3D: a link from brains to photonic neural networks

D. Brunner, X. Porte, J. Moughames, M Kadic, M. Jacquot, L. Larger

FEMTO-ST / Optics Dept., CNRS Univ. Bourgogne-Franche-Comté, Besançon, France

AI FOR PHOTONICS

How it all began

BULLETIN OF
MATHEMATICAL BIOPHYSICS
VOLUME 5, 1943

A LOGICAL CALCULUS OF THE
IDEAS IMMANENT IN NERVOUS ACTIVITY

WARREN S. MCCULLOCH AND WALTER PITTS

FROM THE UNIVERSITY OF ILLINOIS, COLLEGE OF MEDICINE,
DEPARTMENT OF PSYCHIATRY AT THE ILLINOIS NEUROPSYCHIATRIC INSTITUTE,
AND THE UNIVERSITY OF CHICAGO

Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behaving under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time. Various applications of the calculus are discussed.

The Organization of Behavior

A NEUROPSYCHOLOGICAL THEORY

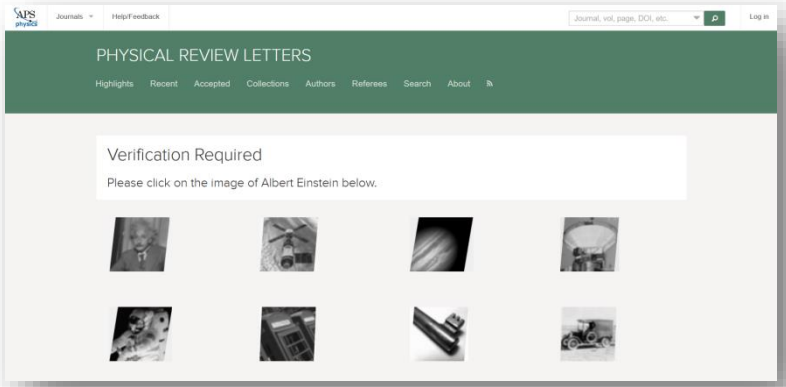
D. O. HEBB
McGill University

1949
New York · JOHN WILEY & SONS, *Inc.*
London · CHAPMAN & HALL, *Limited*

- Neural networks are not a new idea
- Learning / training ideas already 6 years later

Neural network: what for?

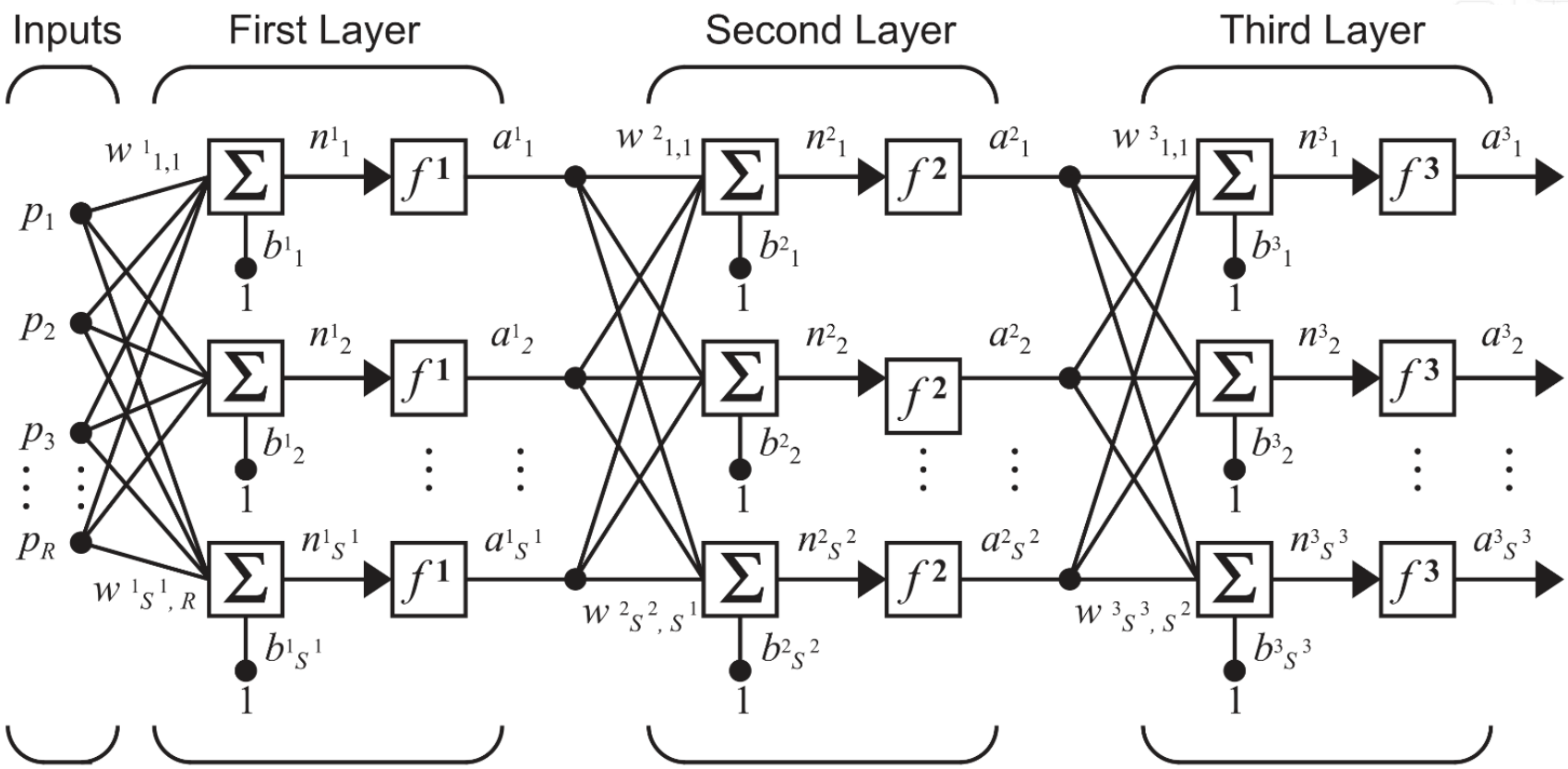
Sci-Hub: Marie Curie?



Postman: Cat /Dog ?

$$f[u(n)]$$

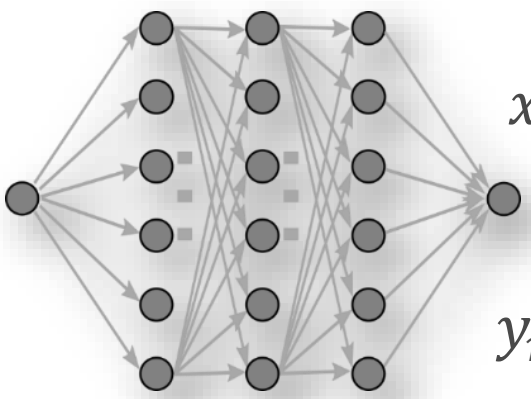
Neural Networks



$$\mathbf{a}^1 = \mathbf{f}^1(\mathbf{W}^1\mathbf{p}+\mathbf{b}^1) \qquad \mathbf{a}^2 = \mathbf{f}^2(\mathbf{W}^2\mathbf{a}^1+\mathbf{b}^2) \qquad \mathbf{a}^3 = \mathbf{f}^3(\mathbf{W}^3\mathbf{a}^2+\mathbf{b}^3)$$

$$\mathbf{a}^3 = \mathbf{f}^3(\mathbf{W}^3\mathbf{f}^2(\mathbf{W}^2\mathbf{f}^1(\mathbf{W}^1\mathbf{p}+\mathbf{b}^1)+\mathbf{b}^2)+\mathbf{b}^3)$$

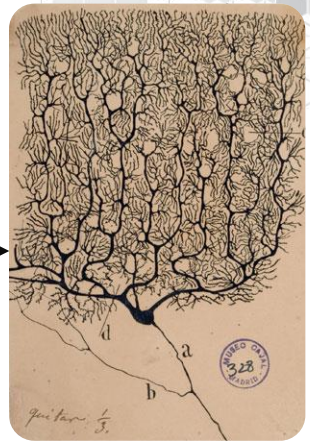
NNs and photonics



$$x_n^i = \sum_{m=1}^{N_i} \boxed{W_{m,n}^i} \cdot x_m^{i-1} + b_n^i$$

interconnect

$$y_n^i = f[x_n^i]$$



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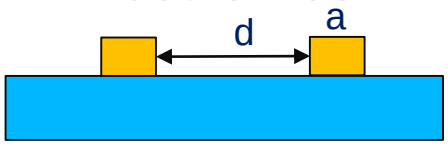
The interconnect

- Curse (for electronics) and blessing (*maybe* for photonics)

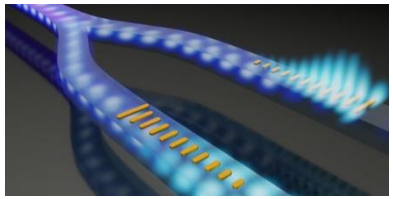
Electronics



- $E = CV^2$
- Scaling: $C \propto \frac{\pi \epsilon l}{\ln\left(\frac{d}{2a} + \sqrt{\frac{d^2}{4a^2} + 1}\right)}$
- Only log. Ratio, linear in length

Photonics

- No capacities, no induction, low loss propagation
- But: **much** larger feature sizes



Li et al., Nature NT 12, 675 (2017).

Relevance of NN hardware:

MIT Technology Review

Artificial Intelligence / Machine Learning

Training a single AI model can emit as much carbon as five cars in their lifetimes

Deep learning has a terrible carbon footprint.

by **Karen Hao** Jun 6, 2019

The privatization of AI research

The results underscore another growing problem in AI, too: the sheer intensity of resources now required to produce paper-worthy results has made it increasingly challenging for people working in academia to continue contributing to research.

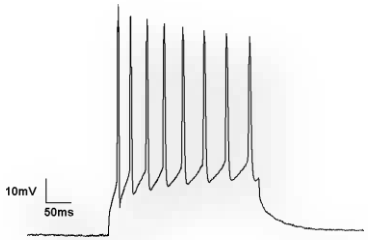
Reddy agrees. “Human brains can do amazing things with little power consumption,” he says. “The bigger question is how can we build such machines.”

Some context: ‘slow’ brain is very fast

© Simon Thorpe, ANR project ANACONDA

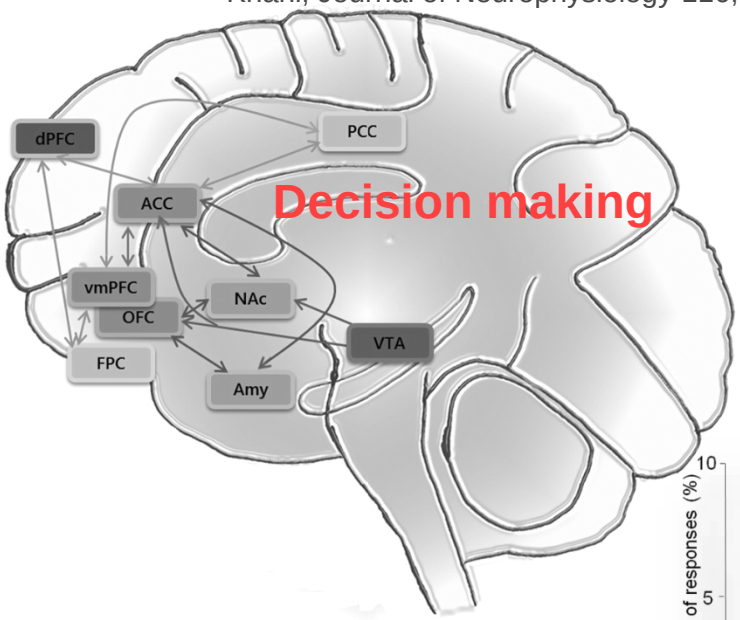
- Human eye: >500 M image sensors
- **You are capable to infer several times a second**

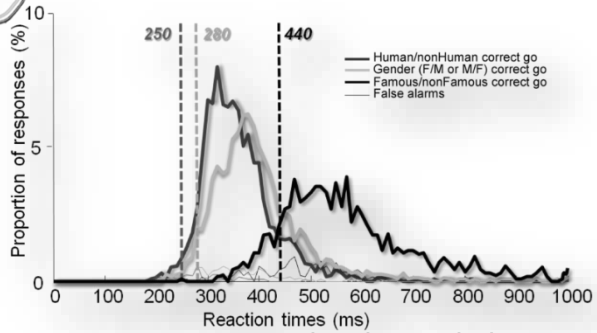
Energy and speed: ultimate benchmark



By Bilz0r - Wikipedia

Khani, Journal of Neurophysiology 116, 724 (2016).





Barragan-Jason, Frontiers in psychology 3, 454 (2012).

- Neuronal response time ~10 ms
- ~10 (hierarchical) regions involved
  - Optical propagation along nerve
- Reaction time: 200 to 400 ms
- **Brain operates at bandwidth of 'components'**
- **Parallelism**

Energy and speed: ultimate benchmark

- Basic brain facts

Table 1. Basic Statistics of Human Neocortex

Property	Value	Source
Surface area (mm^2)	190,000	[7, 24]
Thickness (mm)	2.5	[6, 25]
Glucose Consumption (µmol/g/min)	0.40	[10–12]
Glia/mm^3	38,000	[7]
Neurons/mm^3	40,000	[6, 26]
Synapses/mm^3	7×10^8	[5, 27, 28]
Axon Length m/mm^3	4,000	[5]
Average Axon Diameter (µm)	0.3	[5]
Dendrite Length m/mm^3	400	[5]
Average Dendrite Diameter (µm)	0.9	[5]

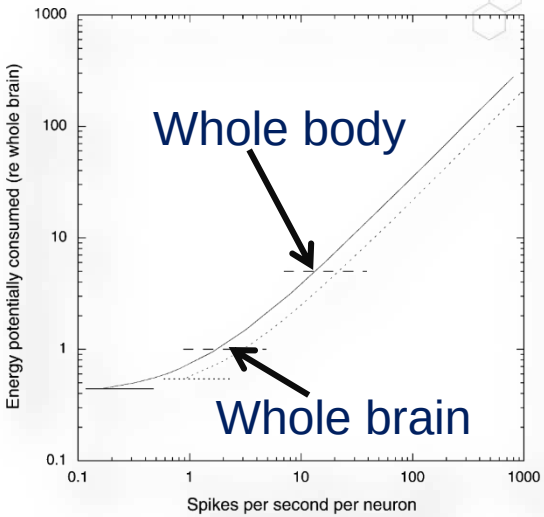


Figure 2. Energy Potentially Consumed by Cortex as a Function of the Average Sustained Level of Activity in All Neurons

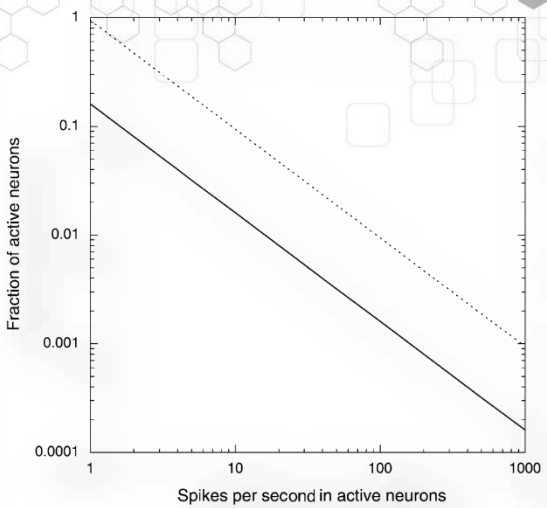
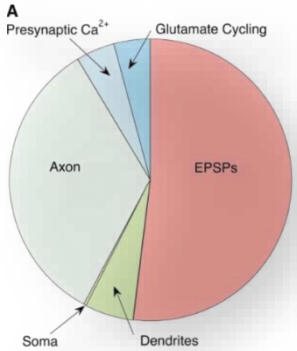


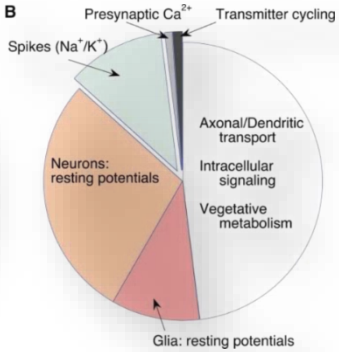
Figure 3. Fraction of Cortical Neurons that Can Be Active, as a Function of the Average Spike Rate in Those Neurons that Are Active

- Brain: majority of energy by action potential & potentiation

neuron



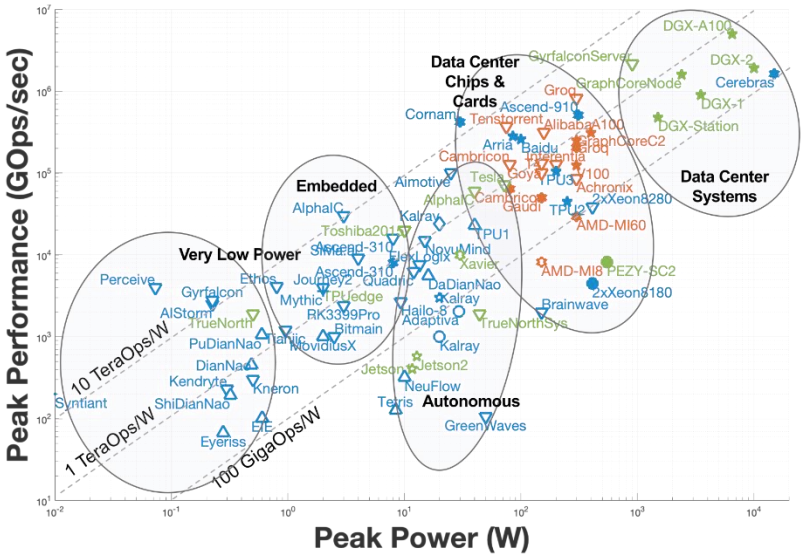
cortex



- Spiking, Signal:>90 %
- Cortex: 44 % of E/Brain
- **Negligible emulation overhead**
- **The way to 20 W**

Lennie, Current Biology 13, 493 (2003).

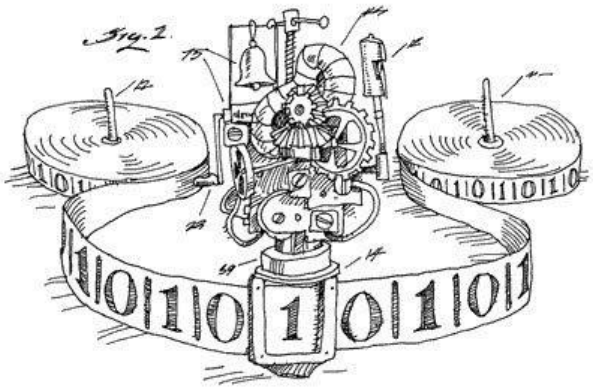
Architecture and energy consumption



- Silicon: ~10^{12} Ops/W
- Brain: ~10^{14} Ops/W

But:

- MAC: ~1 pJ
- Synaptic event: ~5 fJ
- ➢ Operation ≠ ‘Operation’



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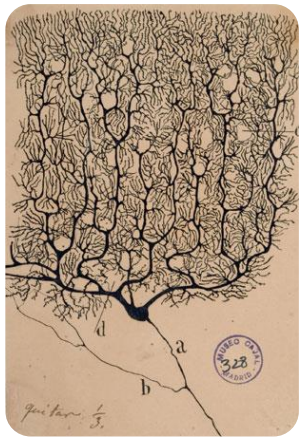

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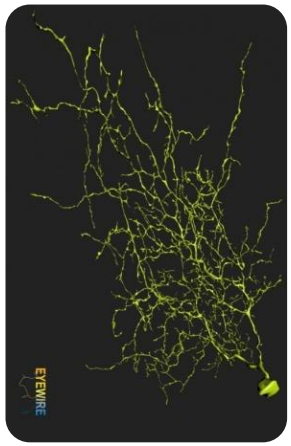
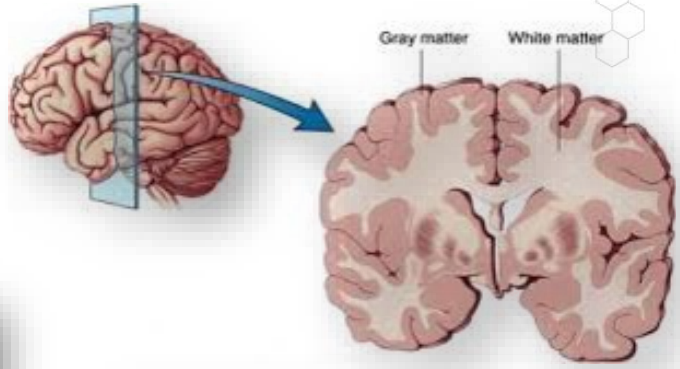
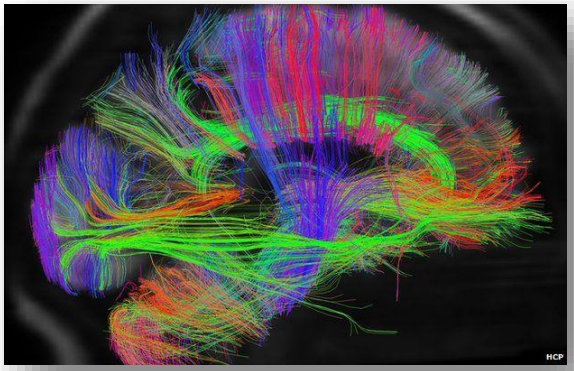
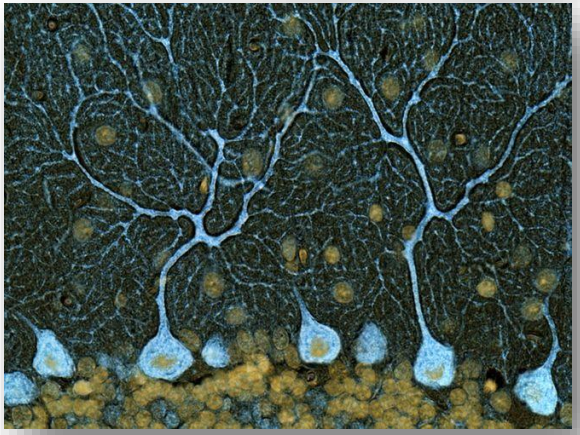


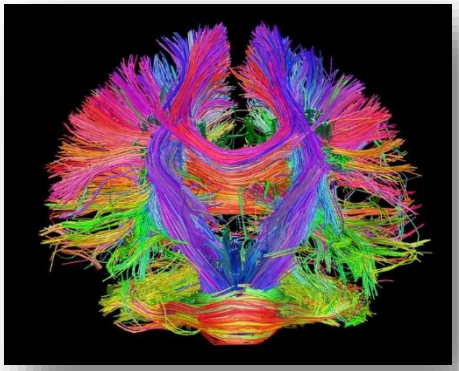
How does the brain do it?





Human Connectome project



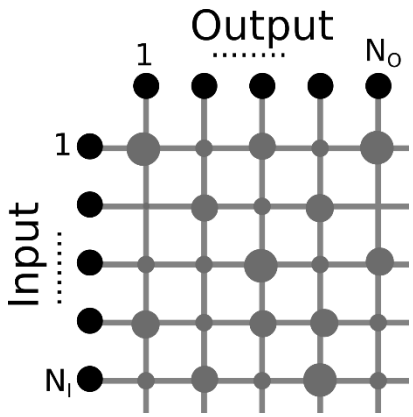


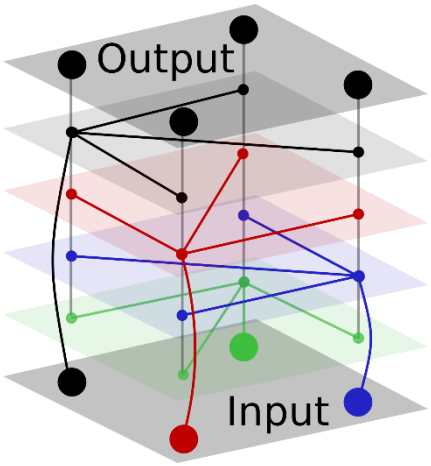
Human Connectome project

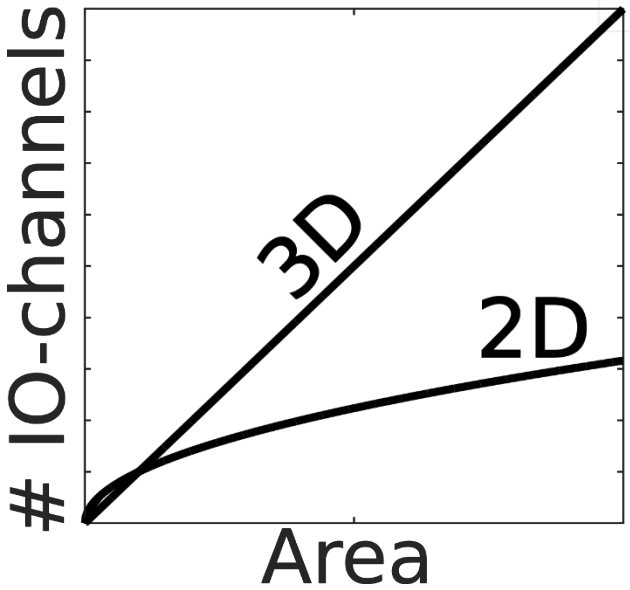
1. 3D connections: scalable
   - Neurons: 2D
   - Connections: 3D
2. Fractal branching
   - Space/resource efficient
   - Efficient transport

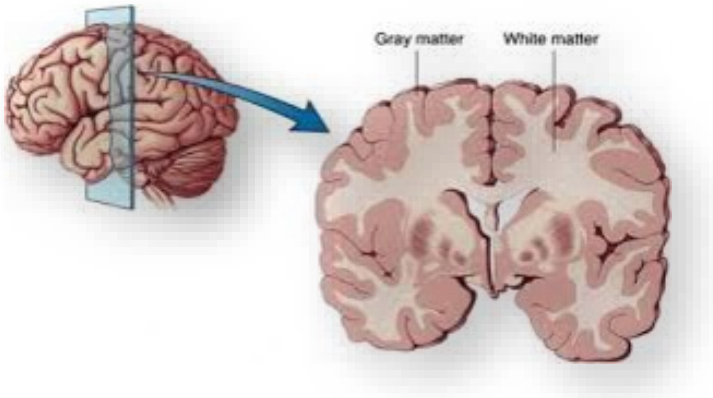
Dinc, Psaltis, Brunner, Photoniques **104**, 34 (2020).

Rooting N inputs to N outputs









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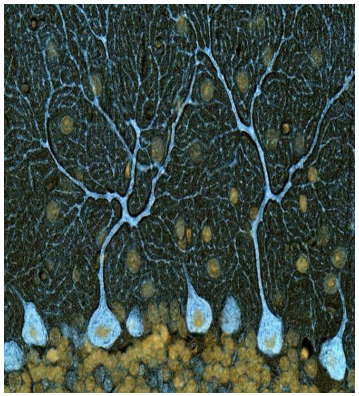
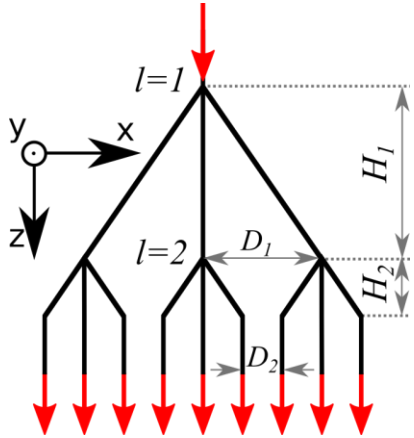
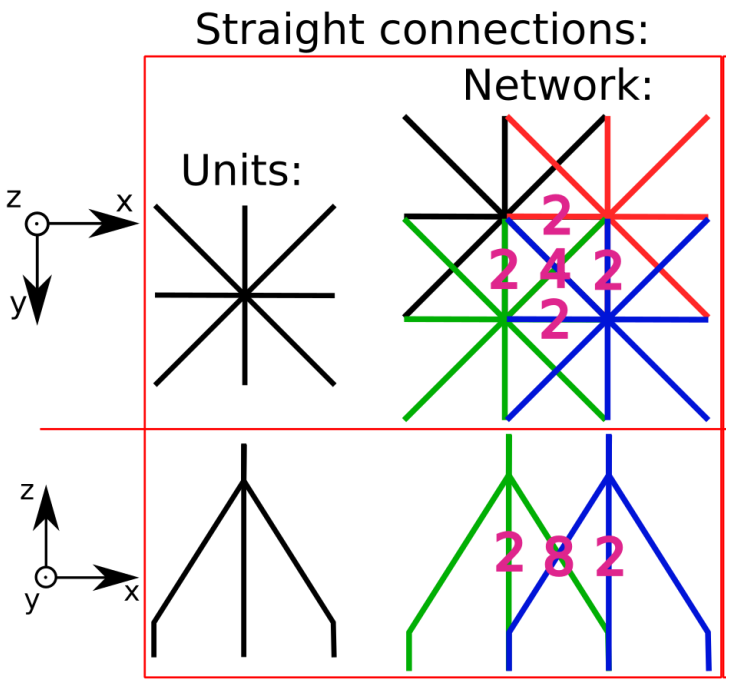




Fractal branching

- $C = b^{2l}$, b: bifurcations, l: layers
  - Exponential scaling (good)
- Straight connections: intersections
- Chirality removes ‘shorts’
- Scale free: ‘unit cell’ design approach

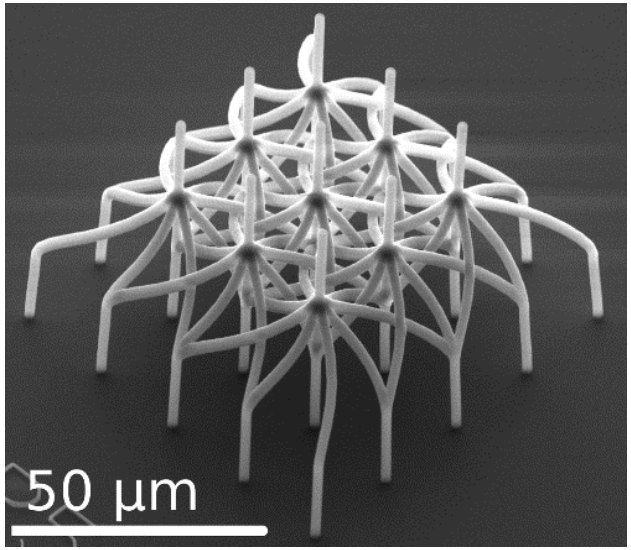


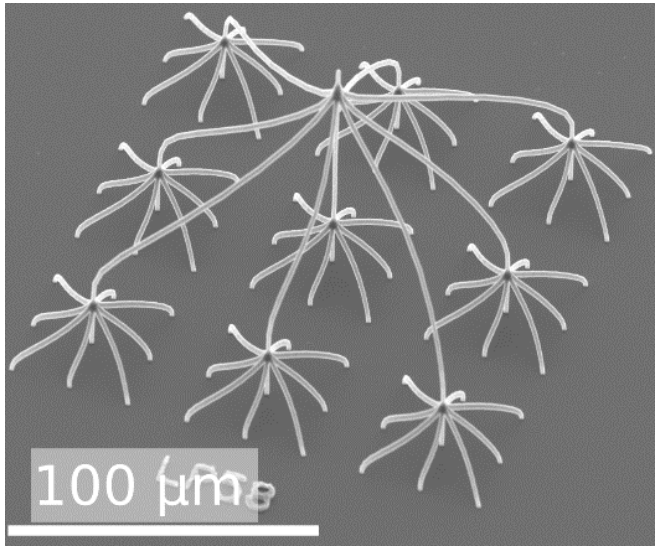
Moughames, et al., Optica **7**, 640 (2020).

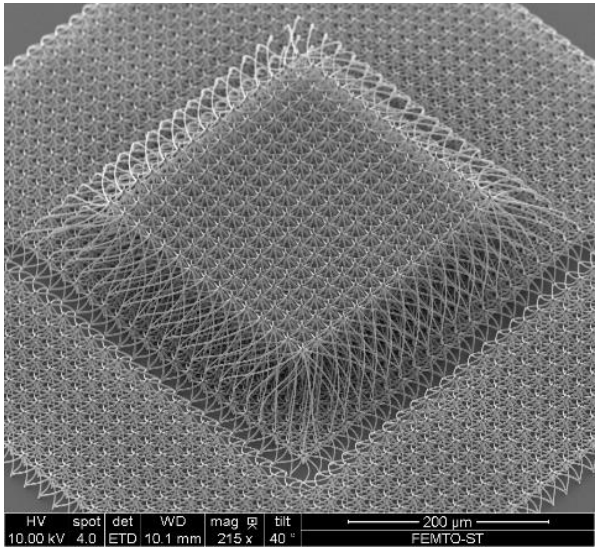
3D long-range connected network:

Lindenmann, et al., Opt. Express 20, 17667 (2019).

3D printing: 2 photon polymerization (Nanoscribe)
Waveguides: 1.2 µm diameter, 20 µm pitch







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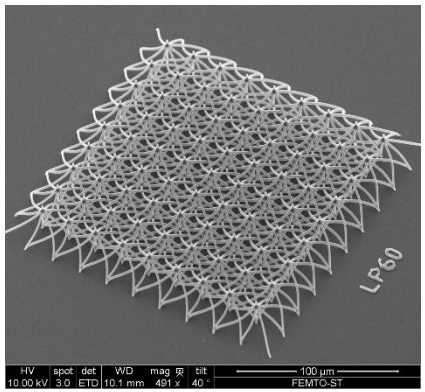
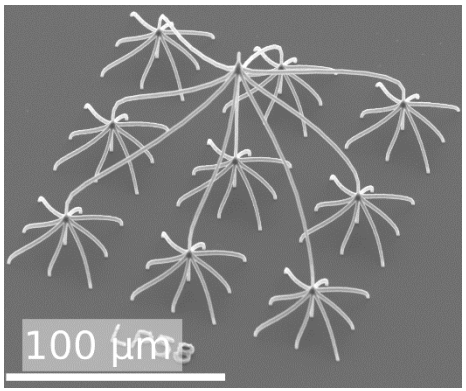
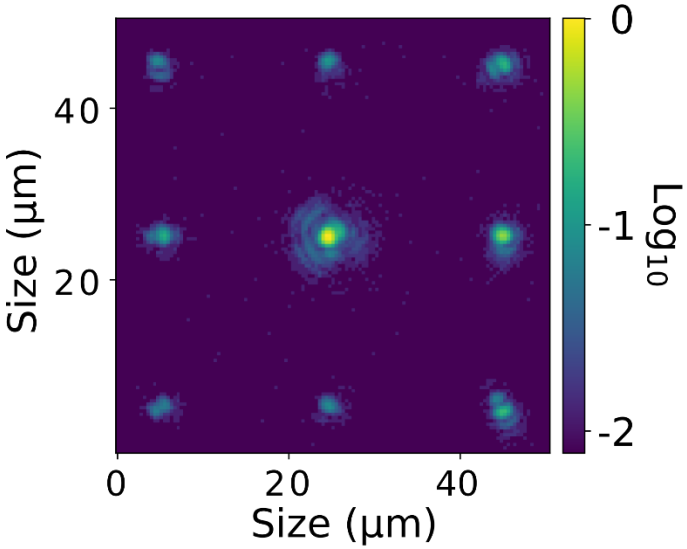
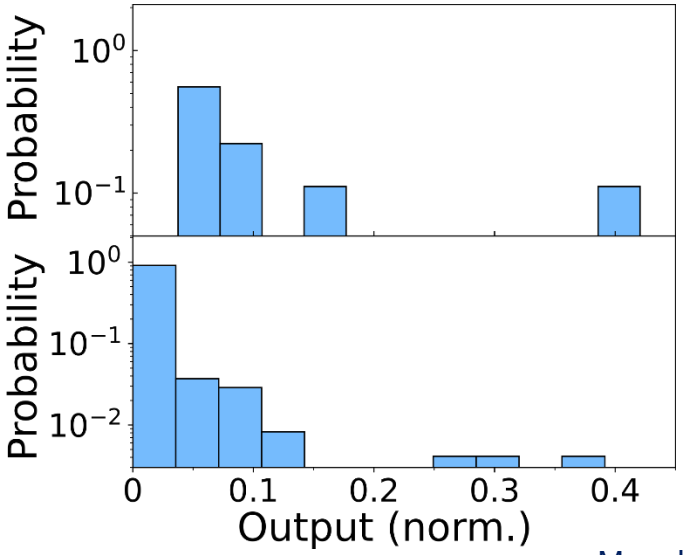








Losses:

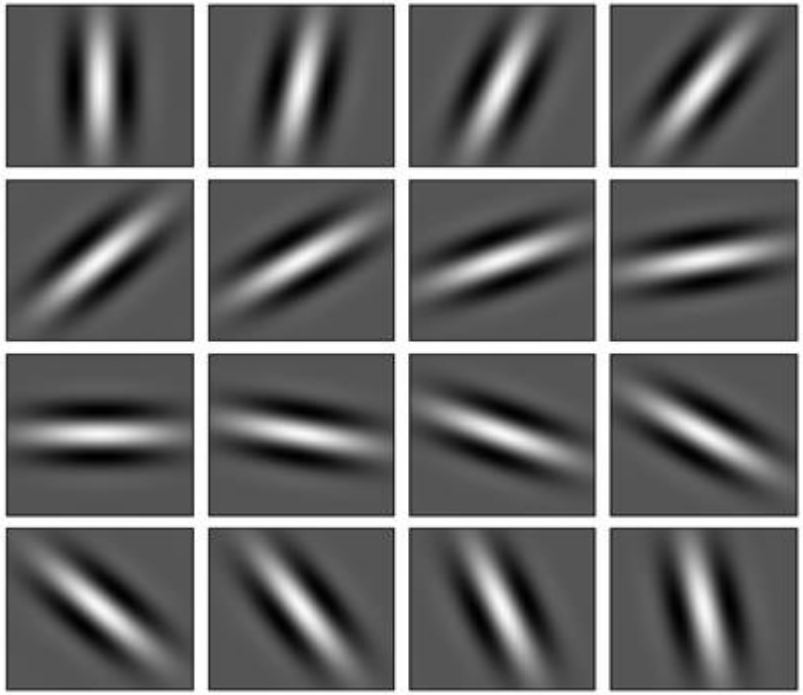
- 1x9: 5.5 dB
- 1x81: 10.6 dB

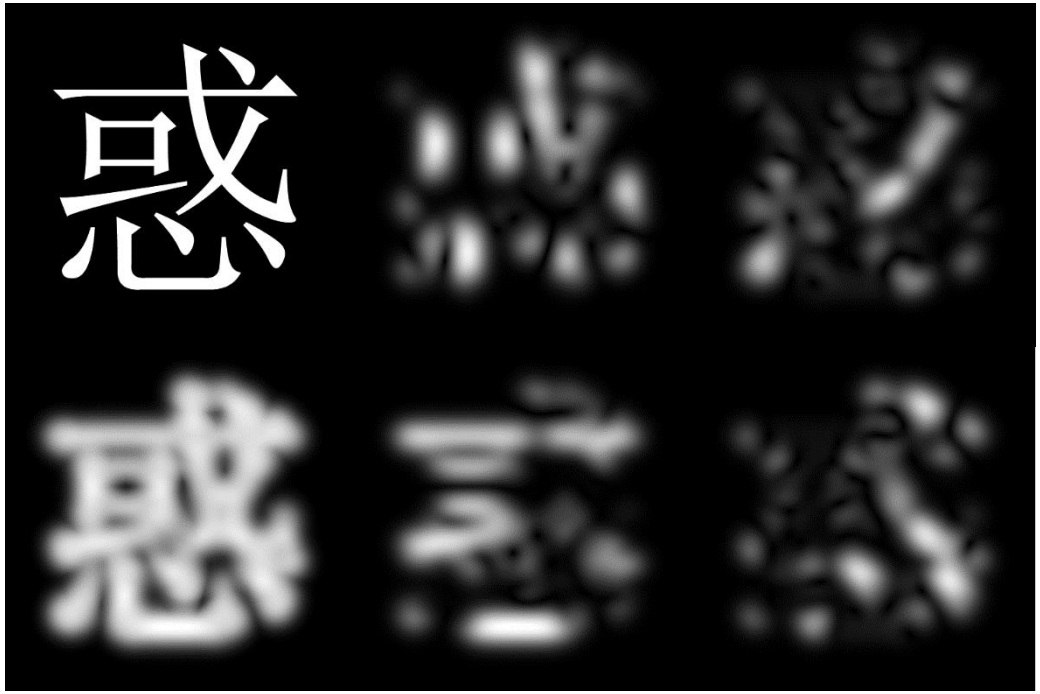
Causes:

- Inj.: 2.71 dB
- Prop.: 1.14 dB
- Coupl.: 1.67 dB

Moughames, et al., Optica **7**, 640 (2020).

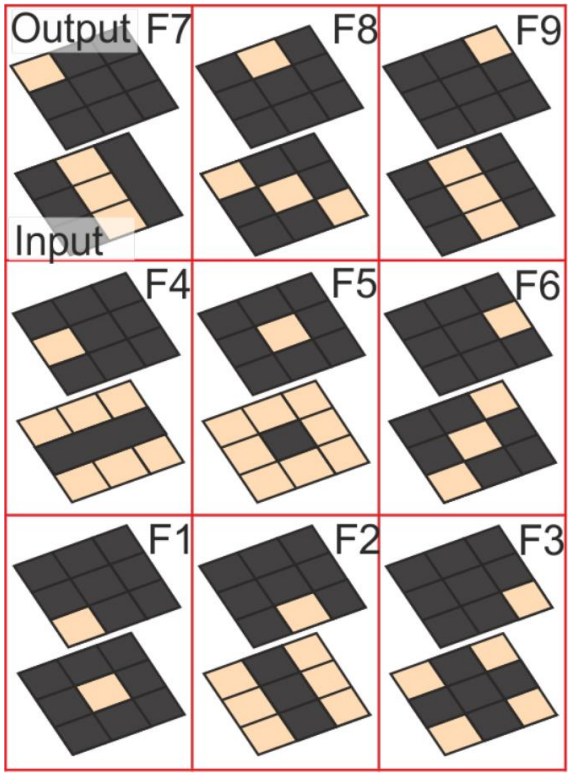
First functionality: ‘Gabor’ filters

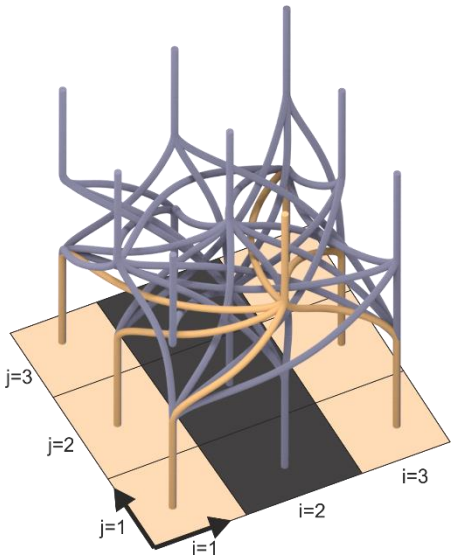




Moughames, et al., arXiv:1912.08203 (2019).

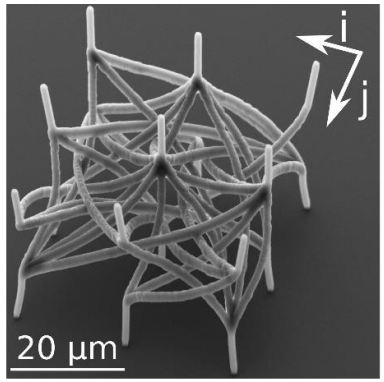
3D Spatial filters (convolutional NN):

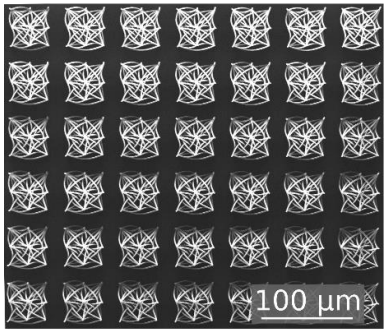


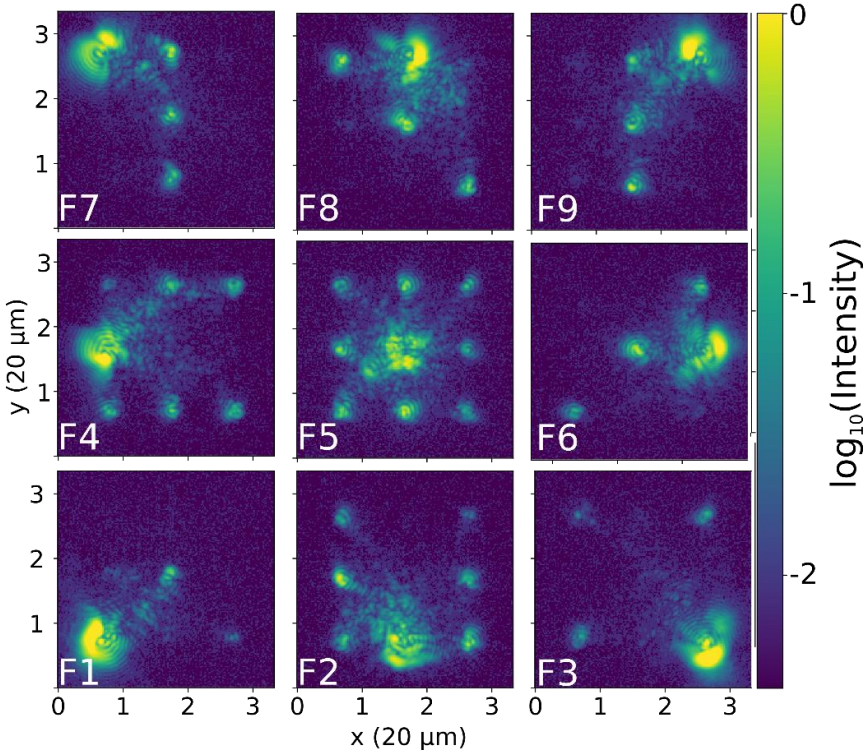


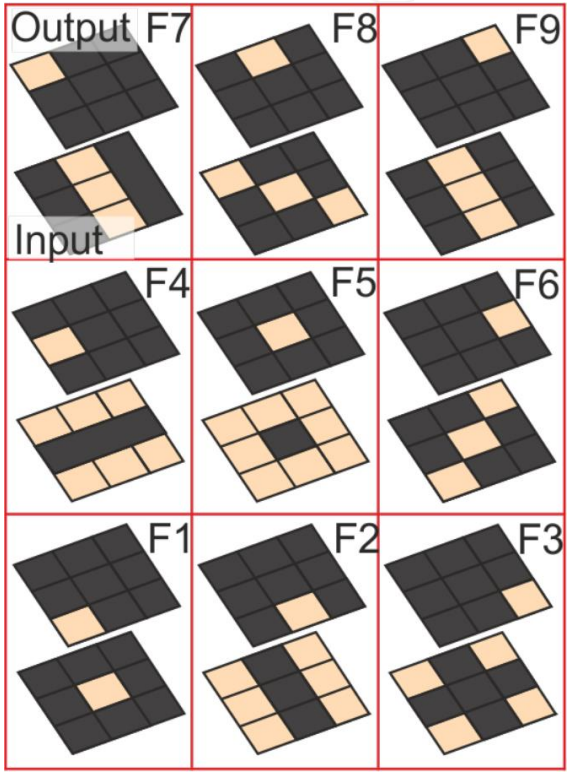
Moughames, et al., Optica **7**, 640 (2020).

Array of Haar filters:





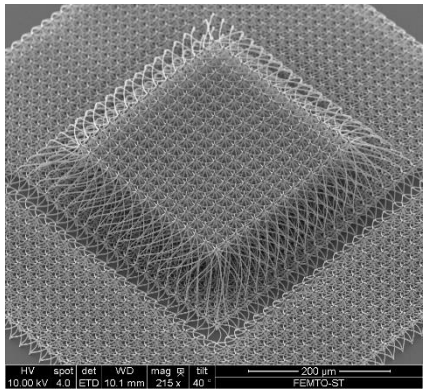




Moughames, et al., Optica **7**, 640 (2020).

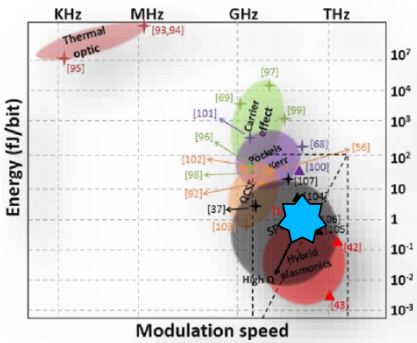
NN breakthrough: long term effort

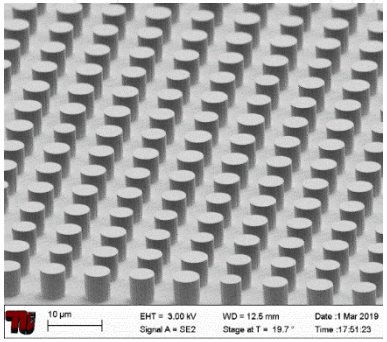
Parallel networks



Moughames, et al., arXiv:1912.08203 (2019).

Photonic neurons



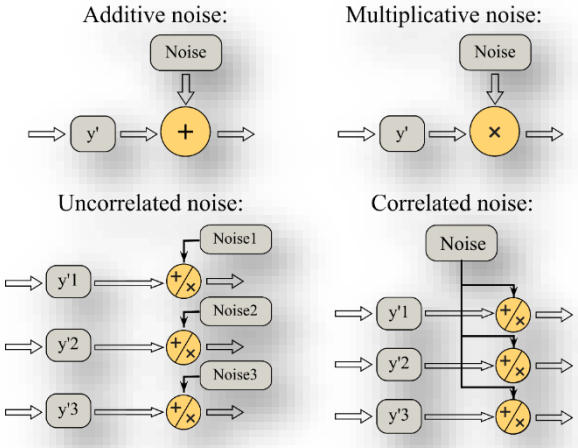


Liu et al., Laser and Photonics Reviews 9, 172 (2015).
Heuser, et al., J. Appl. Phys 3, 116103 (2018).

Hardware-motivated learning

Bueno, et al., Optica 5, 756 (2015).

Noise

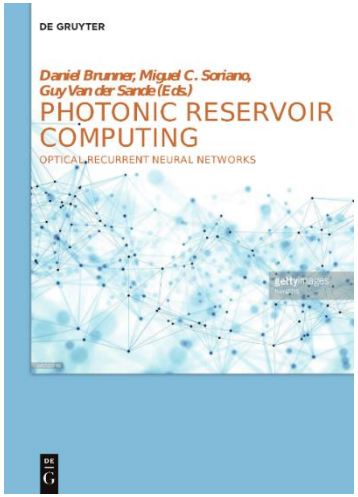


Semenova , et al., Chaos 29, 103128 (2015).

Summary

- Physical substrates: topology inspiration from Brain
- Address hardware-motivated learning challenge
- Next:
  - Address hardware-motivated learning challenge
  - application “advantage”

Conference @ SPIE Optics and Photonics – most likely virtual



Emerging Topics in Artificial Intelligence 2021 OP112)

Conference Chairs: **Giovanni Volpe,** Göteborgs Univ. (Sweden); **Joana B. Pereira,** Karolinska Institute (Sweden); **Daniel Brunner,** Institut Franche-Comte Electronique Mecanique Thermique et Optique (France); **Aydogan Ozcan,** Univ. of California, Los Angeles (USA)