boldsymbol{\Phi}}(\boldsymbol{x} \mid \boldsymbol{y})}{p_{\boldsymbol{\theta}}(\boldsymbol{x} \mid \boldsymbol{y})}}_{=\mathrm{D}_{\mathrm{KL}}(q_{\boldsymbol{\Phi}}(\boldsymbol{x}|\boldsymbol{y}) \| p_{\boldsymbol{\theta}}(\boldsymbol{x}|\boldsymbol{y}))}$$

[KW14] D. P. Kingma and M. Welling, “Auto-encoding variational Bayes,” in *Proc. ICLR*, 2014.
[BKM17] D. M. Blei, A. Kucukelbir, and J. D. McAuliffe, “Variational inference: A review for statisticians,” *J. Amer. Statist. Assoc.* **112**(518) (2017).

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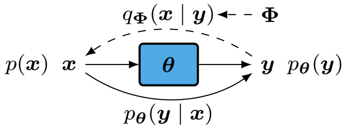

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- Kullback-Leibler divergence $\mathrm{D}_{\mathsf{KL}}(q_{\boldsymbol{\Phi}}(\boldsymbol{x} \mid \boldsymbol{y}) \| p_{\boldsymbol{\theta}}(\boldsymbol{x} \mid \boldsymbol{y})) \;\geq\; 0$
  - $\Rightarrow$ Evidence lower bound (**ELBO**): $\mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\Phi}, \boldsymbol{y})$

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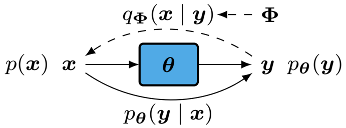

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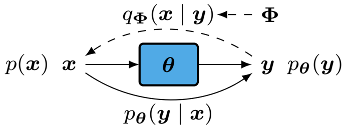
  $\Rightarrow$ Evidence lower bound (**ELBO**): $\mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\Phi}, \boldsymbol{y})$

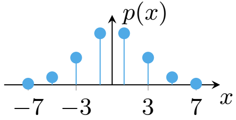
- **Optimization**: $\mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\Phi}, \boldsymbol{y}) \uparrow \;\; \Rightarrow \;\; \mathrm{D}_{\mathsf{KL}}(q_{\boldsymbol{\Phi}}(\boldsymbol{x} \mid \boldsymbol{y}) \| p_{\boldsymbol{\theta}}(\boldsymbol{x} \mid \boldsymbol{y})) \to 0$

[KW14] D. P. Kingma and M. Welling, “Auto-encoding variational Bayes,” in *Proc. ICLR*, 2014.
[BKM17] D. M. Blei, A. Kucukelbir, and J. D. McAuliffe, “Variational inference: A review for statisticians,” *J. Amer. Statist. Assoc.* **112**(518) (2017).

Variational Inference via VAE Paradigm (2)

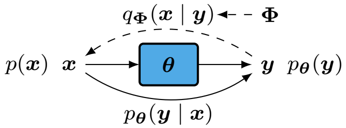


$$\mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\Phi}, \boldsymbol{y}) = B(\boldsymbol{h}, \boldsymbol{\Phi}, \boldsymbol{y}) - A(\boldsymbol{\Phi}, \boldsymbol{y})$$



- $A(\boldsymbol{\Phi}, \boldsymbol{y}) = \mathrm{D}_{\mathrm{KL}}(q_{\boldsymbol{\Phi}}(\boldsymbol{x} \mid \boldsymbol{y}) \| p(\boldsymbol{x}))$
  - *Tries to shape* $q_{\boldsymbol{\Phi}}(\boldsymbol{x} \mid \boldsymbol{y})$ *similar to* $p(\boldsymbol{x})$

Variational Inference via VAE Paradigm (2)



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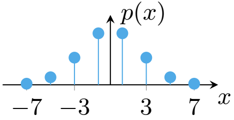

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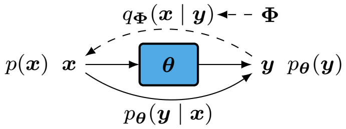
  - *Tries to shape* $q_{\boldsymbol{\Phi}}(\boldsymbol{x} \mid \boldsymbol{y})$ *similar to* $p(\boldsymbol{x})$
- $B(\boldsymbol{h}, \boldsymbol{\Phi}, \boldsymbol{y})$
  - *Matches equalizer output to received symbols*

Variational Inference via VAE Paradigm (2)



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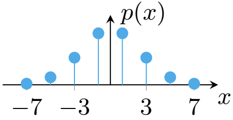

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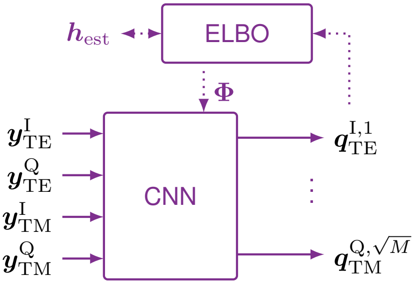
  - *Tries to shape* $q_{\boldsymbol{\Phi}}(\boldsymbol{x} \mid \boldsymbol{y})$ *similar to* $p(\boldsymbol{x})$
- $B(\boldsymbol{h}, \boldsymbol{\Phi}, \boldsymbol{y})$
  - *Matches equalizer output to received symbols*

$\Rightarrow$ **Blind approach**: requires only $p(\boldsymbol{x})$, not $\boldsymbol{x}$

$\Rightarrow$ $q_{\boldsymbol{\Phi}}(\boldsymbol{x} \mid \boldsymbol{y})$ can be used in conjunction with Soft-FEC

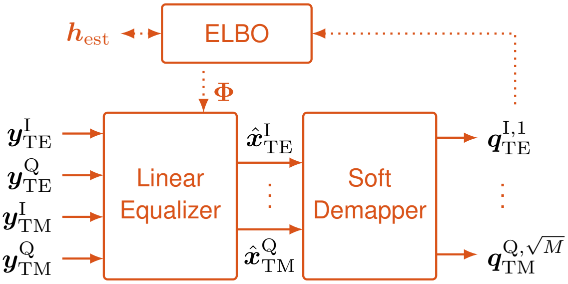
VAE Equalizer – Neural Network (VAE-NN)



- Convolutional Neural Network (CNN) has two tasks: equalization *and* demapping
- Outputs $q_{\boldsymbol{\Phi}}(\boldsymbol{x} \mid \boldsymbol{y})$
- Potentially capable of compensating non-linearities

[CB18] A. Caciularu and D. Burshtein, “Blind channel equalization using variational autoencoders,” *Proc. IEEE ICC*, Kansas City, USA (2018).

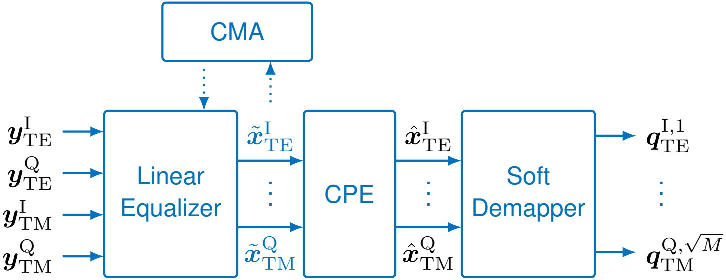
VAE Equalizer – Linear Equalizer (VAE-LE)



- Equalization and demapping are split
- Classical butterfly structure with FIR filters
- Outputs estimated symbols and soft demapper computes $q_{\boldsymbol{\Phi}}(\boldsymbol{x} \mid \boldsymbol{y})$
- Targets compensation of linear impairments

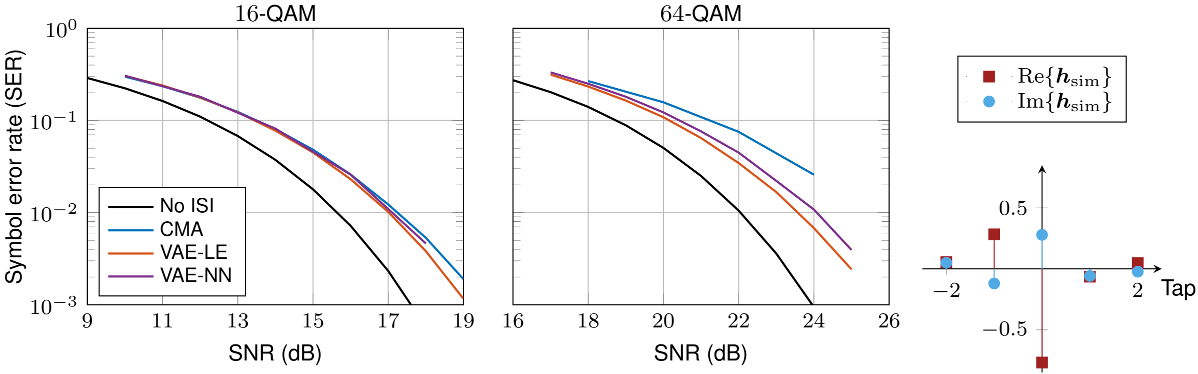
[LBS21] V. Lauinger, F. Buchali, L. S., “Blind equalization for coherent optical communications based on variational inference,” *Proc. Adv. Photon. Congr., SPPCOM*, Jul. 2021

Reference: CMA-based Equalizer



- **State-of-the-art** blind adaptive equalizer in optical comm.
- Carrier Phase Estimation (CPE) required (e.g. Viterbi-Viterbi algorithm)
- Targets compensation of linear impairments

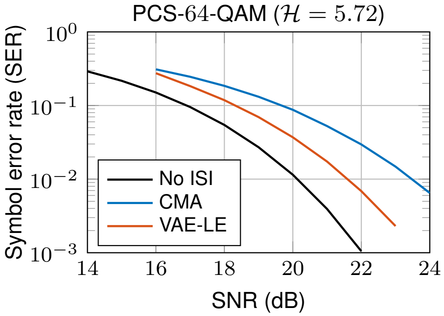
Simulation Results: Conventional QAM

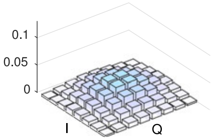


- Single polarization
- 2 samples per symbol
- Batch-wise update with Adam optimizer

[LBS21] V. Lauinger, F. Buchali, L. S., “Blind equalization for coherent optical communications based on variational inference,” *Proc. Adv. Photon. Congr., SPPCOM*, Jul. 2021

Simulation Results: PCS-QAM





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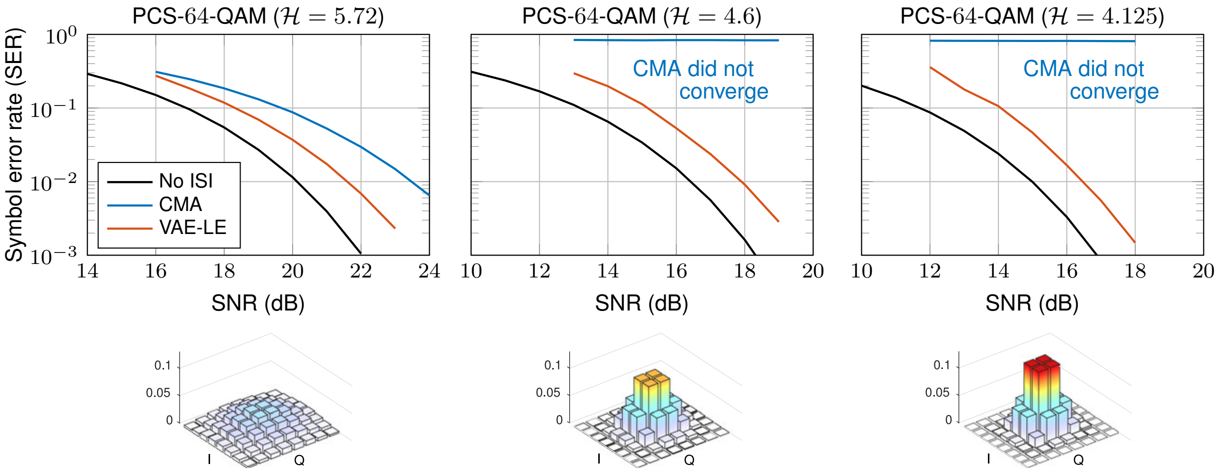

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Overview

- Introduction
- Application 1: Waveform Optimization for Short-Reach Optical Communications
  - Simple Transmitter Using Feed-Forward Neural Networks
  - Improved Transceivers Using Reccurent Neural Networks
- Application 2: Distance-agnostic Transceivers
- Application 3: In-Situ Optimization of Transmitters
- Application 4: Blind Equalization Using Variational Autoencoders
- Conclusions and Outlook

Conclusion and Outlook

- Neural networks are and will be **integral part** of optical communication systems
- Machine learning enables design of **novel waveforms and modulation formats**
- Machine learning enables **novel applications** that are difficult with traditional approaches, e.g. distance agnostic transceivers
- Generative networks can be used to **model** (part of) the communication system for model-based optimization
- Powerful tools from the machine learning community can be used to design **novel receiver algorithms**

FIN

Karlsruher Institut für Technologie

Questions?

GEFÖRDERT VOM

Bundesministerium für Bildung und Forschung

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Established by the European Commission

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