# Optical Bistability As Neural Network Nonlinear Activation Function

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# Introduction

### **All-optical Artificial Neural Networks**

Applying integrated photonics to artificial neural networks architecture design

Develop simulations on standard software libraries that help performance comparisons

#### Introduction

Artificial Neural Networks

Microring Resonator

**ANN Simulations** 

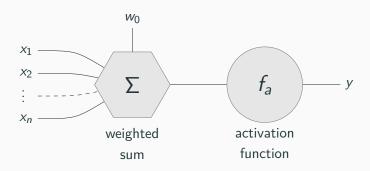
## **Artificial Neural Networks**

#### **ANNs**

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.



What can they do?

### ANNs can solve complex problems:

- classification
- clustering
- pattern recognition
- time series prediction

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ANNs can obtain arbitrary decision regions<sup>1</sup>

The amount of free parameters in an ANN, allow .

<sup>&</sup>lt;sup>1</sup>R. O. Duda et al., Pattern classification, (John Wiley & Sons, 2012)

- training
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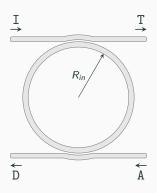
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# Microring Resonator

#### **MRR**

Consider a MRR in the Add-Drop Filter configuration

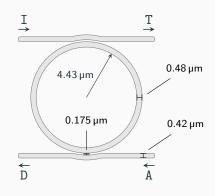
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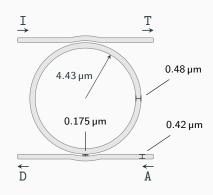
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$$T(\omega) = f[I(\omega)]$$
$$D(\omega) = f[I(\omega)]$$

Coupling is governed by

$$\tau$$
 and  $\kappa$ 



# Theory

Linear

## Theory

Nonlinear

# **Experiments**

Setup

# **ANN Simulations**

### **Simulation Framework**

What means simulating? PyTorch library

#### **Fundamental blocks**

```
model (FF[f_a])
loss criteria (CEL)
weight update criteria (SGD)
```

 $\mathsf{model}\; \big(\mathit{FF}[\mathit{f_a}]\big)$ 

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

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

Stochastic Gradient Descent with momentum and learning rate scheduler.

#### **Operation Tests**

ReLU vs Sigmoid vs ffit

# **Conclusion**

#### **Overview**

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

#### **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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Continue the current work with a quantitative analysis of specific features

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



