

Optical Bistability As Neural Network Nonlinear Activation Function

Davide Bazzanella

20th March 2018

Università degli studi di Trento

All-Optical Neural Networks

2018-03-09

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Introduction

All-optical Artificial Neural Networks

All-Optical Neural Networks

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└ All-optical Artificial Neural Networks

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Applying integrated photonics to artificial neural networks
architecture design

Develop simulations on standard software libraries that help
performance comparisons

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ANN Simulations

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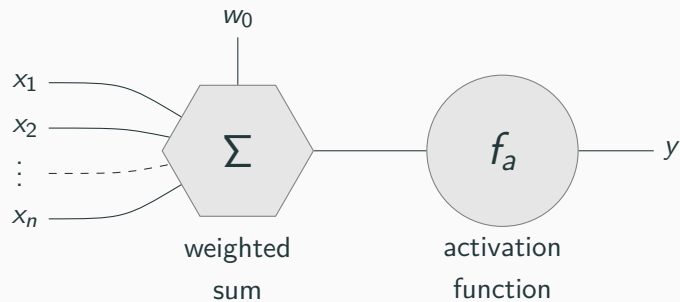
Artificial Neural Networks

Artificial Neural Networks

Artificial Neural Networks are computation systems, composed by a collection of nodes that work seemingly biological neurons.

ANNs blocks

ANNs are composed by single units, *nodes*, which elaborate the information in a way loosely similar to biological neurons.



All-Optical Neural Networks

- Artificial Neural Networks

- ANNs blocks

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What can they do?

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└ What can they do?

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ANNs can solve complex problems:

- classification
- clustering
- pattern recognition
- time series prediction

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figures/foo.png

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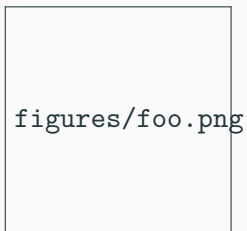
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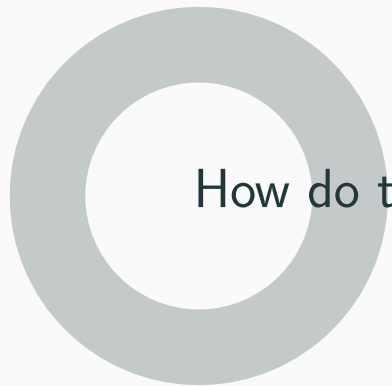
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How do they work?

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└ How do they work?

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ANNs can obtain arbitrary decision regions¹

The amount of free parameters in an ANN, allow .. ?



¹R. O. Duda et al., *Pattern classification*, (John Wiley & Sons, 2012)

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How do they work?

- training
 - evaluate loss
 - adjust parameters
- validation
- test

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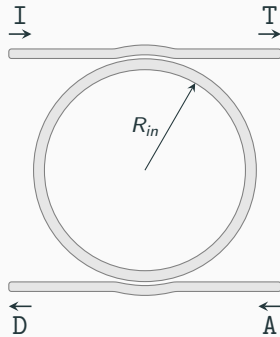
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Microring Resonator

Consider a MRR in the
Add-Drop Filter configuration

$$T(\omega) = f[I(\omega)]$$

$$D(\omega) = f[I(\omega)]$$



$$T(\omega) = f[I(\omega)]$$

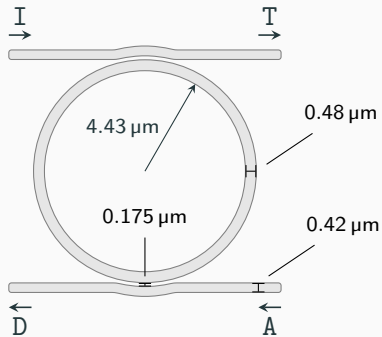
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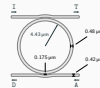
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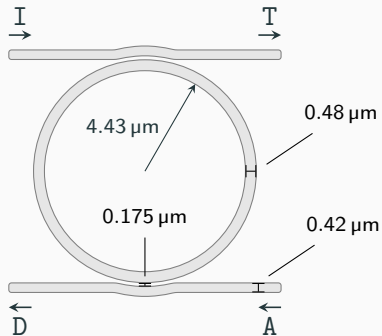
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Coupling is governed by

τ and κ .



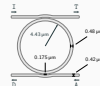
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Linear

Nonlinear

Experiments

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└─ Microring Resonator

└─ Experiments

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Experiments

(1) (2)

ANN Simulations

What means simulating? PyTorch library

model ($FF[f_a]$)

loss criteria (CEL)

weight update criteria (SGD)

model ($FF[f_a]$)

$$L(y, \hat{y}) = f_{\text{CEL}}(y, \hat{y}) = -\frac{1}{N} \sum_{n=1}^N \sum_{i=1}^C y_{n,i} \log(\hat{y}_{n,i})$$

Cross-Entropy Loss (also known as negative log likelihood),

$$L(y, \hat{y}) = f_{\text{CEL}}(y, \hat{y}) = -\frac{1}{N} \sum_{n=1}^N \sum_{i=1}^C y_{n,i} \log(\hat{y}_{n,i})$$

Stochastic Gradient Descent
with *momentum*
and *learning rate scheduler*.

ReLU vs Sigmoid vs f_{fit}

Conclusion

I assembled an experimental setup from scratch

I characterized the response of the MRR in several aspects

I implemented the bistable response in standard software libraries

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Continue the current work with a quantitative analysis of specific features

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└ Future Perspectives

Continue the current work with a quantitative analysis of specific features

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Enhance the physical theory to describe time dependent phenomena

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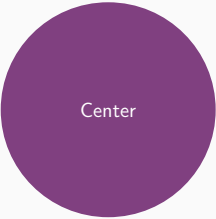
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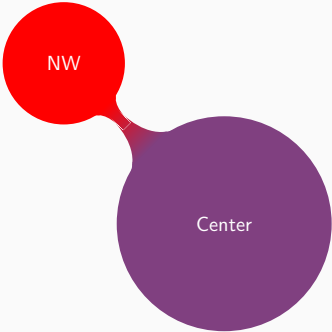
Proceed with the development of the simulations to include all the characteristics of the physical system



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- All-Optical Neural Networks
 - └ Conclusion
 - └ Mindmap





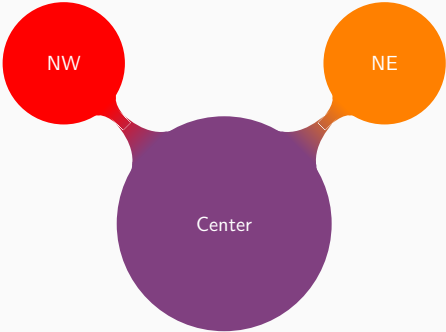
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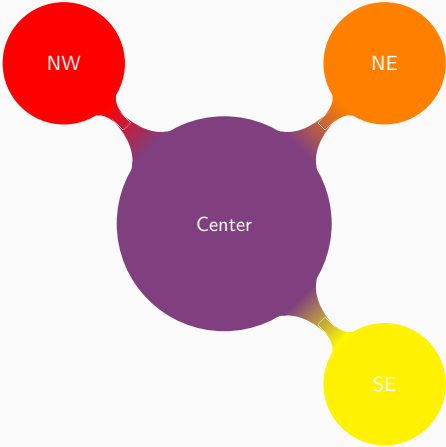
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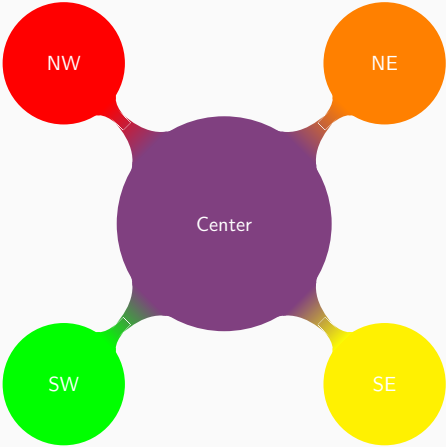


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Mindmap





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└ Mindmap

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Mindmap

A small thumbnail version of the mind map diagram, showing a central purple circle with four colored nodes: red (NW), orange (NE), yellow (SE), and green (SW).