Machine learning for Raman amplifier design and quantum phase estimation

Darko Zibar

1. Machine learning in photonic systems (M-LiPS) group, DTU Fotonik, Technical University of Denmark, DK-2800, Kgs. Lyngby

email: dazi@fotonik.dtu.dk

DTU Fotonik
Department of Photonics Engineering

Acknowledgements

-Francesco Da Ros
-Simone Gaiarin
-Hou-Man Chin
-Molly Piels, Juniper
-Tobias Gehring, DTU Physics
-Nitin Jain, DTU Physics
-Ulrik L. Andersen, DTU Physics
-Andrea Carena, Polotecnico Di Torino
-Bernhard Schmauss, University of Erlangen-Nurnberg

-Rasmus Jones
-Julio Diniz
-Martin Djurhuss
-Jakob Thrane

-Jesper Wass
-Nicola De Renzis
-Giovanni Brajato

Research topics

- Nonlinear Fourier Transform techniques for optical communication
- Noise characterization of lasers and frequency combs, (Menlo systems, UCSB, NBI)
- End-to-end machine learning
- Machine learning for optical fibre sensing (collaboration with Friedrich Alexander University of Erlangen-Nurnberg)
- Quantum phase estimation (collaboration with DTU Physics)
- Receiver design for quantum communication (collaboration with DTU Physics)

The focus of the group is on the application of machine learning techniques to optical communication, quantum communication and optical sensing

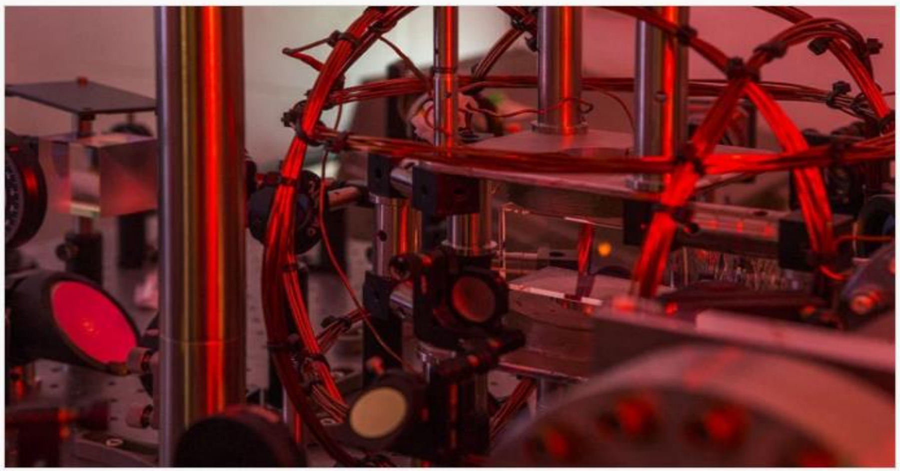
Outline

- Machine learning in physical sciences
- Inverse system learning
- Inverse system learning for Raman amplifier design
- Optical phase tracking framework for frequency combs
- Quantum phase estimation
- Conclusion and outlook

Machine learning in physical sciences

AI learns and recreates Nobel-winning experiment

Posted May 16, 2016 by Devin Coldewey



Australian physicists, perhaps searching for a way to shorten the work week, have created an AI that can run and even improve a complex physics experiment with little oversight. The research could eventually allow human scientists to focus on high-level problems and research design, leaving the nuts and bolts to a robotic lab assistant.

VIEW FROM... ECOC 2017

Machine learning under the spotlight

The field of machine learning potentially brings a new set of powerful tools to optical communications and photonics. However, to separate hype from reality it is vital that such tools are evaluated properly and used judiciously.

Darko Zibar, Henk Wymeersch and Ilya Lyubomirsky

Recently, there has been an increasing amount of research that applies machine-learning techniques to tasks in optical communication. Specific applications have varied from optoelectronic component characterization, performance prediction and system optimization, to, more recently, quantum communication. The question that remains to be answered, however, is whether the application of such schemes is simply hype with limited real impact or whether it can truly bring significant advantages with orders of magnitude improvement and reduced human involvement compared with conventional methods.

NATURE PHOTONICS | VOL 11 | DECEMBER 2017 | 745–751 | www.nature.com/naturephotonics 749

news & views

MACHINE LEARNING

New tool in the box

A recent burst of activity in applying machine learning to tackle fundamental questions in physics suggests that associated techniques may soon become as common in physics as numerical simulations or calculus.

Lenka Zdeborová

Google and Tri Alpha Energy Develop an Algorithm to Advance Nuclear Fusion Research

It's like visiting an AI optometrist, but in a nuclear research laboratory.

by Katie Fehrenbacher

July 26, 2017

Machine learning in physical sciences

CLEO

Laser Science to Photonic Applications

(/)

Technical Conference: 5 – 10 May 2019

Exhibition: 7 – 9 May 2019

San Jose Convention Center, San Jose, California, USA

HOME (/HOME/) > PROGRAM & SPEAKERS (/HOME/PROGRAM/) > SPECIAL SYMPOSIA (/HOME/PROGRAM/SPECIAL-SYMPOSIA/)

Machine Learning Photons: Where Machine Learning and Photonics Intersect

OFC

Artificial Intelligence for Data Centers Operators and Optical Network Providers - Why and When?

Organizer:
Antonio Napoli, *Infinera, Germany*; Danish Rafique, *ADVA Optical Networking, Germany*; Yawei Yin, *Alibaba Group, China*

nature photonics — REVIEW ARTICLE
https://doi.org/10.1038/s41566-018-0246-9

Inverse design in nanophotonics

Sean Molesky[1], Zin Lin[2], Alexander Y. Piggott[3], Weiliang Jin[1], Jelena Vucković[3] and Alejandro W. Rodriguez[1]*

optica

Training of photonic neural networks through *in situ* backpropagation and gradient measurement

Tyler W. Hughes,[1] Momchil Minkov,[2] Yu Shi,[2] and Shanhui Fan[2,*]

[1]*Department of Applied Physics, Stanford University, Stanford, California 94305, USA*
[2]*Ginzton Laboratory and Department of Electrical Engineering, Stanford University, Stanford, California 94305, USA*

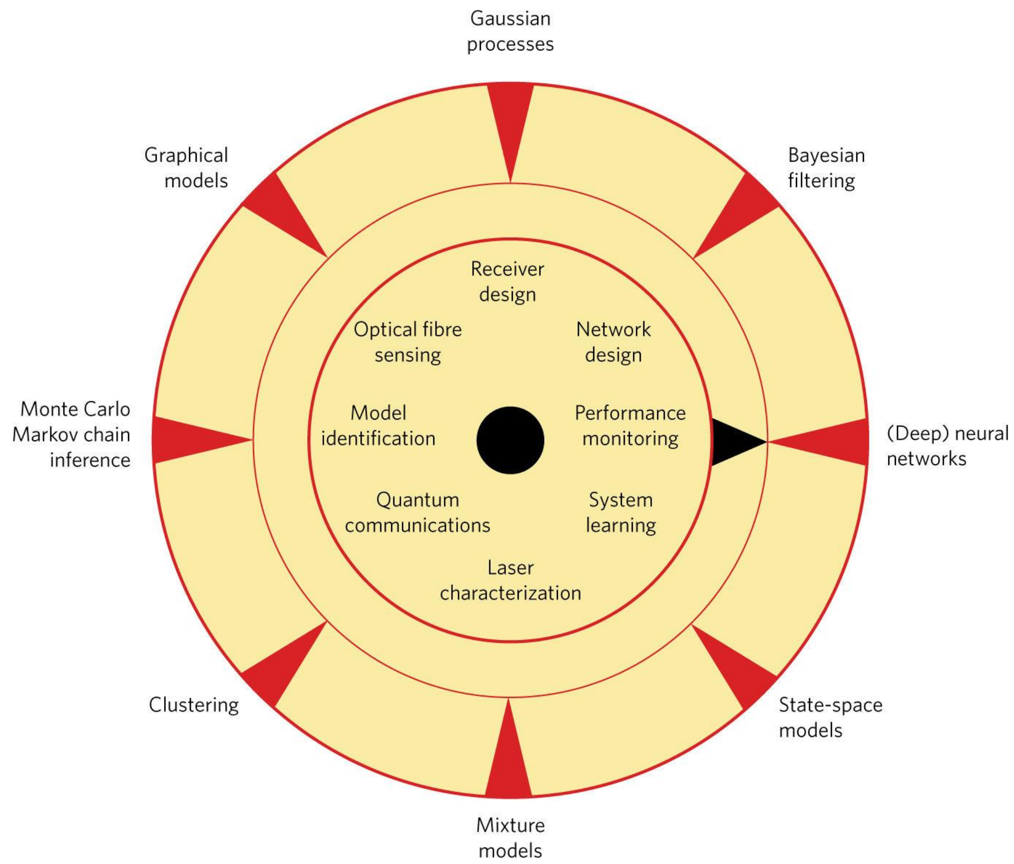
Tornatore *et al.* VOL. 10, NO. 10/OCTOBER 2018/J. OPT. COMMUN. NETW. ML1

Introduction to the JOCN Special Issue on Machine Learning and Data Analytics for Optical Communications and Networking

Massimo Tornatore, Martin Birk, Alan Pak Tao Lau, Qiong Zhang, and Darko Zibar

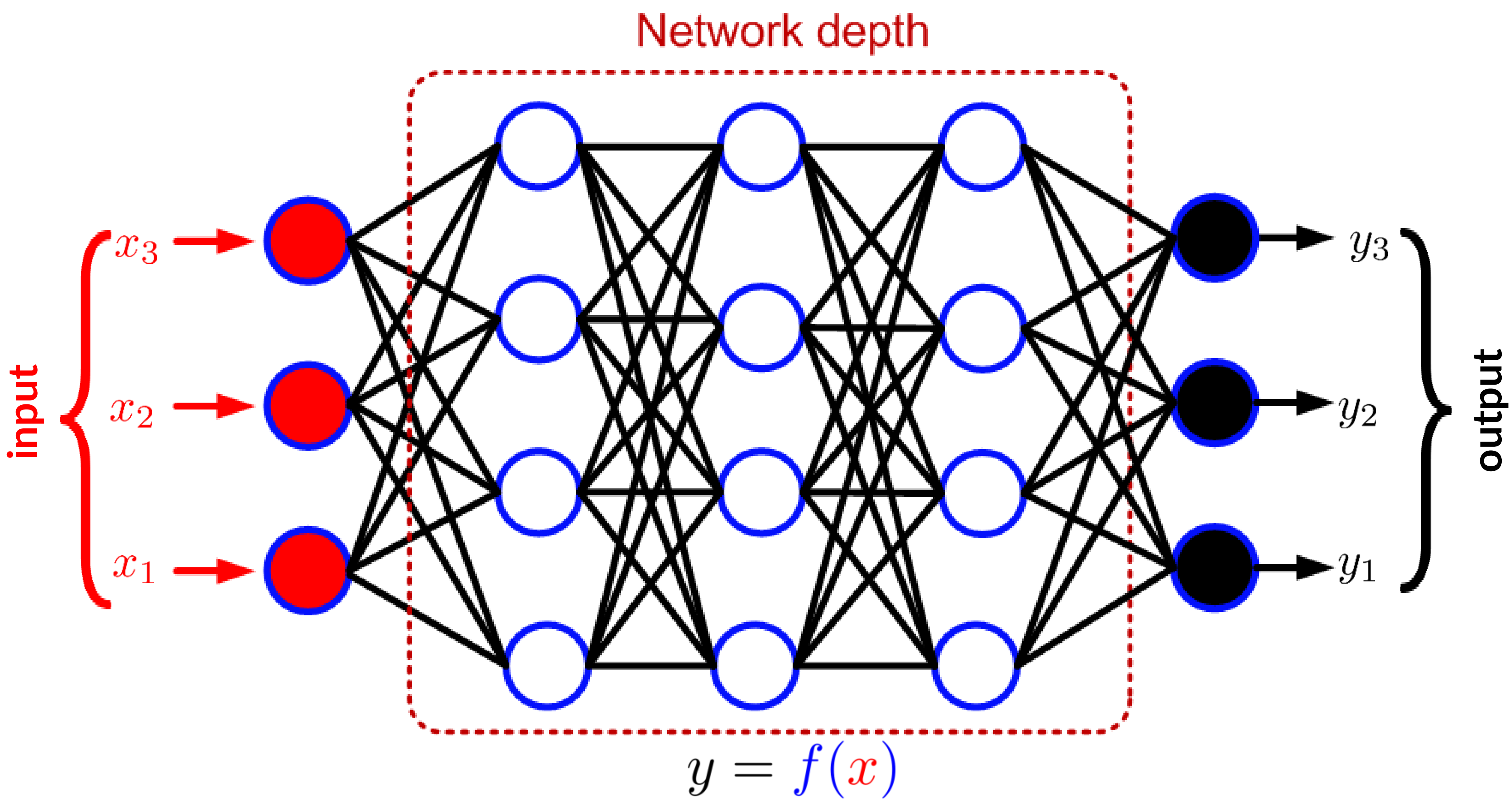
Machine learning in optical communication

- Optical performance monitoring
- Quantum communication
- Amplifier design
- Laser noise characterization
- Impairment compensation
- End-to-end learning
- Network optimization
- Network failure detection



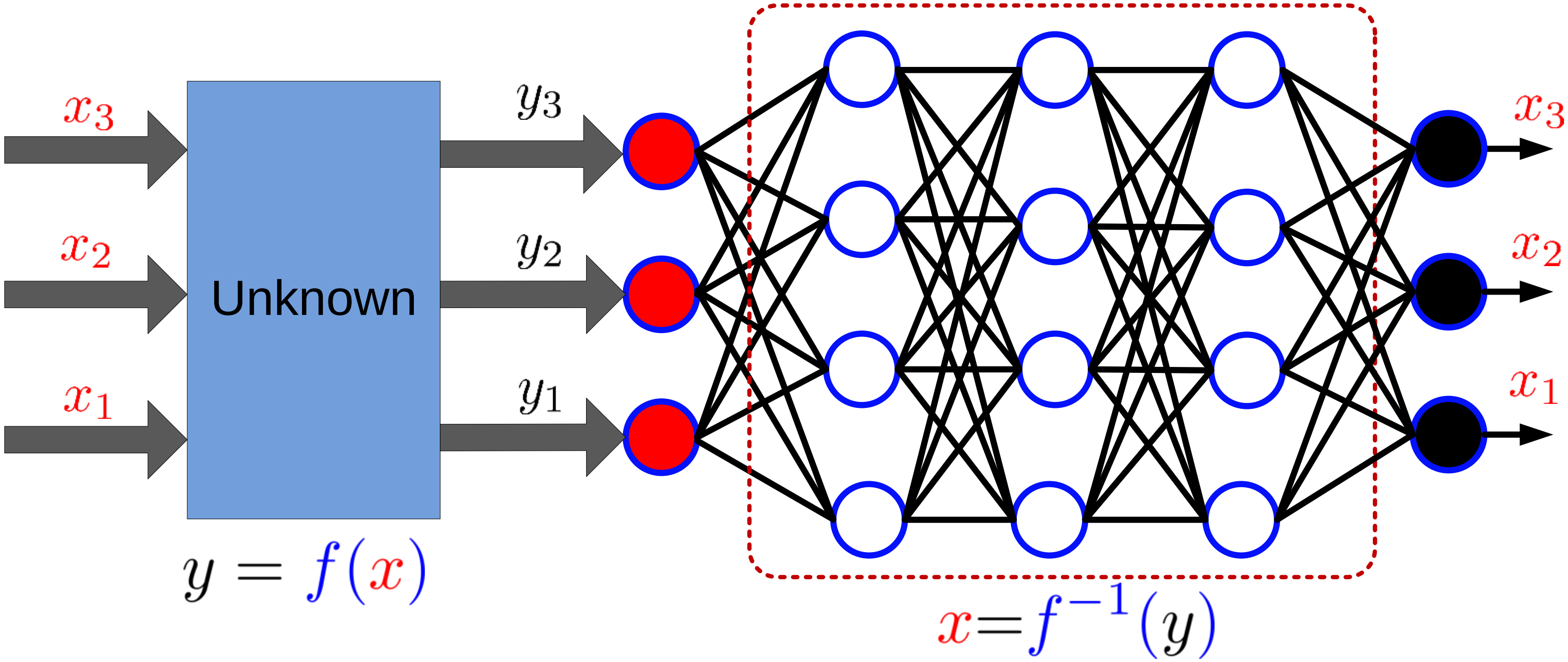
D. Zibar et al Nature Photonics, (11) 749-751, 2017

Supervised learning: deep neural networks



Neural network learns the input-output mapping, $f(\cdot)$,using training data and perform prediction for *new input* data: $y_{new} = f(x_{new})$

Deep learning for inverse system modelling



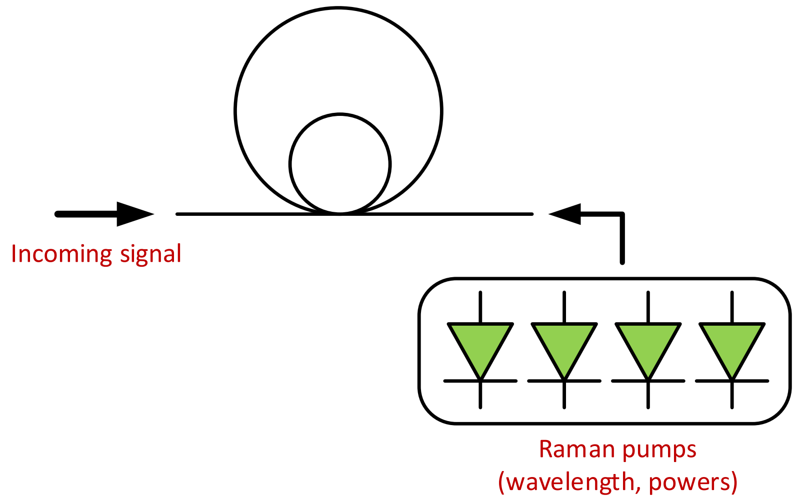
-Problem if the mapping function is not bijective

Learning the inverse mapping using deep neural networks

Raman amplifier for optical communication

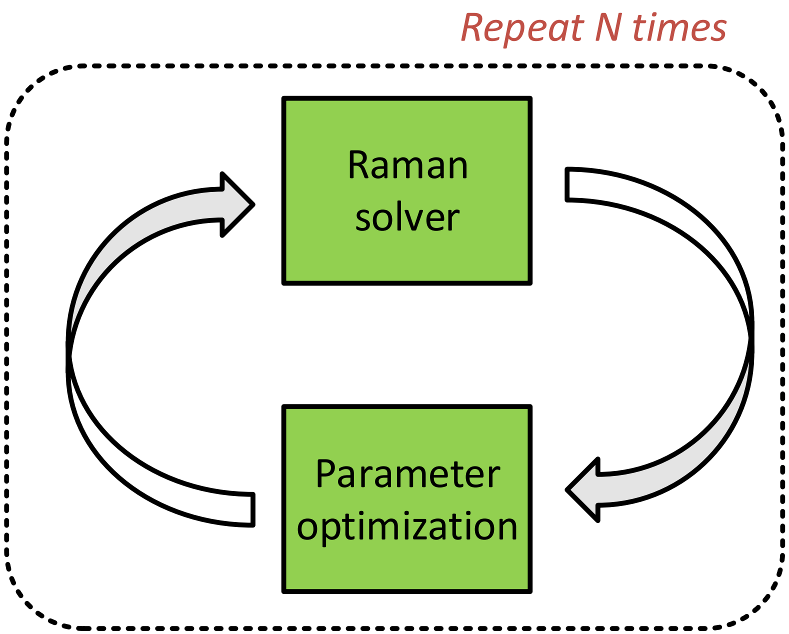
Name	O-Band	E-Band	S-Band	C-band	L-Band
Wavelength range (nm)	1260-1360	1360-1460	1460-1530	1530-1565	1565-1625
C-band system				35 nm	
C+L-band system				95 nm	
WON	365 nm				

Fig. 1: Optical wavelength bands in the low-loss window of single-mode fibres. Wideband optical networks (WON) offer more than 10× increased optical bandwidth compared to C-band systems.



Employing O, E, S and L band requires rethinking optical amplification

State-of-the-art: Raman amplifier optimization

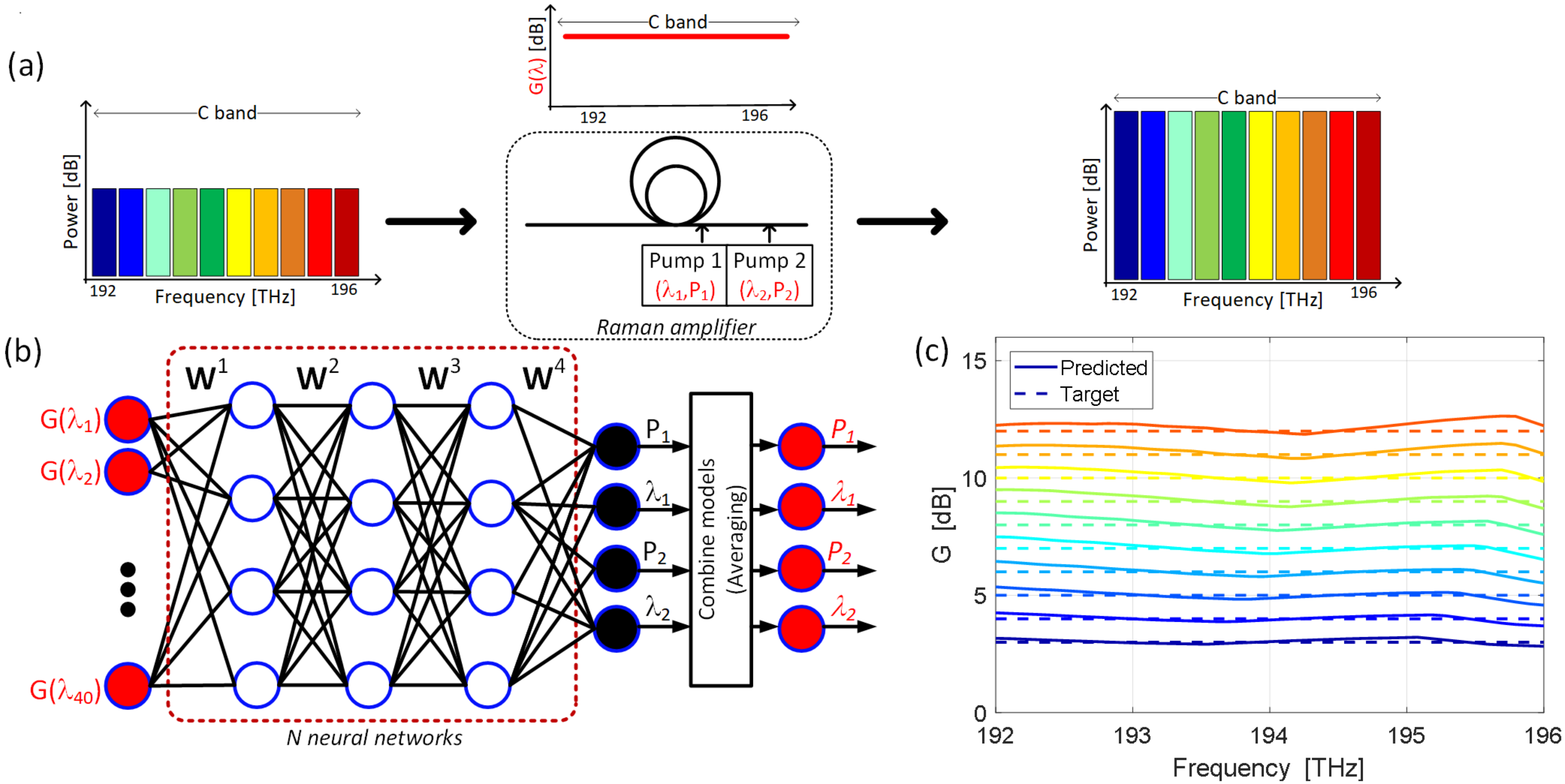


- High complexity due to Raman solver
- Long convergence time
- Restart optimization for new gain profile
- Rely on genetic algorithms

Objective: given a Raman gain profile determine pump powers and wavelengths

[1] B. Neto, OpEx 2007, [2] X. Liu, OpEx 2004, [3] P. Xia, PTL 2003

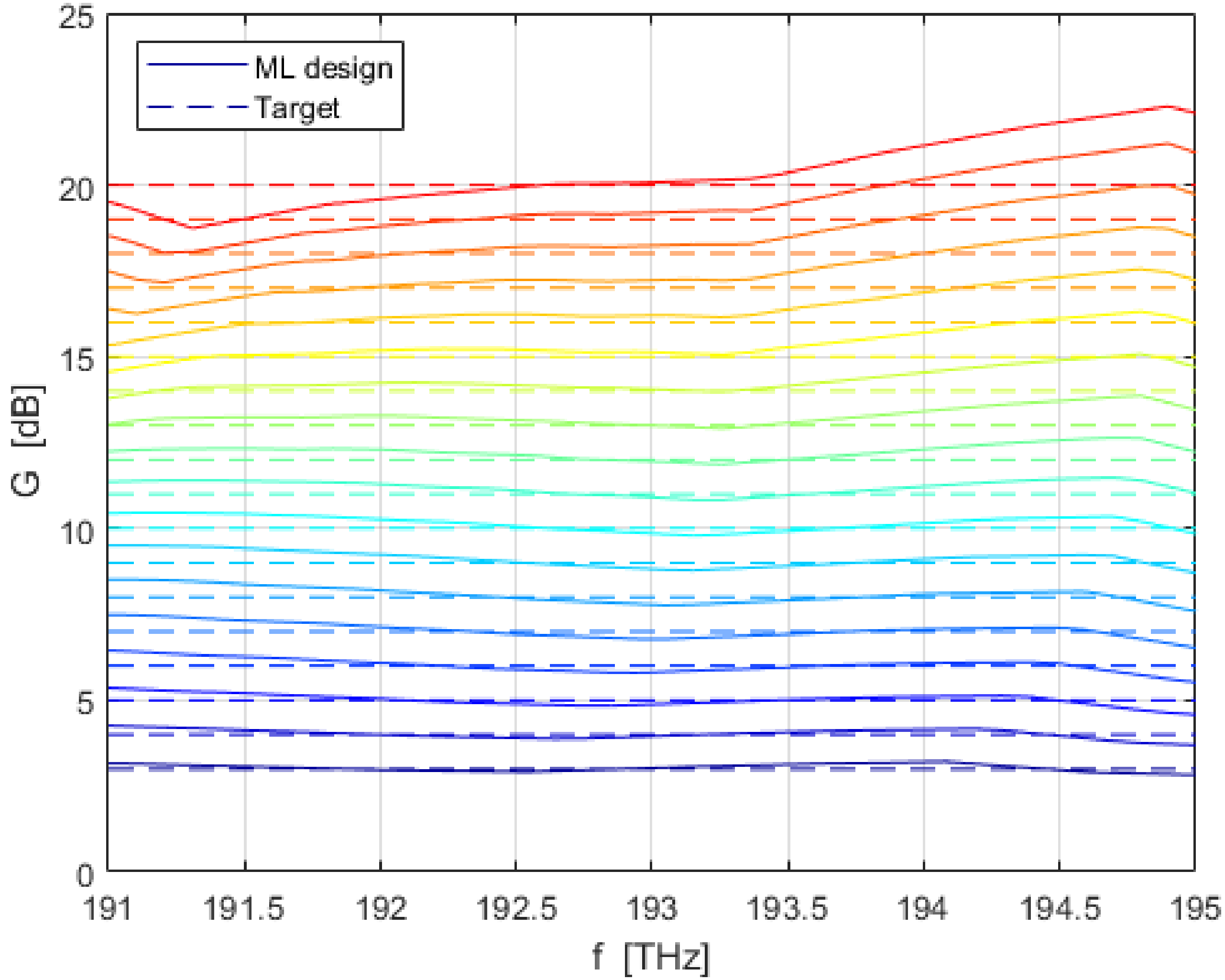
Raman amplifier design using machine learning



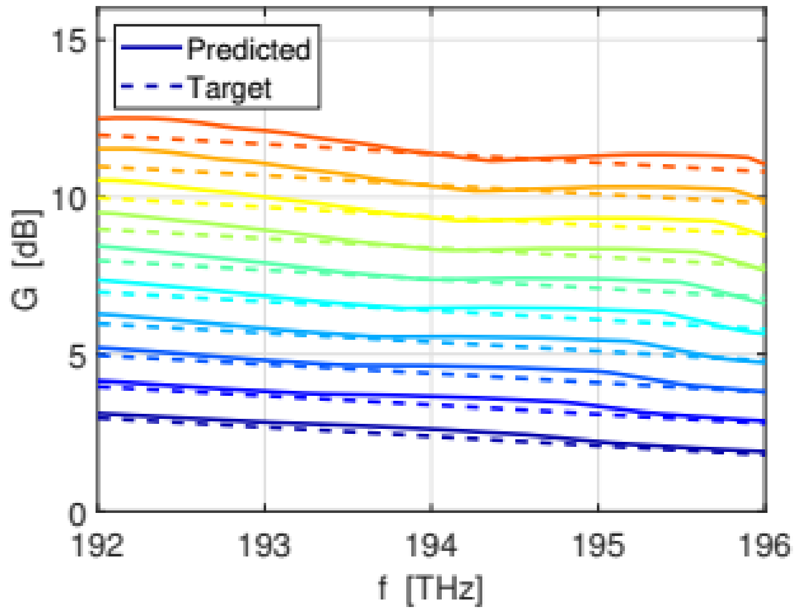
Zibar et al, submitted to OFC 2019 (arXiv:1811.10381v1)

Simulation set-up and results

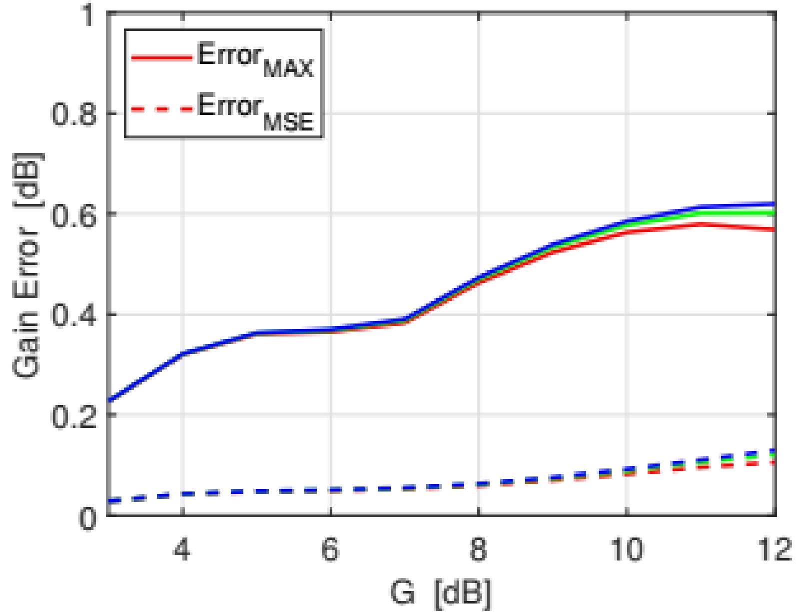
- In a multi-span system with hybrid EDFA Raman amplification, we c



Results



(a) Gain versus frequency

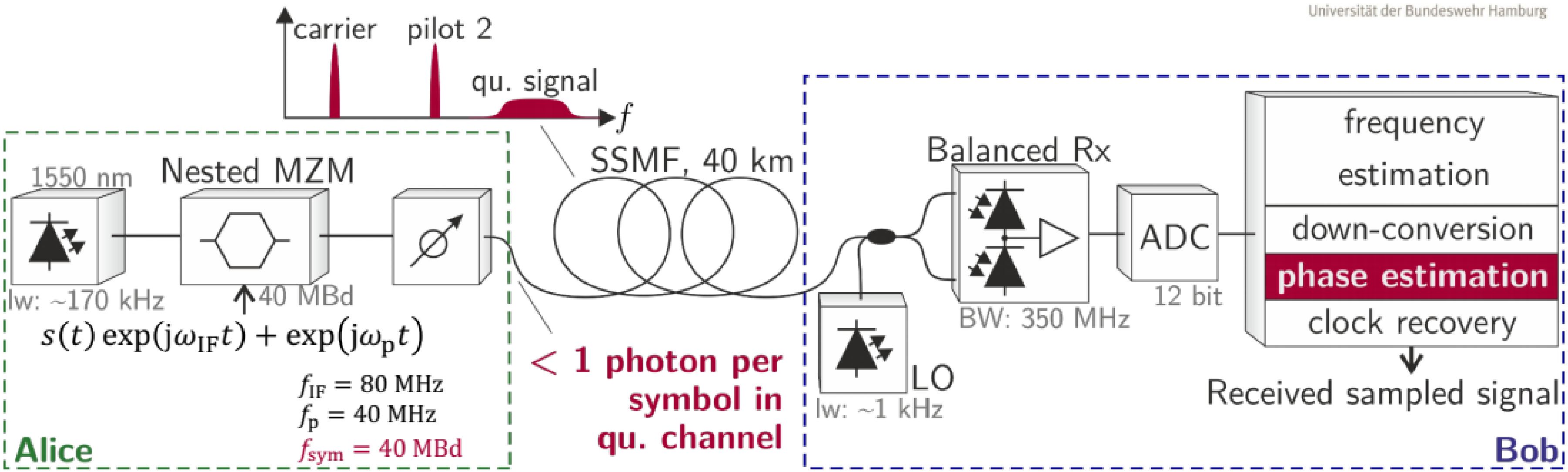


(b) Error for different input powers

The learned model works for any gain profile and the re-training is not required

Phase noise estimation for quantum communication

Universität der Bundeswehr Hamburg



Kleis and Schaeffer, Optics Letters 2018

Homodyne receiver: $SNR = 4N_p$

Phase diversity homodyne receiver: $SNR = 2N_p$

Received signal: $y(t) = a_k \cos(\Delta\omega t + \Delta\phi(t))$

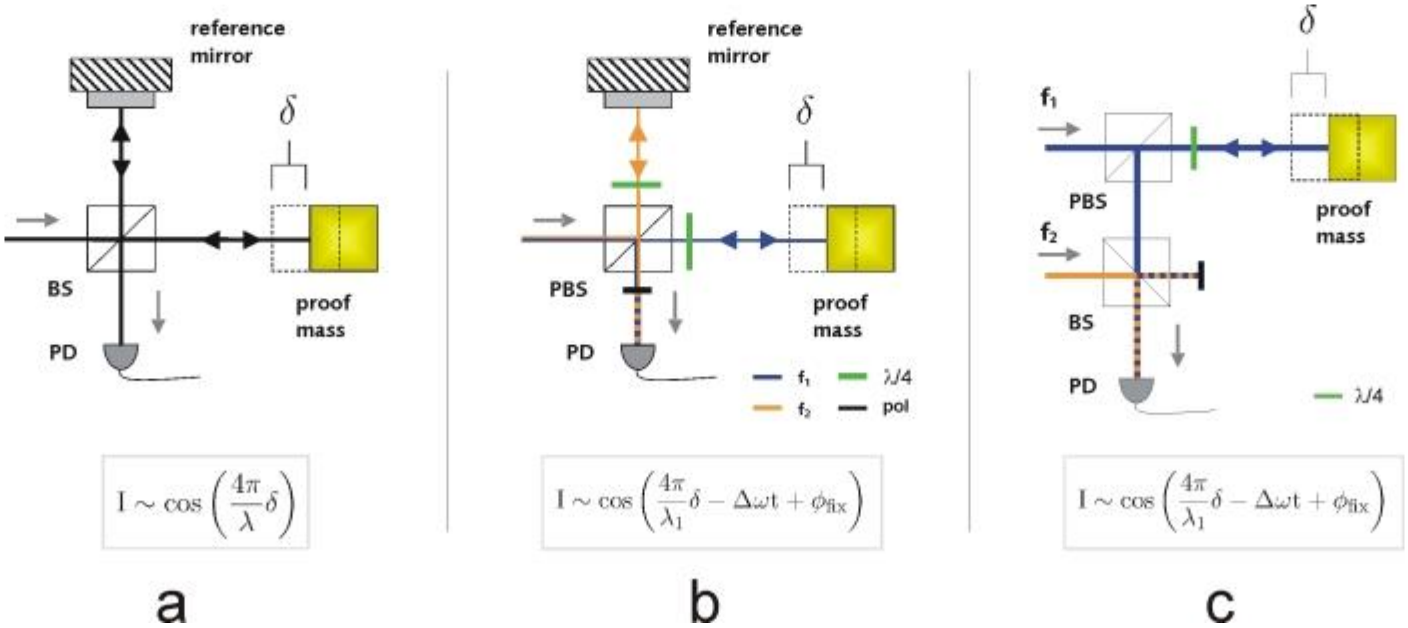
Pilot tones have low power

N_P :Average num. of photons/symbol

a_k : Gaussian modulation

Ultra-sensitive (optimal) detection of optical phase needed at the shot noise limit

Phase estimation for quantum sensing



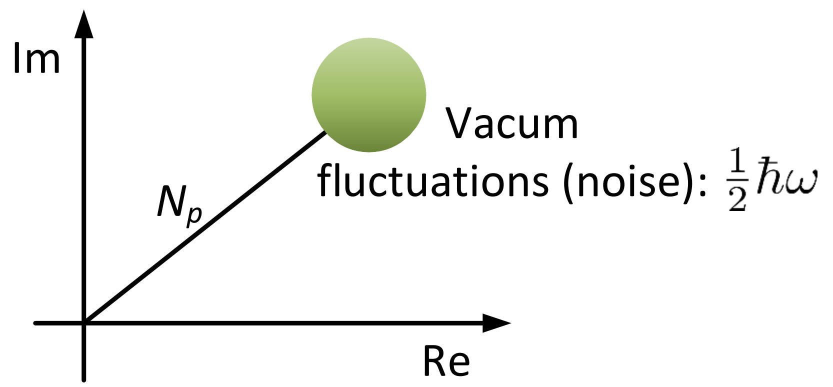
Courtesy of Prof. Achim Peters

https://www.physics.hu-berlin.de/en/qom/research/sensor

Ultra-sensitive (optimal) detection fixed phase shift

Quantum phase estimation

- System limited by quantum noise only (shot-noise limited system)
- Due to Heisenberg uncertainty, optical phase not a single numerical value
- Number of photons N_p instead of SNR: $N_p = \frac{P_s}{\hbar\omega\Delta\nu}$ ← Laser linewidth
- SNR for shot-noise limited system: $SNR = \frac{\eta P_s}{\hbar\omega B}$ ← Receiver bandwidth
- Phasor diagram of light in coherent state:

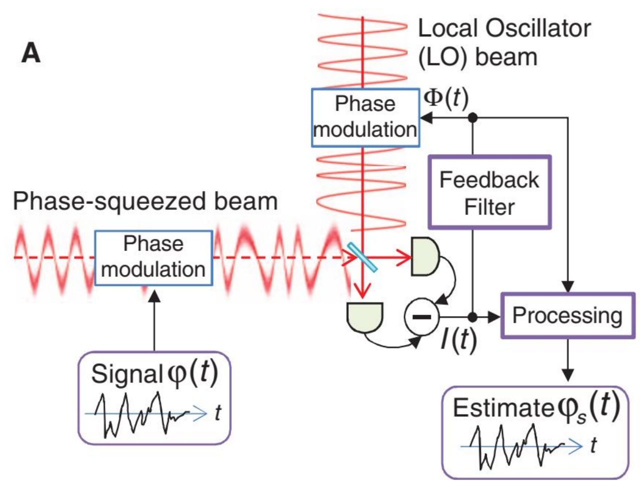


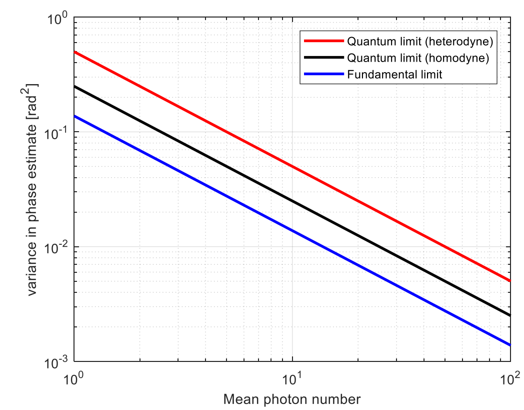
Is this model valid for $N_p \rightarrow 1$? Can we detect optical phase if SNR<1?

State-of-the-art: evaluation of the accuracy

- Variance is employed for accuracy estimation (tricky in the experiements)
- Laser phase noise artificially induced as Wiener process (highly problematic)
- Receiver bandwidth and linewidth equal: $B \approx \Delta\nu$
- Same laser used as transmitter and LO
- SNR is high as the linewidth is chosen to be relatively small
- For homodyne detection quantum noise limited variance: $\sigma_{qn}^2 = \frac{1}{2\sqrt{\frac{P_s}{\hbar\omega\Delta\nu}}}$

[1] Yonezawa, Science 2011





Conclusion and outlook

- Optical phase tracking has applications in various fields
- General Bayesian framework for ultra-sensitive phase detection presented
- Phase evolution model learned from data
- Tracking of mean phase and also covariance matrix demonstrated
- Quantum limited performance achieved
- Significant improvement to standard frequency noise measurements