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Create the Future, Collaborate Together

MPSoC'25, June 16, 2025

Optical Streaming Processor Utilizing Integrated Photonic Circuits

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Outline

- Why optical computing is reignited?
- How to do optical computing in photonics?
- Our works: optical streaming processors implementing novel models in photonics

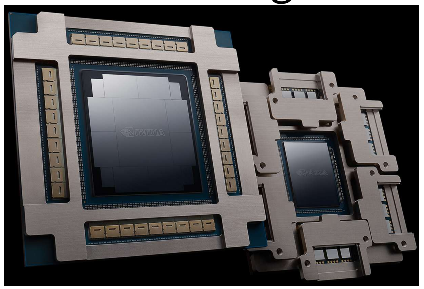
Why optical computing is reignited?

(1) Power issue and demands for computational power
- Computational power doubles per 10 months
- Energy consumption is already substantial, and is increasing rapidly
- End of Moore's law→ stagnation of digital processor performance
- End of Dennard law → energy efficiency gains slows

(2) Advances in optical interconnects and photonics-electronics co-integration

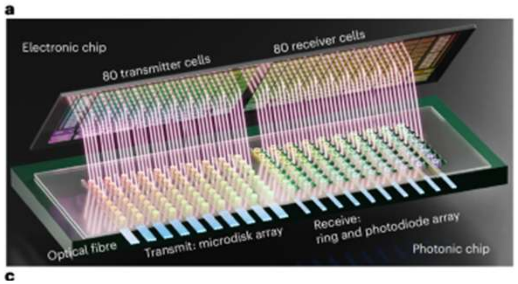
(3) Physical system computes better in energy efficiency

On-Package



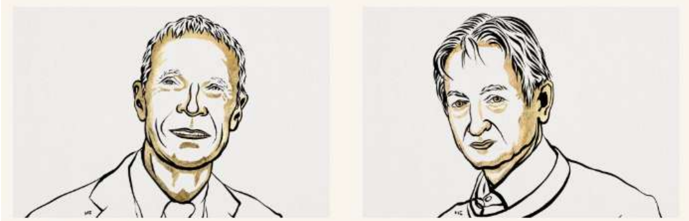
https://nvidianews.nvidia.com/news/nvidia-spectrum-x-co-packaged-optics-networking-switches-ai-factories

On-Chip



https://www.nature.com/articles/s41566-025-01633-0

Physical concepts + machine learning



John Hopfield. Ill. Niklas Elmehed © Nobel Prize Outreach

Geoffrey Hinton. Ill. Niklas Elmehed © Nobel Prize Outreach

"They used physics to find patterns in information"

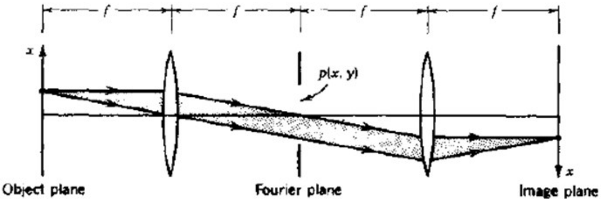
https://www.nobelprize.org/

Intrigue constructing optical physical analog AI system

Optical computing: Hype or hope?

Energy saved or not?

Example: Optical Fourier transformation



I'd to call it lens instead of computing since

Three elements required

- On-demand use input
- Reconfigurable
- Result interpretation

➔ Overhead consumes additional powers

Pros and cons

Pros:

Low energy
Low latency
High clock speed
High bandwidth
High parallelism
Network compatibility

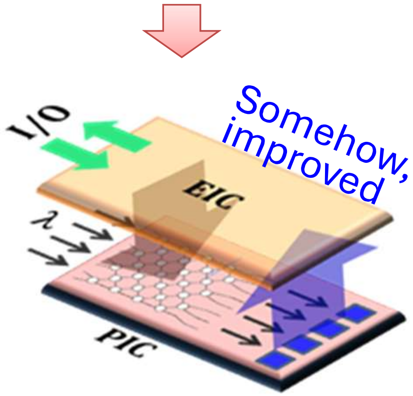
Cons:

Scalability
Programmability
Nonlinearity
Trainability
Stability
Low resolution
Area efficiency

Why it failed?

Lost to VLSI due to

- Scalability
- Low integration
- Programmability
- Not easy to use



What we are expecting

- One-shot
- All-optical
- High-throughput
- Applicable scale
- System-level energy efficiency
- Less digital intervene

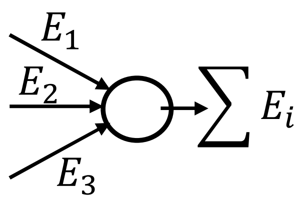
Comments:

- System evaluation is of necessity
- Concerns of heavy overhead related to digital processors and memory
- It is time to re-evaluate the possibilities of optical computing

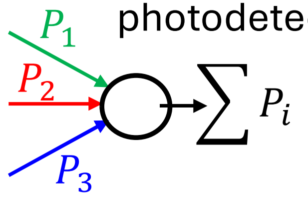
How to do computing in photonics?: scalar operations

- Addition
  - Electrical field addition (coherent)
  - Optical power addition (incoherent)

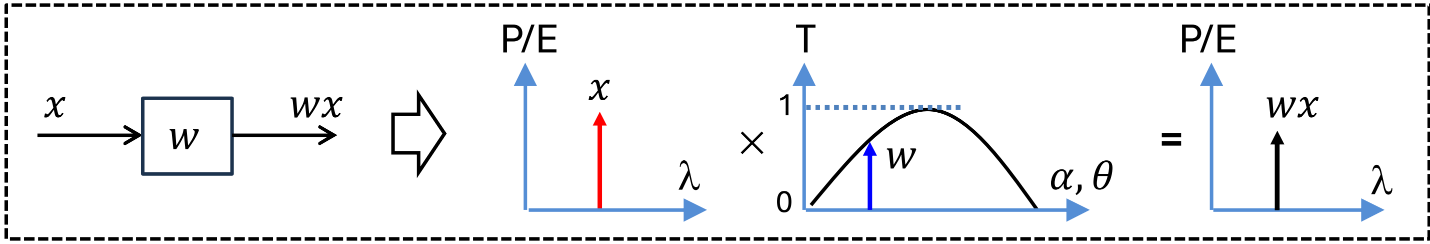
interferometer



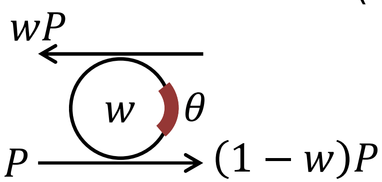
photodetector



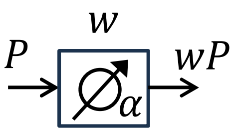
- Scalar multiplication



Incoherent (i.e., power)

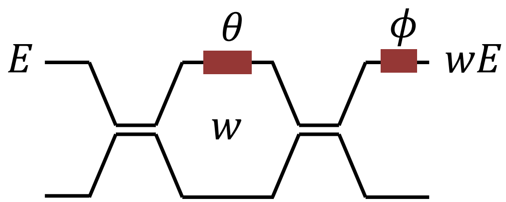


Ring

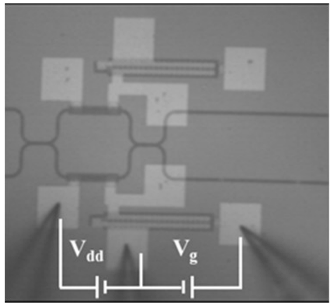


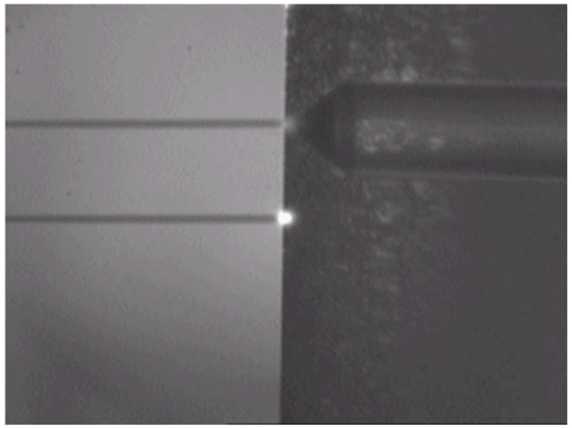
VOA

Coherent (i.e., electrical field)



MZI





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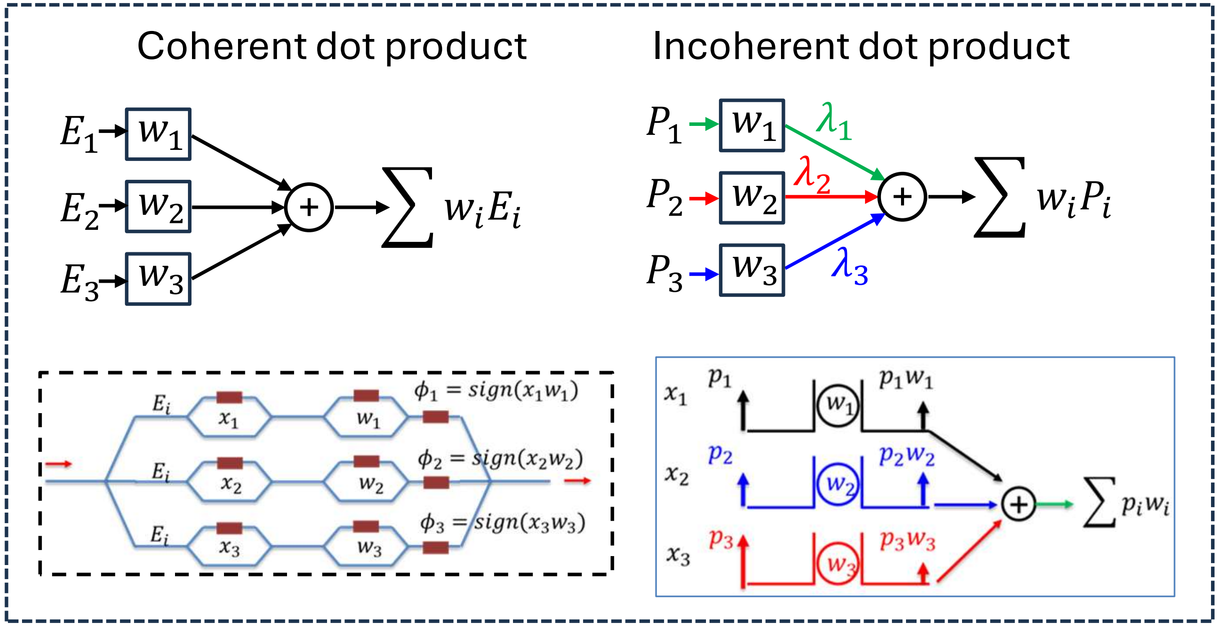
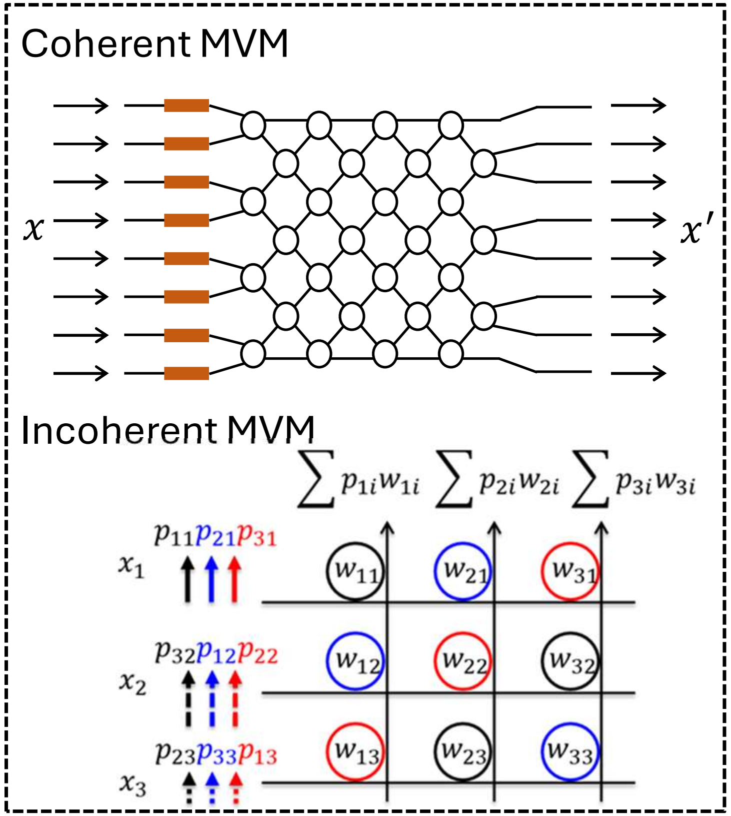
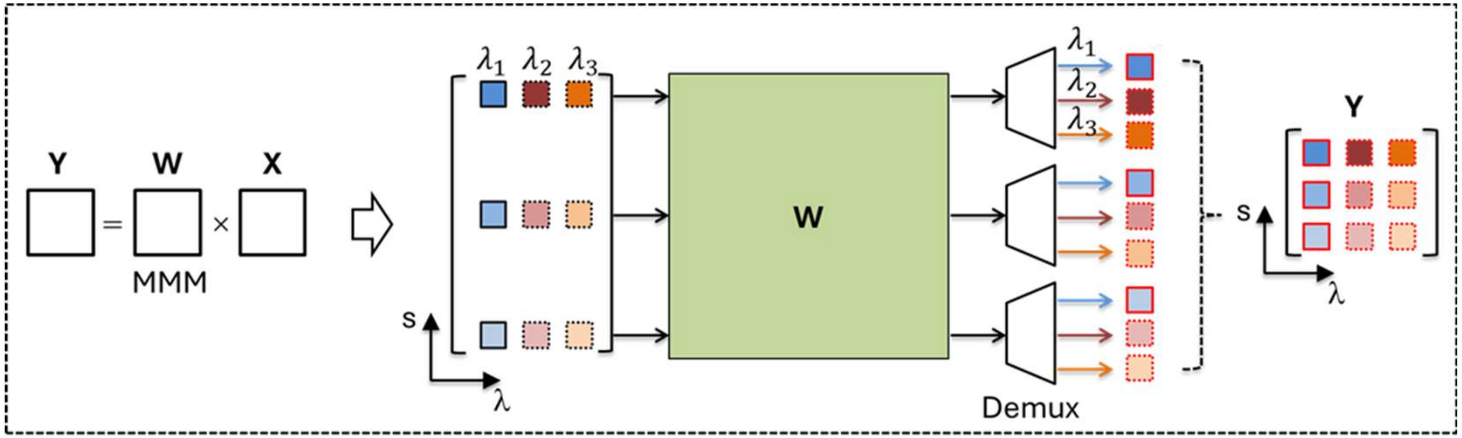
Multiplexing for linear operations





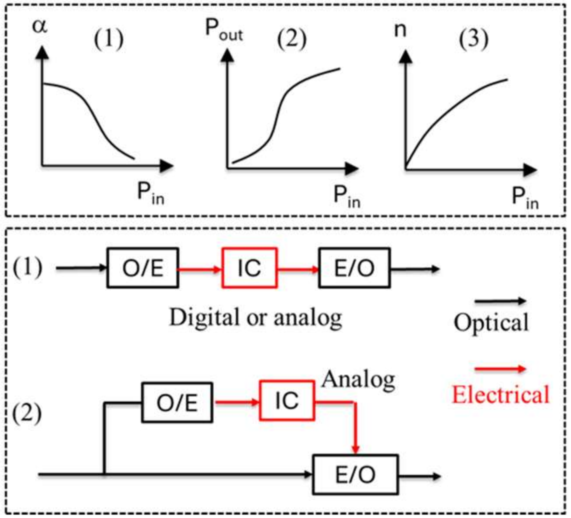


Massive parallelism by sharing hardware, offering scalable and energy efficient linear operations.

How nonlinear functions can be achieved in photonics?

All-optical

OEO



- Saturation absorber
- TPA
- SOA
- $\chi^{(3)}$...

O→PD → TIA/ADC → E

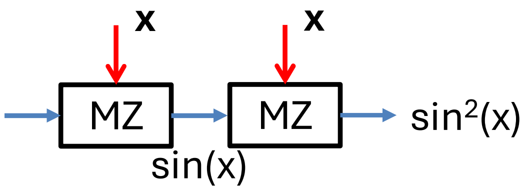
Digital circuits

Analog circuits

E→DAC/Driver →Laser/modulator → O

Towards traditional activation functions

Data-encoding enabled nonlinearity



- We are focusing on wide nonlinearities to construct new models instead of replacing traditional ones
- Despite of same technology, new possibility and effects are achievable
- Offering new merits in solving some remaining challenges

Support vector machine (SVM)-like nonlinear projection

Bilinear projection

Vertically hierarchical PNN

EO Hopfield network

Towards challenges of :

Nonlinearity

Scalability
Small-sample learning

Our works: optical streaming processors implementing novel models

Linear transformation

Linear + EO-hybrid nonlinearity

Linear + All-optical nonlinearity

2022 2023 2024 2025

Our approach

Data-encoding nonlinearity

Multiple operators

Bilinear

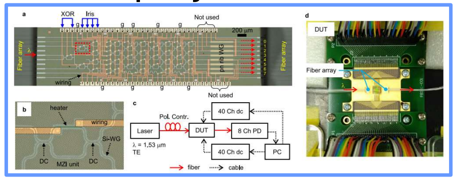
Nonlinearity

Spatiotemporal encoding
Physical intelligence

Loss-robust architecture

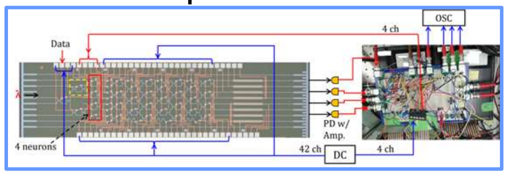
Scalability

SVM (support vector machine)-like nonlinear projection-based PNN

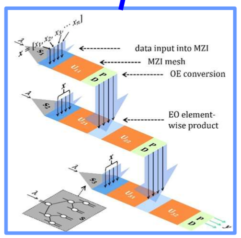


Nature Communications 13, 3261 (2022)

EO-Hopfield network

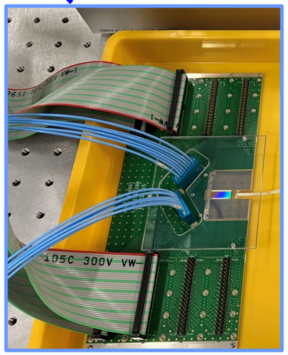


OFC 2023, W3G.2.(Invited talk)



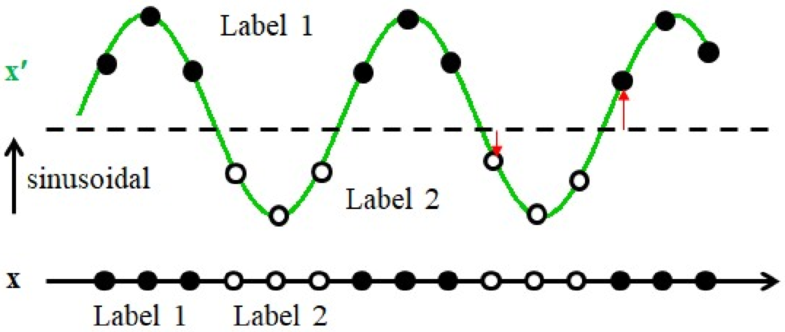
Vertically hierarchical PNN

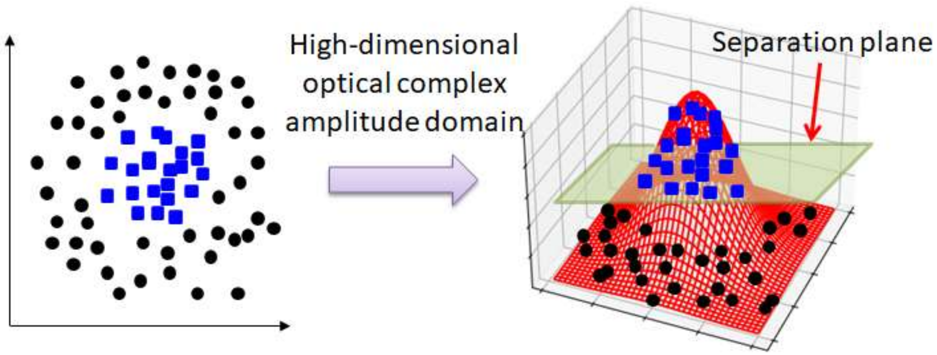
APL Photonics 9, 056110 (2024)



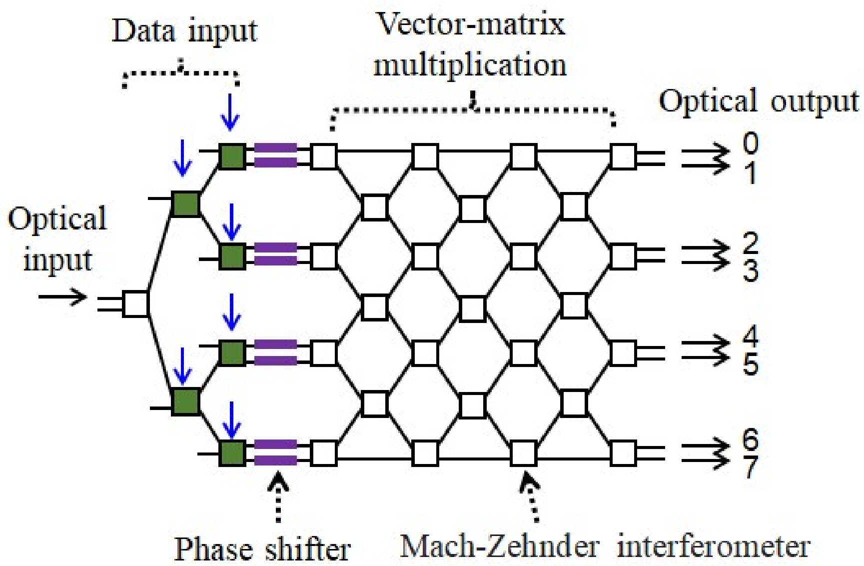
Gate modulated PNN

(1) Nonlinear projection-based PNN





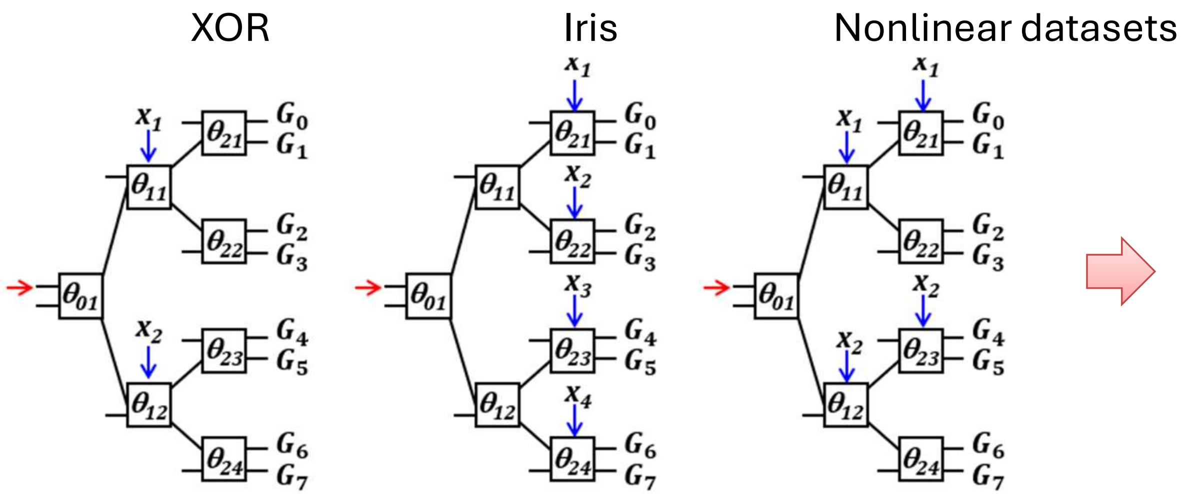
- For multilayer perceptron (MLP), it is using $y = wf(\ldots(wf(wx + b) + b))$ to approximate a nonlinear function.
- We are thinking reversely: constructing nonlinear projection function firstly, that may enable easy separation.

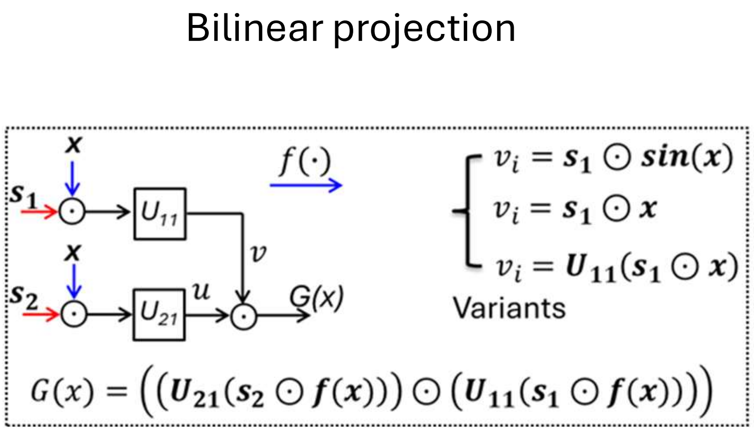


Nonlinear projection + linear separation

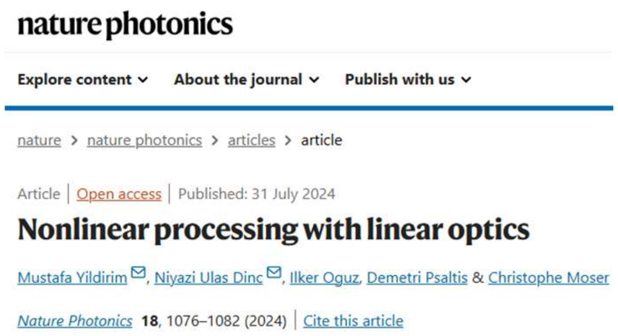
- Leveraging phase-amplitude (EO) nonlinearity of MZI
- Linear separation by VMM afterwards
- Maximum-power port position indicates the result
- Only passive circuits

Encoding the data into MZI network





- Encoding the data into MZI networks
- Leveraging EO nonlinearity associated with data encoding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Mustafa Yildirim, Niyazi Ulas Dinc, Ilker Oguz, Demetri Psaltis & Christophe Moser

Nature Photonics 18, 1076–1082 (2024) | Cite this article

$$E_{out} = HT_{Ln}(\mathbf{x}) \ldots HT_{L2}(\mathbf{x}) HT_{L1}(\mathbf{x}) E_{il}$$


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Nonlinear optical encoding enabled by recurrent linear scattering

Fei Xia, Kyungduk Kim, Yaniv Eliezer, SeungYun Han, Liam Shaughnessy, Sylvain Gigan & Hui Cao

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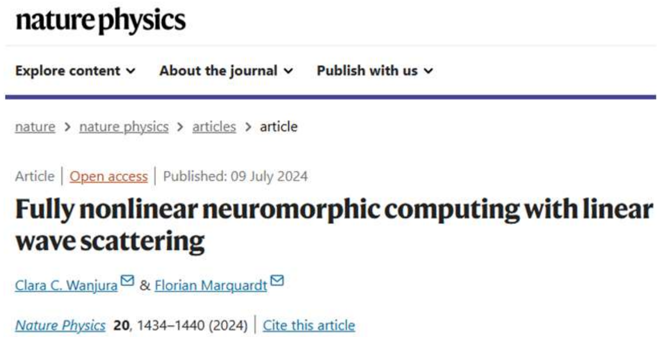
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Fully nonlinear neuromorphic computing with linear wave scattering

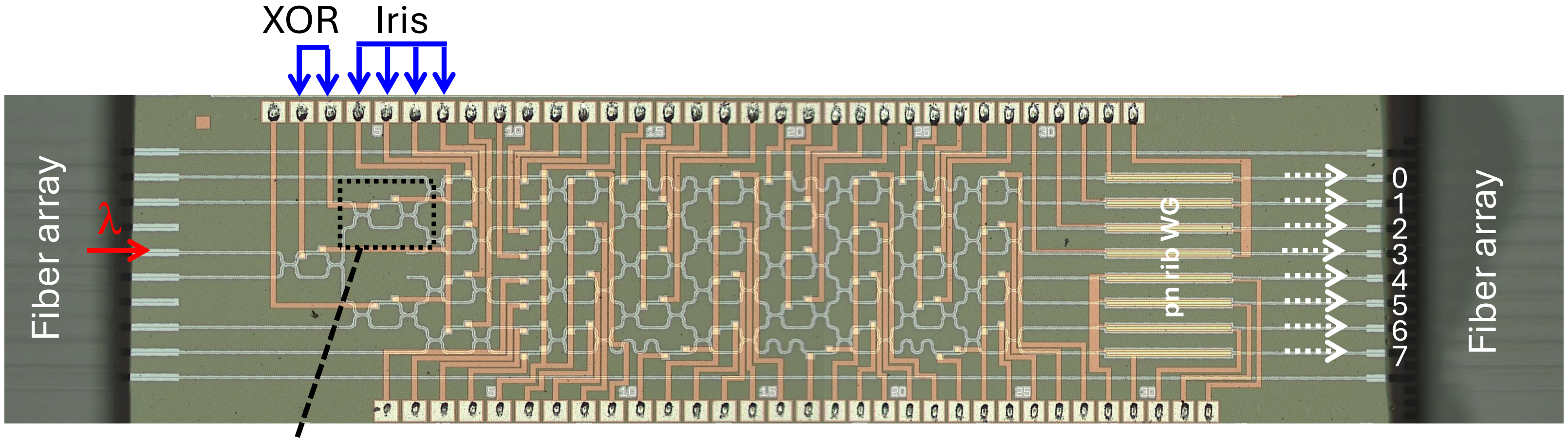
Clara C. Wanjura & Florian Marquardt

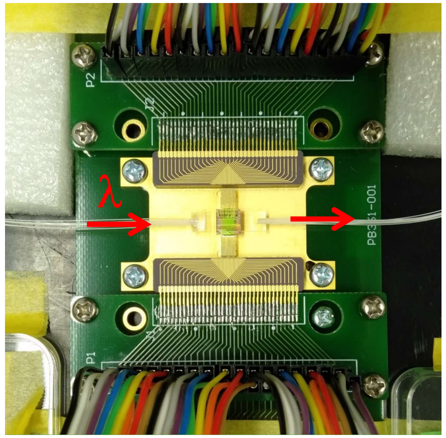
Nature Physics 20, 1434–1440 (2024) | Cite this article

Input replication improved nonlinear expressivity

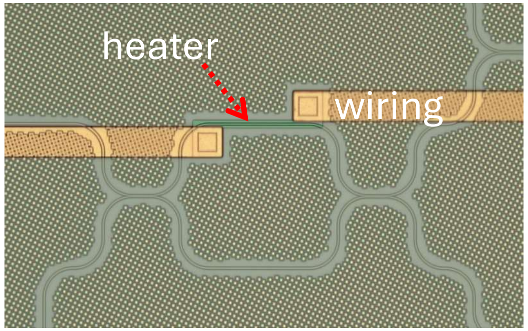
Device and module

Nature Communications 13, 3261 (2022)

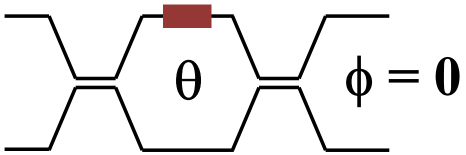


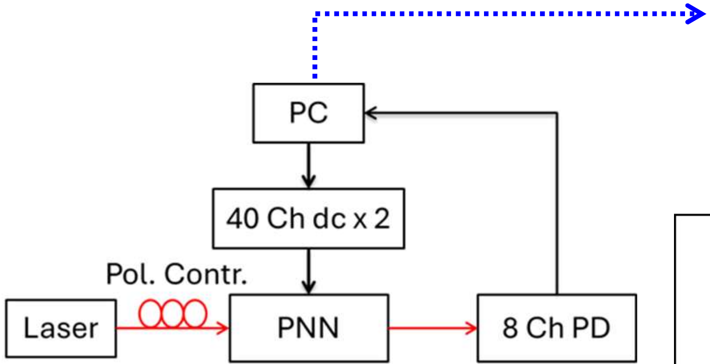


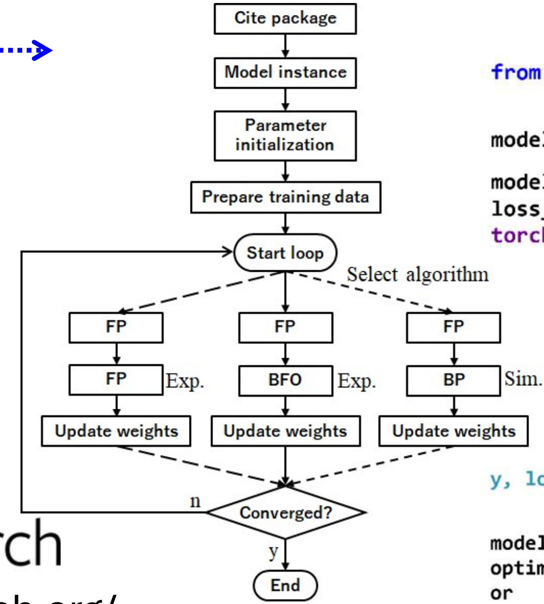
PNN module



MZI unit



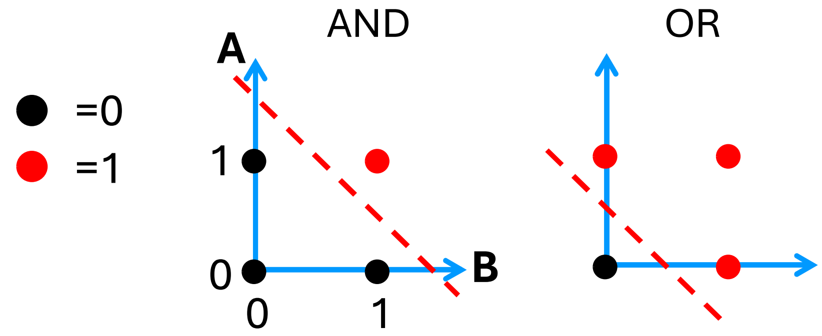


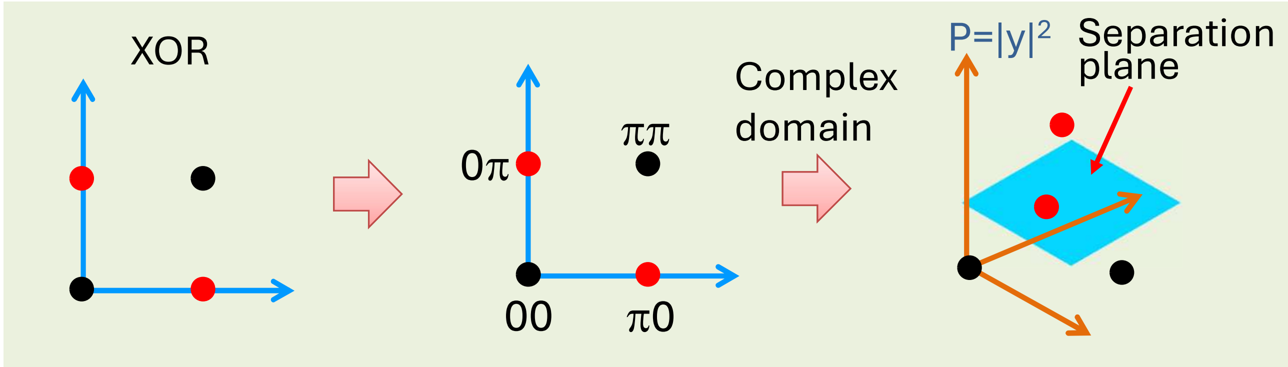


PyTorch
https://pytorch.org/

```
from pcnet import PhotonicClassifier

model = PhotonicClassifier()

model.weight_init()
loss_func =
torch.nn.MSELoss(reduction='sum')

y, loss = model(x)

model.FFGrad(x, yt, loss, 0.001)
optimizer.step()
or
model.BFOEng(xb, yb, loss, 0.001, …)
```

Classification experiment: Boolean logic

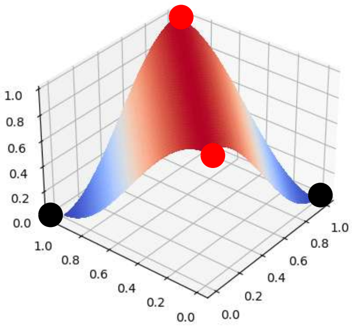




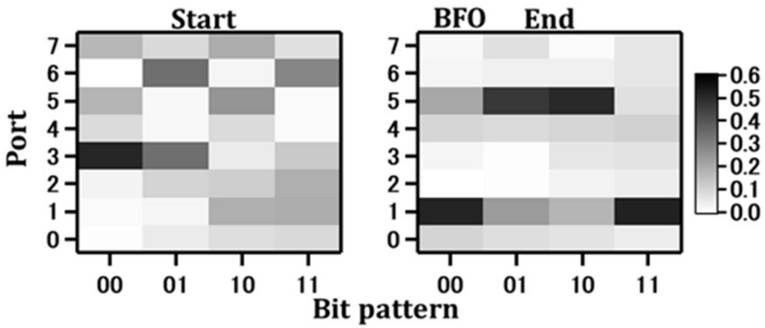
XOR

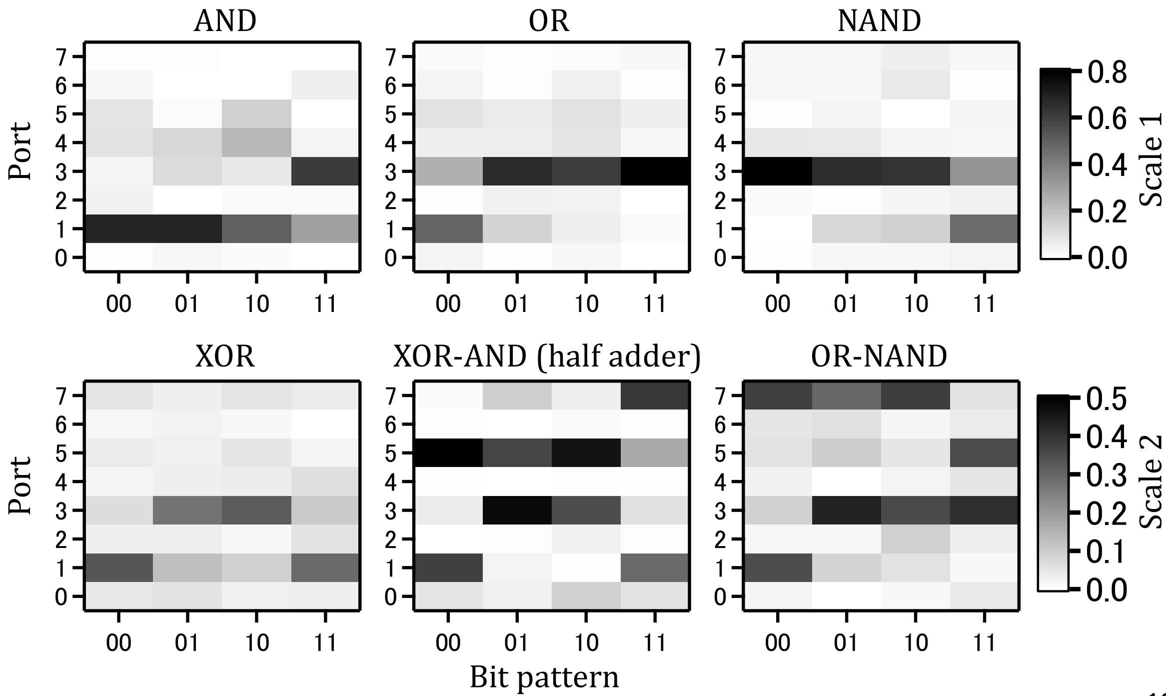
A	B	X
0	0	0
0	1	1
1	0	1
1	1	0

- Port 1 → 0
- Port 5 → 1



Optical power mapping



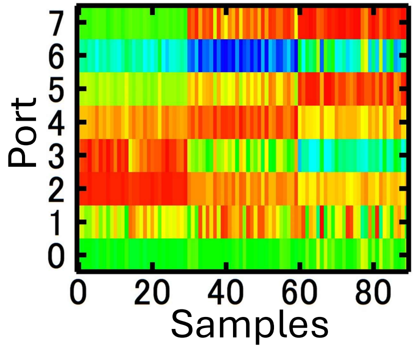


Classification experiment: Iris dataset

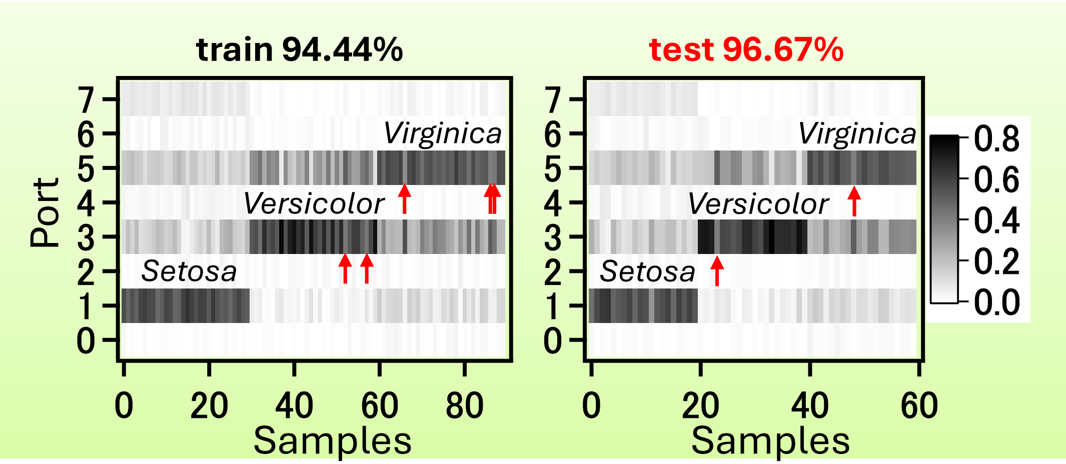
https://archive.ics.uci.edu/ml/datasets/iris

No.	Sepal length	Sepal width	Petal length	Petal width	Species
1	5.1	3.5	1.4	0.2	Setosa
2	4.9	3	1.4	0.2	Setosa
3	4.7	3.2	1.3	0.2	Setosa
:	:	:	:	:	:
51	7	3.2	4.7	1.4	Versicolor
52	6.4	3.2	4.5	1.5	Versicolor
53	6.9	3.1	4.9	1.5	Versicolor
:	:	:	:	:	:
101	6.3	3.3	6	2.5	Virginica
102	5.8	2.7	5.1	1.9	Virginica
103	7.1	3	5.9	2.1	Virginica
:	:	:	:	:	:

Optical power before training



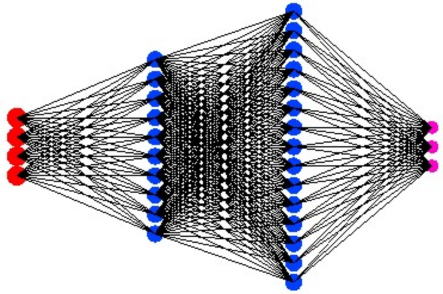
- Data normalization
- Port assignments
  - Port 1 → *Setosa*
  - Port 3 → *Versicolor*
  - Port 5 → *Virginica*



Optical power mapping after training

Two examples of digital NN

https://python.atelierkobato.com/variety/



- 4×10×15×3
- ReLU
- 235 weights
- ~97%

Conferences > 2018 International Conference...

A Model of Deep Neural Network for Iris Classification With Different Activation Functions

Publisher: IEEE Cite This PDF

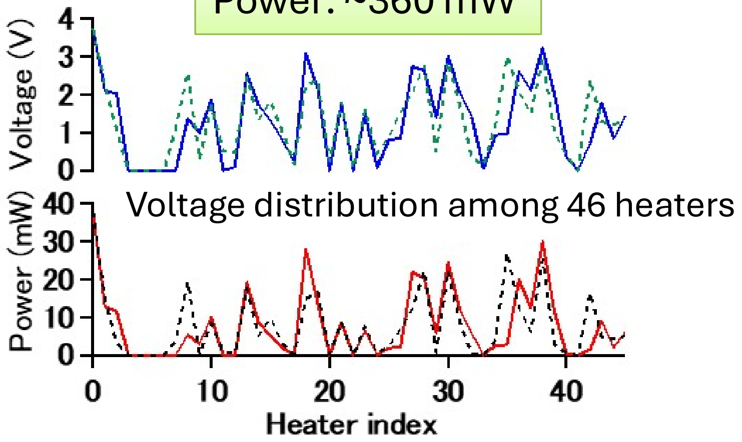
DOI: 10.1109/IDAP.2018.8620866

1st Hidden Layer	2nd Hidden Layer	Epoch Number	Accuracy Rate
Relu	Sigmoid	100	86%
		200	86%
		300	86%
		400	86%
Relu	Tanh	100	90%
		200	90%
		300	90%
		400	90%
Relu	Relu	100	90%
		200	90%
		300	90%
		400	90%

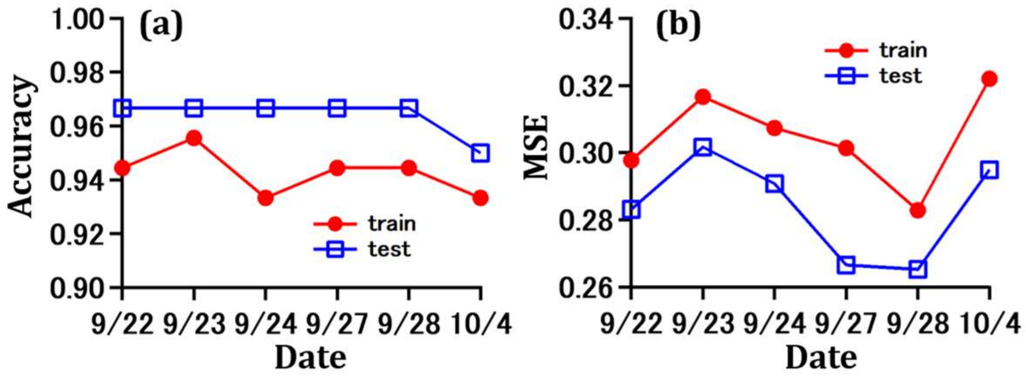
86-90%

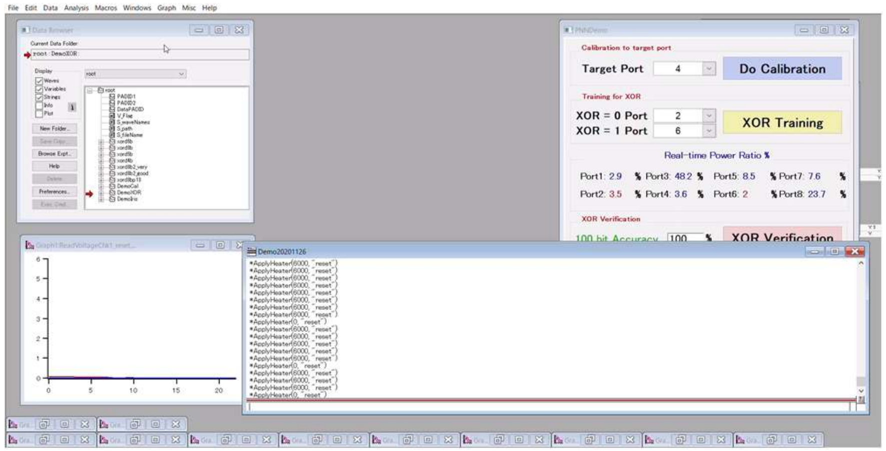
Details of experimental results

Power: ~360 mW

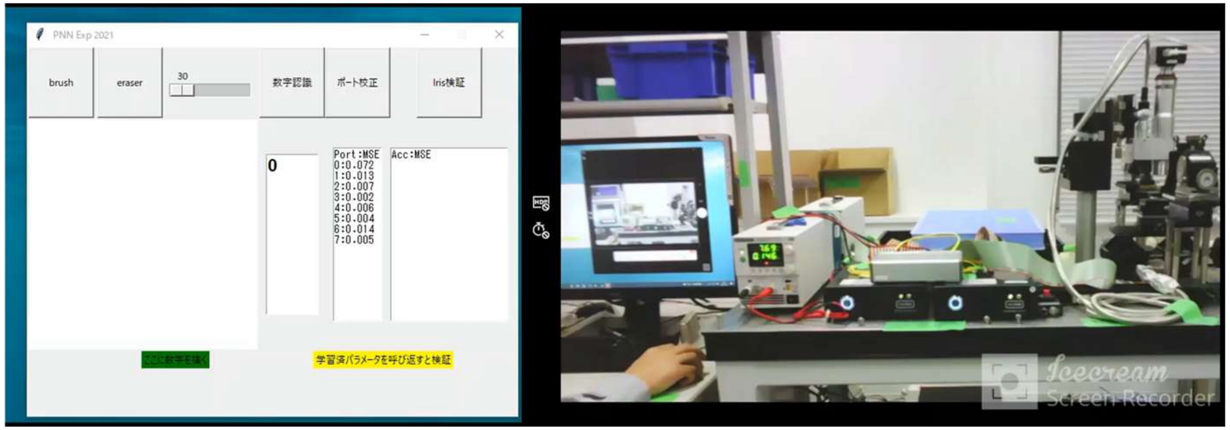


Long time stability





XOR video using BFO algorithm



Demo video

- ✓ Electronics for IO only
- ✓ Computing is done just by optical propagation
- ✓ Latency < 100 ps

(2) Bilinear projection in gate modulated PNN

$$z_1 = Wx, z_2 = Vx$$

Bilinear $\quad B = z_1 \otimes z_2$

$$B_i = \sum W_{ij} x_j \cdot \underline{V_{ik} x_k}$$

Variants

$$v_i = \sum W_{ij} x_j \cdot \underline{x_k}$$

$$v_i = \underline{\sum W_{ij} x_j} \cdot \underline{sin(x_k)}$$

arXiv:2002.05202v1,12 Feb 2020

GLU Variants Improve Transformer

Noam Shazeer
Google
noam@google.com

February 14, 2020

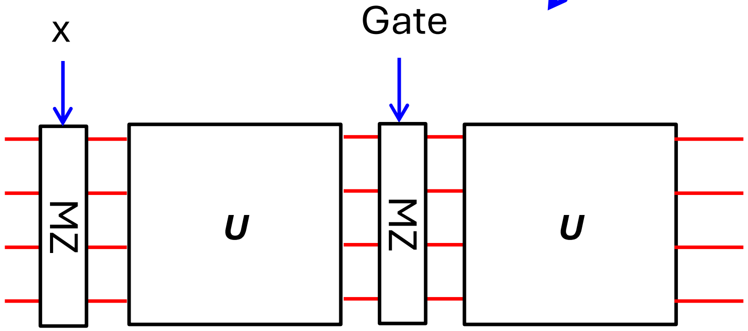
These variants have shown improvements over traditional activation functions when used in Transformer models.

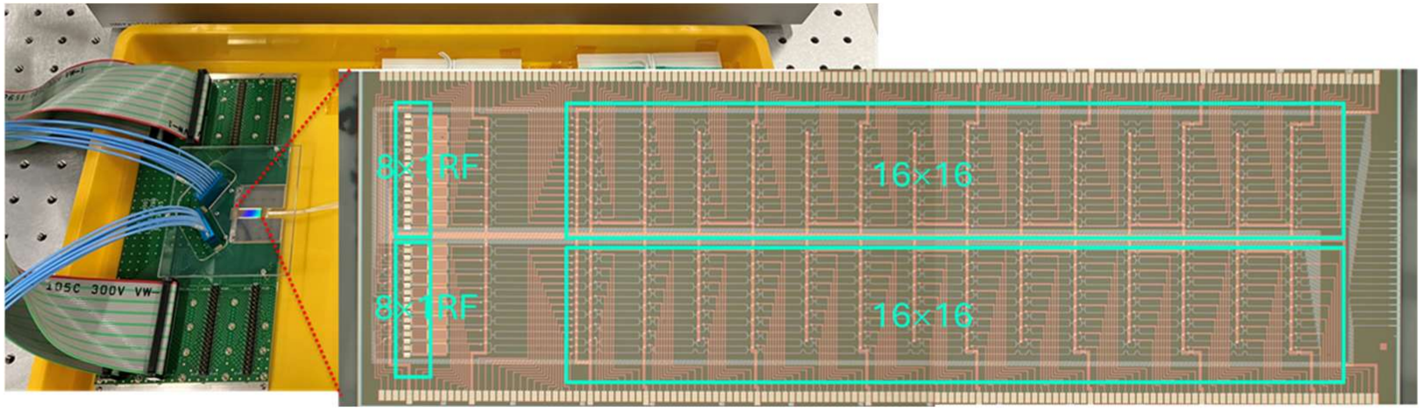
Abstract

Gated Linear Units [Dauphin et al., 2016] consist of the component-wise product of two linear projections, one of which is first passed through a sigmoid function. Variations on GLU are possible, using different nonlinear (or even linear) functions in place of sigmoid. We test these variants in the feed-forward sublayers of the Transformer [Vaswani et al., 2017] sequence-to-sequence model, and find that some of them yield quality improvements over the typically-used ReLU or GELU activations.

$$\mathrm{GLU}(x, W, V, b, c) = \sigma(xW + b) \otimes (xV + c)$$

$$\mathrm{Bilinear}(x, W, V, b, c) = (xW + b) \otimes (xV + c)$$





Acknowledgments

https://www.jst.go.jp/kisoken/crest/

JST CREST (JPMJCR21C3)

JSPS KAKENHI JP23H01885

https://www.jst.go.jp/kisoken/crest/

JST CREST (JPMJCR24R3) (2024 newly launched)

AIST SCR Platform

Thank you for kind attention!