Integrated Nanophotonic Structures for Optical Computing

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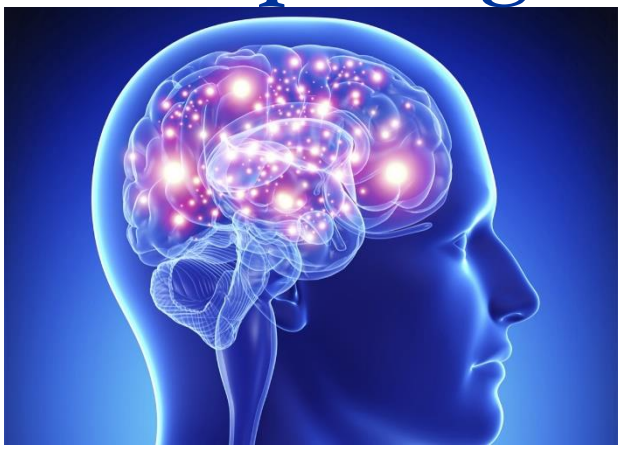
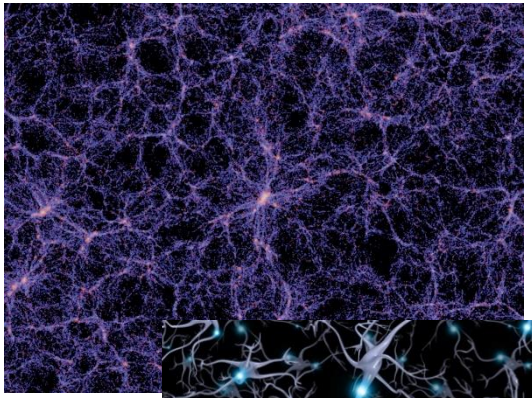
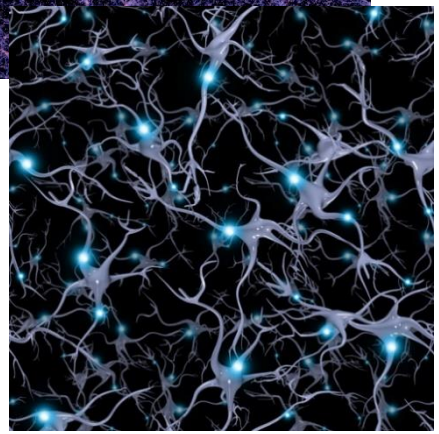
Introduction: Brain-inspired Computing



- The gap between brains and computers regarding both their cognitive capability and power efficiency is remarkably huge.
- Brain computation: Massively parallel, intrinsically self-organizing
  - 100 billion Neurons
  - 100 trillion Synopsys
- Brain-inspired computing approaches
  - Reservoir computing: Stochastic computing using large dynamical systems
  - Neuromorphic computing through spike processing

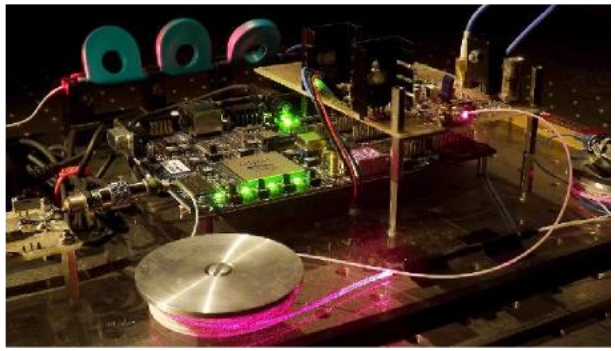




Introduction: Reservoir Computing (RC)

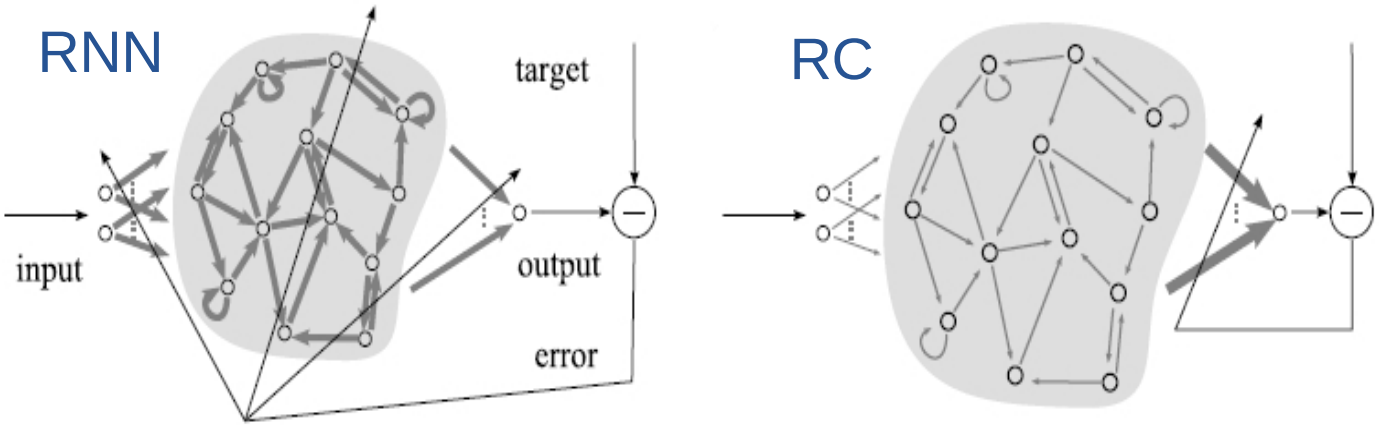
Conceptual viewpoint: from *rules* to *controlled freedom*

- Conventional computing (Binary digIT, logic gates)
- Digital computers & algorithms, more and more complex
- Optics and Parallel computing (SLM)
- Nano-photonics for optical computing revival?



Reservoir Computing

- Foundation of the RC concept: Recurrent Neural Network (RNN)



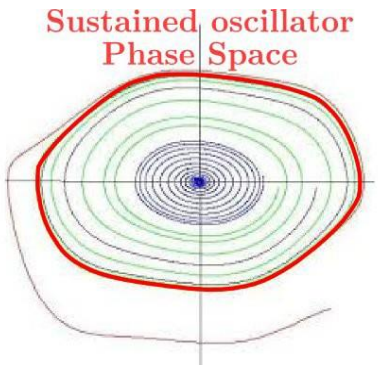
- "Randomly" fixed internal network connectivity
- Train how to read the reservoir response (only bold arrows)

M. Lukoševičius and H. Jaeger, "Reservoir Computing approaches to RNN training", *Comp.Sci.Rev.* 3 127-149 (2009)

Reservoir Computing

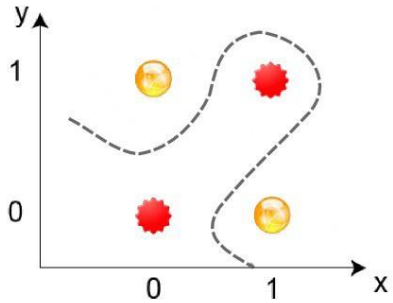
- Essential feature: dynamic (not static) *nonlinear transient computing*

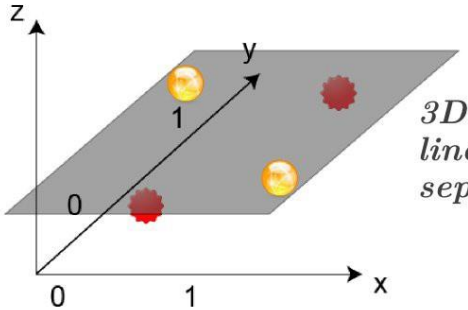
Asymptotic vs.
Transient dynamics
(huge space for transients
out of the stable solution)



- *Complexity versus dimensionality*

2D: classes are not linearly separable



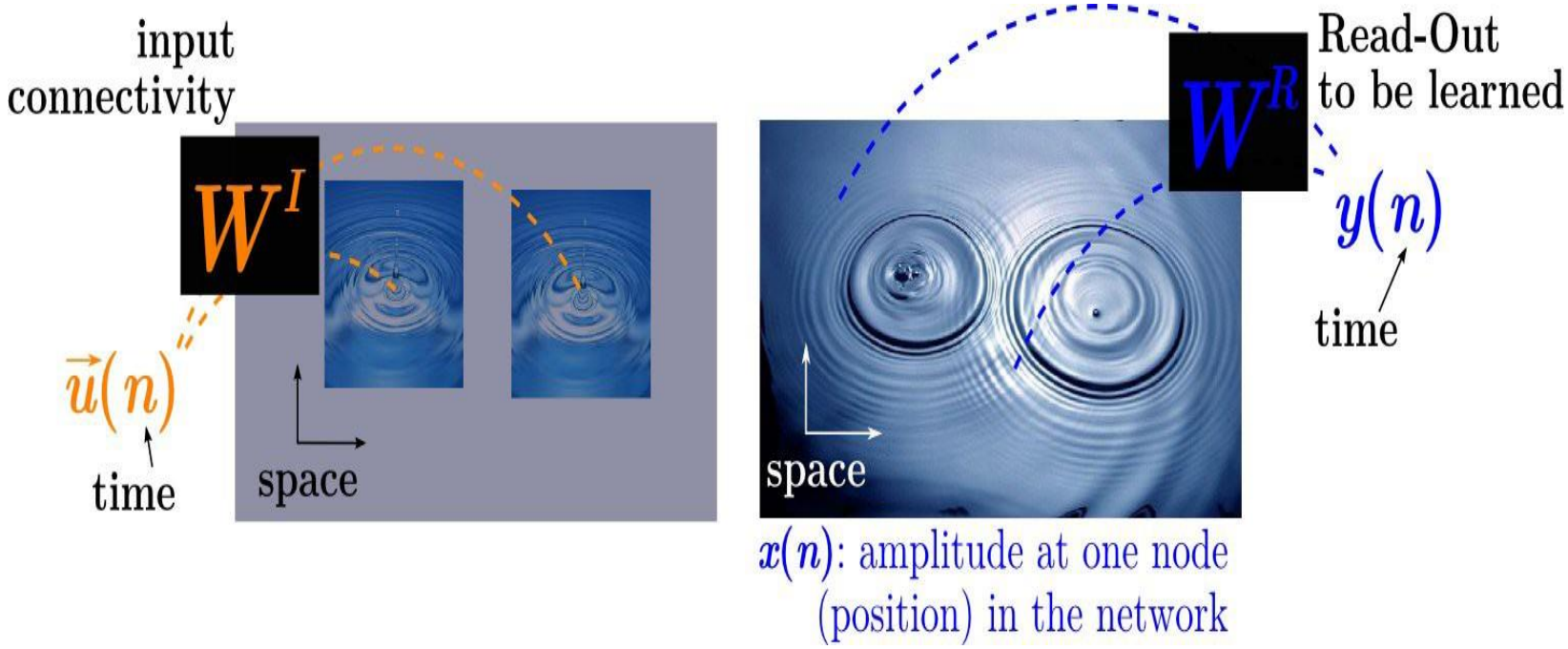


3D: classes are linearly separable

M. Lukoševičius and H. Jaeger, "Reservoir Computing approaches to RNN training", *Comp.Sci.Rev.* 3 127-149 (2009)

Reservoir Computing

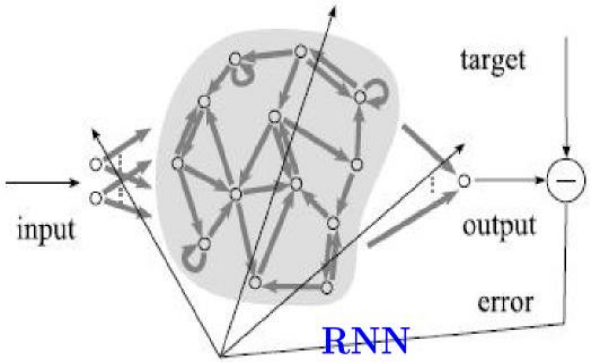
- Input triggers a transient in the dynamical system
- Read-Out W^R is to be learned via a simple process, e.g., using a MATLAB code line: $W^R_{opt} = Y_{target}\, X^T (X\, X^T - \lambda\, I)^{-1}$

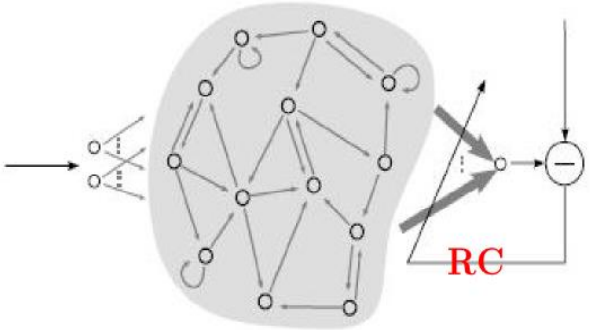


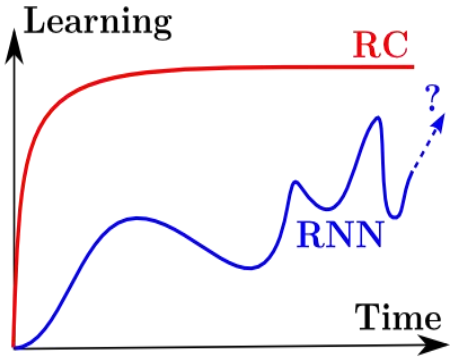
M. Lukoševičius and H. Jaeger, "Reservoir Computing approaches to RNN training", *Comp.Sci.Rev.* 3 127-149 (2009)

Unique Features of RC

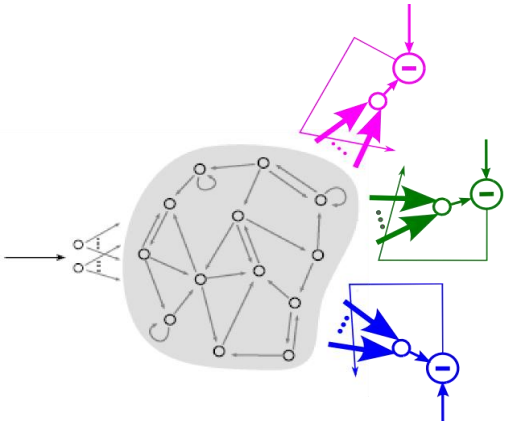
- Speed-up & simplify the training, without computational power loss!







- Can learn simultaneous multi-tasking (same input & Reservoir)



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- Already efficient, and considerable scope for improvement

Prospects of Photonic RC

- Photonic brain inspired computing: a platform for high-performance cognitive computing
- Applications: Image and temporal signal processing (e.g., pattern detection). Solving NP-hard problems

Adapted from Brain-Inspired Computing, Presented by Matt Grob Qualcomm

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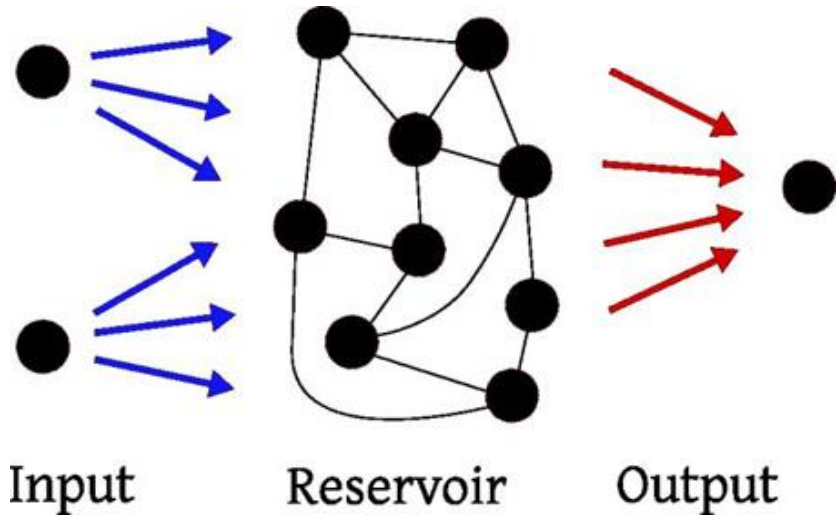
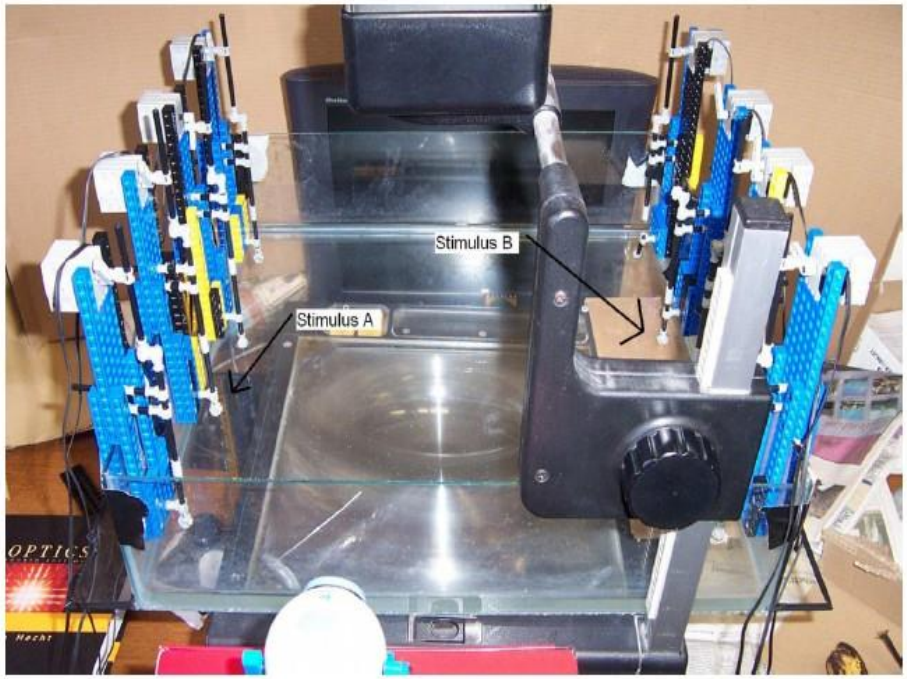
Achievements of Computer-simulated RC

- Predicting chaotic dynamics: 10^3 improvement
- Nonlinear wireless channel equalization: 10^2 improvement
- Japanese Vowel benchmark: 0% test error rate (previous best: 1.8%)
- Isolated spoken digits recognition 0.6% to 0%

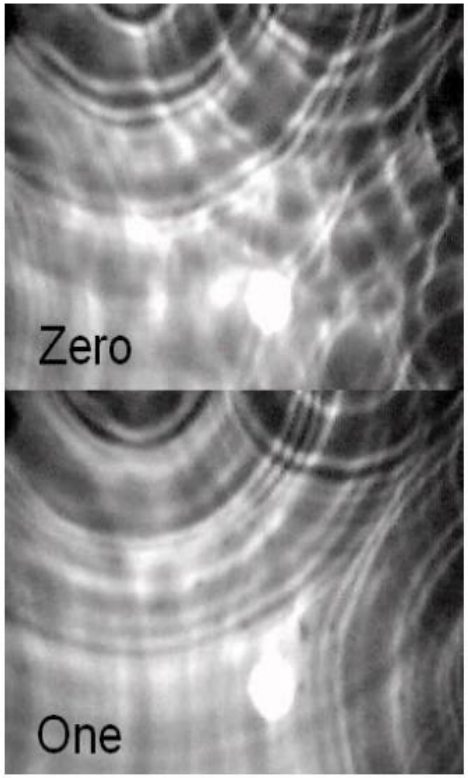


RC Implementations

- Bucket of liquid



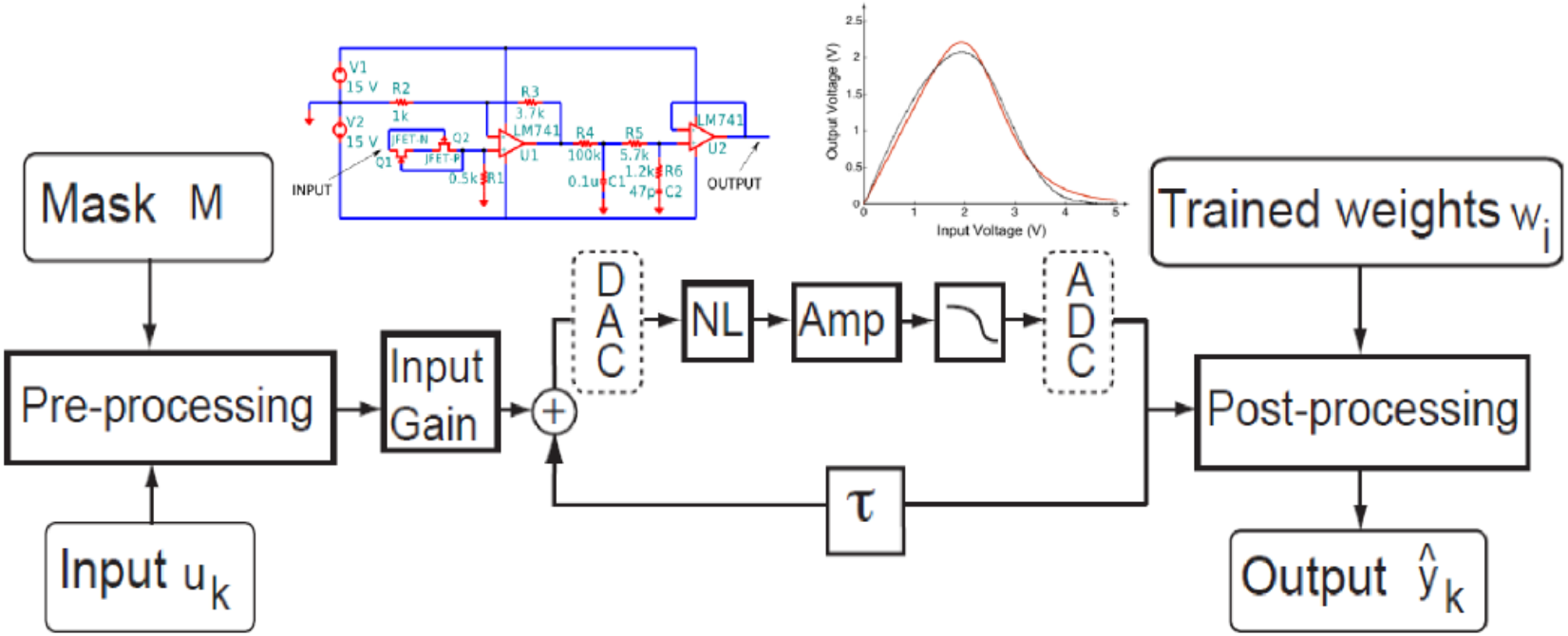
[Fernando, Sojakka, '03]



Fernando & Sojakka, "Advances in Artificial Life", pp.588-597 (2003, Springer)

RC Implementations

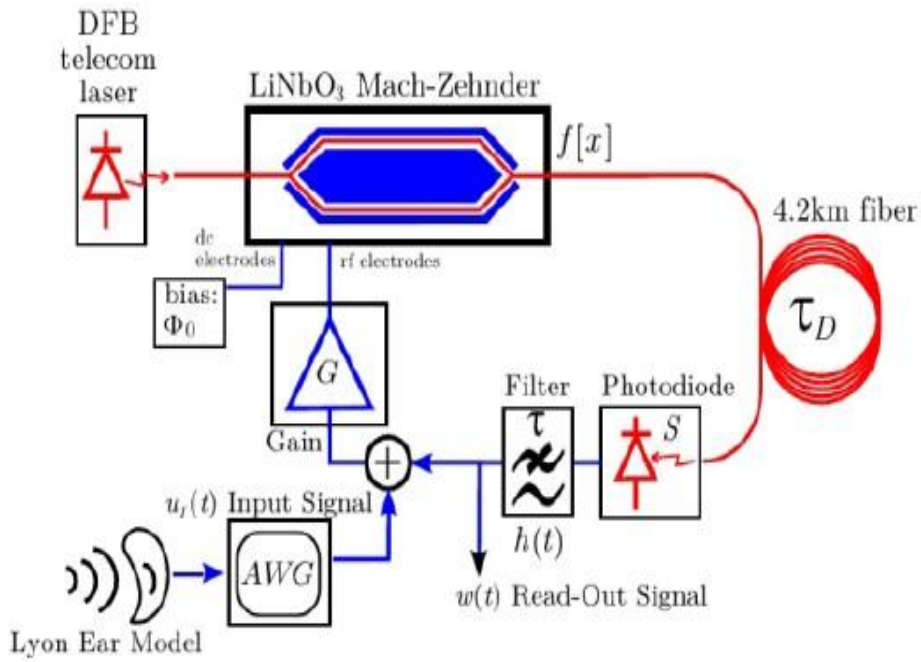
- Low-speed analog electronics

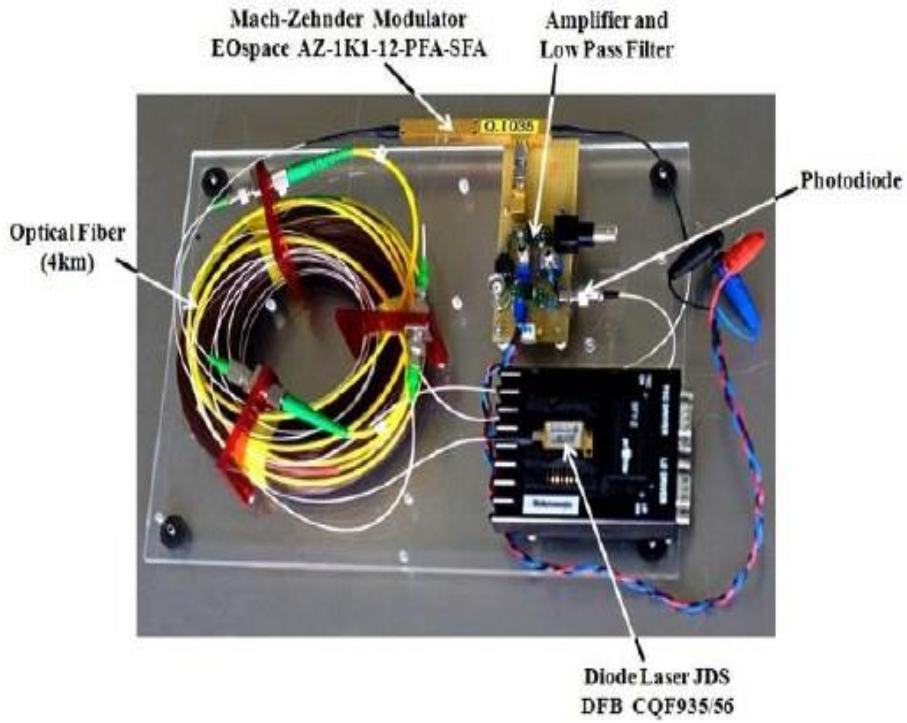


Appeltant *et al.*, *Nature Commun.* 2:468 (2011)

RC Implementations

- Moderate-speed optoelectronics

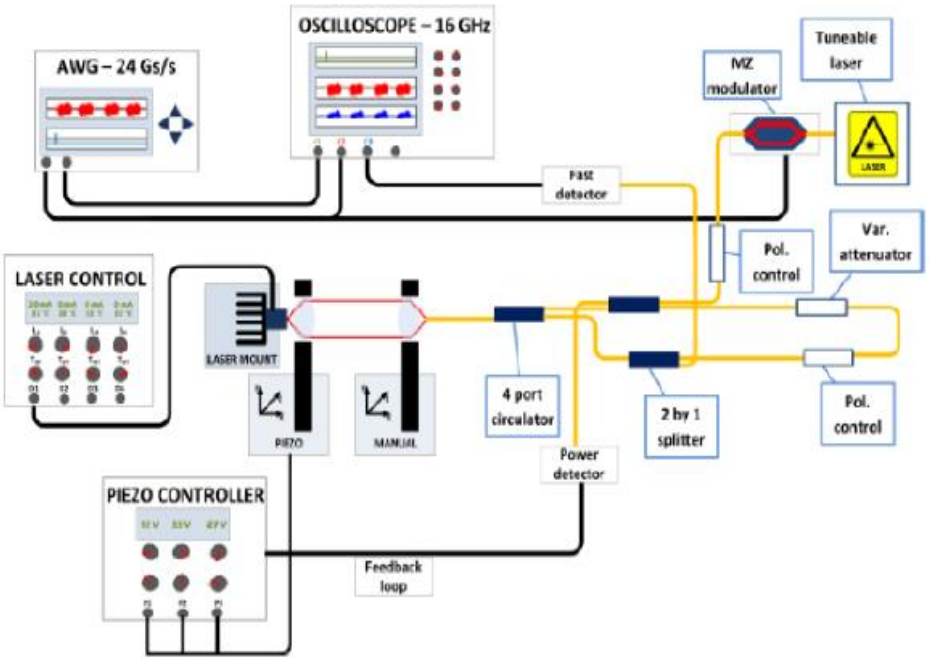


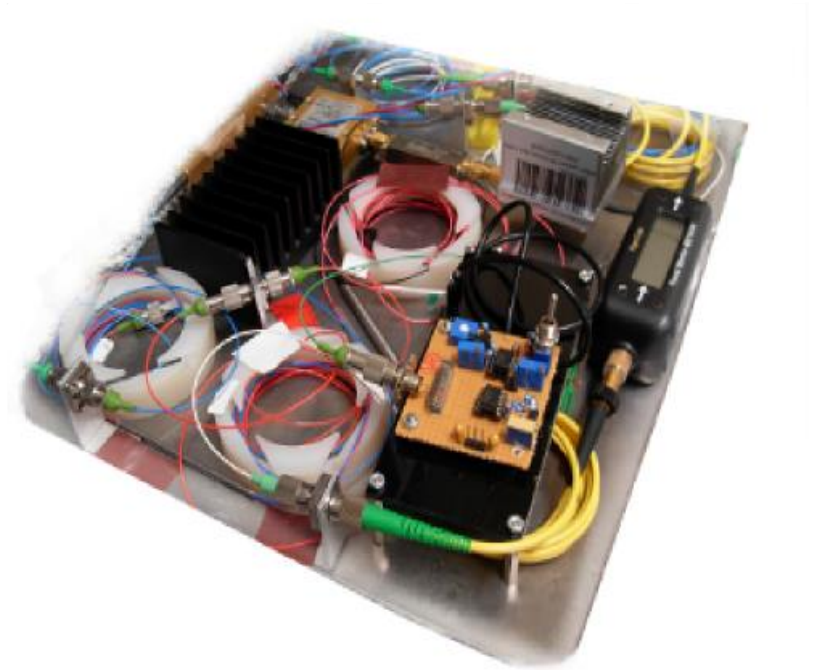


Larger *et al.*, *Opt.Expr.* 20(3) 3241. Paquot *et al.*, *Sci.Rep.* 2:287. Martinenghi *et al.*, *Phys.Rev.Lett.* 108 244101. (2012)

RC Implementations

- High-speed all-optical and optoelectronic



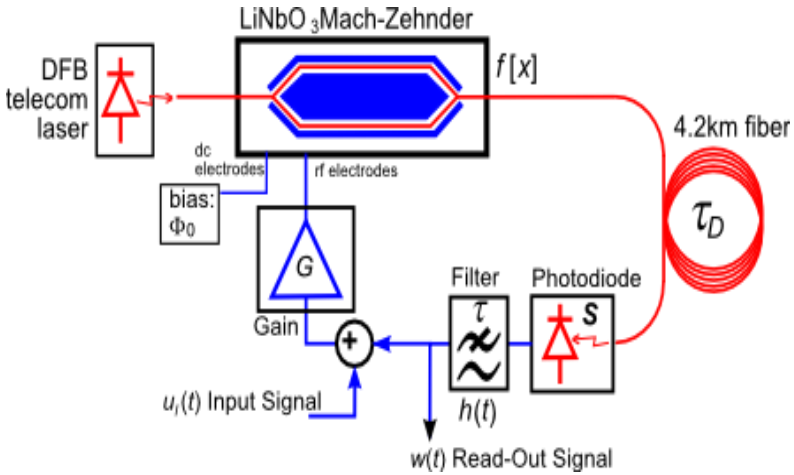


Practical RC Implementation: Requirements

Physical hardware fulfilling the role of a neural network:

- Should provide a high-dimensional dynamical response
- Should own appropriate dynamical properties (fading memory, approximation property, separation property)
- Should allow for suitable connectivity within the reservoir

One possible solution for the reservoir: Delay dynamics

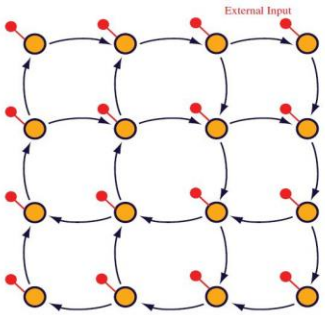


Photonic RC Implementation

"Actual" Spatio-temporal dynamics

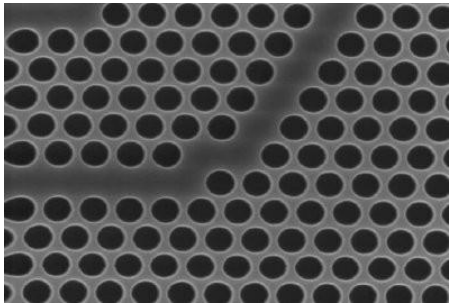
- Network of coupled SOAs (active)

  Vandoorne *et al.*, *Opt.Expr.* 2008 & *IEEE Trans. Neural Network* 2011



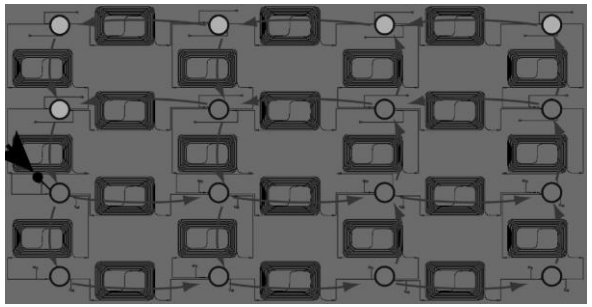
- Network with photonic crystal structures

  Fiers *et al.*, *IEEE Trans. Neur. Netw. & Learn. Syst.* 2014



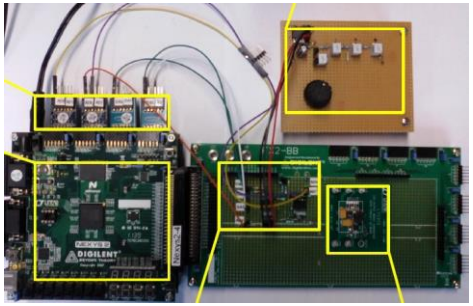
- On-chip network of coupled delay lines (passive)

  Vandoorne *et al.*, *Nature Comm.* 2014



Photonic RC Implementation

Emulated "virtual" through delay dynamics

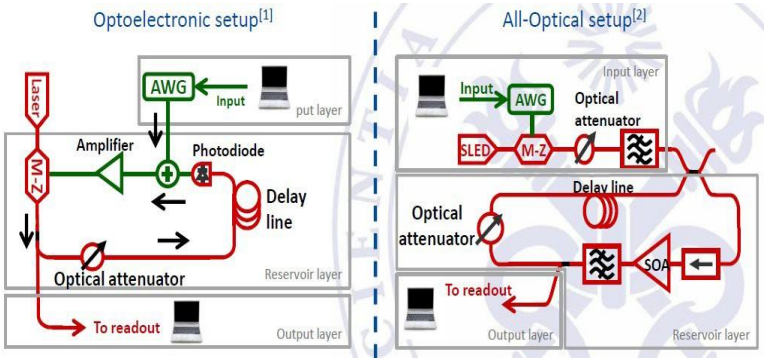


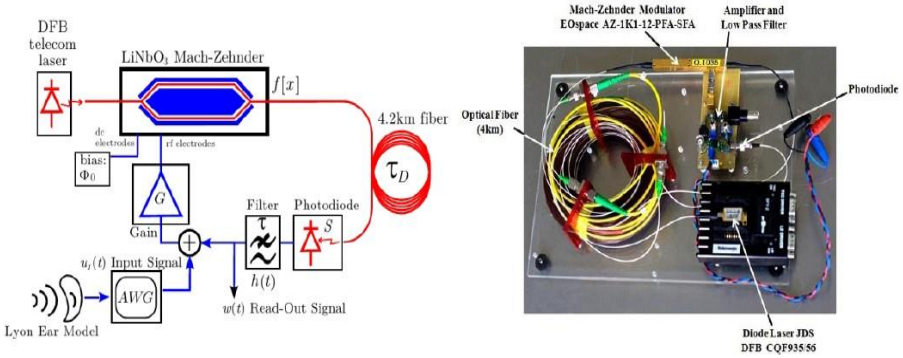
- Mackey-Glass delay electronic circuit

  Appeltant *et al.*, *Nature Comm.* 2011. Keuninckx *et al.* 2013

- Ikeda-like (electro-)optic delay dynamic

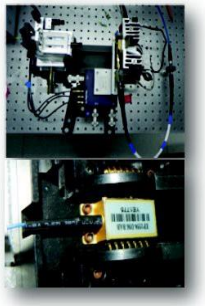
  Larger *et al.*, *Opt.Expr.* 2012. Paquot *et al.*, *Sci.Reports* 2012, Duport *et al.*, *Opt.Expr.* 2012. .

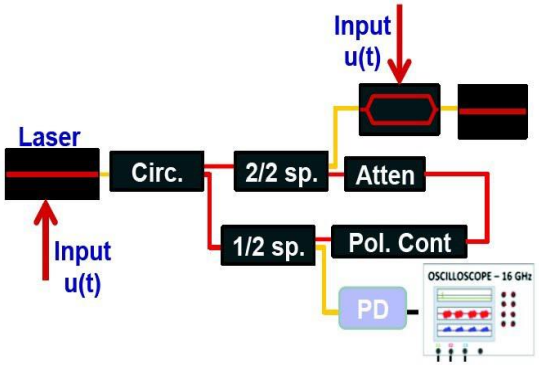




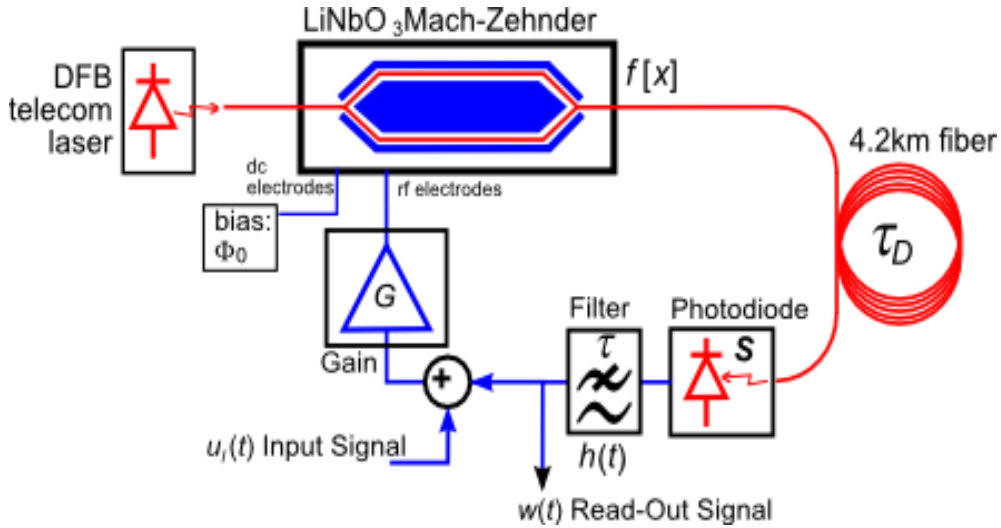
- External cavity laser diode

  Brunner *et al.*, *Nature Comm.* 2013





RC with Nonlinear Delay Dynamics: Optoelectronic Implementation

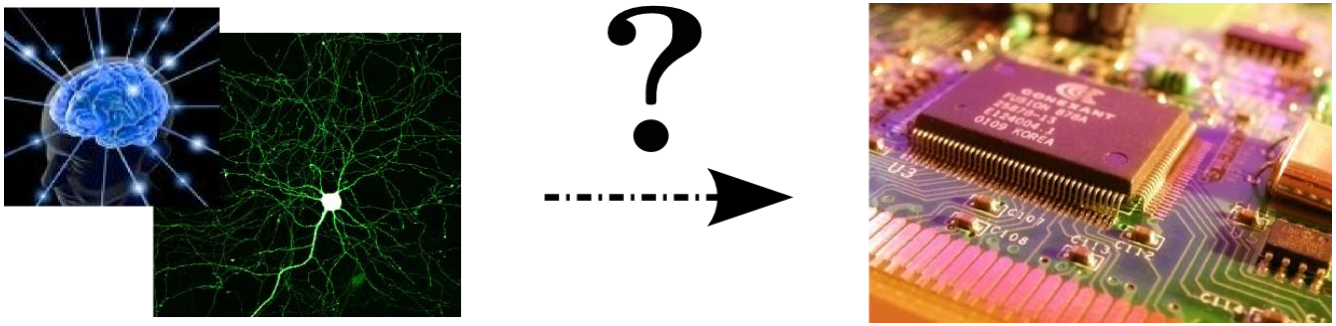


- Successfully used for optical chaos communications
- Well-known in high spectral purity microwave generation
- Experimental basis for the first demonstrations of photonic RC
- 1st electronic demonstrator based on a similar delay dynamics
- Latest high-speed photonic RC also involve delay dynamics

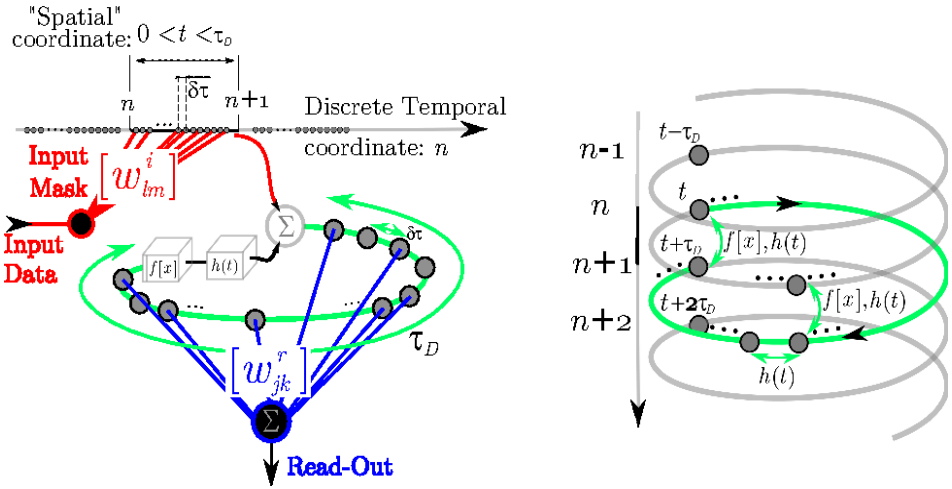
Brunner *et al.*, *Nature Comm.* 4:1364. Jacquot *et al.*, *CLEO Europe*. (2013)

Time-multiplexing to Address Virtual Nodes

- Designing a complex and controlled 3D network of nodes as a brain: a very difficult technological challenge



- Serial processing: common in many communication systems
- Delay dynamics known as virtual Space-Time dynamics



Rescaling and Spatio-Temporal Viewpoint

- Normalization wrt delay τ_D: $\boldsymbol{s = t/\tau_D}$ **and** $\boldsymbol{\varepsilon = \tau/\tau_D}$

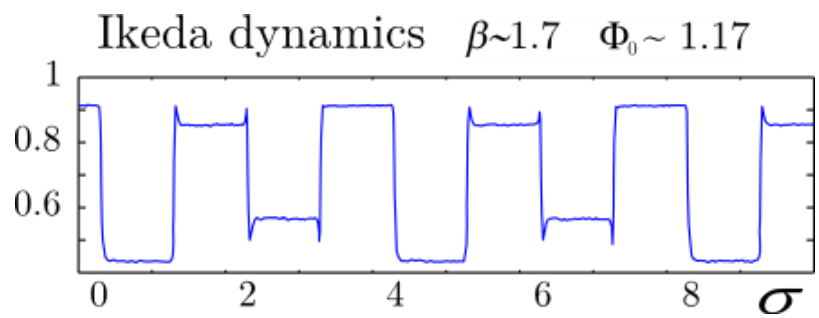
$$\boldsymbol{\varepsilon \dot{x}(s) = -x(s) + f_{\mathrm{NL}}[x(s-1)]} \quad \text{where} \quad \dot{x} = \frac{\mathbf{d}x}{\mathbf{d}s}.$$

Large delay case: $\varepsilon < 1$, potentially high-dimensional attractor

$\infty-$dimensional phase space, initial condition: $x(s)$, $s \in [-1, 0]$

- Space-Time representation
  - Virtual space variable σ,

    $\boldsymbol{\sigma \in [0; 1+\gamma]}$ with $\gamma = \boldsymbol{O(\varepsilon)}$



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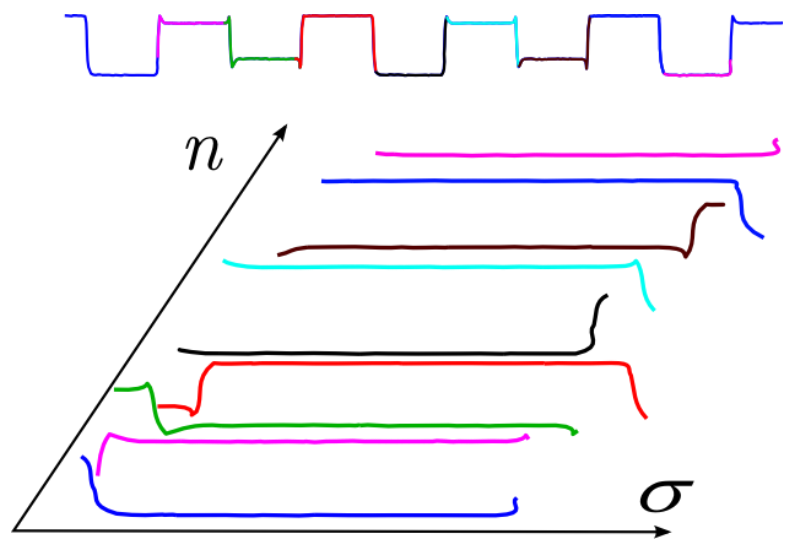
  - Discrete time n

$$\boldsymbol{n \rightarrow (n+1)}$$

$$\boldsymbol{s = n(1+\gamma) + \sigma \rightarrow s = (n+1)(1+\gamma) + \sigma}$$



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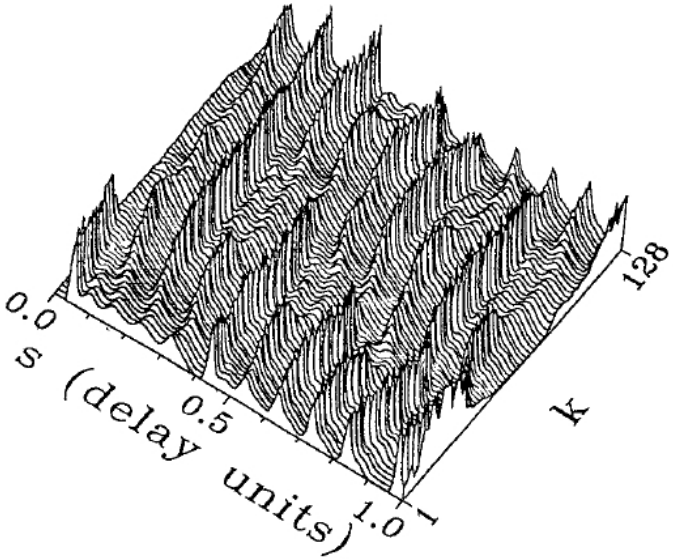
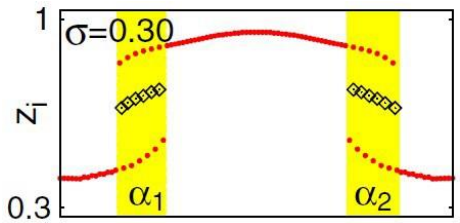
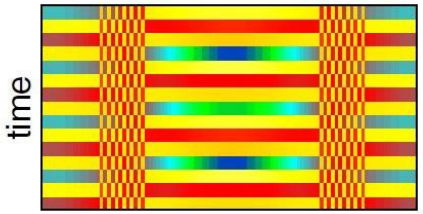


F.T. Arecchi, *et al.* Phys. Rev. A, 1992

Space-Time Analogy with DDE





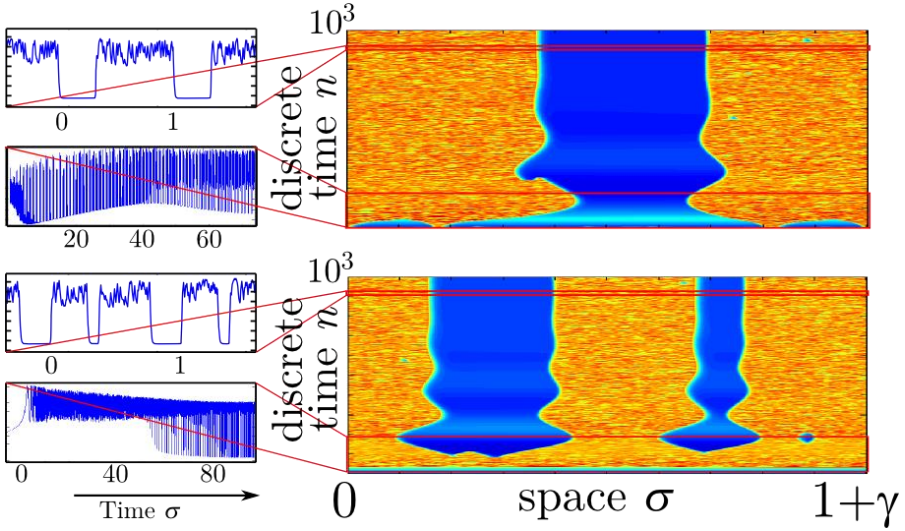
- What is a Chimera in Nonlinear Dynamics?
  - Network of coupled oscillators with clusters of incongruent motions
  - Predicted numerically in 2002, derived for a particular case in 2004, and 1st observed experimentally in 2012
  - Does not exist with local or global coupling
- Features allowing for Chimera states?
  - Network of oscillators, thus spatio-temporal dynamics
  - Requires non-local nonlinear coupling between oscillator nodes
  - Important parameters: coupling strength, and coupling distance

Y. Kuramoto and D. Battogtokh, *Nonlinear Phenom. Complex Syst.* 5, 380 (2002); D. M. Abrams and S. H. Strogatz, *Phys. Rev. Lett.* 93, 174102 (2004); I. Omelchenko *et al. Phys. Rev. Lett.* 106 234102 (2011); A. M. Hagerstrom *et al.* & M. Tinsley *et al.*, *Nat. Phys.* 8, 658 & 662 (2012)

Virtual Chimera in (σ, n) Space

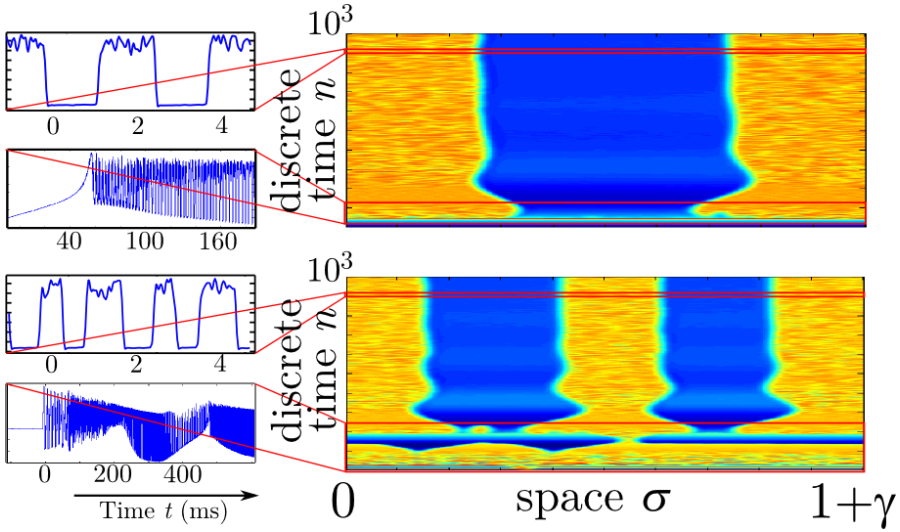
Numerics:

- $\beta = 0.6, v_0 = 1, \varepsilon = 5.10^{-3}$, $\delta = 1.6 \times 10^{-2}$ $(m = 56)$
- Initial conditions: small amplitude white noise (repeated several times with different noise realizations)
- Calculated durations: 1000s of n



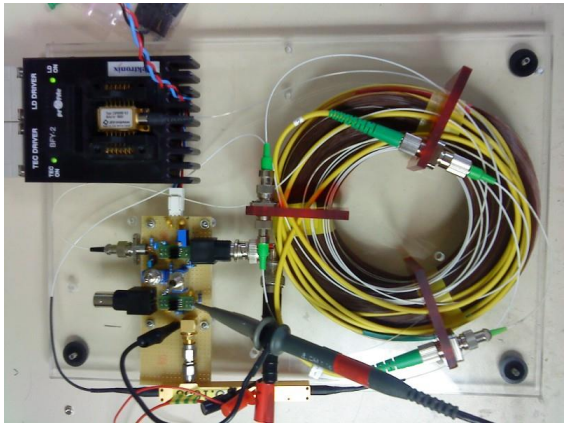
Experiment:

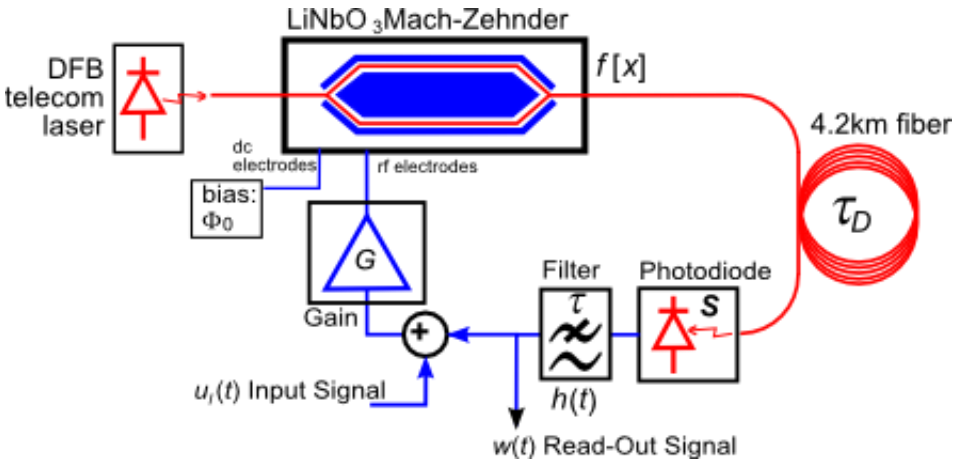
- Close amplitude and time parameters $\tau_D = 2.54$ms, $\theta = 0.16$s, $\tau = 12.7\mu$s
- Initial condition forced by background noise
- Recording of up to 16×10^6 points, allowing for a few thousands



Optoelectronic DDE as a Reservoir

- Experimental setup





- Accurate & simple modeling

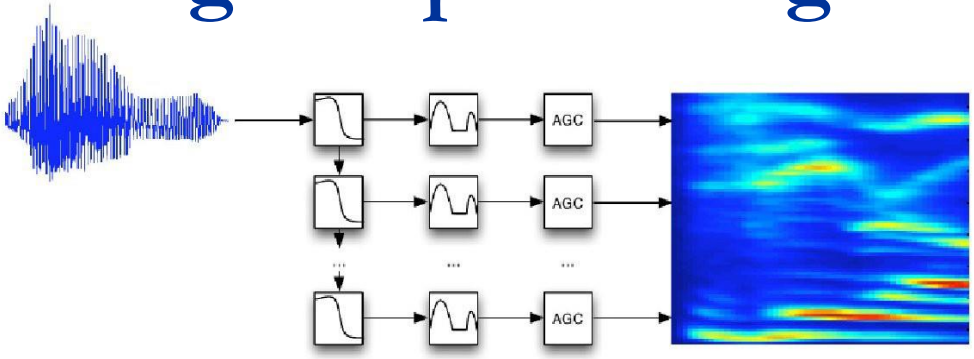
$$\varepsilon \dot{x}(s) + x(s) = \beta \sin^2[x(s-1) + \rho\, u_I(s-1) + \Phi_0]$$

SEVENTH FRAMEWORK PROGRAMME

phocus

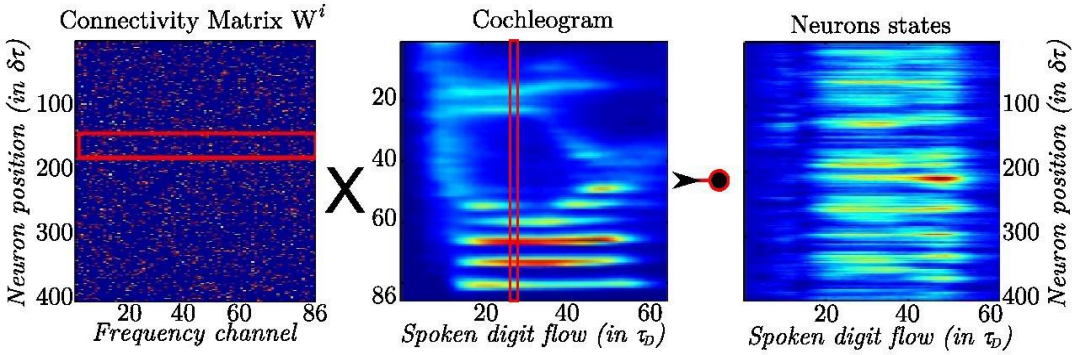
towards a PHOtonic liquid state machine based on delay-CoUpled Systems

Dynamical Processing of Spoken Digits



Input pre-processing

- Lyon Ear model transformation (time & frequency 2D formatting, 60 samples x 86 freq. channel)
- Sparse “connection” of the 86 Freq. channel to the 400 neurons: random connection matrix



Reservoir transient response:

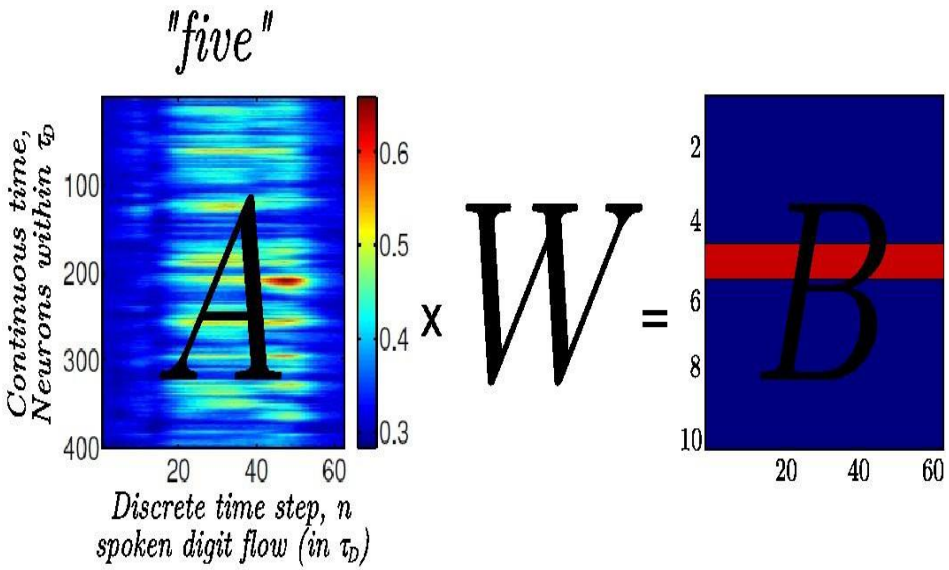
- Time series record for Read-Out post-processing

Read-Out, Training, and Testing

- Training of the Read-Out with target output function
- Learning: optimization of *W* matrix, for each different digit

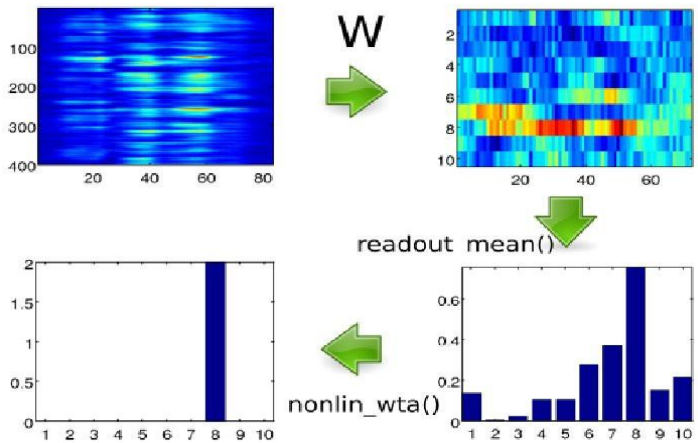
→ Regression problem for $A \times W = B$

$$W_{\text{opt}} = (A^T A - \lambda I)^{-1} A^T B$$

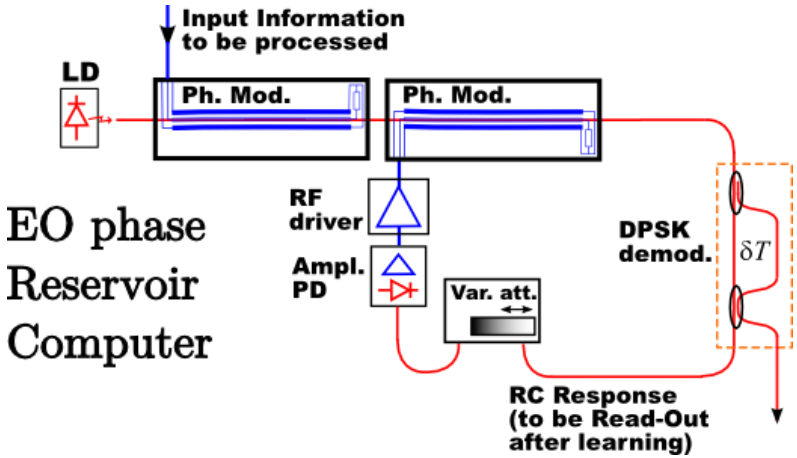


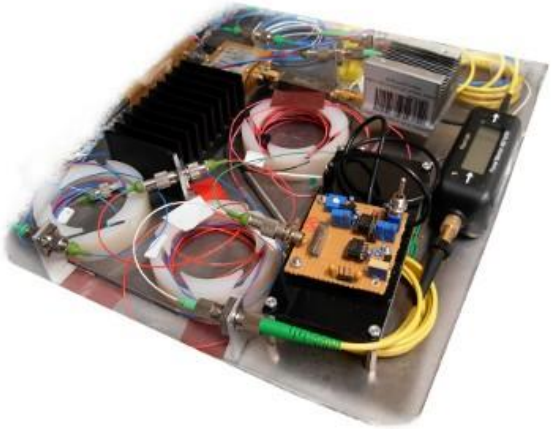
Testing with Training-defined Read-Out

- Test result: State of the art (close to 0% Word Error Rate) in a simple recognition problem and about 1% in the standard test



- With Telecom bandwidth setup: record 1M word/s

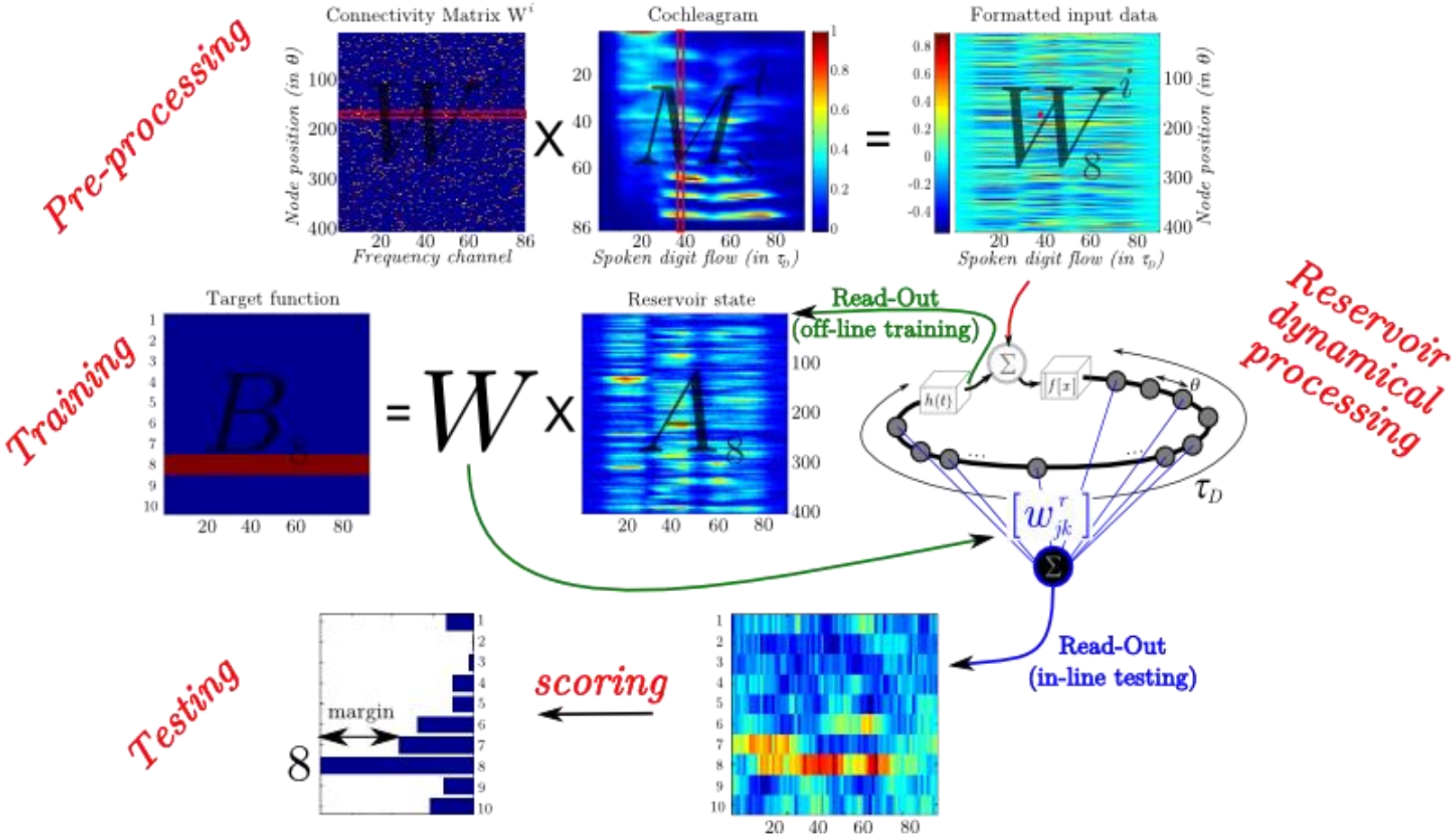




Example of a Benchmark Test with RC

Spoken digit recognition

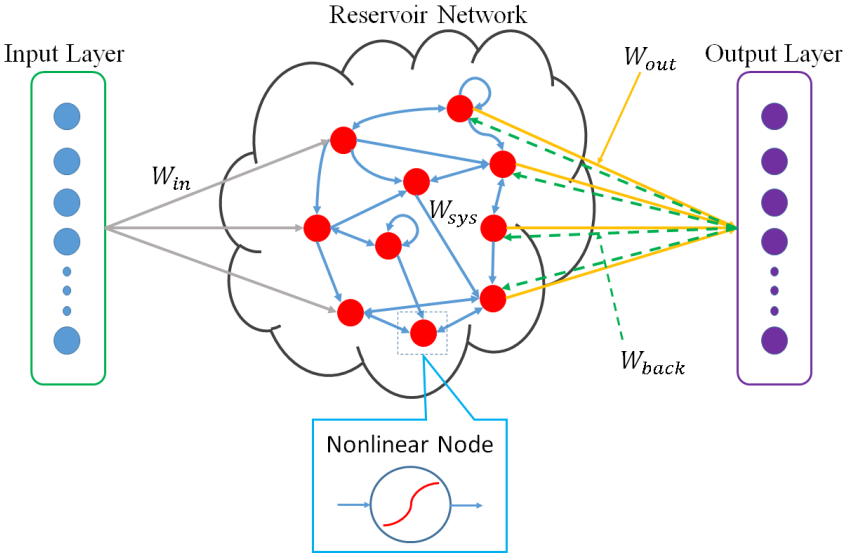
(from TI46 speech corpus, 500 words, 0-9, 5x uttered, 10 speakers)



Prospects of Photonic RC

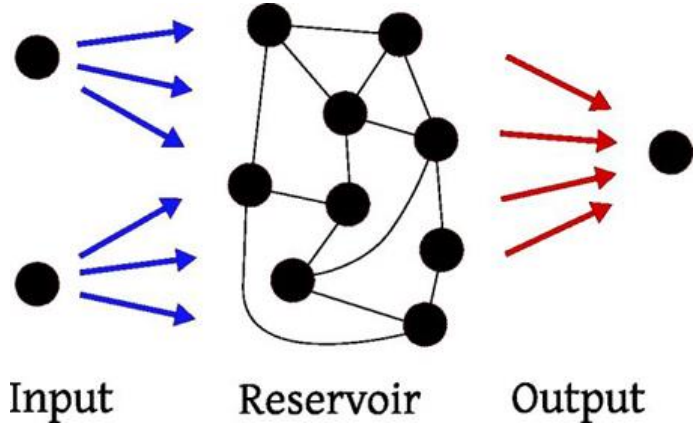
- Deep learning through training artificial recurrent neural network
  - Take advantage of large-scale dynamical systems, without the need to know the details of the dynamical system
  - Training through reconfiguration output mapping

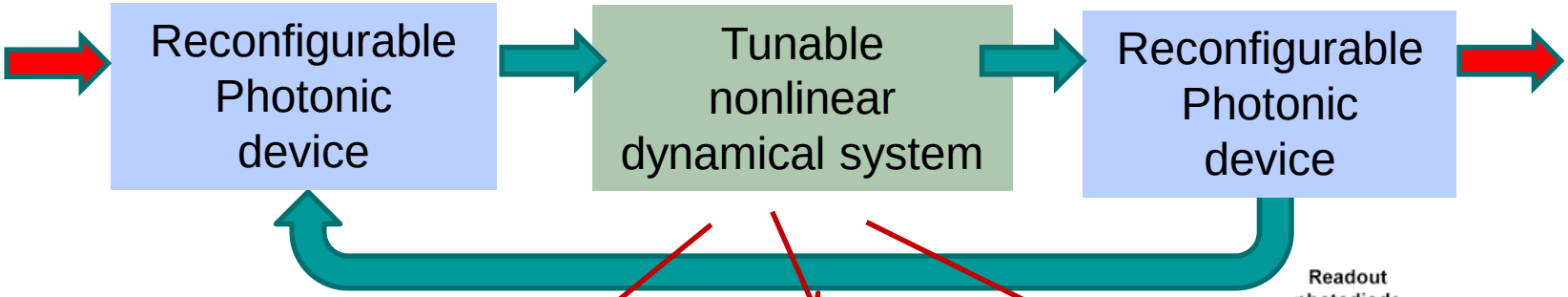
- Photonic reservoir computing
  - Large scale and fast dynamical systems → Very high information processing capacity
  - Potential for very large-scale integration using integrated photonic device

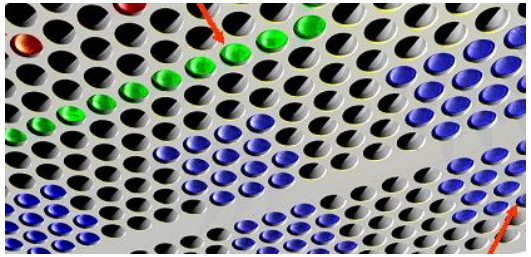


Integrated Photonic Solutions for RC

- Computation based on high-order complex dynamics of a nonlinear system
  - The inputs are applied to the system with appropriate weighting to control the system state
  - The output is generated based on the mixing of the desired states/features

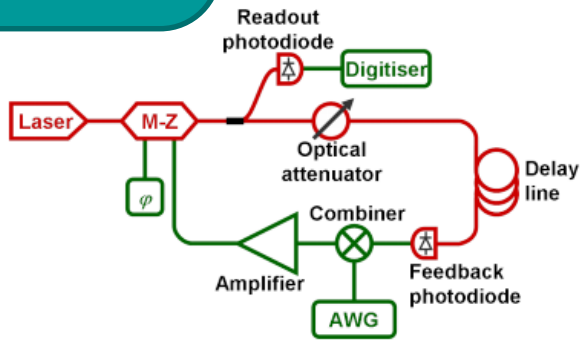






Wave propagation in nonlinear engineered slabs

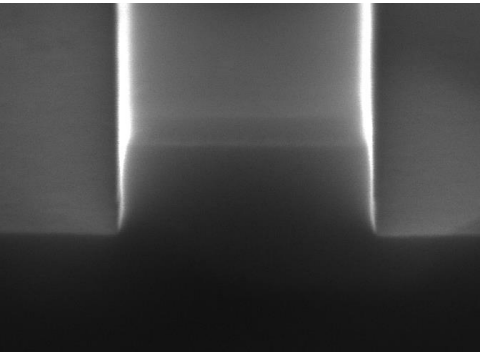
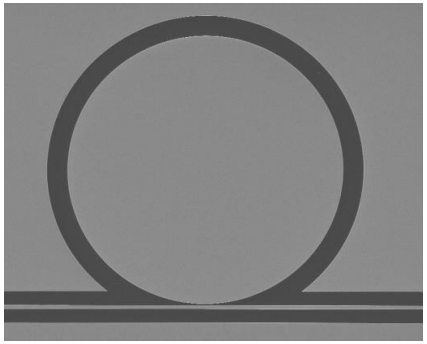
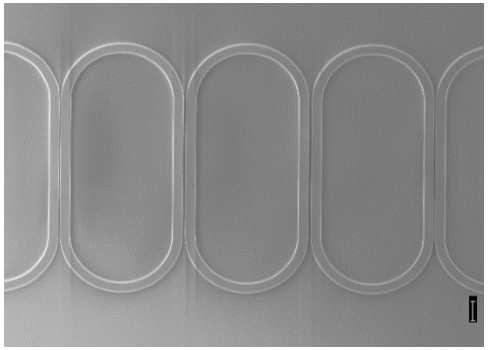
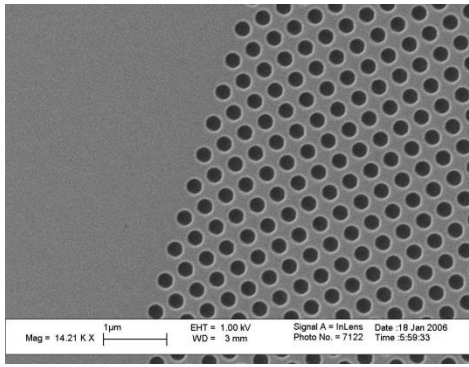
Kerr nonlinearity: Soliton generation in microresonators



Nonlinearity gain: Transient dynamics of ring oscillator

Recent Advances in Si Photonics

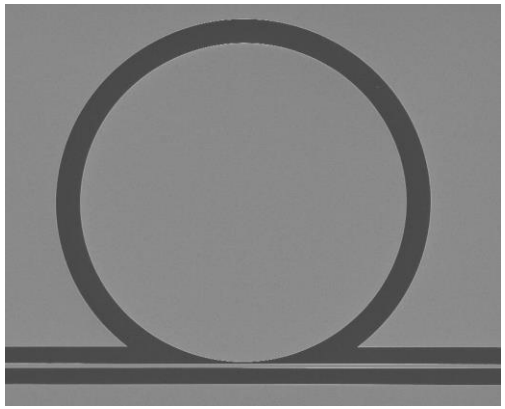
- High speed modulators
- Source and detector integration
- Ultra low loss waveguides
- Ultra high Q resonators
- High performance functional devices (e.g., couplers, high order filters, spectrometers)
- Photonic crystal device technology

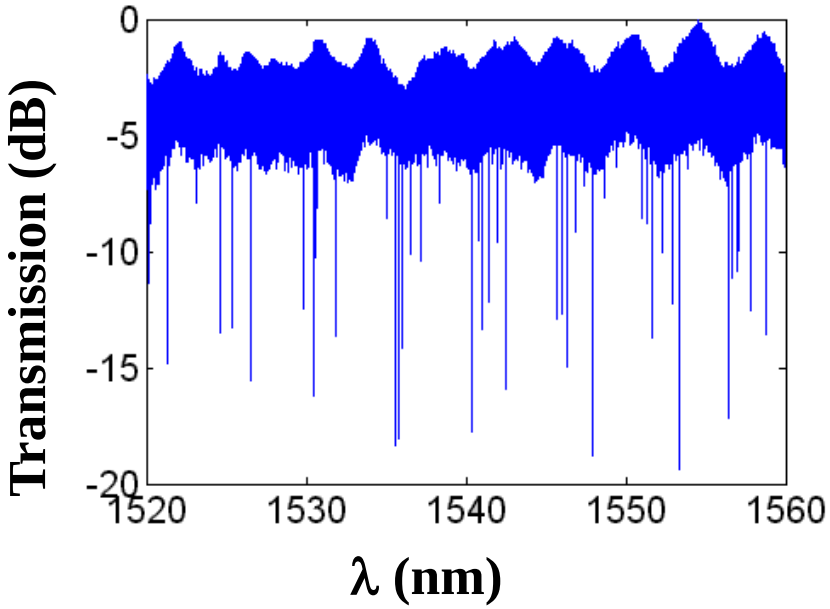





Current performance promises high quality reconfigurable photonics structures

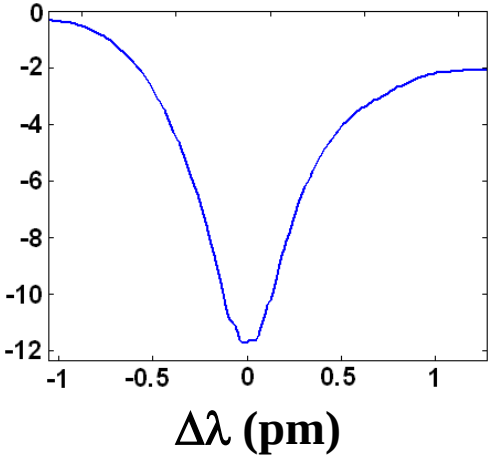
High-Q Microdisk Resonators on Chip

Radius 20 μm





$Q_{Unloaded}$ ~ 3.2 million

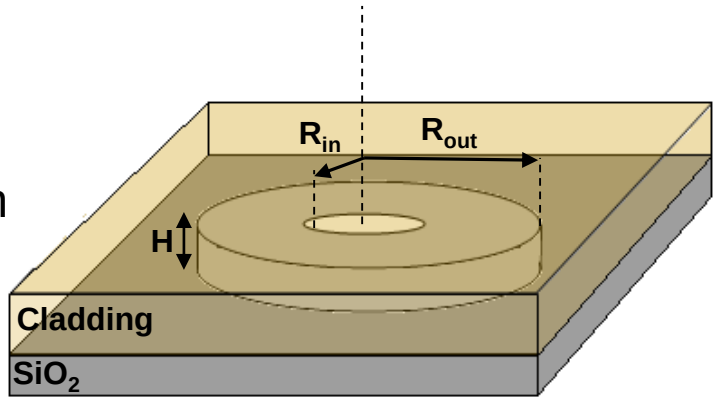


- Highest Qs to date for disks on substrate (visible and IR)
- Features:
  - Higher order modes
  - Small free spectral range (FSR)
  - Number of modes can be controlled by the size of the resonator

Miniaturized Microdisk Resonators

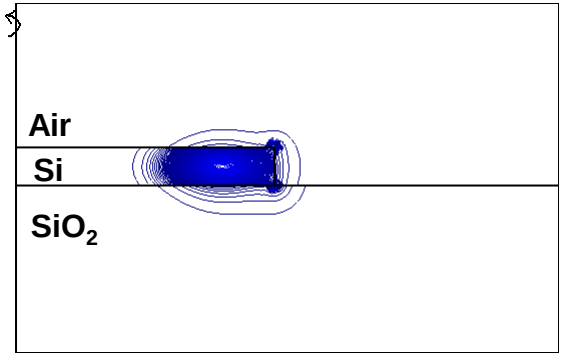
Objectives:

- ❑ Ultra-compact, high Q, large FSR microdisk
- ❑ Single mode operation over a large bandwidth
- ❑ Ultrafast thermal tuning using the zero field region in Si to place the heaters
- ❑ Replacement of microring resonators



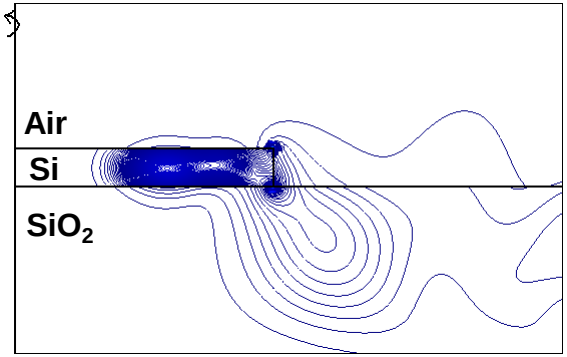
Example

Electric energy: 1st order mode



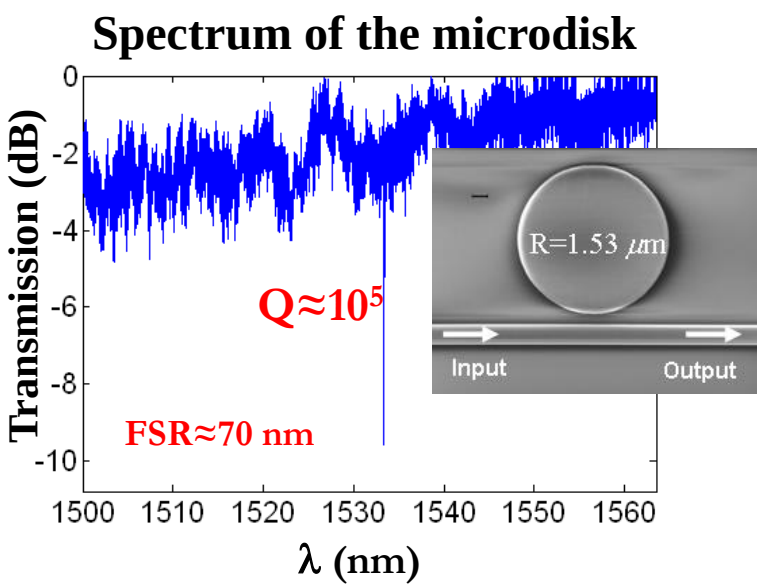
Disk radius = 1.4 μm
Disk thickness = 200 nm

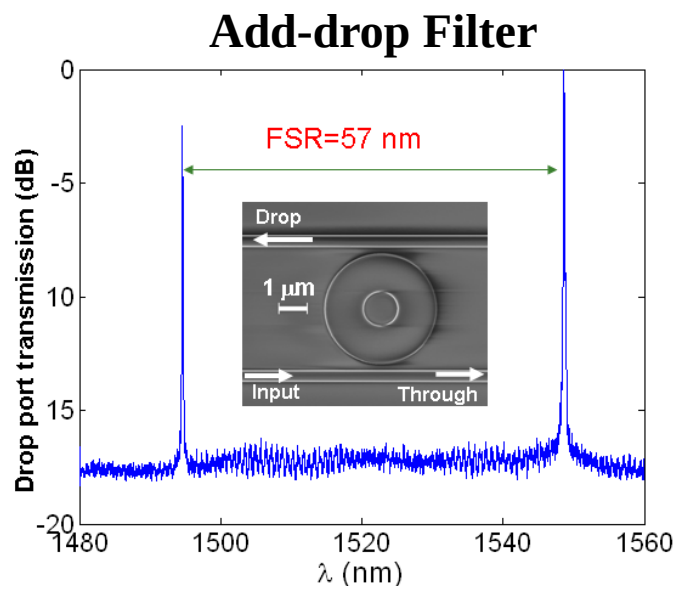
Electric energy: 2nd order mode



Miniaturized Microdisk Resonator in SOI

- Ultra-small and high Q microdisk
- Single mode operation over a large bandwidth



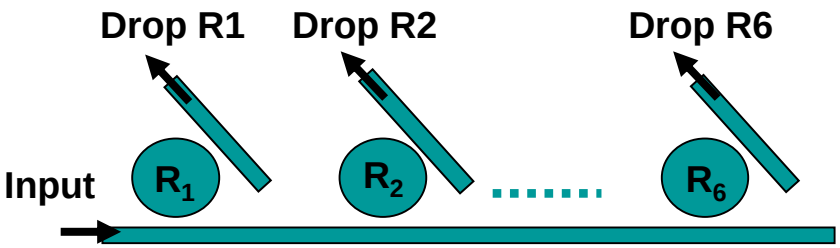


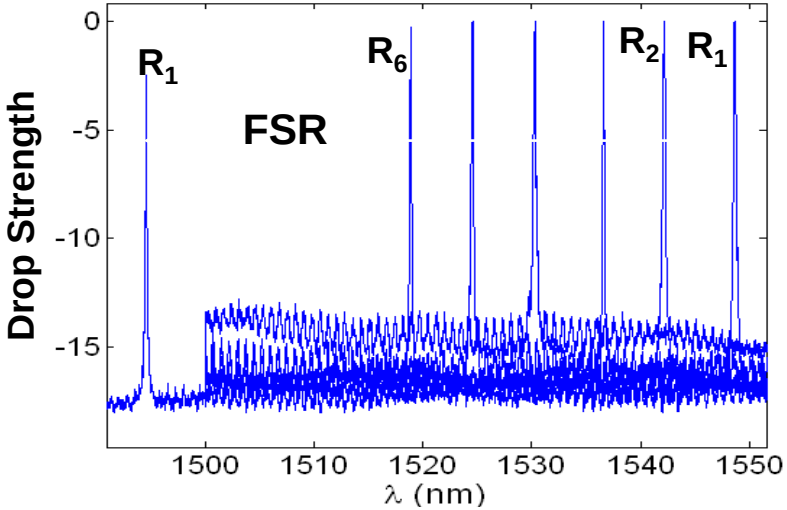
- Q~100,000 and mode volume $0.15(\lambda_0)^3$ was observed
- A microdisk with a radius of 2 μm showed a Q~150,000

Depending on the application, Qs in the range 10^5-10^6 is achievable

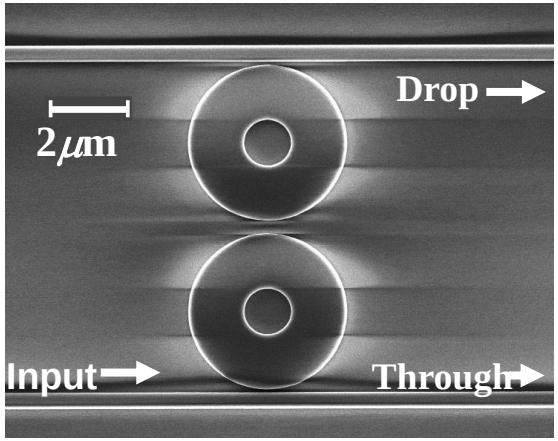
Engineering the Spectral Response of Microdisk Resonators Over a Large Bandwidth

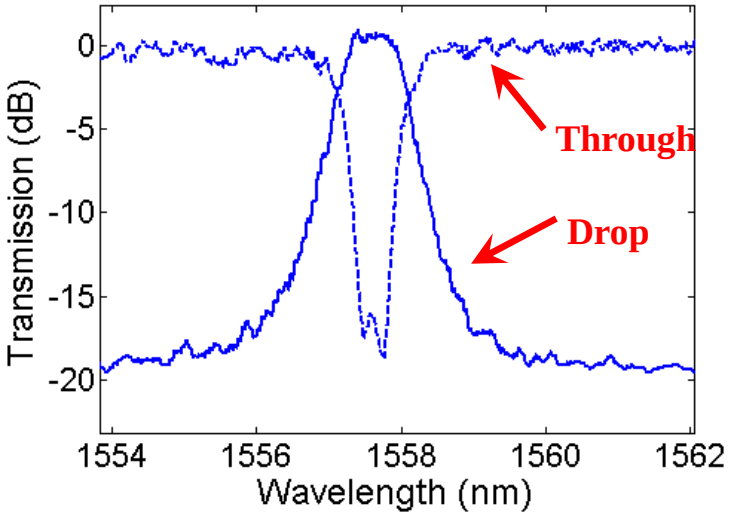
- Experimental response of an array Si resonators with radii around 2μm.





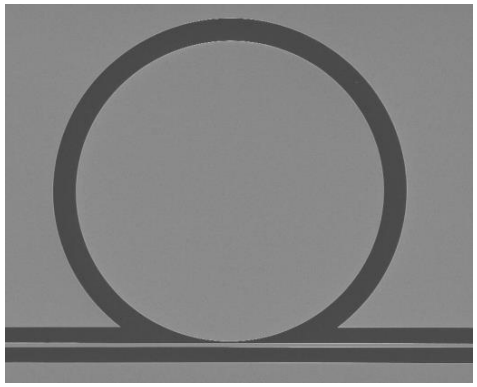
- Experimental response of CROW using disks with radii around 2μm.

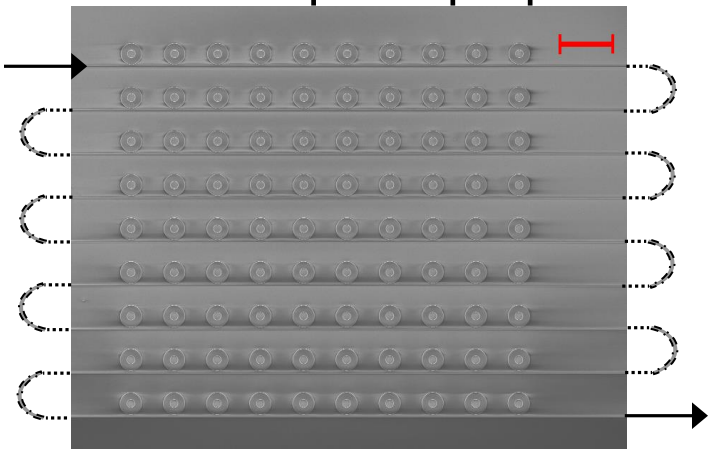




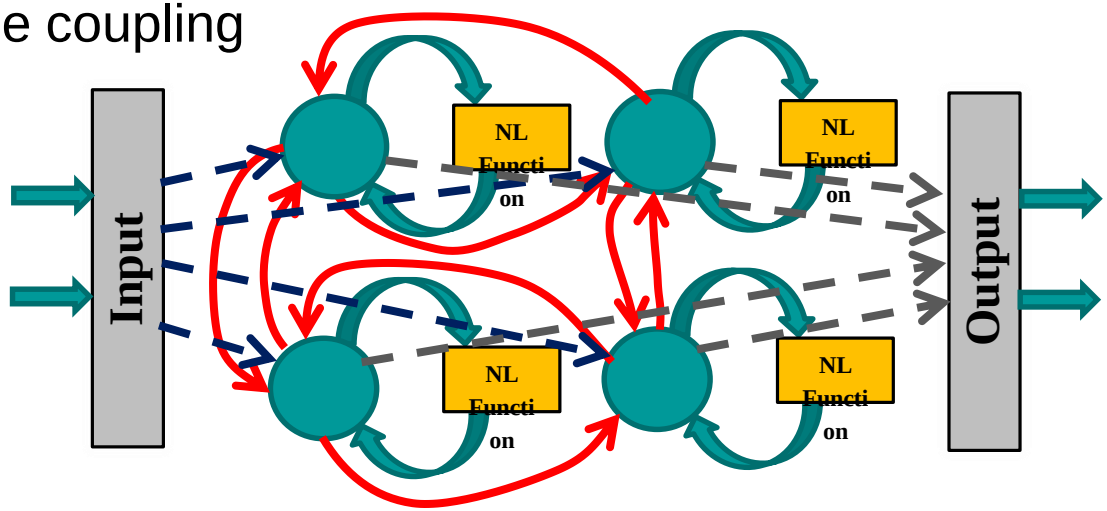
RC Implementation using Microresonators

• Reservoir : A highly multi-mode resonator or a sea of coupled single-mode resonators (with fixed coupling) with nonlinear optical properties





• RNN implementation using an array of single-mode resonators with dynamically controllable coupling



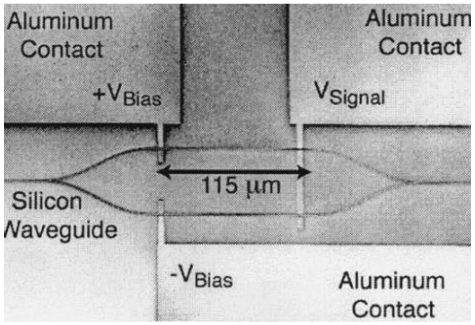
Photonic Reconfiguration in Silicon

Desired Features

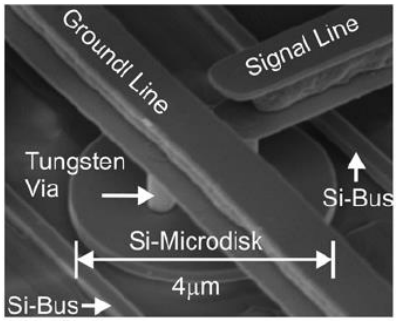
- CMOS compatible
- Low power
- Wide tuning range
- Fast
- Low loss

Methods

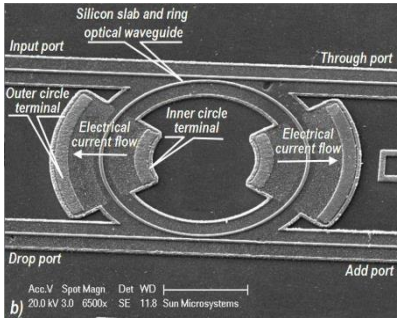
- Free-carrier plasma dispersion
- Thermo-optic effect
- Electro-optic effect in hybrid polymer-based devices
- Opto-mechanical tuning



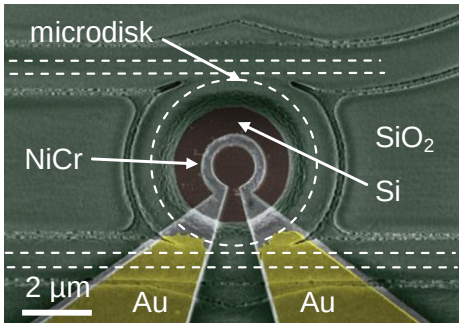
Lyszczarz *et at* 2007



Watts *et al* 2009



Cunninghum *et al*, 2010



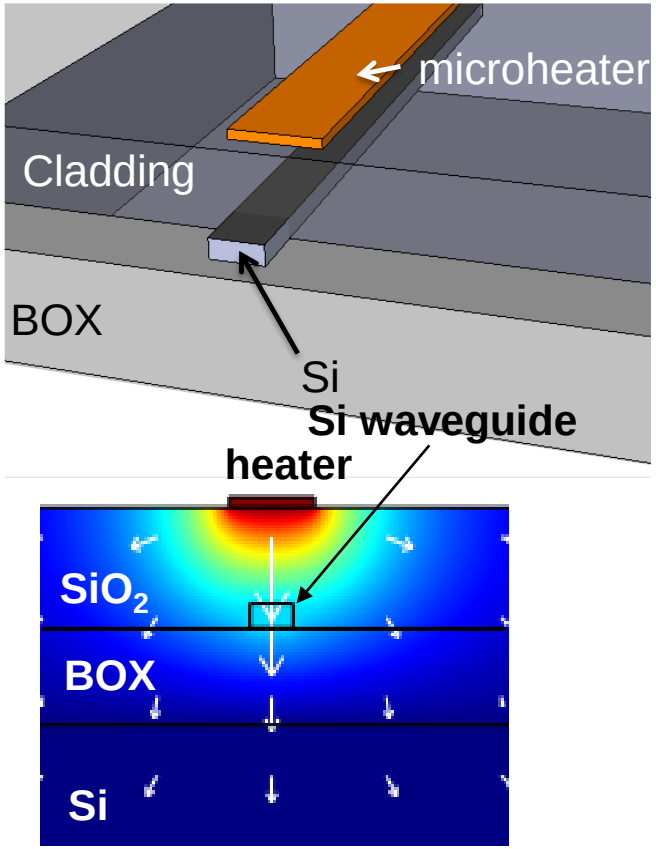
Atabaki, *et al* 2011

Thermo-optic effect suitable for wideband tuning

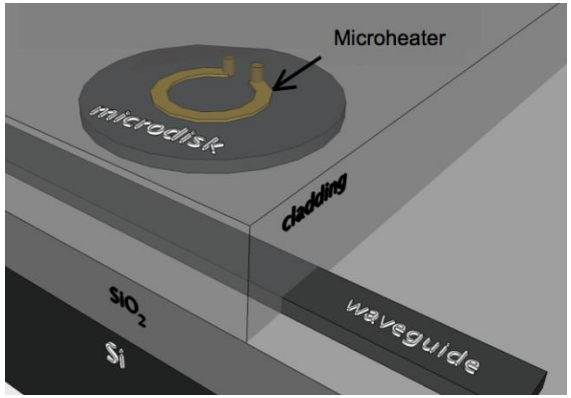
Reconfiguration speed is a bottleneck

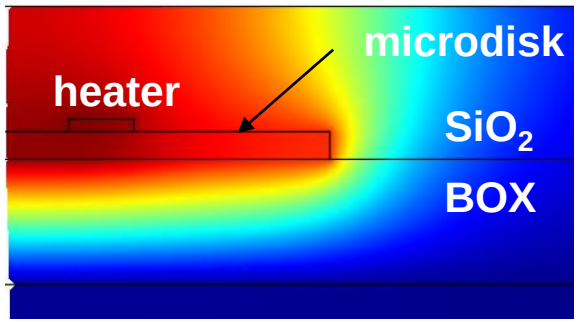
Architectures for Thermal Tuning

- Thin-film micro-heaters over cladding layer
  - Device optimization
  - Pulsed excitation



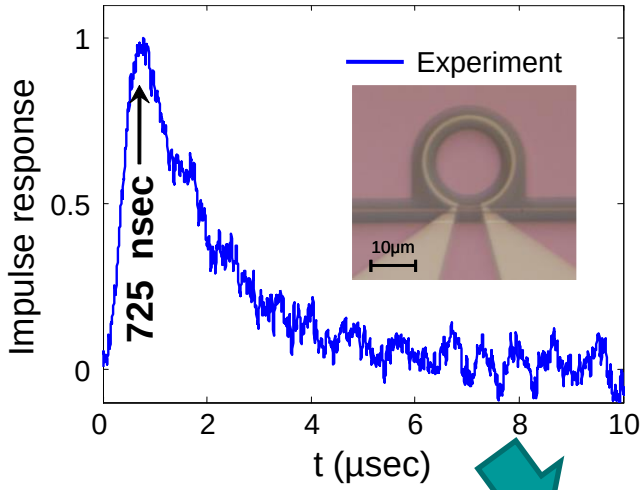
- Thin-film micro-heaters on Si microdisk
  - Possibility to improve reconfiguration speed

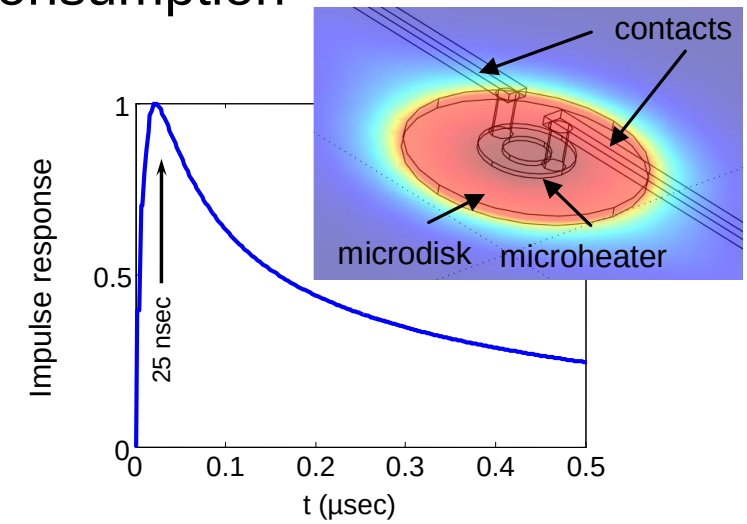


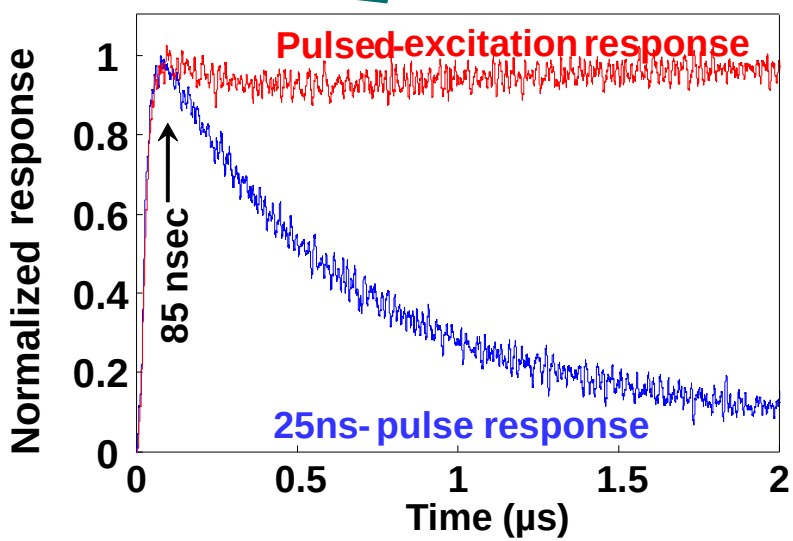


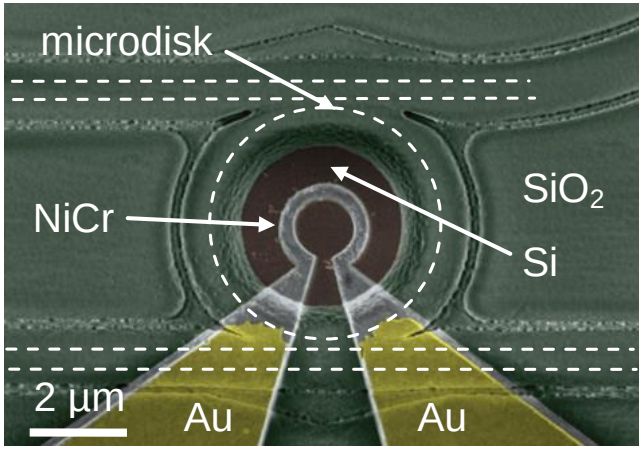
Ultra-fast and Low-Power Thermal Tuning

- Directly heating Si reduced heat propagation delay
- Small microdisk for low power consumption

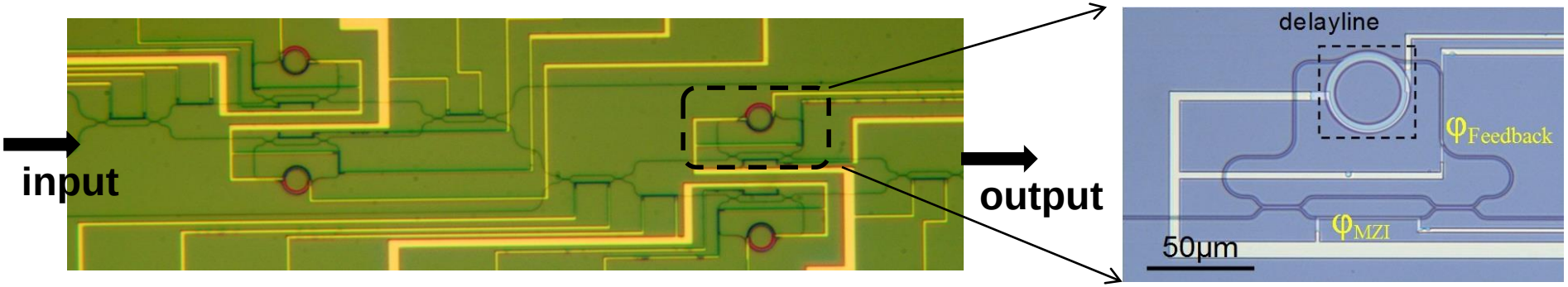




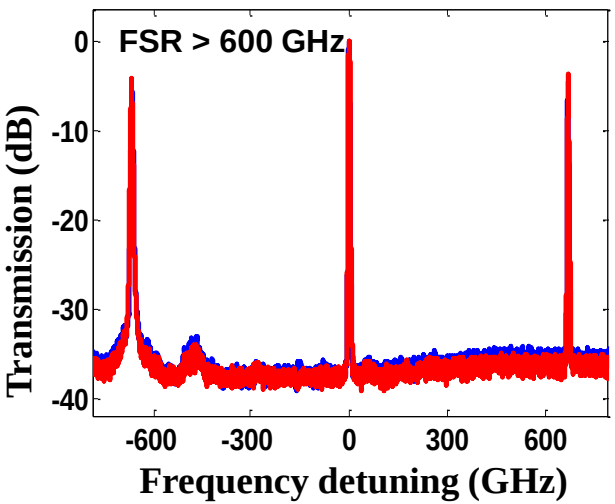




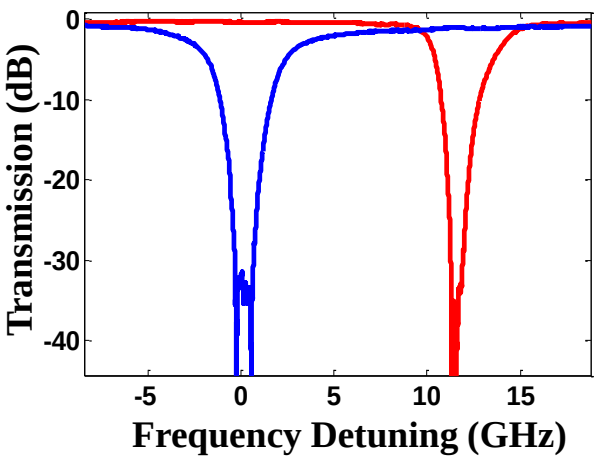
Reconfigurable Coherent Processing/Filter Units



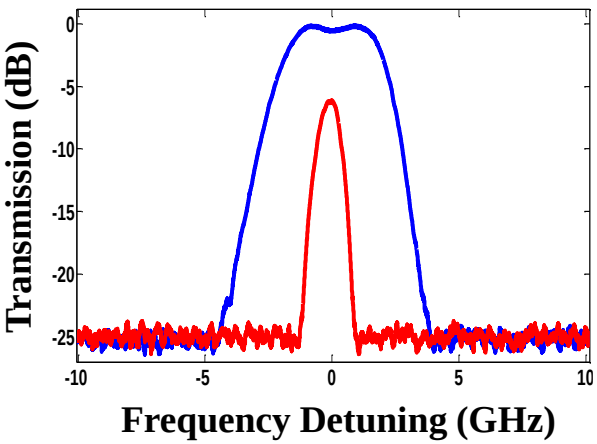
P. Alipour *et al*, group IV photonics 2010



Notch response

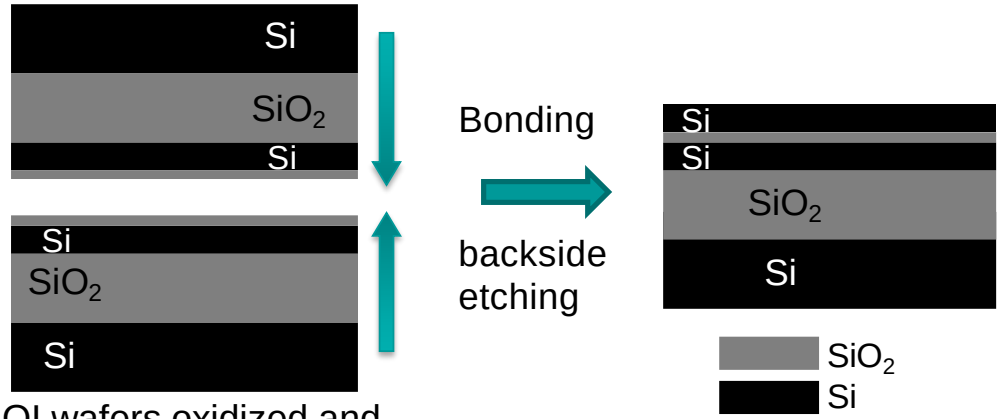


Filter Reconfigurability
900 MHz – 4 GHz



Double-SOI Material Platform

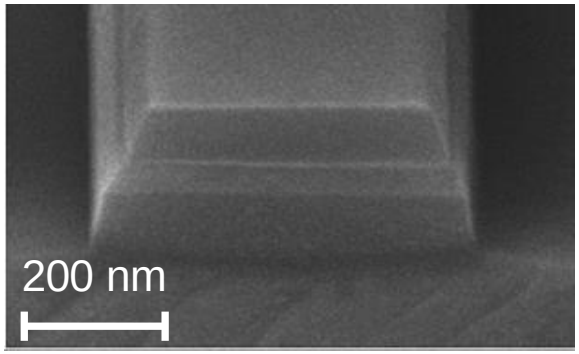
- Fabrication



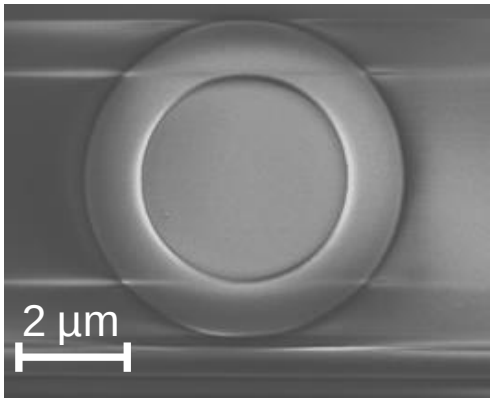
SOI wafers oxidized and surface chemistry activated

- SEM

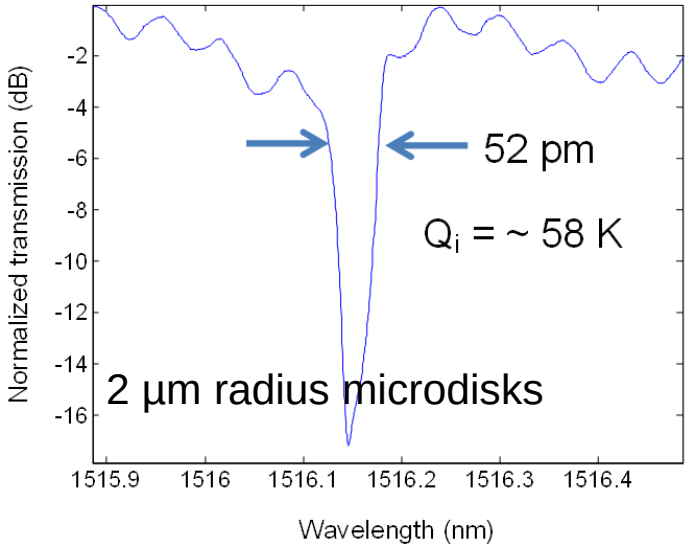
Cross-section of double-SOI waveguide

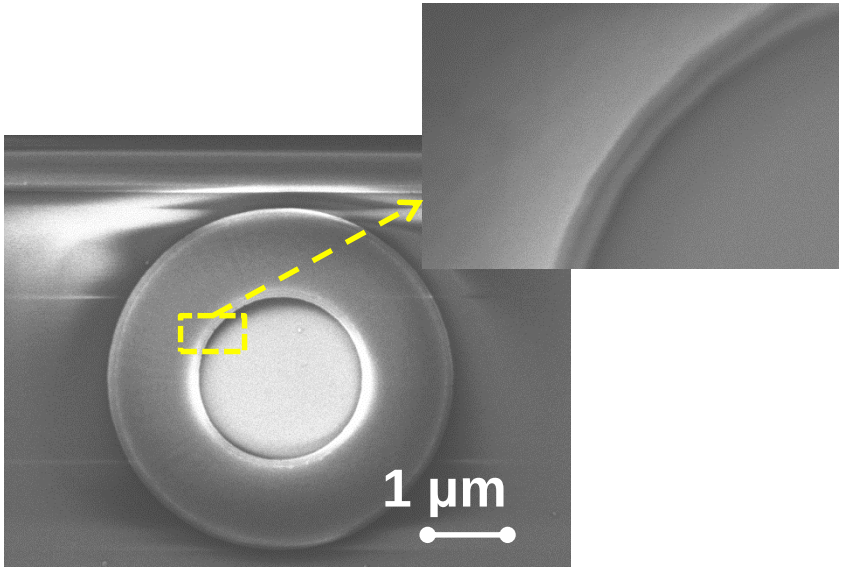


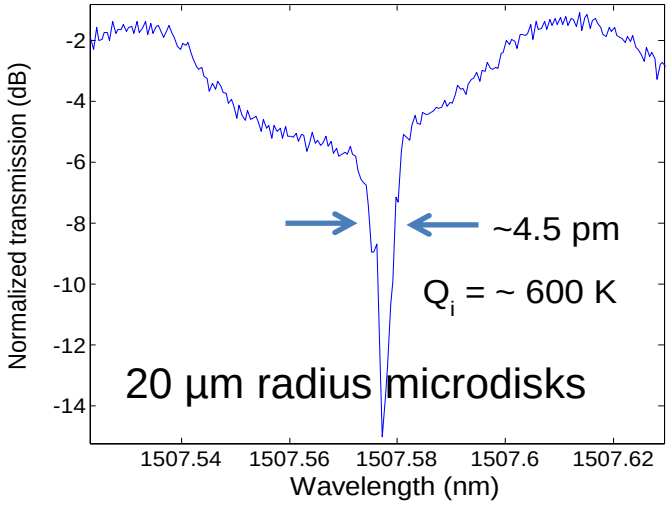
Top view of a double-SOI waveguide-resonator

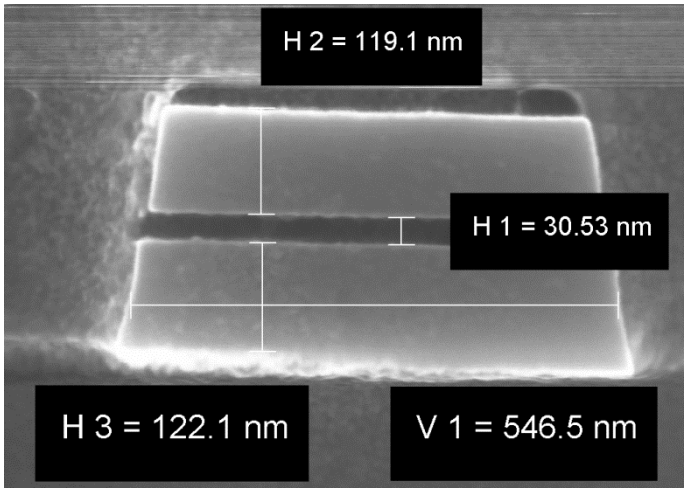


Double-Layer SOI Through Wafer Bonding





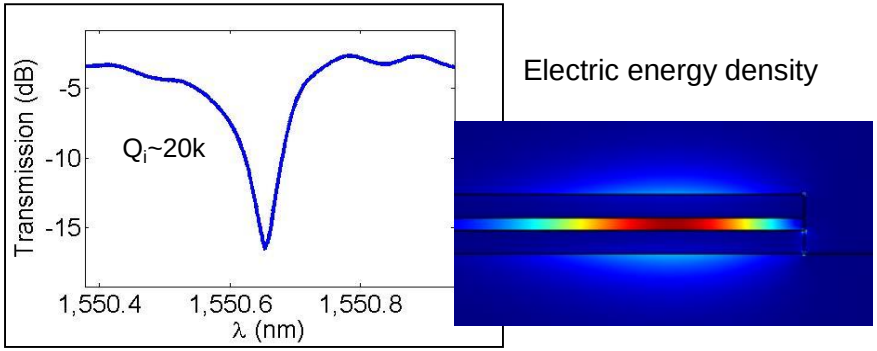




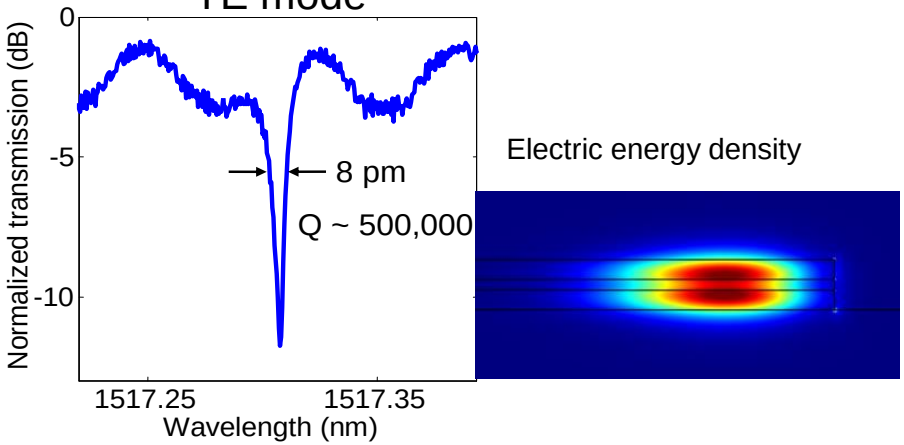
High Q and High-Filed Enhancement Using Slot Structure in Double-Layer SOI Structure

- 20 µm radius microdisks

TM mode



TE mode

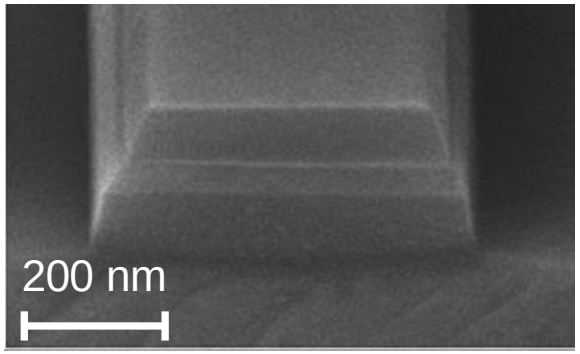


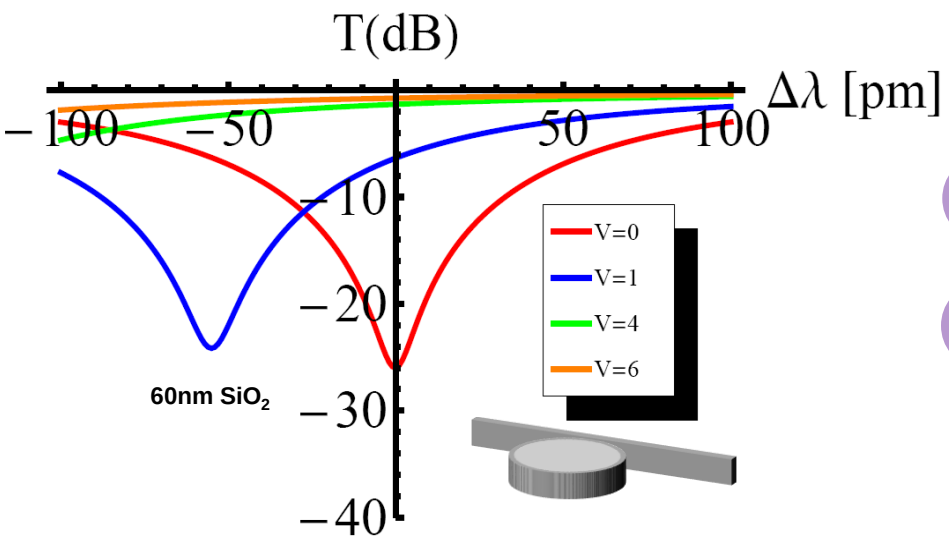
Comparison with the similar state-of-the-art double-layer resonators

	Radius	Q_i (TE)	Q_i (TM)	Fab. Method
This Work	**20 µm**	**500 K**	**20-50 K**	**Bonding**
This Work	**5 µm**	**250 K**	**-**	**Bonding**
M. Lipson, Opt. Exp. **17** (2005).	100 µm	-	83 K	Deposition
H. Atwater, Appl. Phys. Lett. **94** (2009).	200 µm	42 K	13 K	Bonding
L. Pavesi, Opt. Exp. **17**, (2009).	20 µm	-	15 K	Deposition
H. Tang, Opt. Exp. **18**, (2010).	100 µm	~125-175K	-	Deposition
L. Kimerling, Opt. Exp. **15**, (2007).	10 µm	-	15 K	Deposition

Advantages of Double-SOI Platform

- Enhanced nonlinearity by replacing the thin oxide layer with nonlinear optical polymer (RC implementation)
- Very low-power reconfiguration/modulation by carrier accumulation
- Ultra-low-power electrical trimming of the resonance wavelength

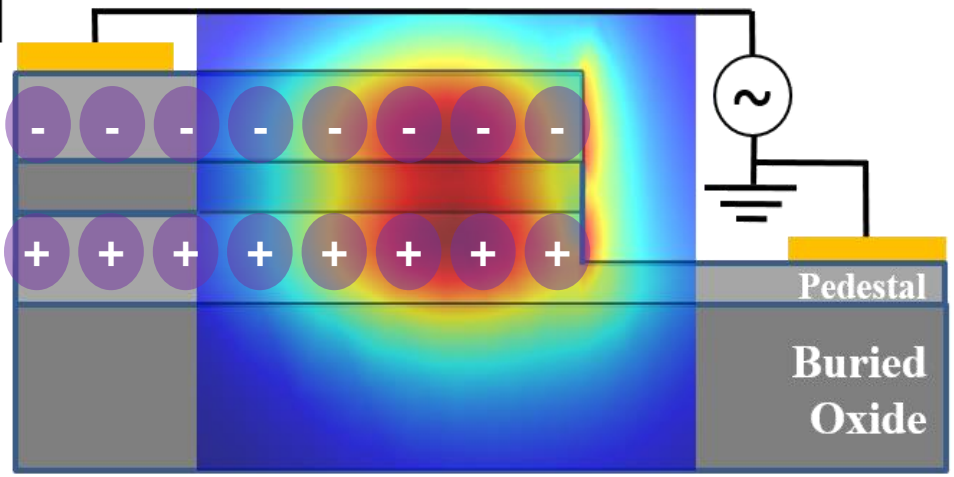




Silicon Dispersion

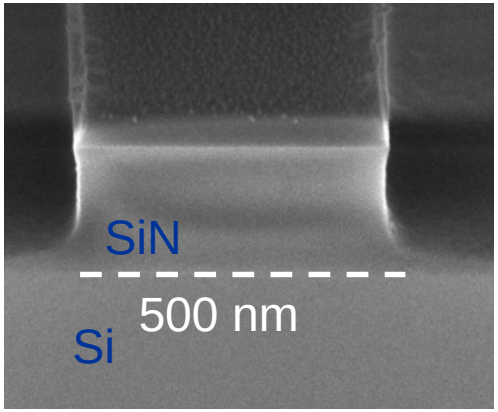
$$\Delta n = -8.8\times10^{-22}\,\mathbf{\Delta n} - 8.5\times10^{-18}\,\mathbf{\Delta p}^{0.8}$$

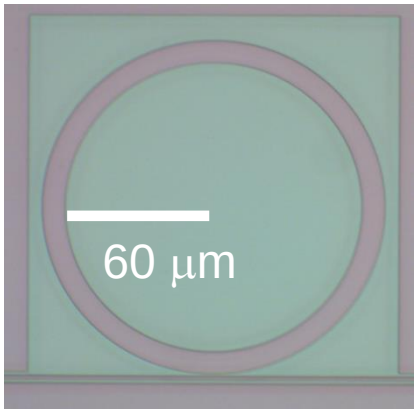
$$\Delta\alpha = 8.5\times10^{-18}\,\mathbf{\Delta n} + 6.0\times10^{-18}\,\mathbf{\Delta p}$$

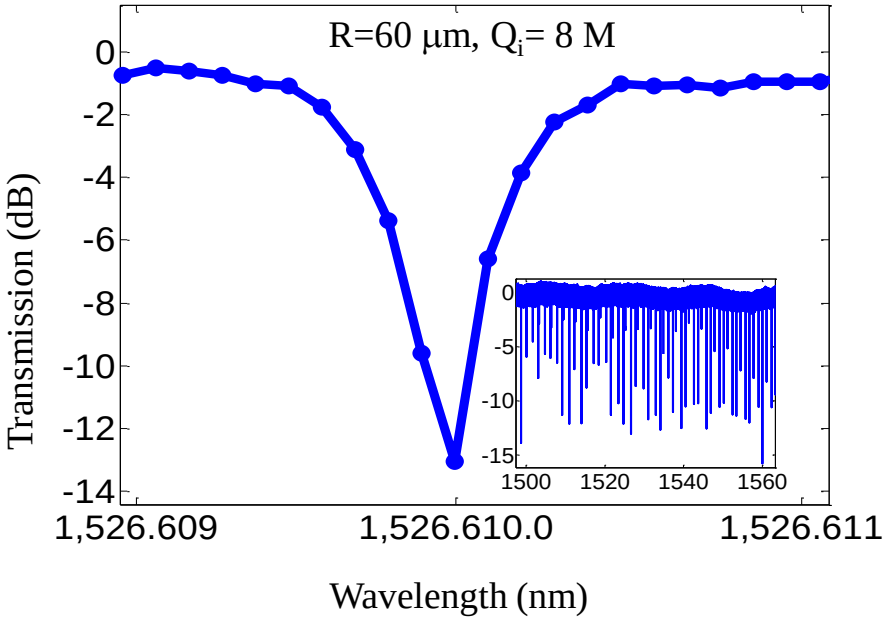


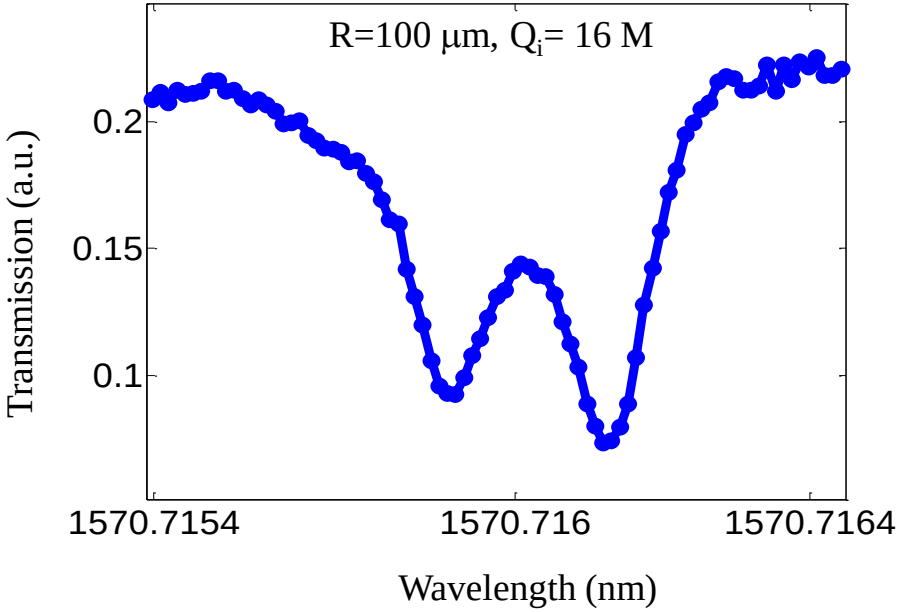
Hybrid Si/SiN Material Platform

- Ultra-high Qs using SiN
- Reconfiguration / adjustable coupling through Si
- Highly efficient coupling (>95% between layers)



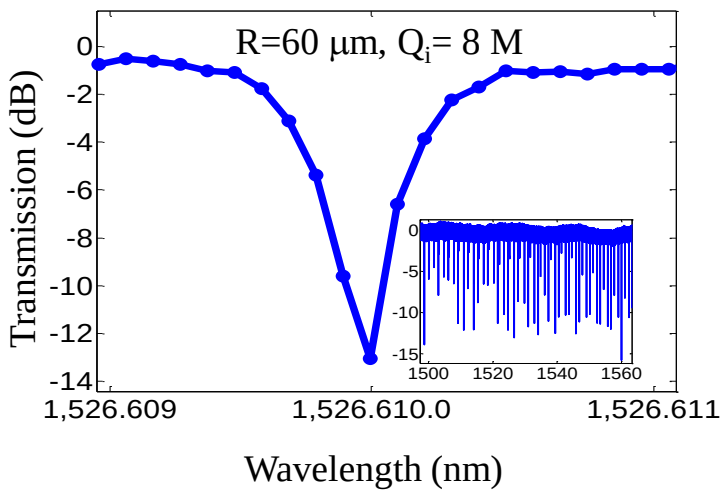


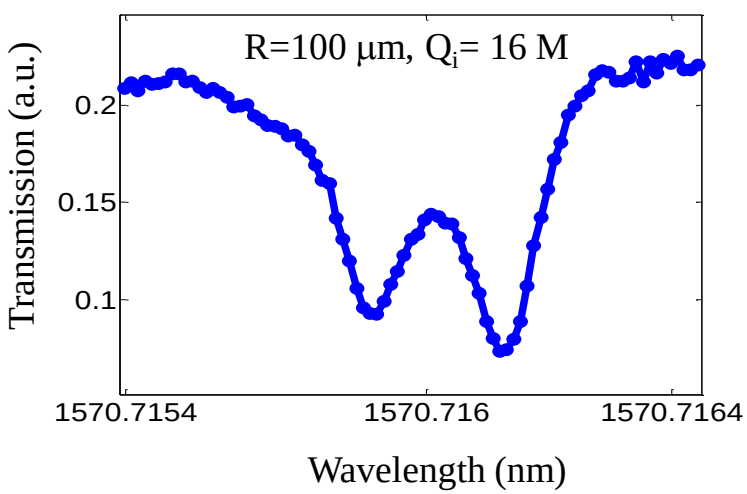


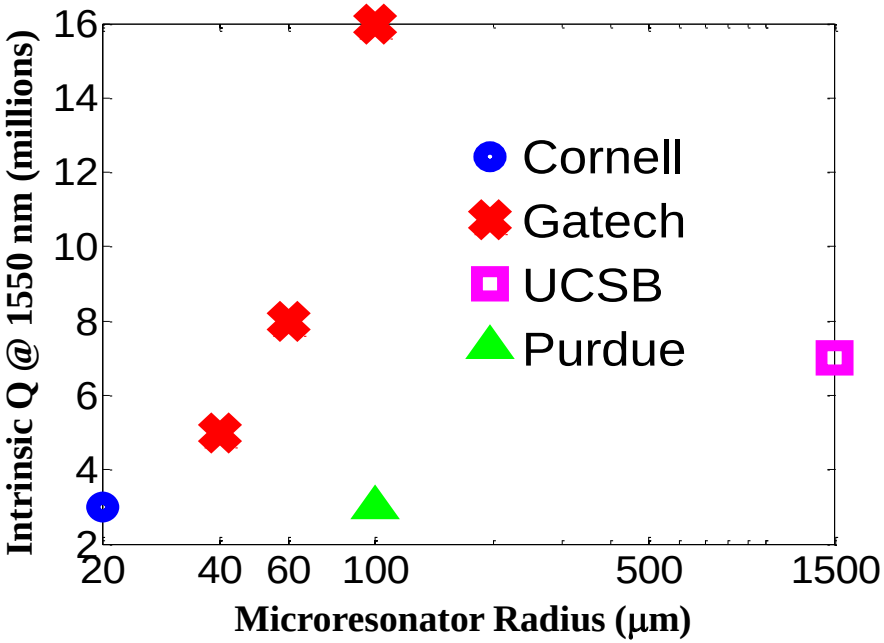


Compact and High Q SiN Microresonators

- Q and Q/V matter in different applications

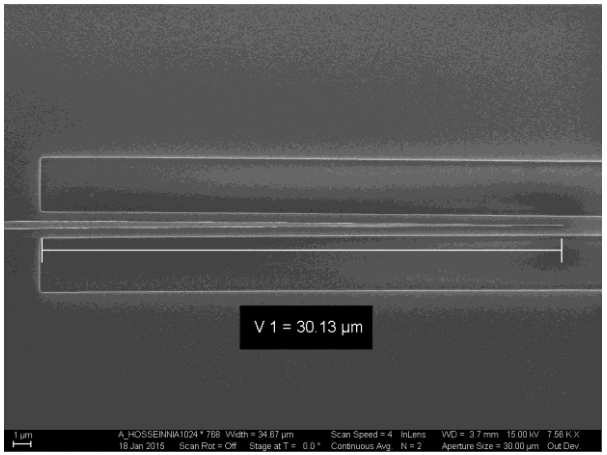


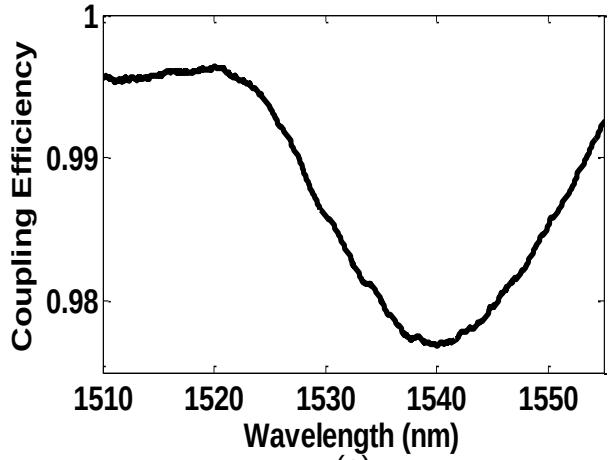




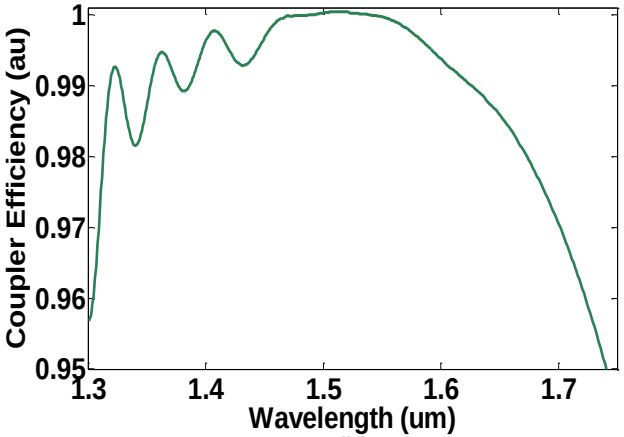
Achieved highest Q to-date for SiN microresonators

Wideband, Low-loss Interlayer Couplers



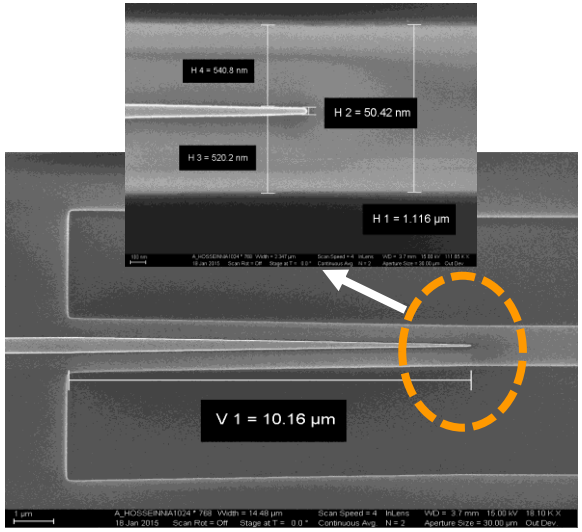


(a)

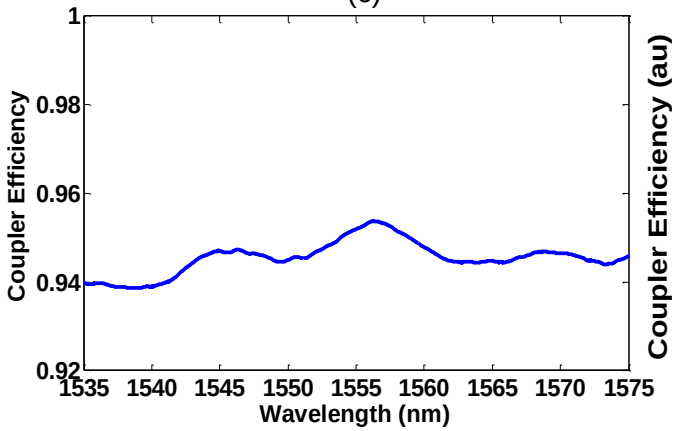


(b)

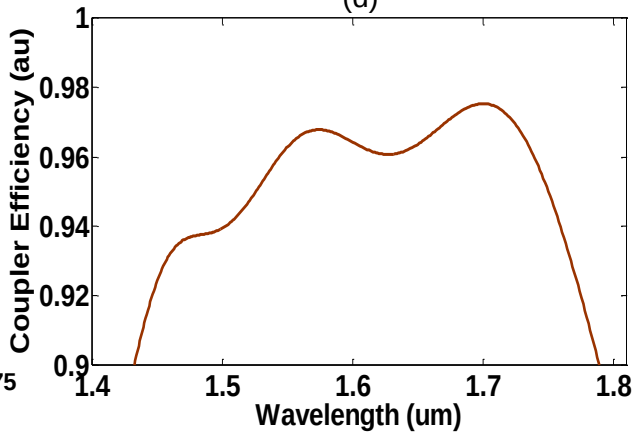
Characterization results (a,c) and FDTD simulation results (b,d) of 30 µm (top) and 10 µm long (bottom) hybrid couplers. The characterization results are bandwidth limited due to input/output access grating bandwidth.



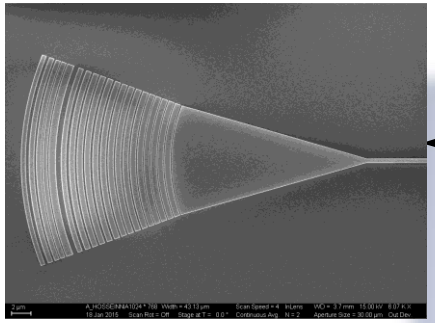
(c)

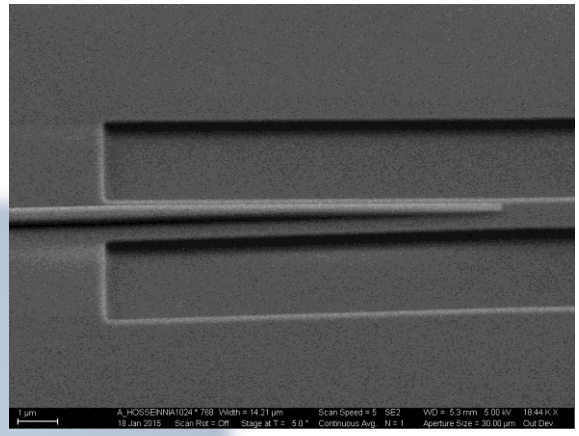


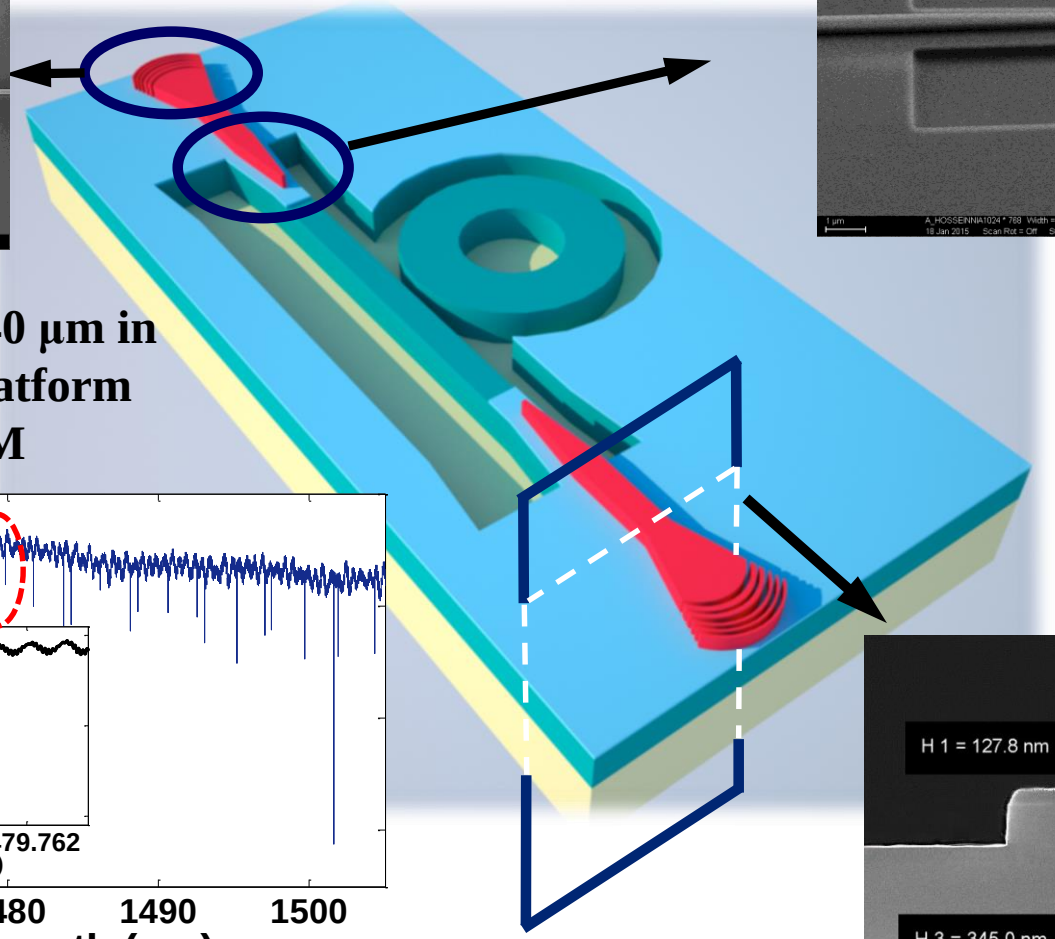
(d)



Demonstration of Hybrid Optical Path







Si

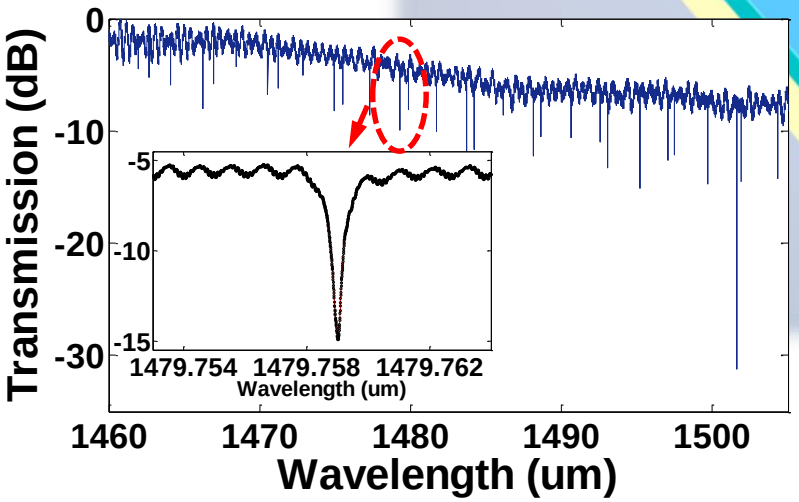
Interface Oxide

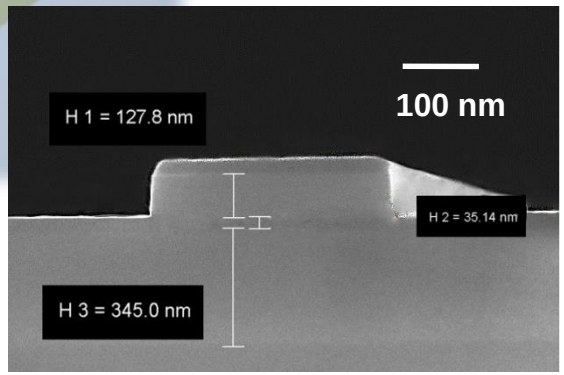
SiN

Buried Oxide

μ-disk of R = 40 μm in the hybrid platform

Q_{int} = 3M





Conclusions

- RC and RNNs implemented in the optical domain offer unique feature for low-power, fast computing with very good performance.

- Implementation of the RC and RNNs in integrated nanophotonic structures can enable ultra-compact, low-power, and fast computing microchips.