

# 硅光芯片&人工智能

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2018.05.11

# Reference

1. Deep learning with coherent nanophotonic circuits, Nature Photon, 2017.
  2. Experimental demonstration of reservoir computing on a silicon photonics chip, Nature communications, 2014.
  3. Neuromorphic Computing Based on Silicon Photonics and Reservoir Computing, IEEE Journal of Selected Topics in Quantum Electronics, 2018.
- (ref 2 and ref 3 are from the same group)

# 涉及到的人工智能概念

- 人工神经网络 (artificial neural network)
  - 后向传播算法 (back propagation algorithm)
  - 深度学习 (deep learning)
- 循环神经网络 (recurrent neural network)
- 监督学习 (supervised learning)

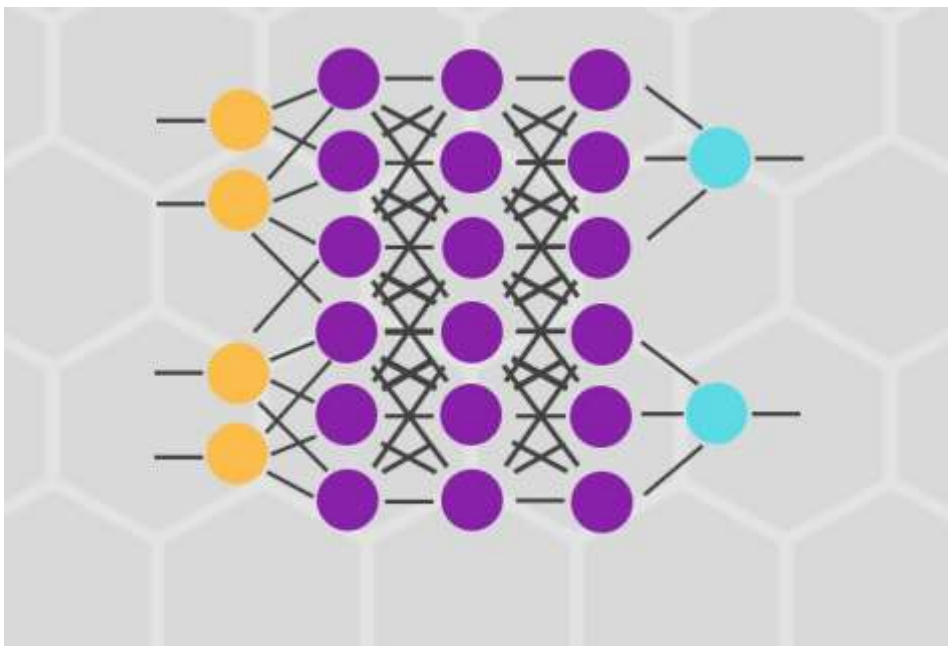
## Advantages of silicon photonics

- improved computational speed
- power efficiency

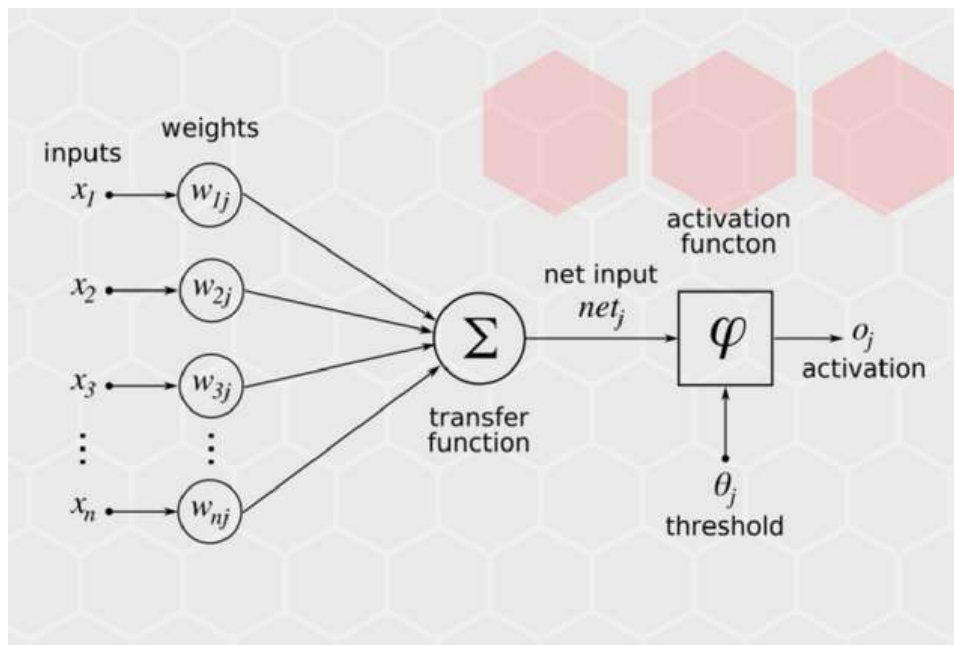
# 文献 1:

- 在硅光芯片上实现了人工神经网络 (artificial neural network) 中的后向传播算法(back propagation)
- 后向传播算法分为两个步骤：正向传播和后向传播
  - 正向传播：使用神经网络计算特征值
  - 后向传播：传递误差，修正模型的参数值
- 参考资料：<https://rubikscode.net/2018/02/19/artificial-neural-networks-series/>

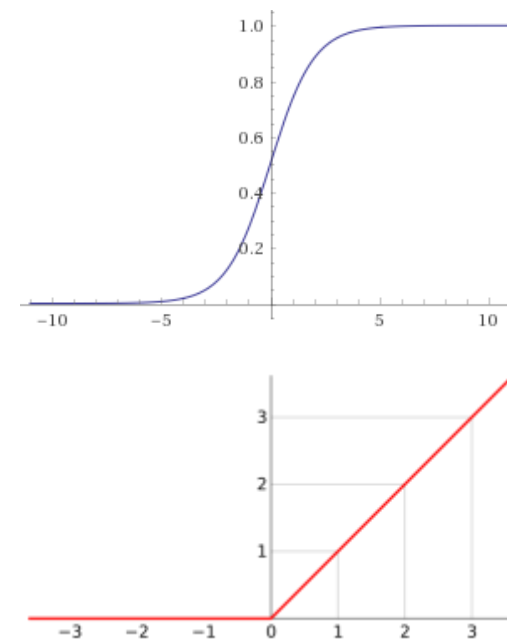
# 正向传播



基本模型  
(输入层、输出层、隐含层)



单个神经元模型



非线性激励函数

# 后向传播

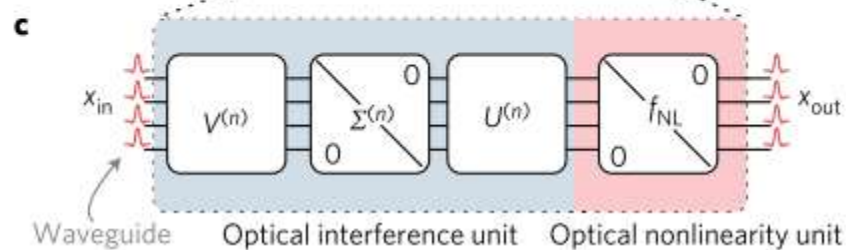
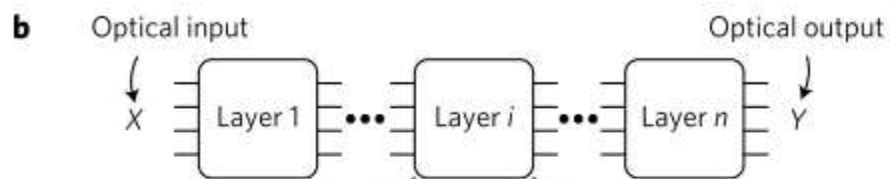
- 误差函数  $C(w, b) \equiv \frac{1}{2n} \sum_x \|y(x) - a\|^2.$

- 误差函数对各个权重求导（此过程可以认为是后向传播过程）

$$\Delta w^{ij} = -\eta \frac{\partial C}{\partial w^{ij}} = -\eta y^i \delta^j$$

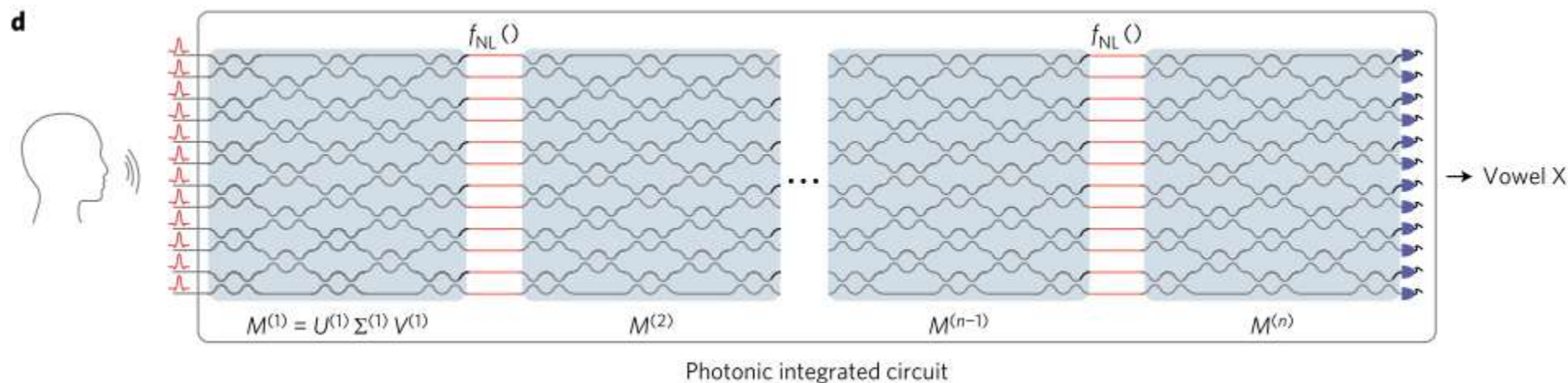
- 乘以学习率（手动），可以得到模型中各个参数的变化量，实现“学习”。

# 系统结构



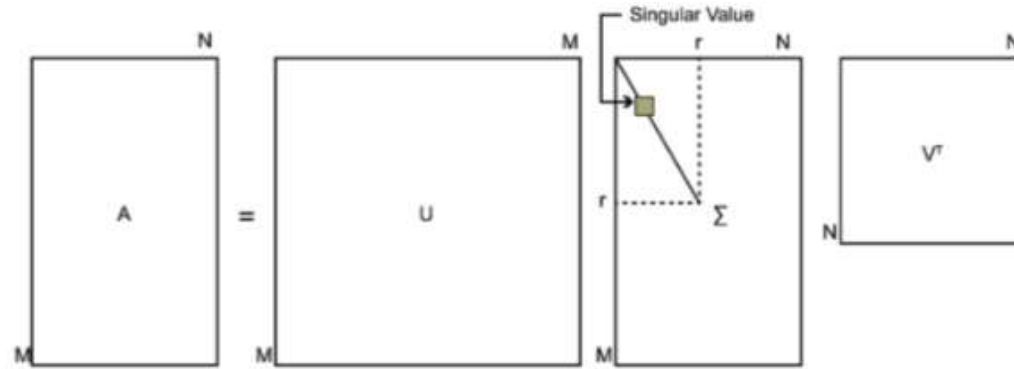
- 光电混合

- 每层由optical interference unit和optical nonlinearity unit组成



# Optical Interference Unit (OIU)

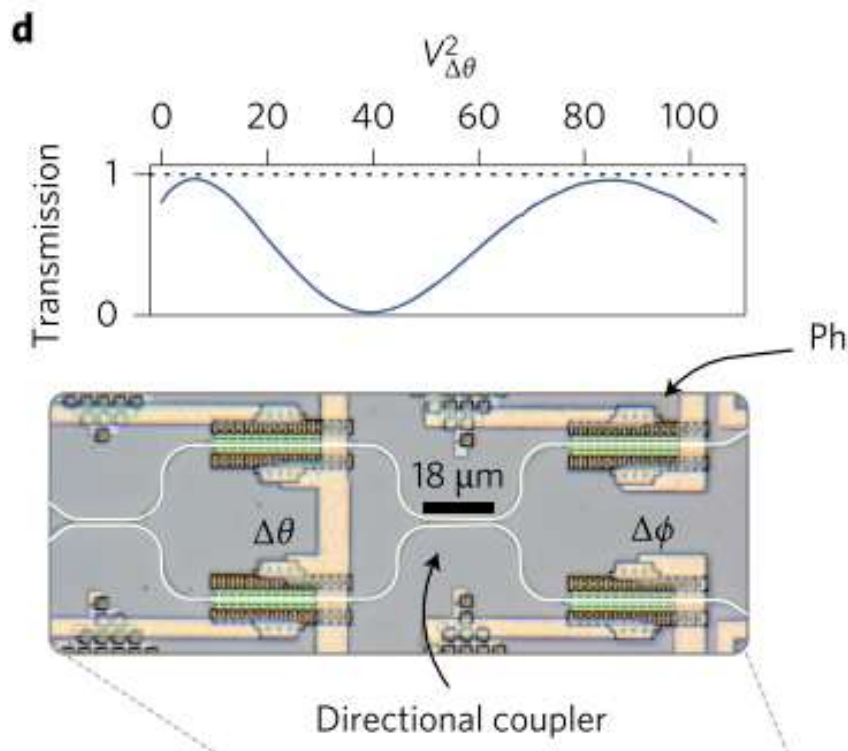
- 理论基础：矩阵的奇异值分解



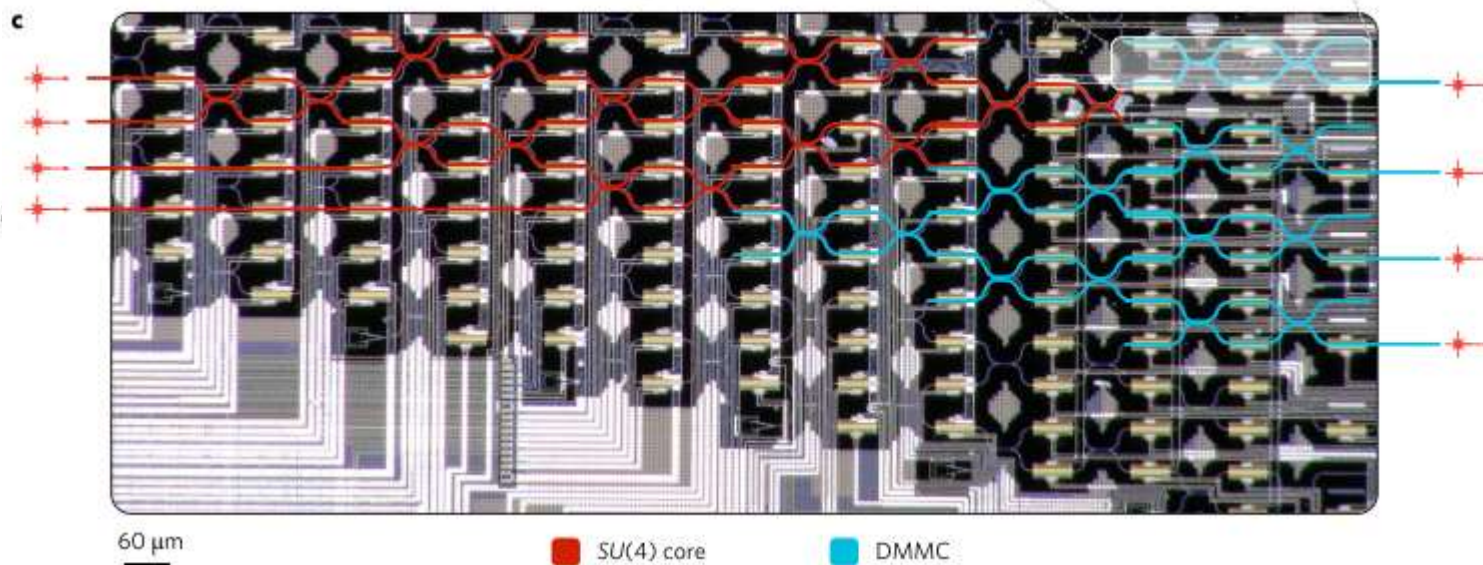
任意一个向量可以表示为三个特殊矩阵的乘积（左奇异向量，对角矩阵，右奇异向量）

- 左、右奇异向量为酉矩阵，其变换可用分束器、相移器完成
- 对角矩阵变换由光衰减器完成





单个结构示意图



芯片示意图

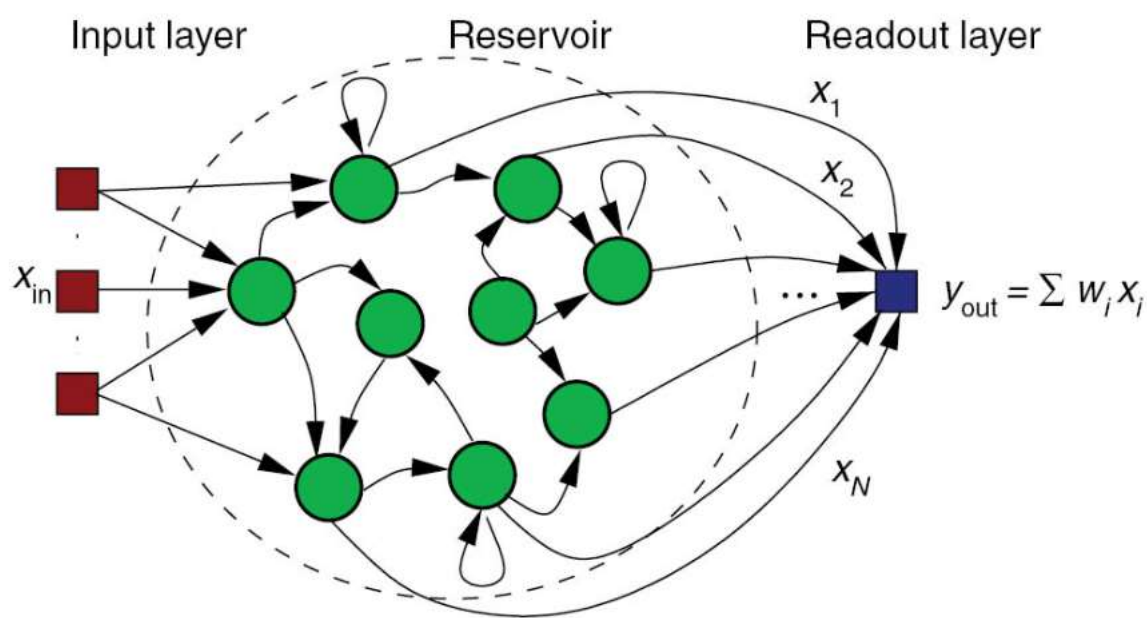
The MZI splitting ratio was controlled with an internal phase shifter (Fig. 2d) and the differential output phase was controlled with the external phase shifter.

# Optical Nonlinearity Unit (ONU)

- 模拟非线性激活函数
- 试想通过饱和吸收体来实现，如：波导上石墨烯层
- 文中用计算机进行模拟处理

# 文献2, 3:

- 在硅光芯片上实现了循环神经网络 (recurrent neural network) 中的水库计算 (reservoir computing)



水库计算的模型

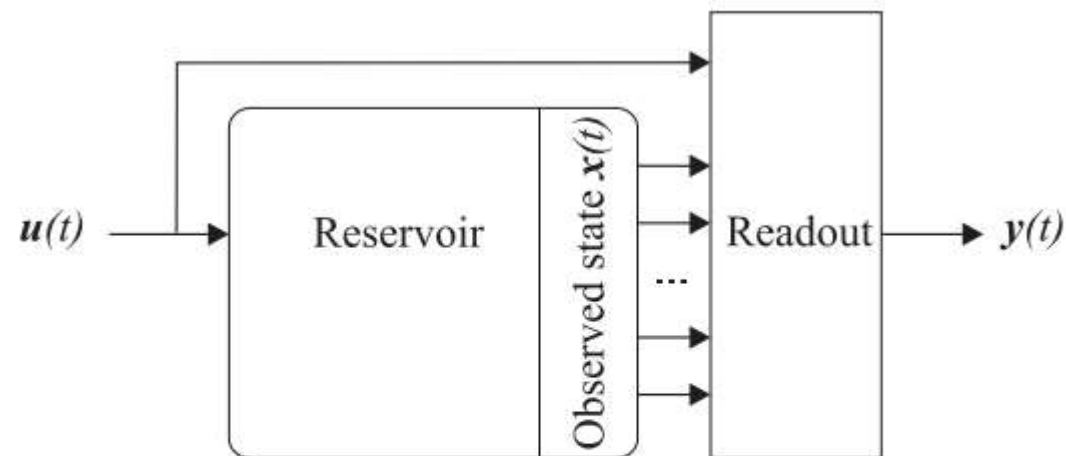
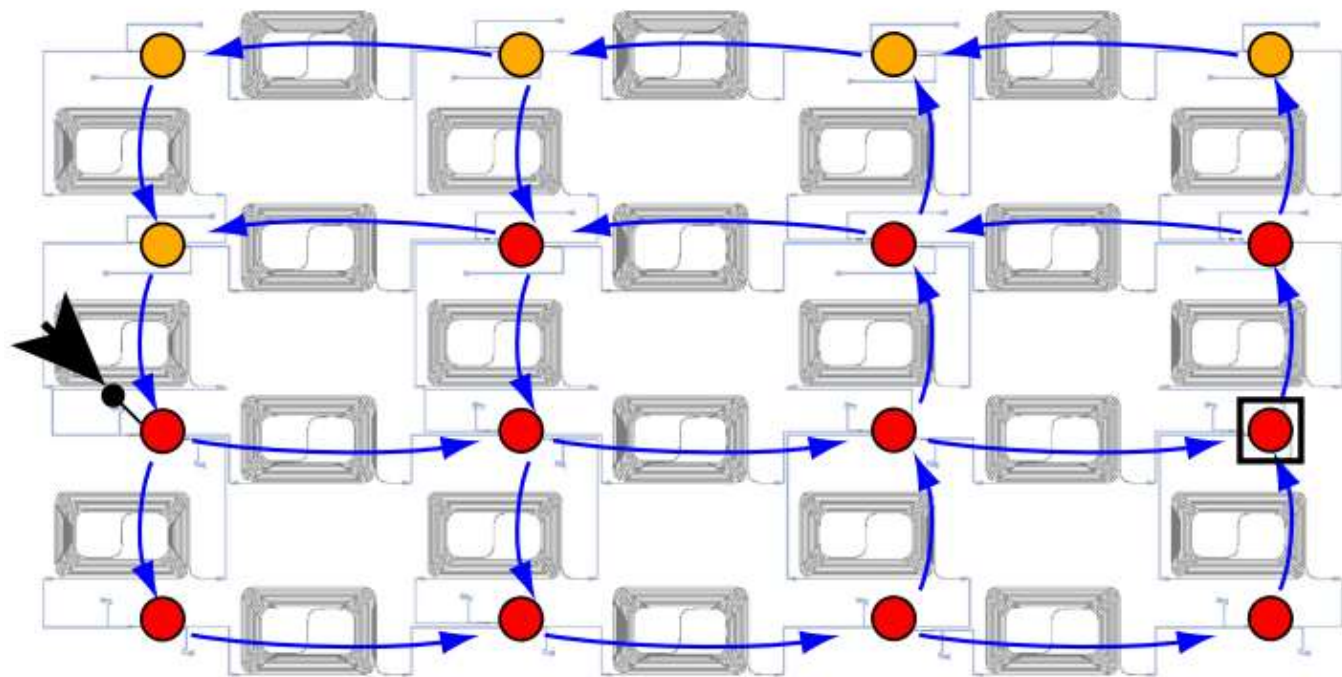


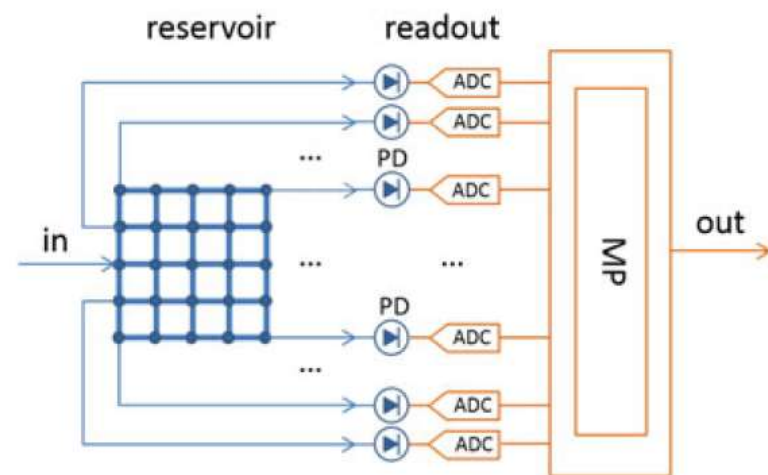
Fig. 1. Schematic representation of a reservoir computing system. The input signal  $u(t)$  is fed into the reservoir and the resulting reservoir states  $x(t)$  are used to learn a linear readout that is then used to generate the output signal  $y(t)$ .

水库中的各个模型参数固定，只需对读取出的向量进行学习。

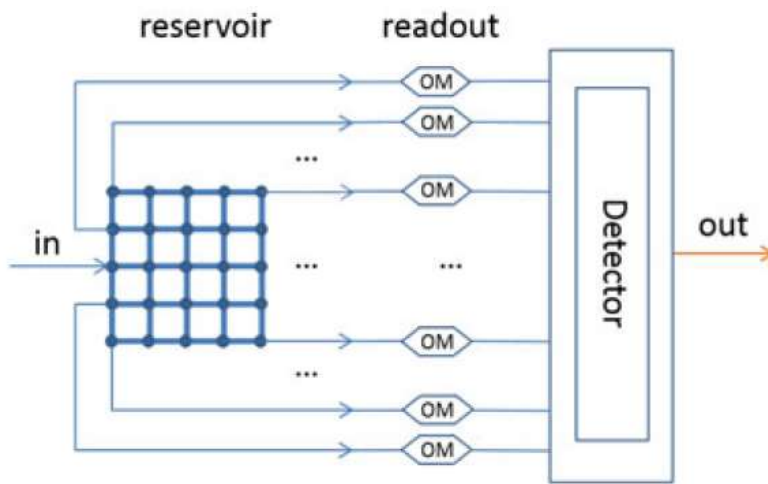
# 结构图



- footprint: 16 mm<sup>2</sup>
- connection: 2 cm,
- interconnection delay: 280 ps
- sampling rates: 125 Mbit/s – 12.5 Gbit/s



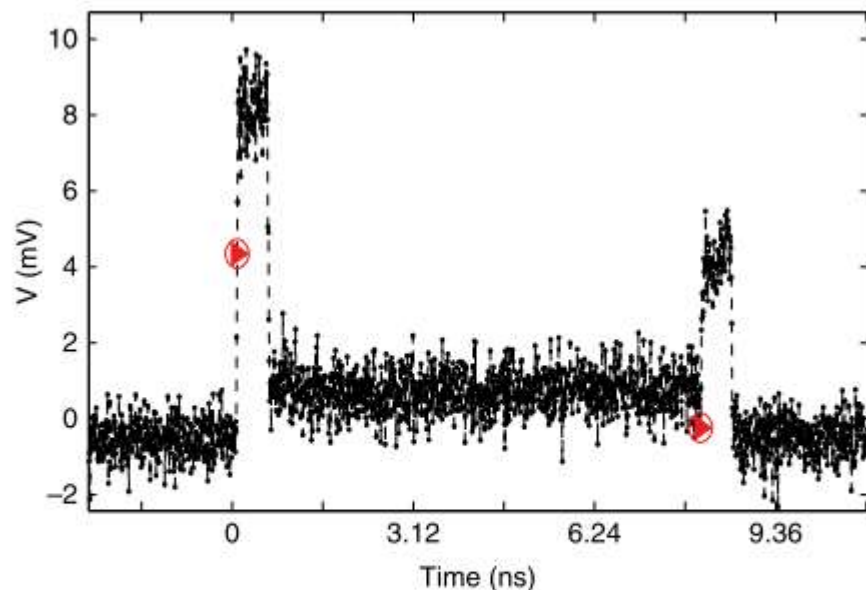
目前使用的结构



设想的结构

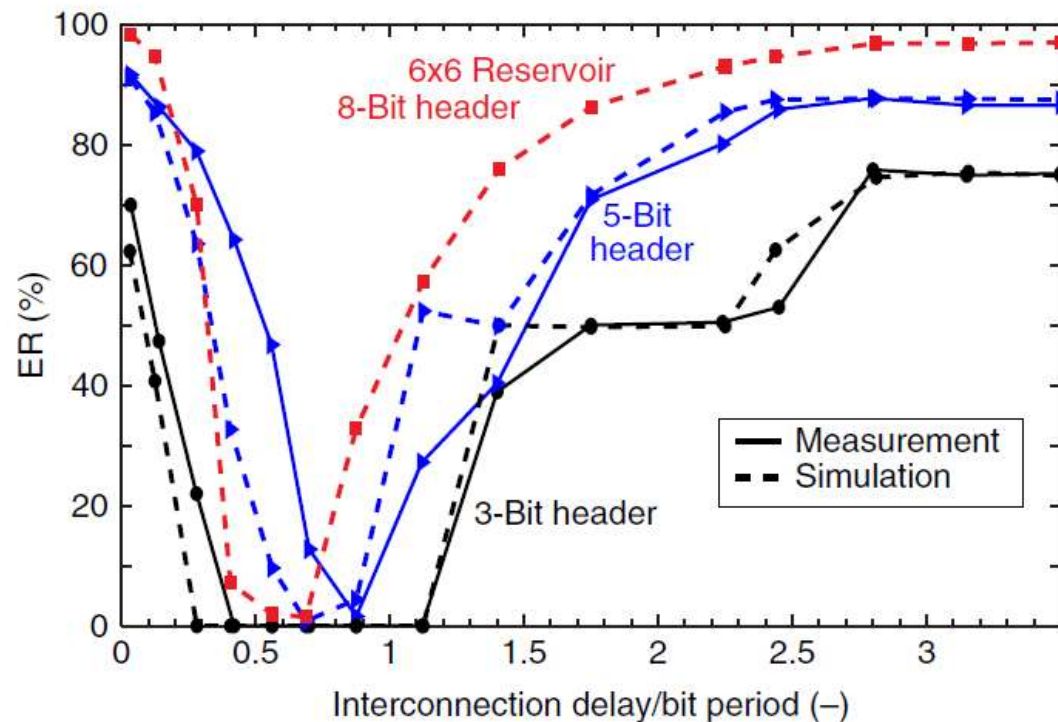


# 训练结果



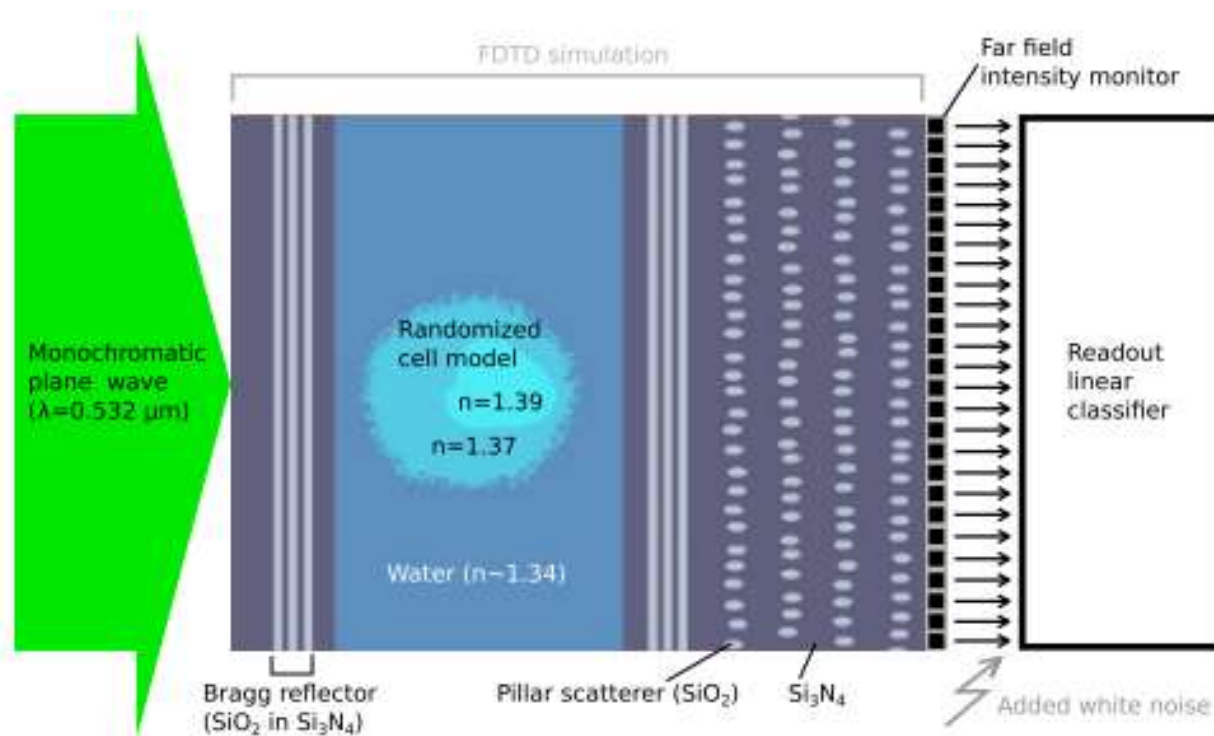
**Figure 8 | Example waveform collected at one of the nodes close to the input of the reservoir.** The input signal consists of 16 'one' bits surrounded by 'zero' bits. Red markers indicate the duration of these 16 bits.

训练模型时唯一可调参数: bit period



**Figure 7 | Isolated digit speech recognition simulation results for coherent networks with three different node types.** Phase information is used and the networks have the optimal delay for the speech task. Passive networks perform as well as networks with nonlinear node types.

# 其他的水库计算模型



Pillar Scatterers