Machine Learning in Photonics

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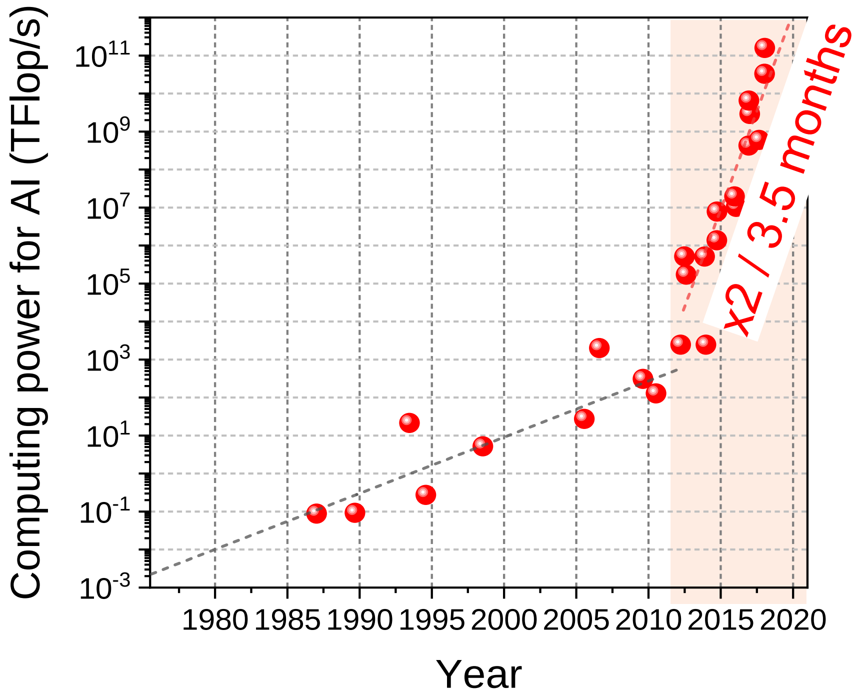
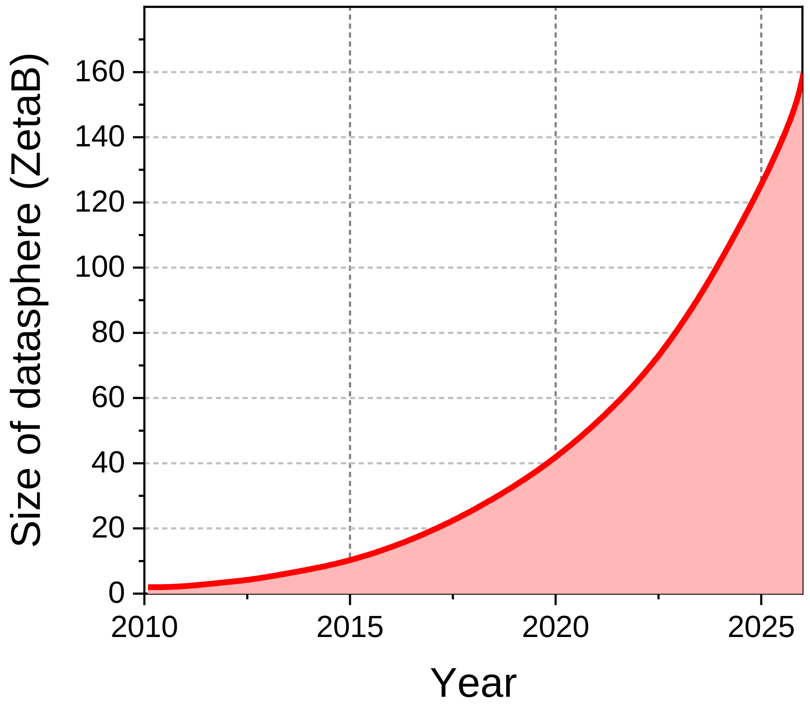
Why machine learning now?

Increase in computing power supports ML growth



Decades of training data available



We now have the **computing power** and **datasets** to train our models.

*OpenAI project
**IDC's Data age 2025 study

Where does machine learning excel?

Learning complex **direct** mappings:

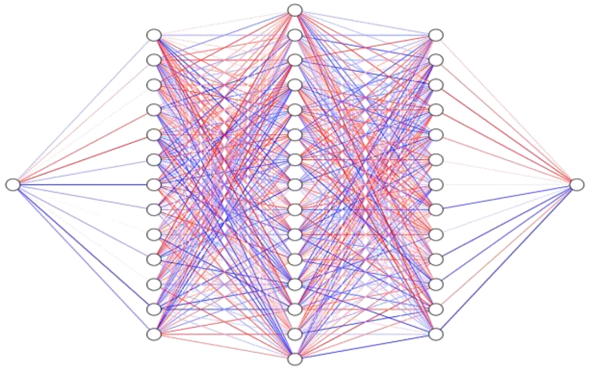
$$X \rightarrow \boxed{f(\cdot)} \rightarrow Y$$

Learning complex **inverse** mappings:

$$Y \rightarrow \boxed{f^{-1}(\cdot)} \rightarrow X$$

Learning **decision rules** for complex mappings:

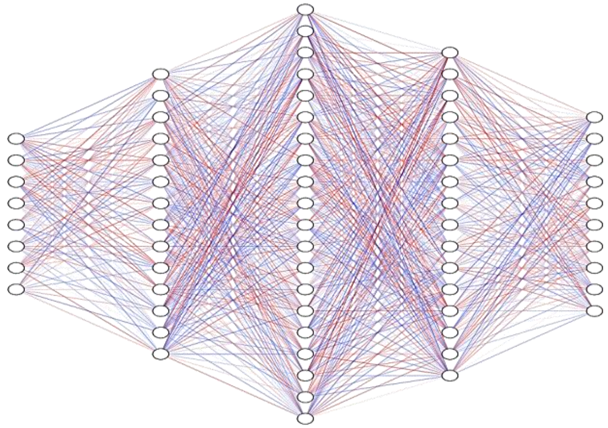
$$X \rightarrow \boxed{f(\cdot)} \rightarrow P(Y = 1|X)$$



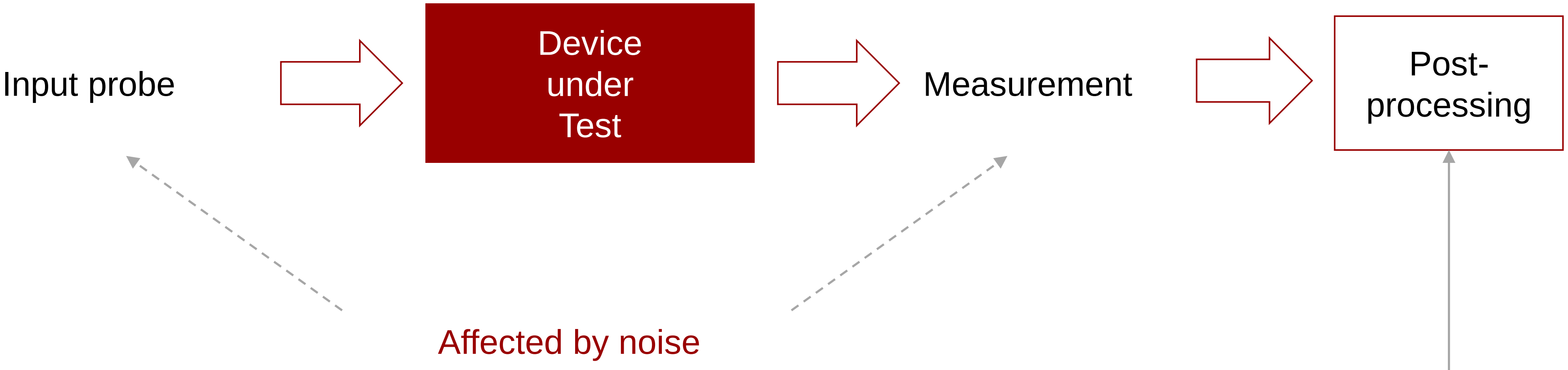
Use neural networks to learn $f(\cdot)$ and $f^{-1}(\cdot)$

Machine learning in photonics

- Enhancing measurement accuracy
  - Bayesian filter for reducing measurement noise
- Inverse system design
  - Optimizing Raman amplifiers
- End-to-end learning and equalization for communication systems
  - Autoencoders for joint transmitter-receiver optimization

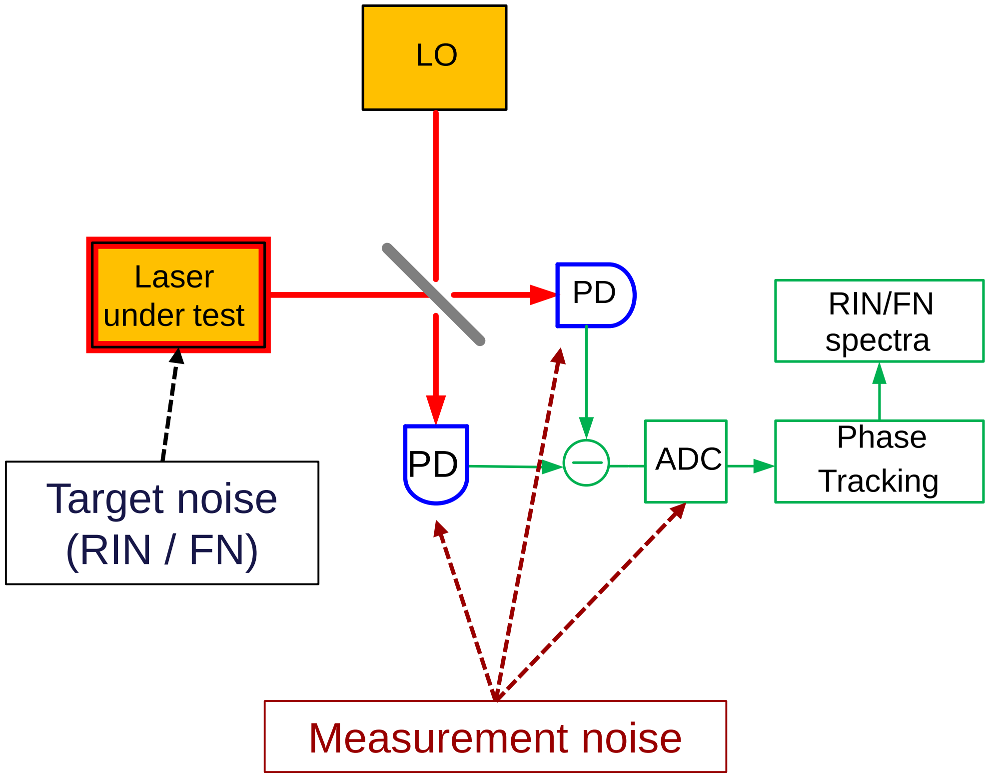


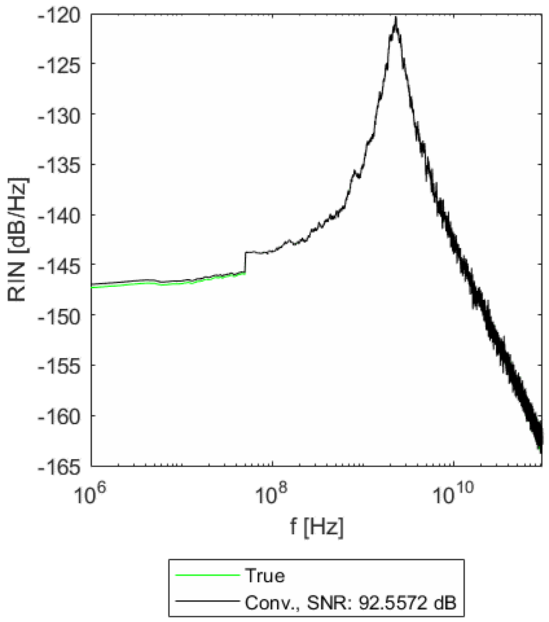
Characterization of photonic components

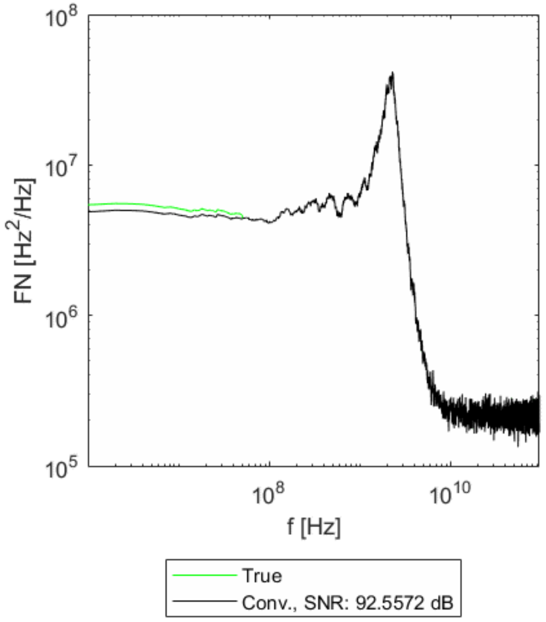


- Thorough calibration of measurement systems → not always easy
- Advance post-processing of the measurements

Characterization of laser noise

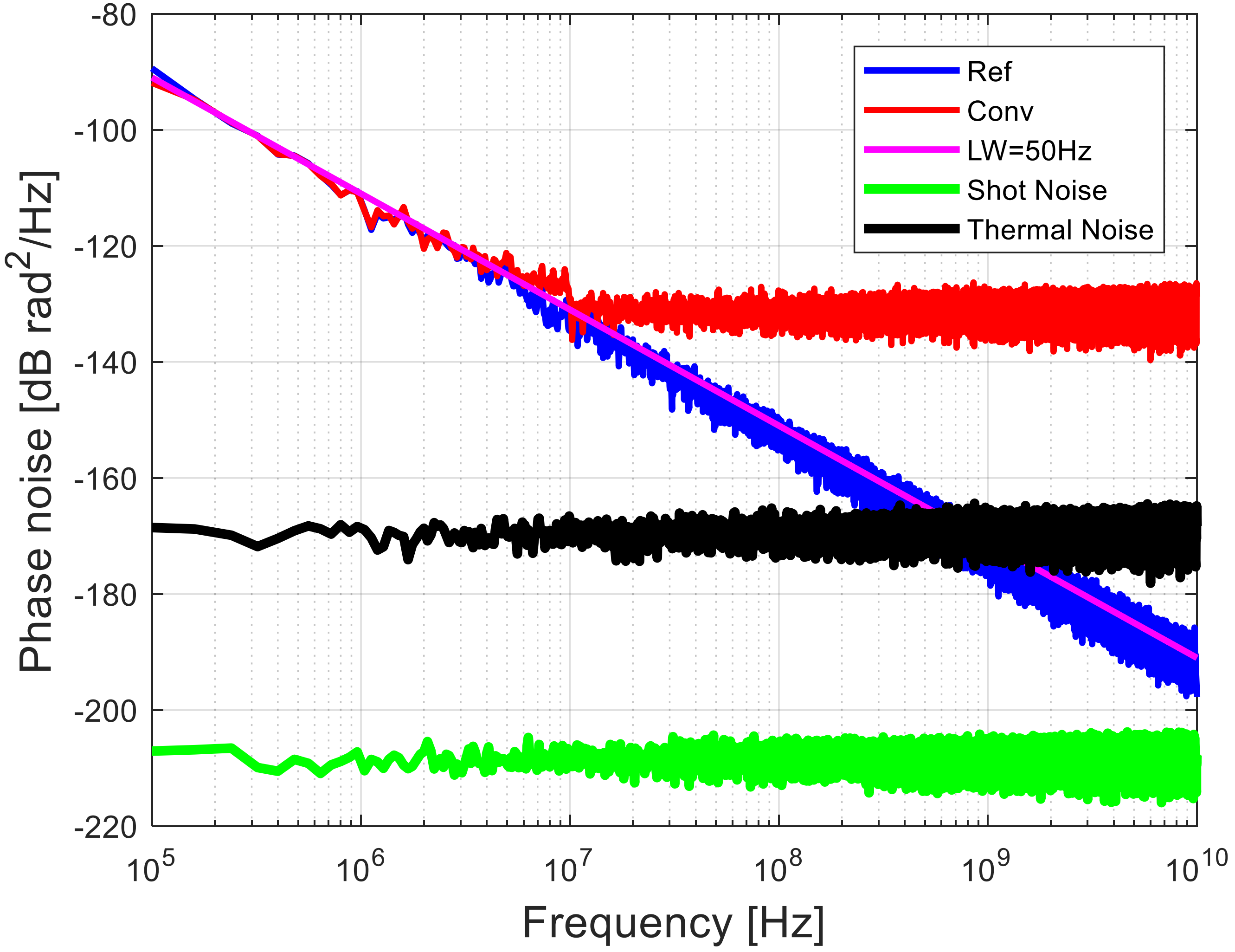


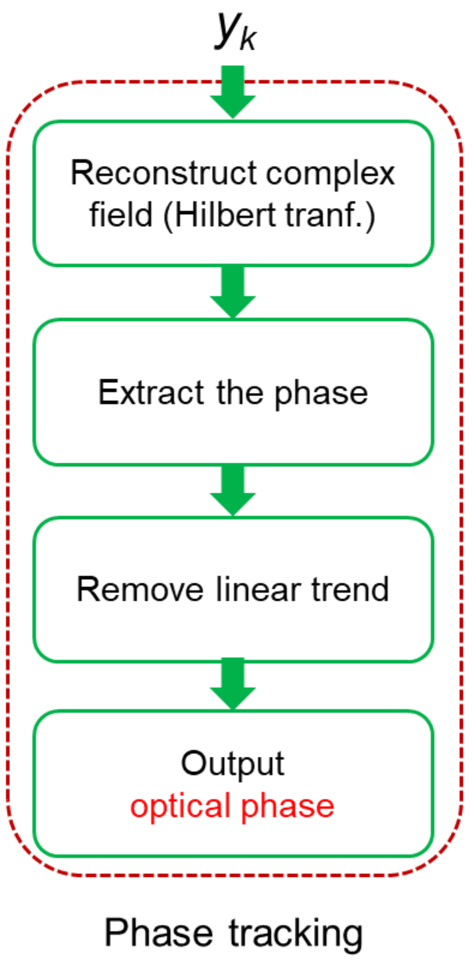




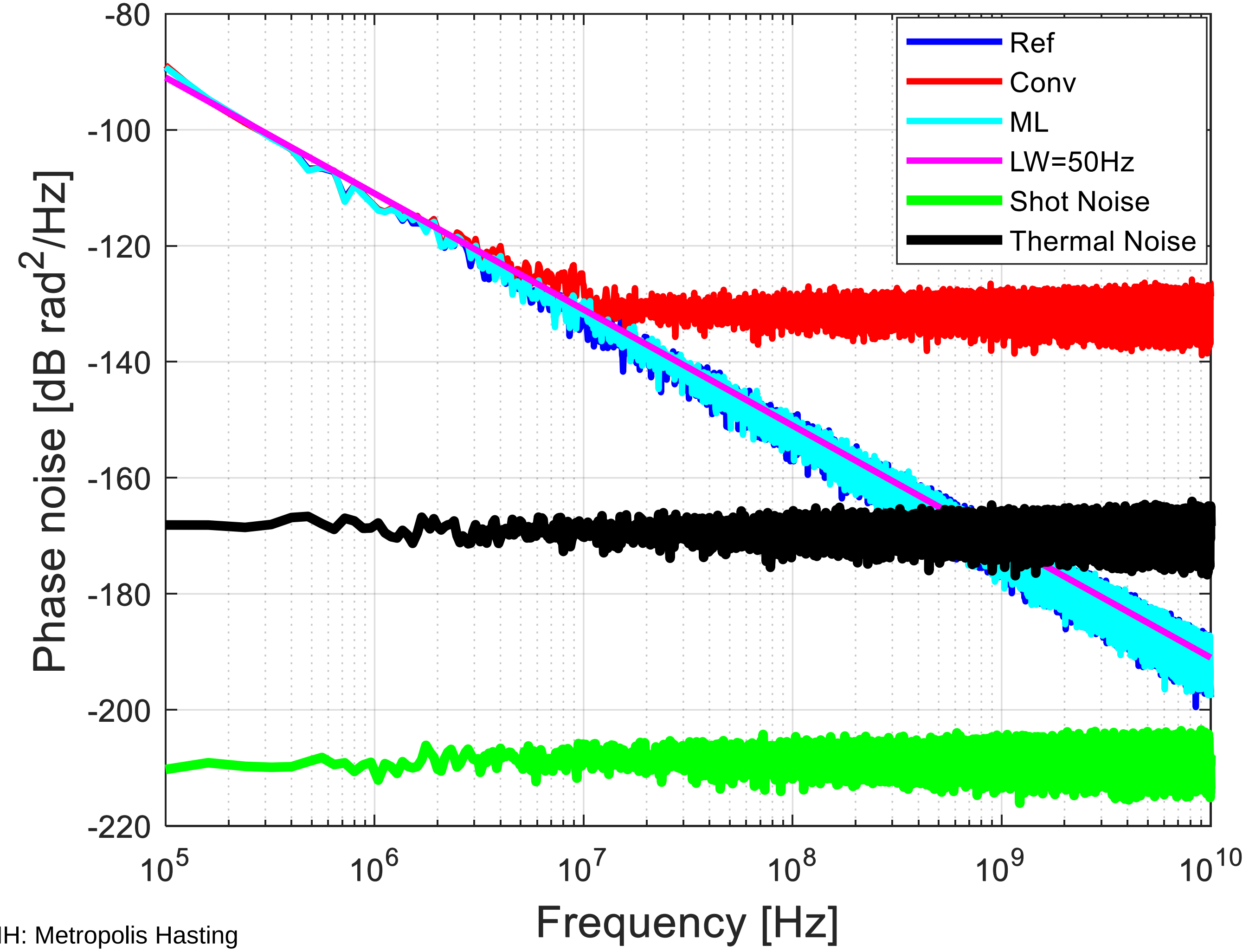
RIN: relative intensity noise, FN: frequency noise, PD: photodetector, ADC: analog-to-digital converter

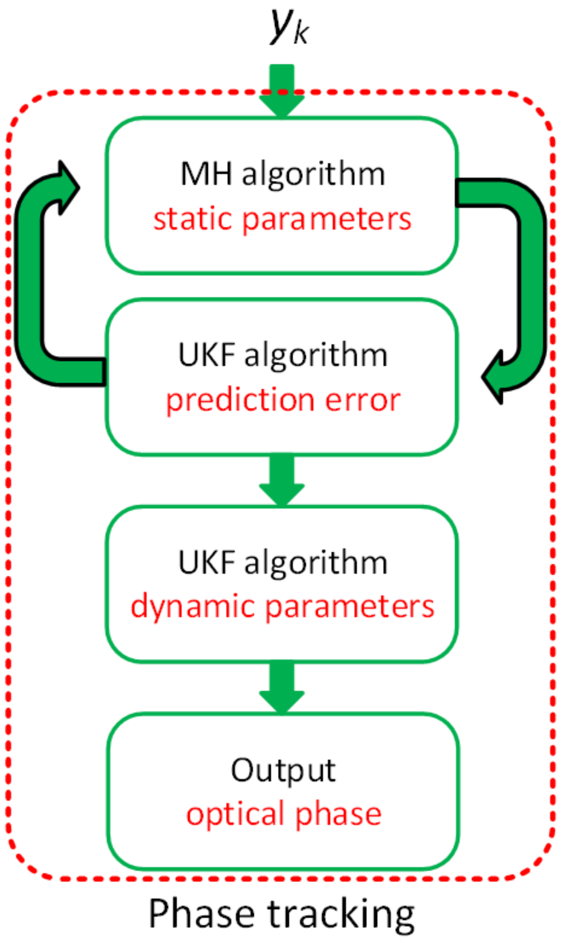
Conventional heterodyne phase measurement





Bayesian filtering framework





<u>State-space model</u>

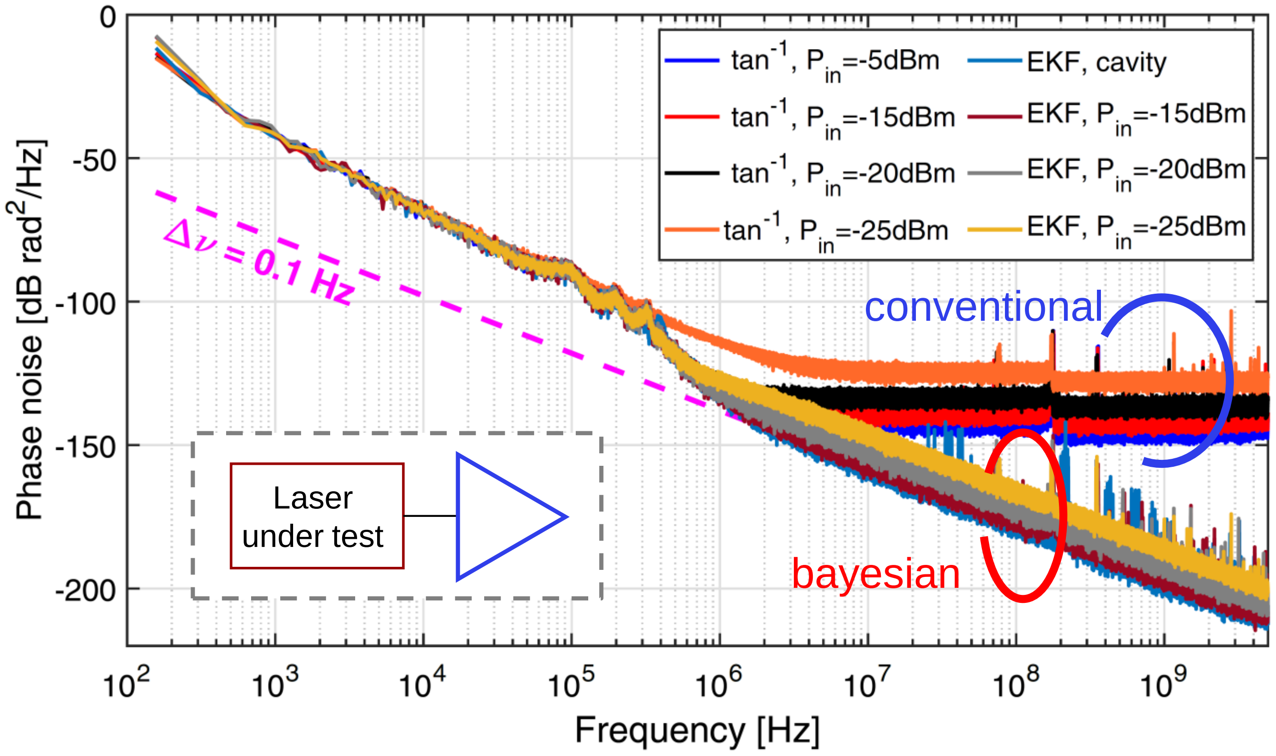
$$\phi_k = \phi_{k-1} + \boxed{q_k^\phi}$$

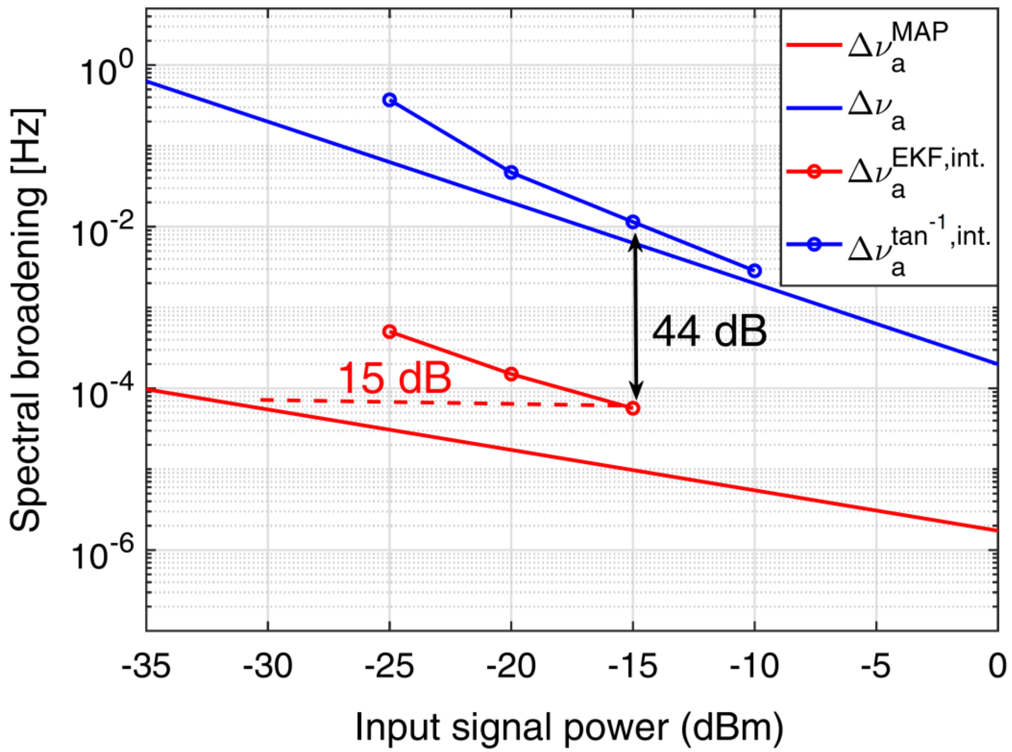
$$y_k^i = A\cos(\Delta\omega k T_s + \phi_k) + \boxed{r_k}$$

MH: Metropolis Hasting
UKF: unscented Kalman filtering

D. Zibar, PTL 2019

Impact of amplification on laser phase noise



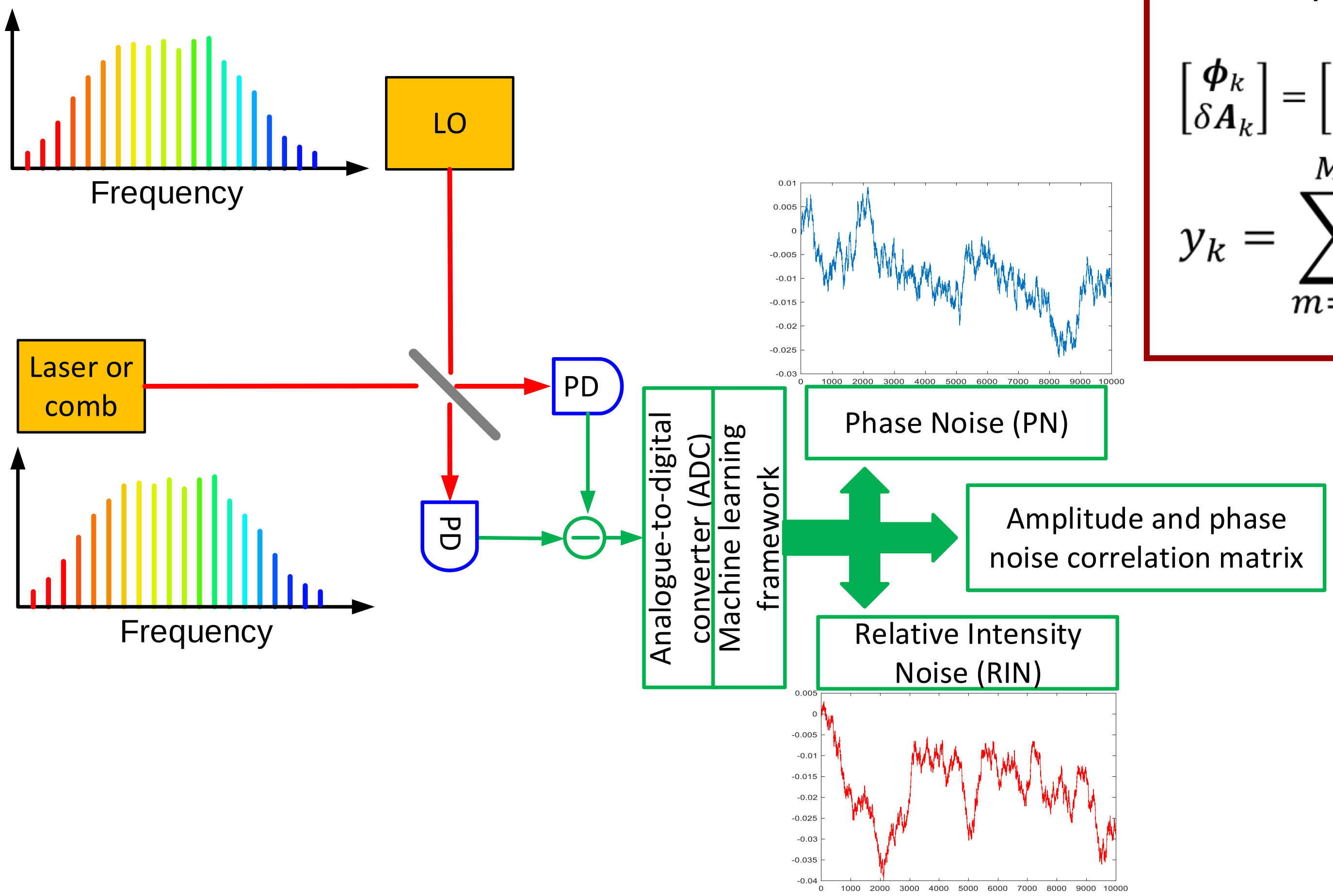


Bayesian filtering allows to approach a MAP phase detector, minimizing the impact of amplification noise.

D. Zibar, Optica 2021

MAP: maximum a posteriori

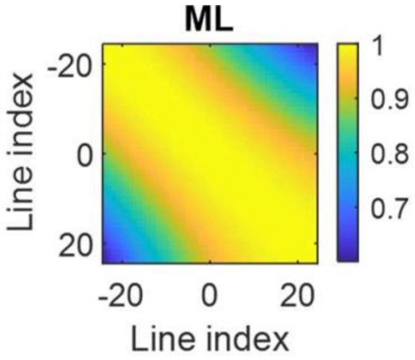
Extension of the framework



State-space model

$$\begin{bmatrix}\boldsymbol{\phi}_k\\ \delta \boldsymbol{A}_k\end{bmatrix} = \begin{bmatrix}\boldsymbol{\phi}_{k-1}\\ \delta \boldsymbol{A}_{k-1}\end{bmatrix} + \boldsymbol{q}_{k-1}, \qquad \text{with } \boldsymbol{q}_{k-1} \sim \mathcal{N}(0, \mathbf{Q}) \text{ ,} \mathbf{Q} = \begin{bmatrix}\mathbf{Q}_{\phi} & \mathbf{Q}_{\phi A}\\ \mathbf{Q}_{A\phi} & \mathbf{Q}_{A}\end{bmatrix}$$

$$y_k = \sum_{m=1}^{M} \bar{A}^m (1 + \delta A_k^m) \cos(\Delta\omega_m k T_S + \phi_k^m) + n_k$$



Extending the state-space model, amplitude and phase noise can be jointly estimated over all comb lines

G. Brajato, Opt. Expr. 2020

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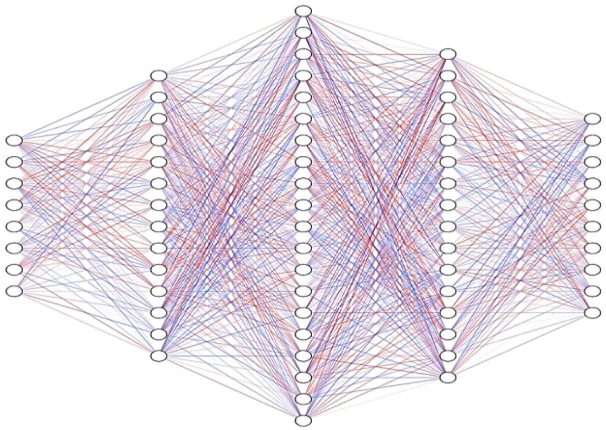


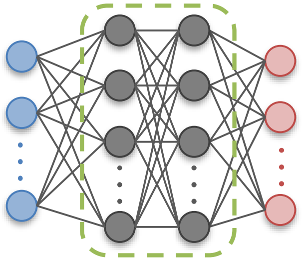
Direct and inverse models of photonic subsystems

$f(\mathbf{X}) = \mathbf{Y}$

Input parameters ($\mathbf{X}$) → Subsystem → System output ($\mathbf{Y}$)

Direct mapping

Input $\mathbf{X}$ →

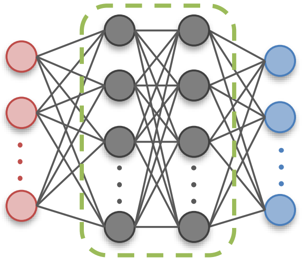


→ **Predicted $\mathbf{Y}$**

$f(\mathbf{X}) = \mathbf{Y}$

Inverse mapping

Target $\mathbf{Y}$ →



→ **Predicted $\mathbf{X}$**

$f^{-1}(\mathbf{Y}) = \mathbf{X}$

Why using NN models?

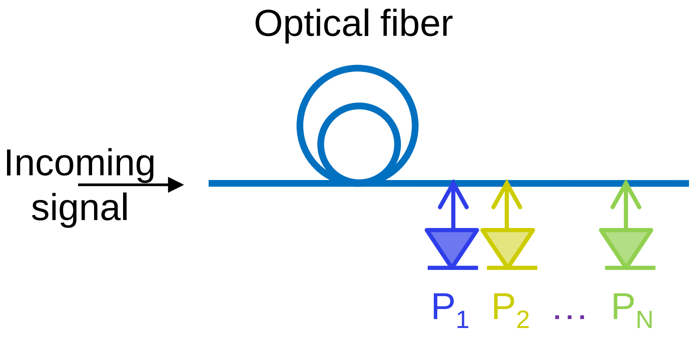
$$f(\mathbf{X}) = \mathbf{Y}$$

Input parameters ($\mathbf{X}$) → Subsystem → Output ($\mathbf{Y}$)

- Sometimes the physical system has an accurate representation but that is difficult to model efficiently
- Sometimes the physical system is too complex to have an accurate representation
- Neural networks can be trained directly from experimental data
- Neural networks are differentiable → take gradient through them and optimize efficiently

If simple and accurate analytical models exist, NNs are an overkill!

The Raman amplifiers example



Well-defined but computationally demanding

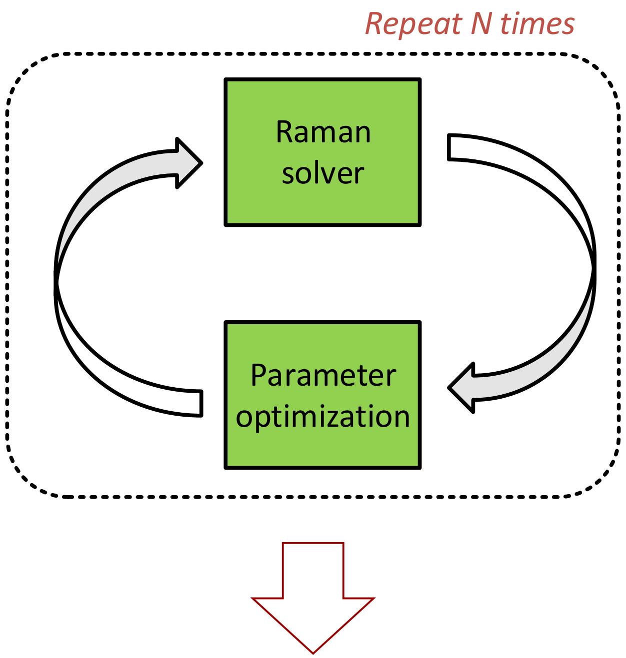
Theoretical model:

$$\frac{dP_s}{dz} = -\alpha_s P_s + C_R(\lambda_s, \lambda_p)\left[P_p^+ + P_p^-\right] P_s \quad (1)$$

$$\pm\frac{dP_p^\pm}{dz} = -\alpha_p P_p^\pm - \left(\frac{\lambda_s}{\lambda_p}\right) C_R(\lambda_s, \lambda_p)\, P_s\, P_p^\pm \quad (2)$$

$$\pm\frac{dP_A^\pm}{dz} = -\alpha_A P_A^\pm + C_R(\lambda_A, \lambda_p) P_p P_A^\pm + C_R(\lambda_A, \lambda_p)[1 + \eta(T)] h\nu_A B_{ref} P_p \quad (3)$$

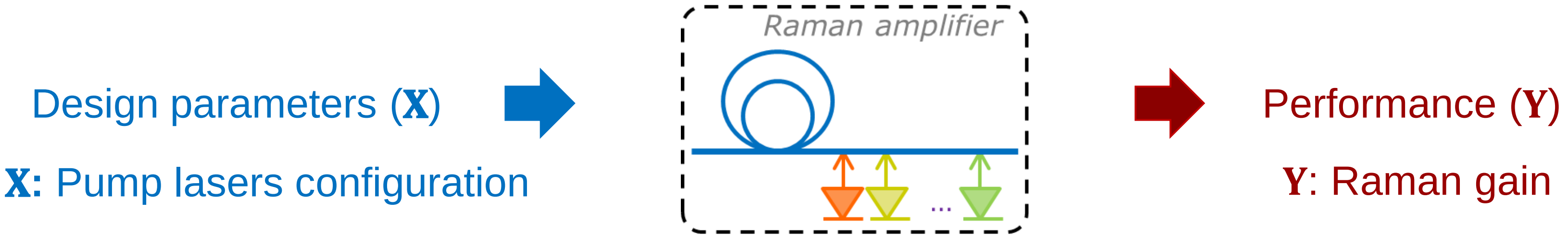
Conventional optimization methods

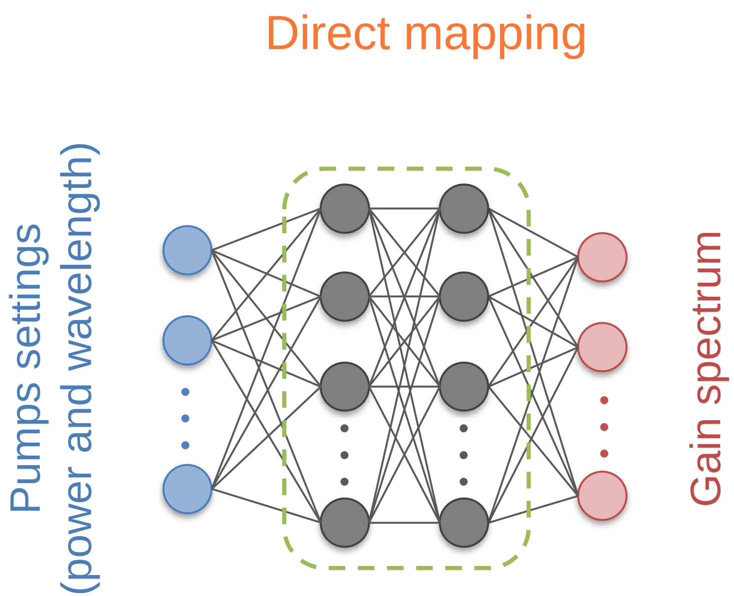


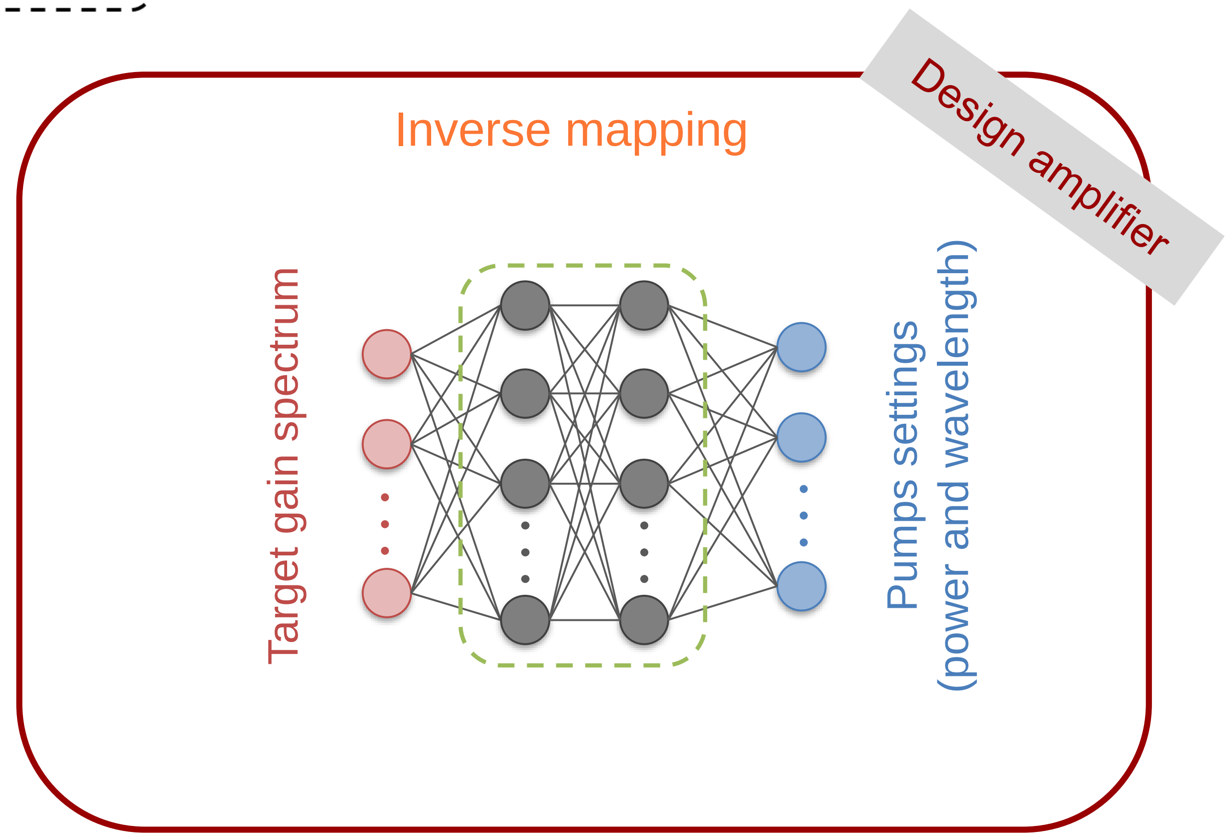
- Rather long convergence time
- Restart optimization for new target gain

Inverse design of Raman amplifiers

$f(\mathbf{X}) = \mathbf{Y}$



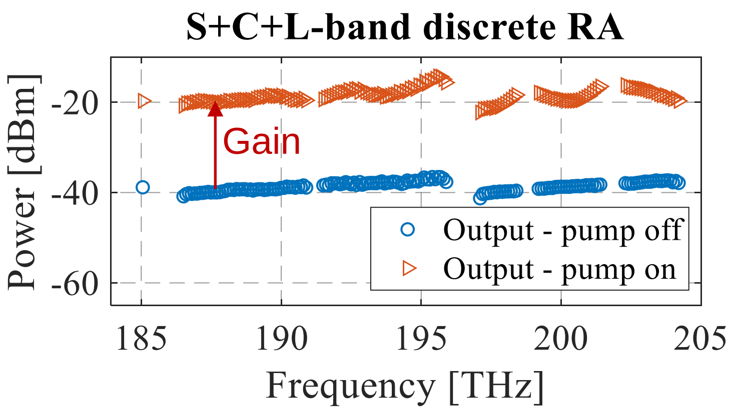


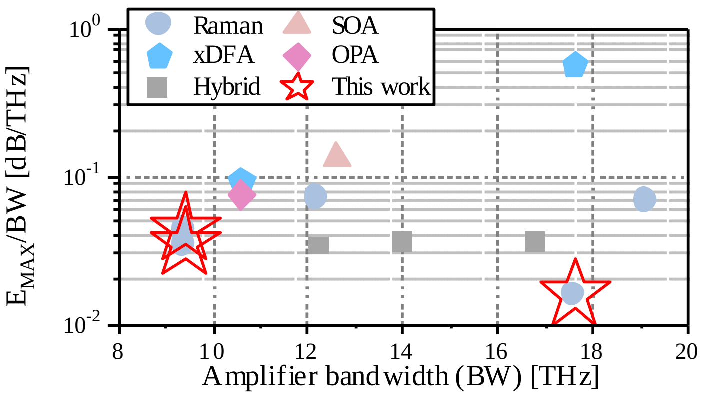


D. Zibar OFC 2019, M1J.1, D.. Zibar, JLT, vol. 38, no. 4, 2019, U. de Moura, OFC 2020, T4B.2.

Experimental data-driven Raman models

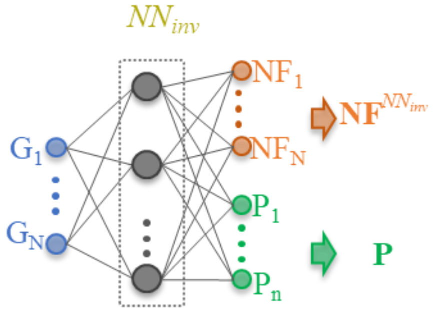
Highly-accurate gain-programmable Raman amplifier covering > 17 THz of bandwidth

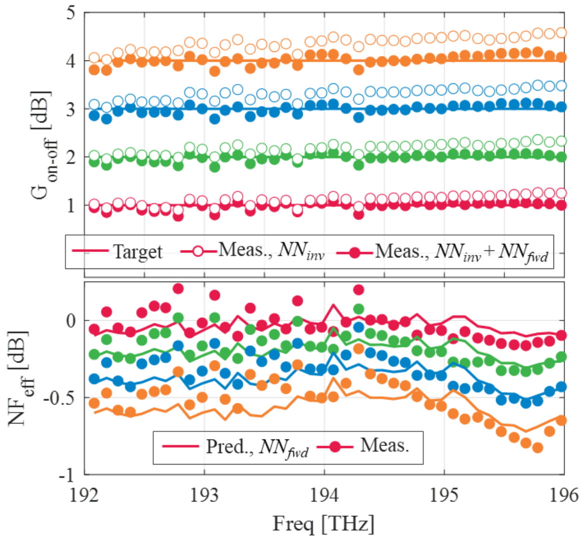




U.C. de Moura JLT 2021

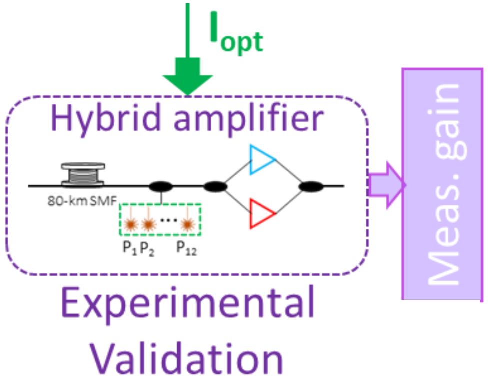
Simultaneous amplifier design and noise figure prediction

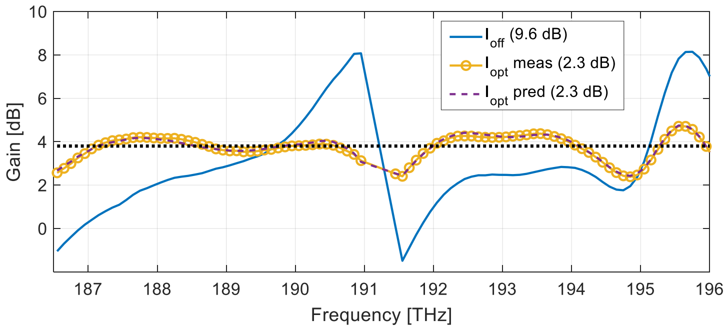




U.C. de Moura OL 2021

Replacing GFFs with Raman pre-amplification





GFF: gain flattening filter

F. Da Ros OFC 2021

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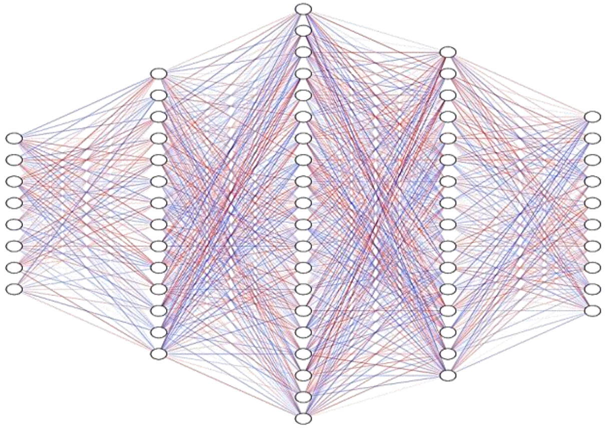
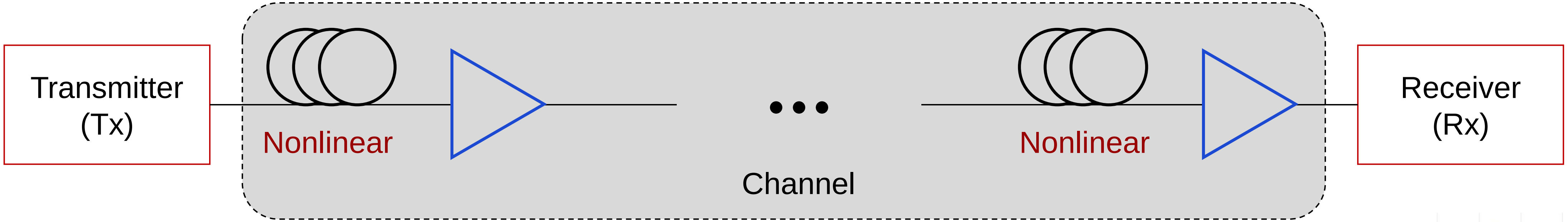
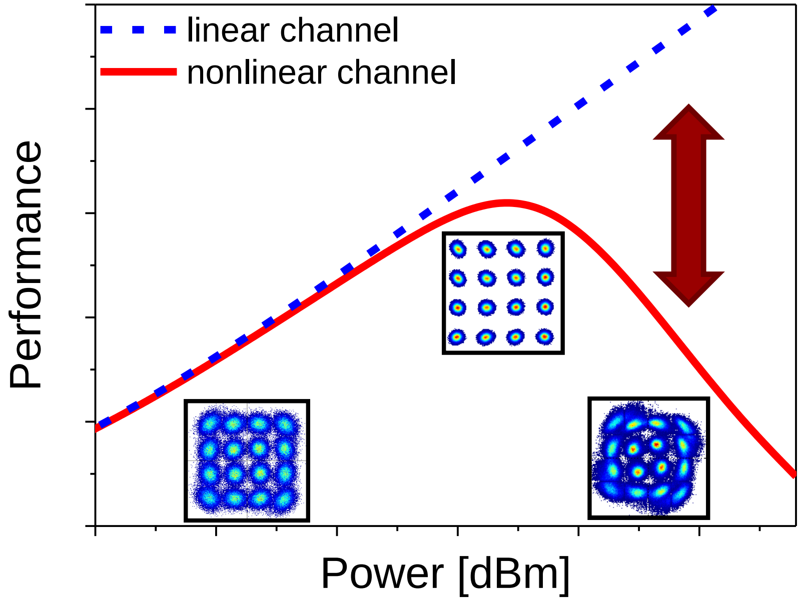
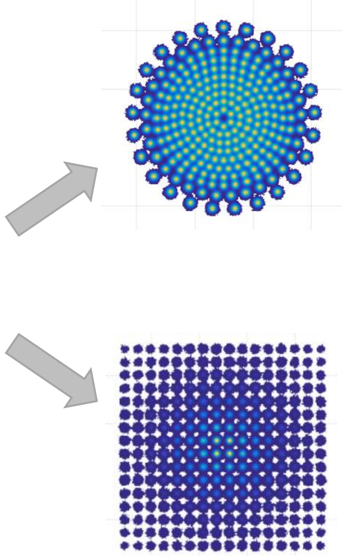


Communication systems





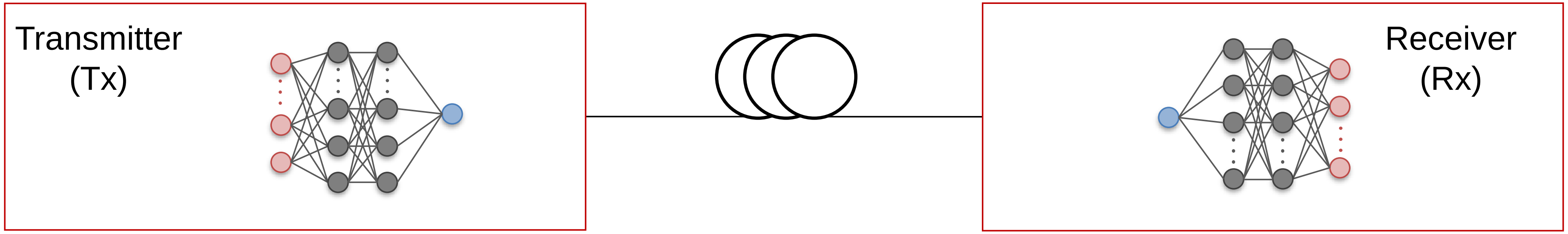
Constellation shaping



Improve the information rate by optimizing the signalling scheme for the desired channel.

Full system (end-to-end) learning

Autoencoder



Encoder

Generate a signal robust to channel impairments

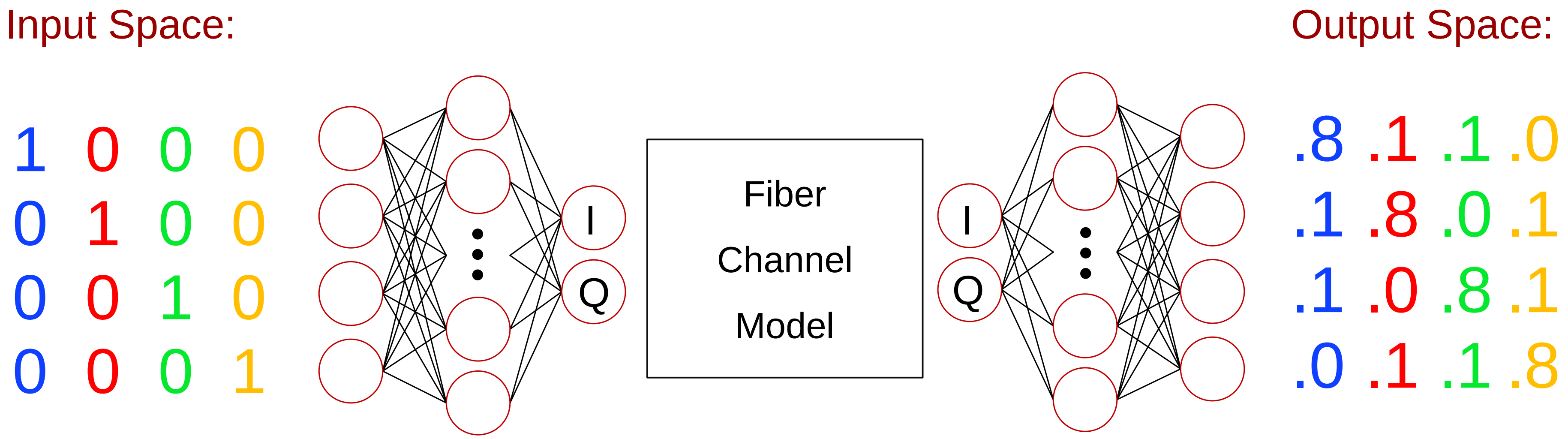
Decoder

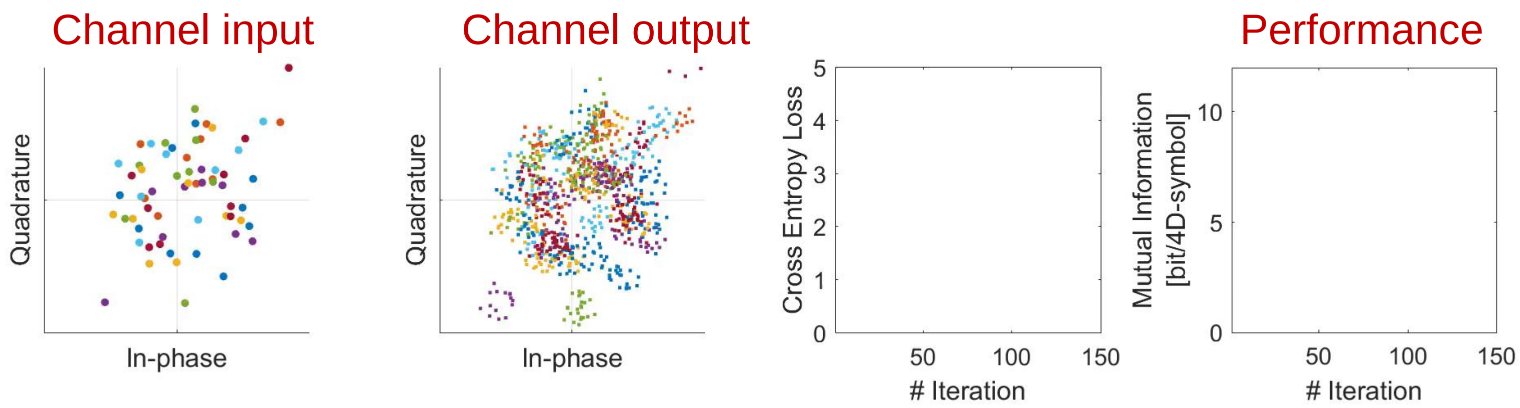
Reconstruct the original signal from the received data with high fidelity

Replace (part of) Tx and Rx and learn the optimum signalling scheme by jointly optimizing encoder and decoder

T. O'Shea, Trans. on Cognitive Comm. and Networking, 2017

Autoencoders for end-to-end learning

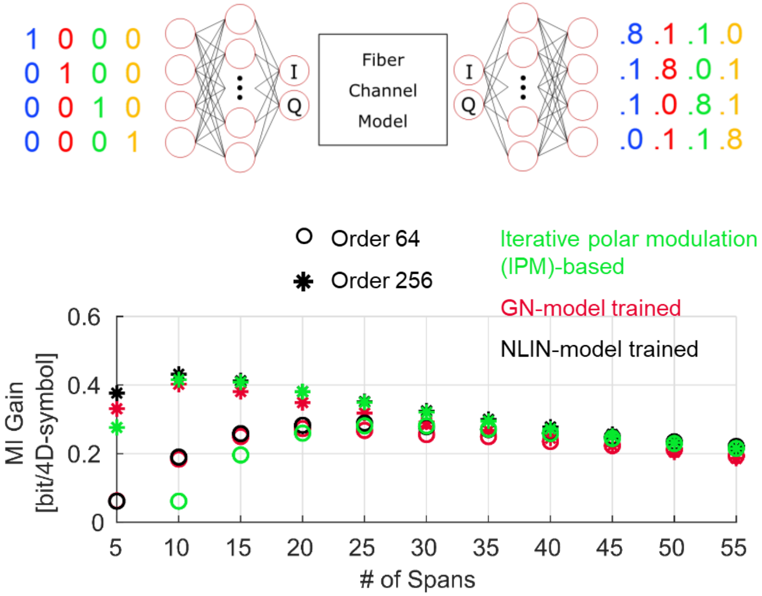




R. T. Jones, ECOC 2018

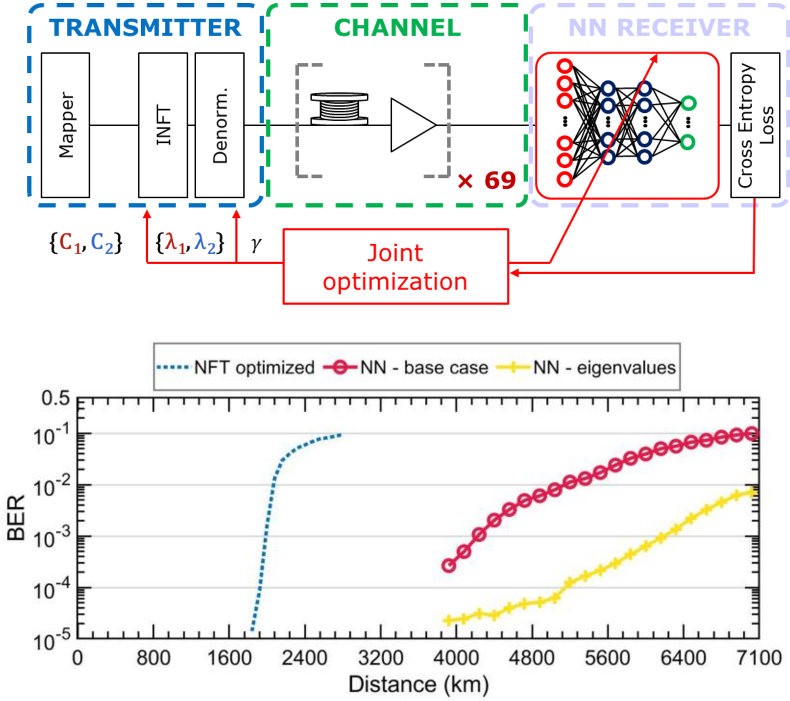
Symbol-based constellation shaping

Shaping trained over **NLIN** and **GN** fiber model



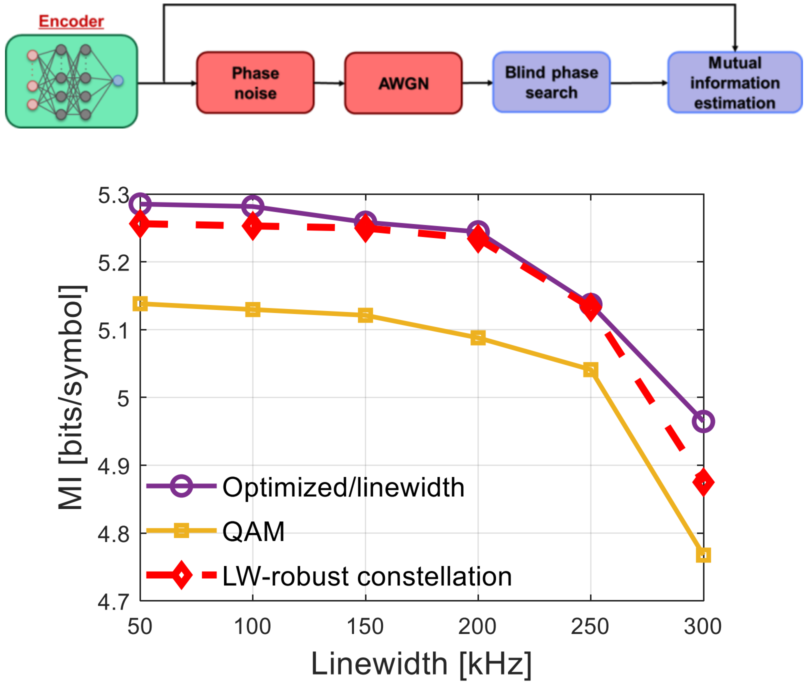
NLIN: nonlinear interference noise
GN: Gaussian noise
R. T. Jones, ECOC 2018

Shaping for NFDM-based transmission over **SSFM** channel



NFDM: nonlinear frequency division multiplexing
SSFM: split-step Fourier method
S. Gaiairin, JLT 2020

Shaping **robust** to system uncertainties, enabling **interoperability**



LW: linewidth
RPN: residual phase noise
O. Jovanovic, ECOC 2021

Conclusions and outlook

MENTOR
{Machine LEarning in optical NeTwORks}

- The **Machine learning** toolbox brings significant advantages to **optics**

- Machine learning is effective in **learning complex mappings**
  - Improve measurements' accuracy
  - Design/optimization of optical components (amplifiers, photonic chips, etc.)
  - Enhance communication over the fiber-optic channel

- A lot of room for interesting research problems

Understanding both **machine learning** and **optics** is required to advance the field.

Acknowledgements

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Questions?

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