# Leaky integrate-and-fire neuron circuit realized by Pearson-Anson oscillation and its noise

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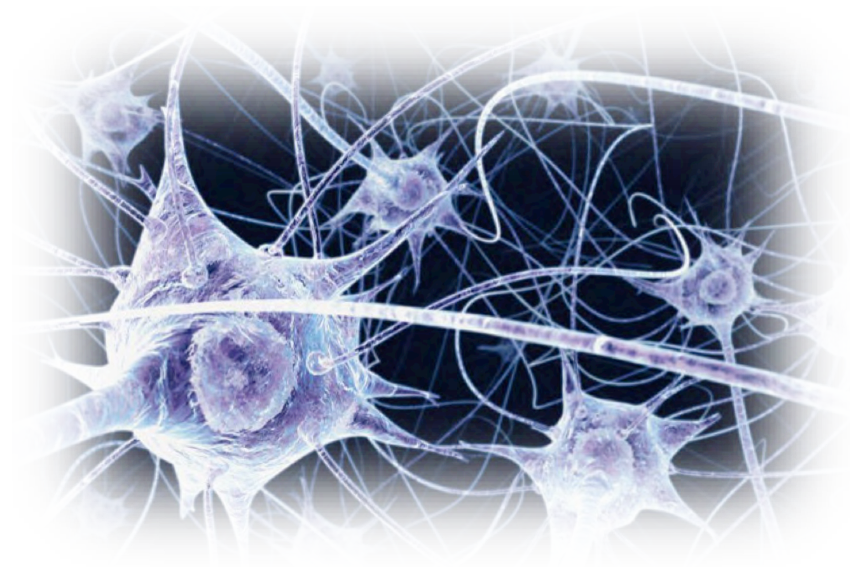


# Outline

- Spiking neural networks for artificial intelligence
- Relaxation oscillation-based leaky integrate-and-fire (ROLIF) neuron
- Pearson-Anson oscillation by monostable resistive switching devices
- Noise properties
- Summary and outlook

## Information theory

**Entropy:**
A measure of information satisfying the following conditions

1. Information (entropy) is a measure of how "surprising" a set of event is.

2. Independent probable events lead to the measure in an additive manner.

$$h\left(P[r_1]P[r_2]\right) = h\left(P[r_1]\right) + h\left(P[r_2]\right)$$

$$h\left(P[r]\right) = -\log_2 P[r]$$

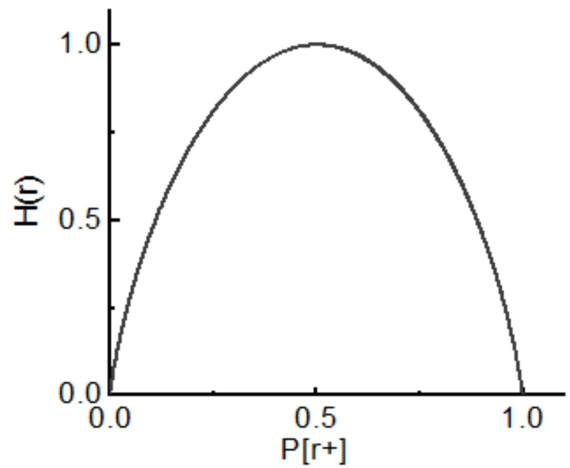
$$H(r) = -\sum_r P[r]\log_2 P[r]$$

Example: Binary (boolean) information

$r_+$ $r_-$

$$P[r_+] = 1 - P[r_-]$$

$$H(r) = -\left(1 - P[r_-]\right)\log_2\left(1 - P[r_-]\right) - P[r_-]\log_2 P[r_-]$$



# Information

| Decimal | | Binary | |
|---|---|---|---|
| 7 | = | 1 1 1 | 3 bit |
| 9 | = | 1 0 0 1 | 4 bit |

- Entropy (Shannon information)

$$H(r) = -\sum_{r} P[r] \log_2 P[r]$$

$r_+$ $r_-$

$H$ = 1 bit

$H$ = 2.58 bit

- 1 bit (boolean) devices

| | 0 (1) | 1 (0) |
|---|---|---|
| TR | Channel on | off |
| Flash | Charge in | out |
| DRAM | Charged | Discharged |
| FRAM | Pr+ | Pr- |
| STTRAM | Parallel | Antiparallel |
| PRAM | High R | Low R |
| RRAM | High R | Low R |

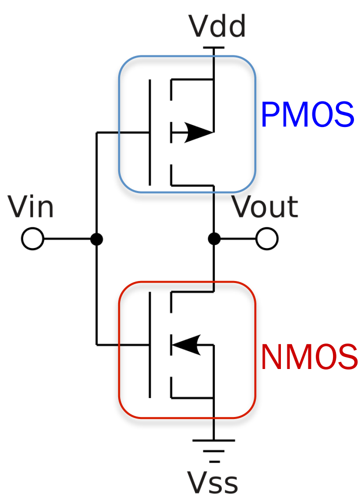
Logic

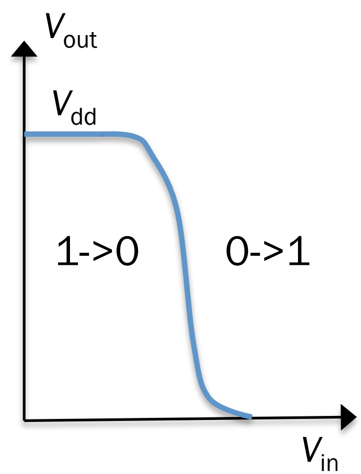
Charge-based

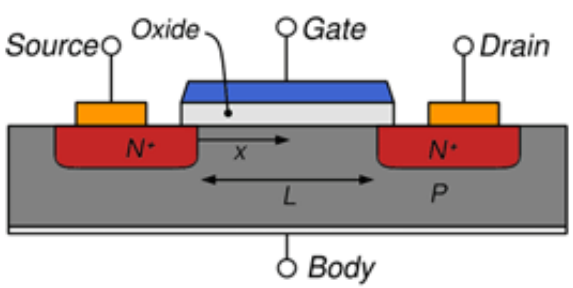
Resistance-based

# Where is the digital tech heading to?

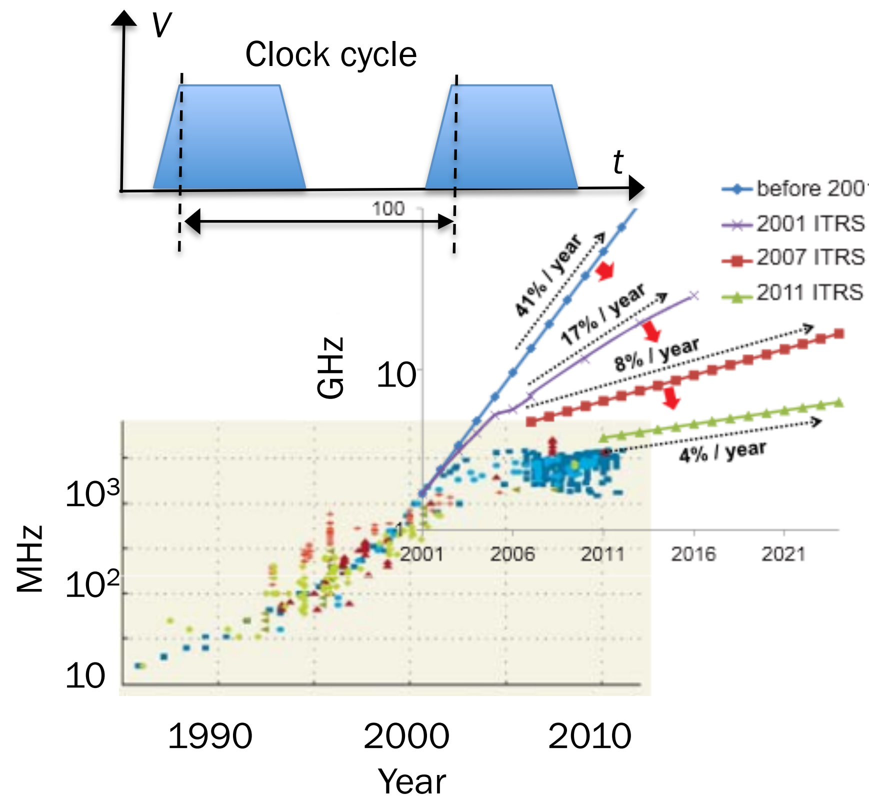
- Complementary Metal-Oxide-Semiconductor



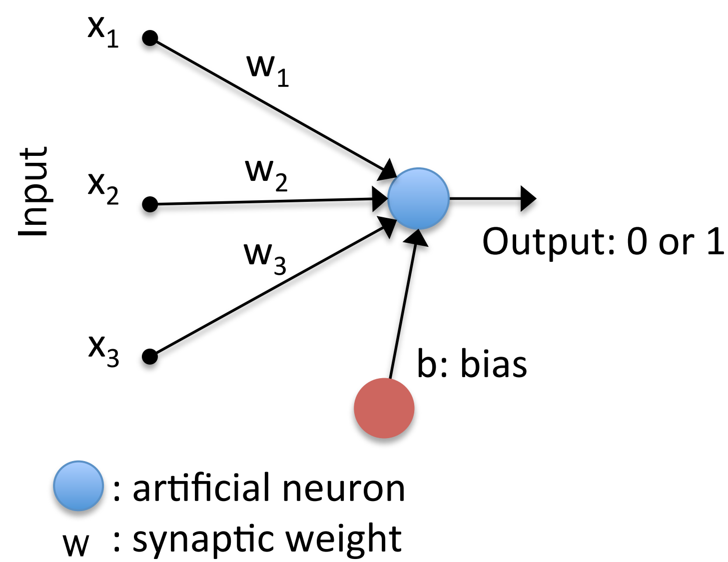

- System clock: synchronous operation

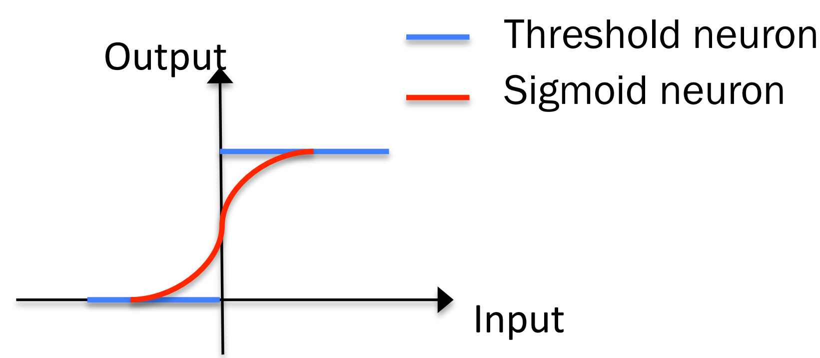


**Artificial Intelligence (AI):**
Decision-making ability of *things*.

**Frequently used terms:**
- Deep learning
- Supervised learning
- Unsupervised learning
- Reinforcement learning
- Artificial neural networks (ANNs)
- Convolutional neural networks (CNNs)
- Deep belief networks
- Perceptron
- Multilayer perceptron (MLP)
- Spiking neural networks (SNNs)

Single layer perceptron
- Artificial Neural Network (ANN)



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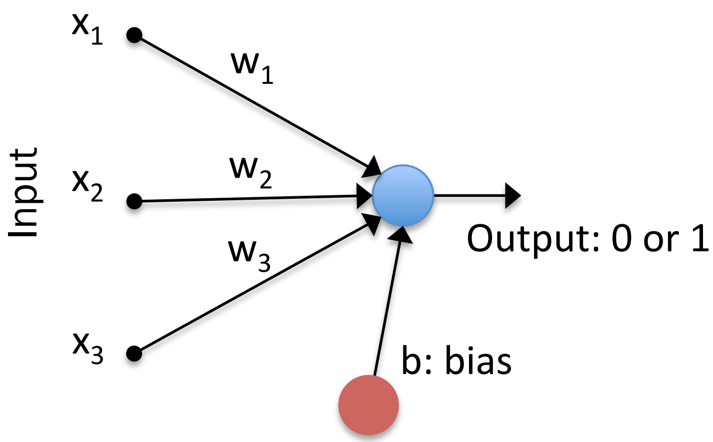
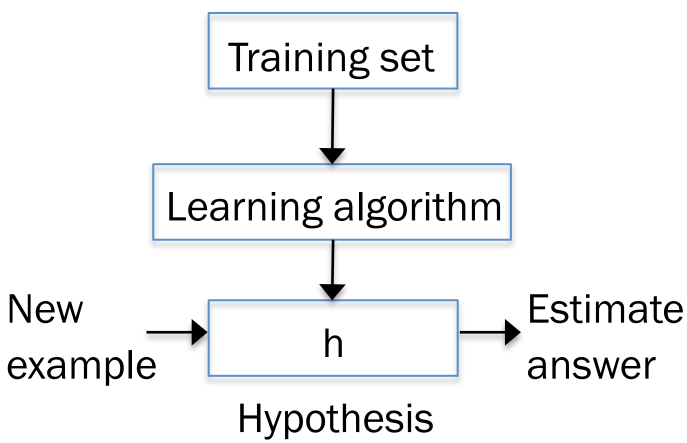
## Supervised learning




## Example: drink (1) or not drink (0)?

m

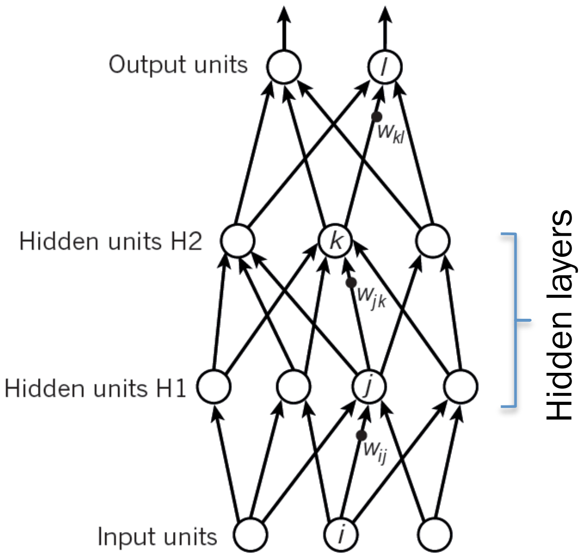
| Weather ($x_1$) | Budget ($x_2$) | Day ($x_3$) | Drink? (y) |
|---|---|---|---|
| | | | |

m = # training examples
x = input variables/ features
y = output variable/target
(x, y) = training example

Repeating training with the training examples updates the w-vector to reduce the cost function.

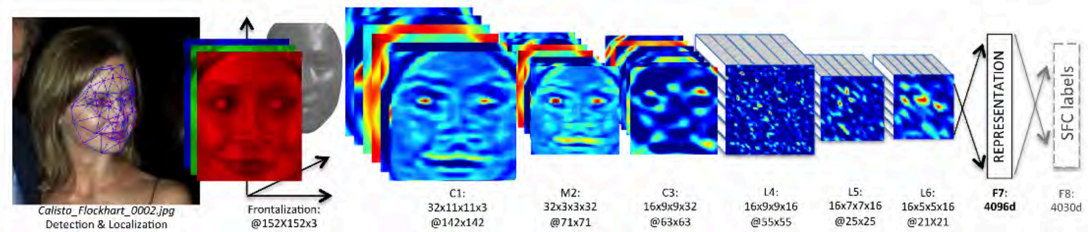
Update method: gradient descent, stochastic gradient descent, online learning

# Feature abstraction




DeepFace by Facebook

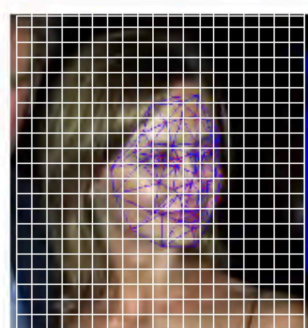
Input: all pixels (features) in the receptive field




Feature abstraction

If else

Can it be done by the conventional digital computation?



Calista_Flockhart_0002.jpg
Detection & Localization

No feature abstraction

The drink problem compress the three features into a single one.

## Hardware spiking neural networks

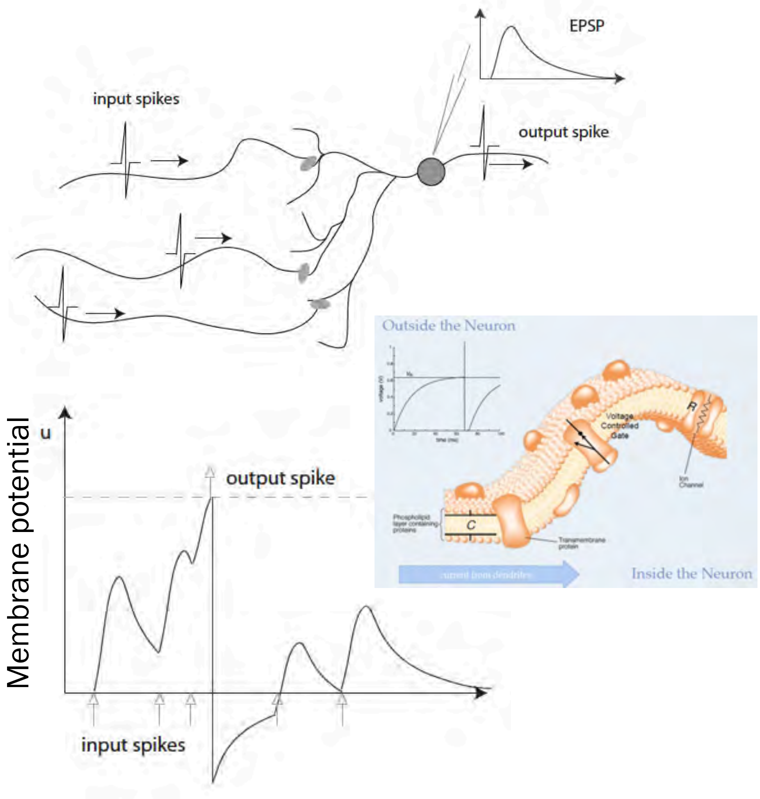
Disadvantages of ANNs:

- No real-time data processing, i.e. static perception (no interaction with our real world)
- Lack of temporal learning

Disadvantages of software-based SNNs and ANNs

- Inefficiency in calculation
- particularly, many feature systems

Self-consistently working hardware SNNs are likely to be a workaround solution to these problems.




Spike response model.

W. Gerstner, *Phys. Rev. E* **1995**, 51, 738.

# In silico artificial neuron models

- Integrate-and-fire neuron

$$i_{syn} = C_m \frac{du_m}{dt}$$

- Leaky integrate-and-fire neuron

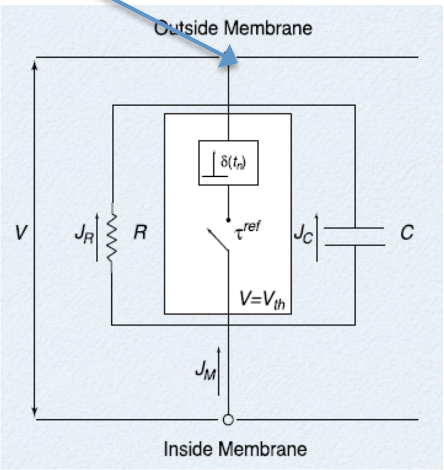
$$i_{syn} = C_m \frac{du_m}{dt} + \frac{1}{R_m}\left(u_m - u_{rest}\right)$$

- Conductance-based neuron model:
  e.g. Hodgkin-Huxley neuron

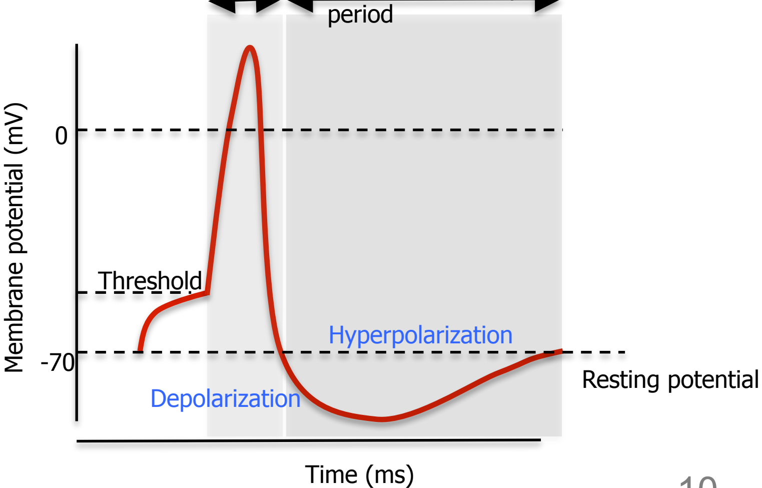
$$C_m \frac{du_m}{dt} = -g^L\left(u_m - u_L\right) - g^E\left(u_m - u_E\right) - g^I\left(u_m - u_L\right)$$

$$g^E = \sum w_j s_j \qquad \frac{ds_i}{dt} = -\frac{s_i}{\tau_s}$$

Synaptic current *i*

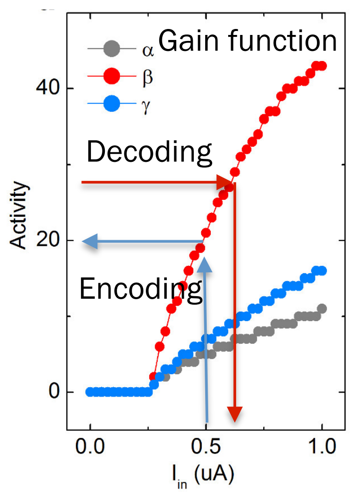


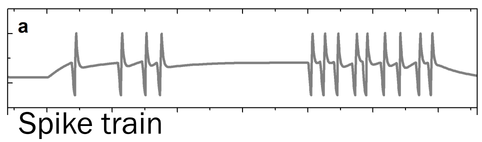

*Eliasmith and Anderson, Neural Engineering*



# What do neurons do?

- Information encoding into spikes
  : integrate-and-fire



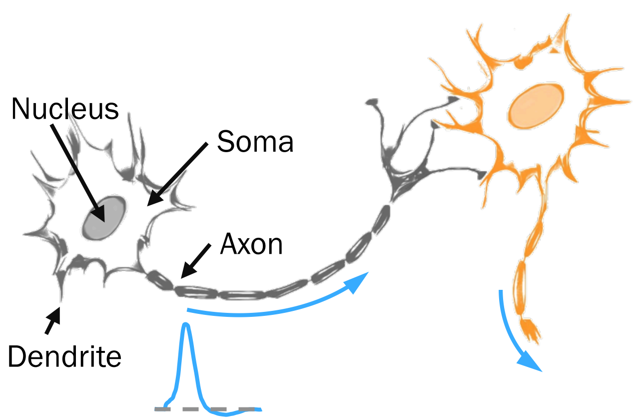




$a = G(I_{in})$ Neural encoding

$I_{in} = G^{-1}(a)$ Neural decoding

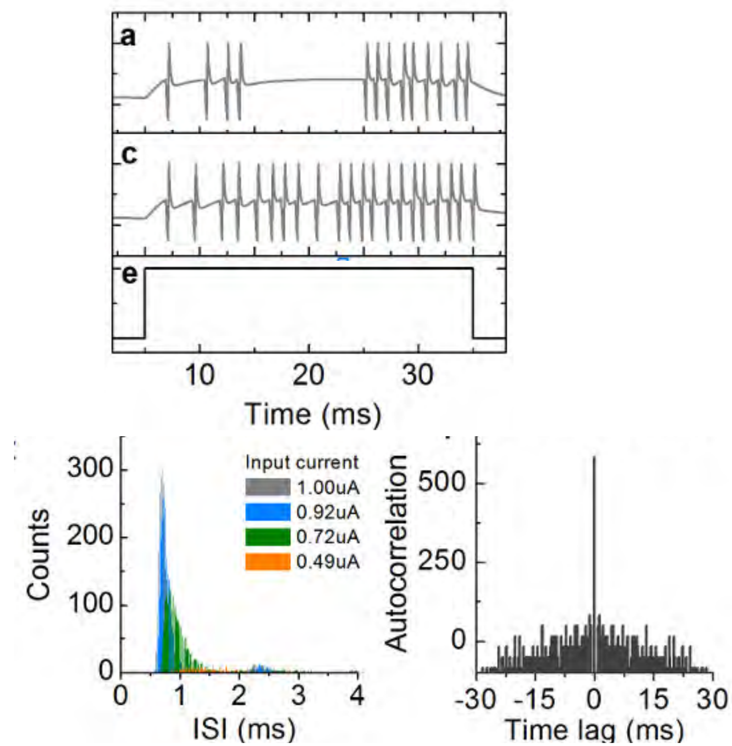
Ideally, a single neuron represents *infinite bits*.
cf. a transistor (1 bit)

*H. Lim, et al., Sci. Rep. 2015, 5, 09776.*




- Signal amplification
  : signal gain required.

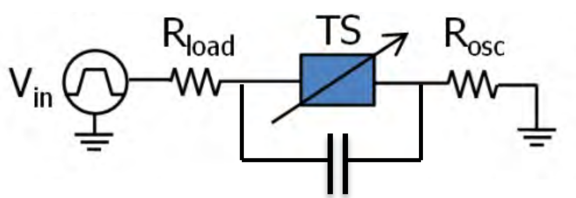
- Random noise
  : random distribution of inter-spike interval



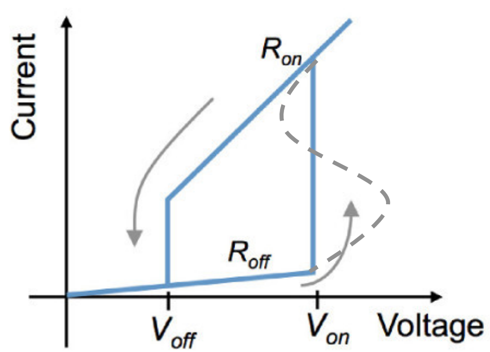

*H. Lim, et al., Sci. Rep. 2015, 5, 09776.*

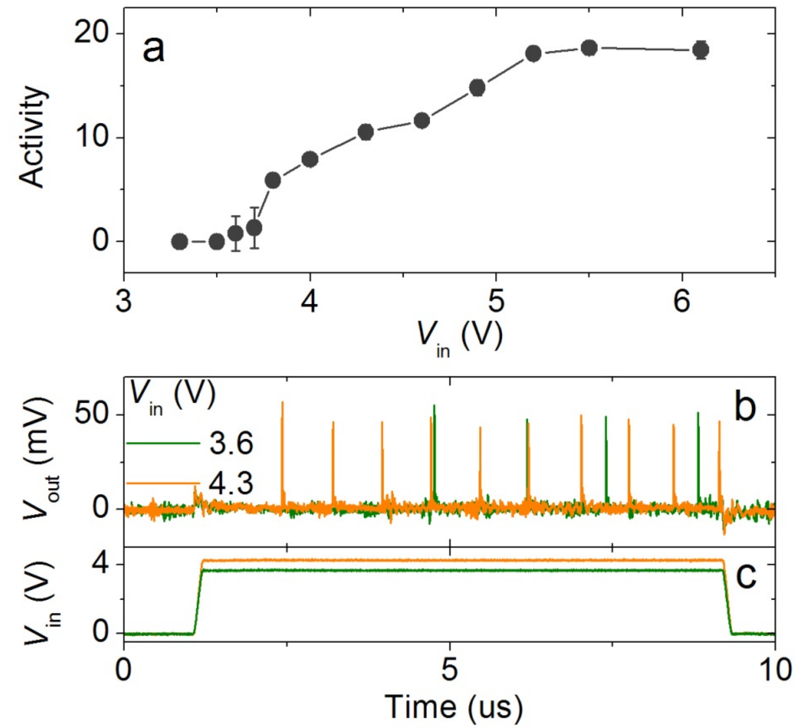
# Relaxation oscillator-based LIF neurons

- Pearson-Anson oscillator with a threshold switch




- Monostable resistive switching (s-type negative differential resistance effect)

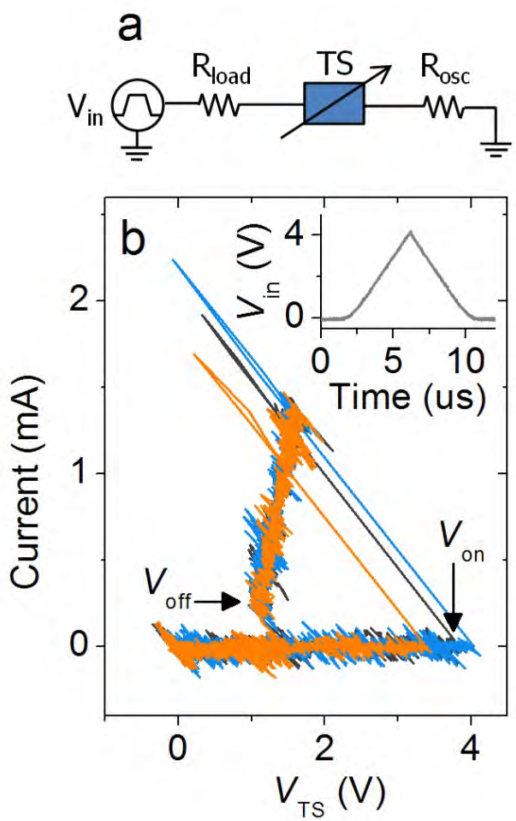



*H. Lim, et al., unpublished results*

# Threshold switching






*H. Lim, et al., unpublished results*

Amorphous higher chalcogenide-based threshold switch:
Pt/GeSe/Pt cells

Other than that?
- MIT systems
- Shockley diode
- Particular transition metal oxides
  e.g. $NbO_x$

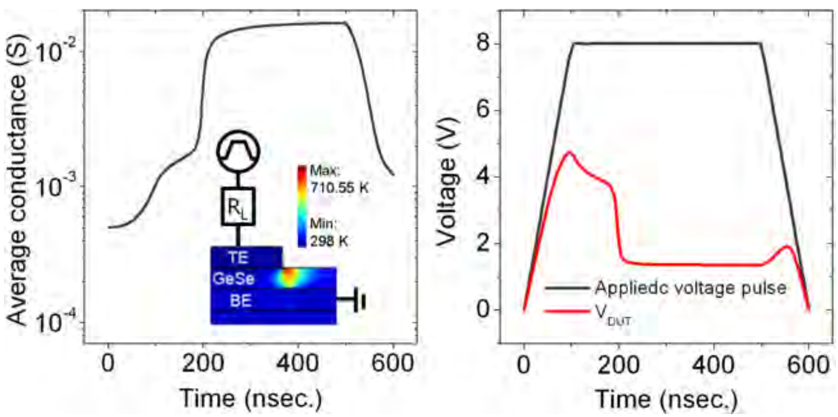
*DSJ et al., Rep. Prog. Phys. 2012, 75, 076502.*

# Mechanism for threshold switching



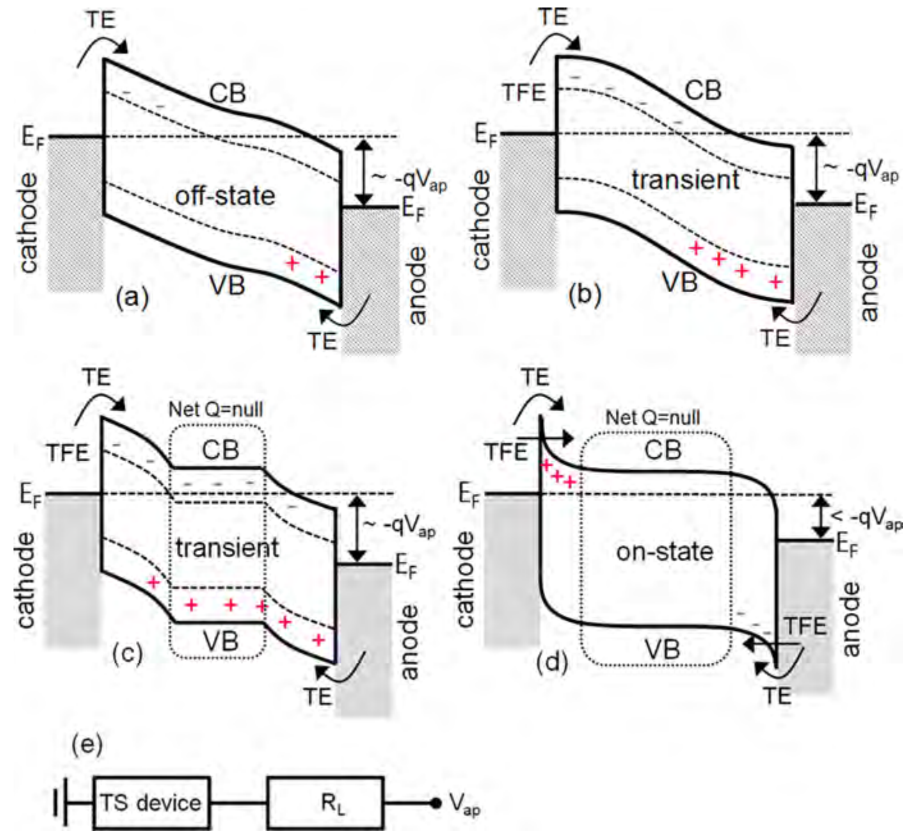
Thermal vs. purely electronic

- Hot electron model




Electrons get cold without lag.

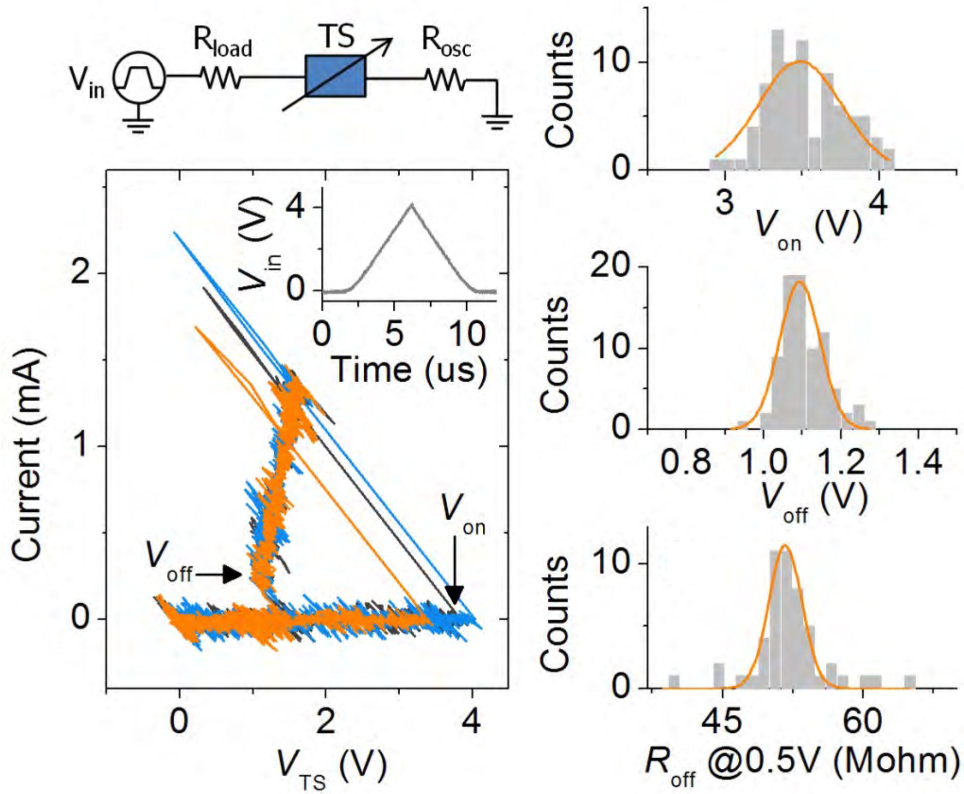
- Double injection (cold electronic carrier)




*DSJ et al., J. Appl. Phys. 2012, 111, 10287.*
*N. F. Mott, Contemp. Phys. 1969, 10, 125.*
*H. K. Henisch, et al., J. Non-Cryst. Solids 1970, 4, 538.*

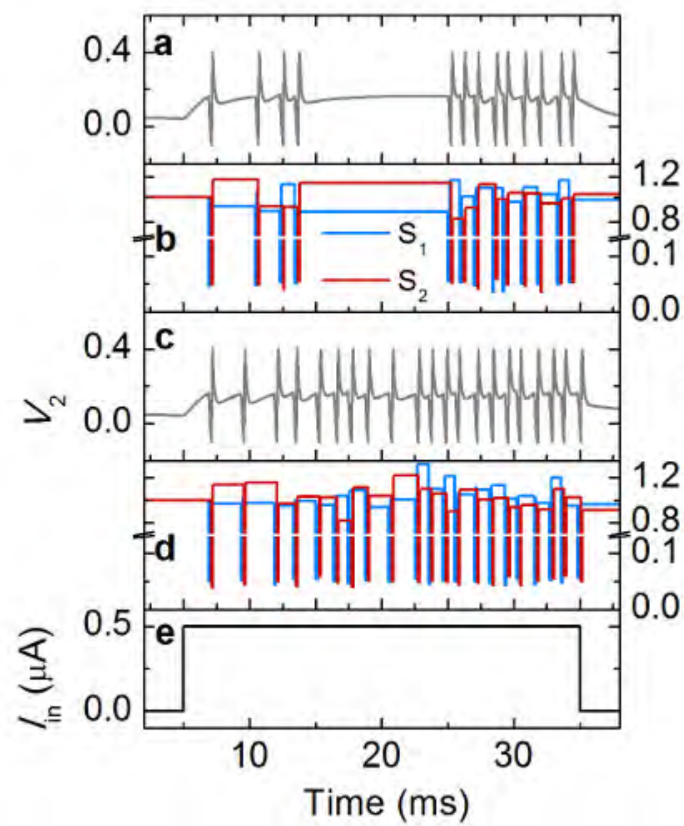
# Heterogeneity vs. noise

- Random variability in switching parameters




*H. Lim, et al., unpublished results*

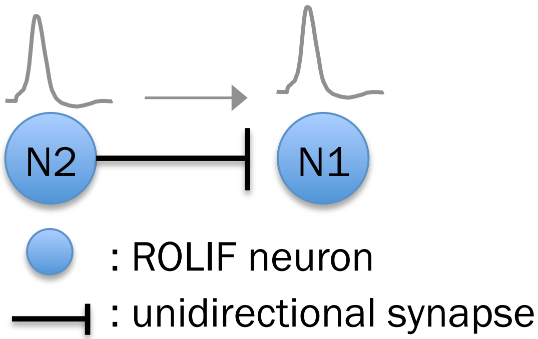
- Theoretical prediction

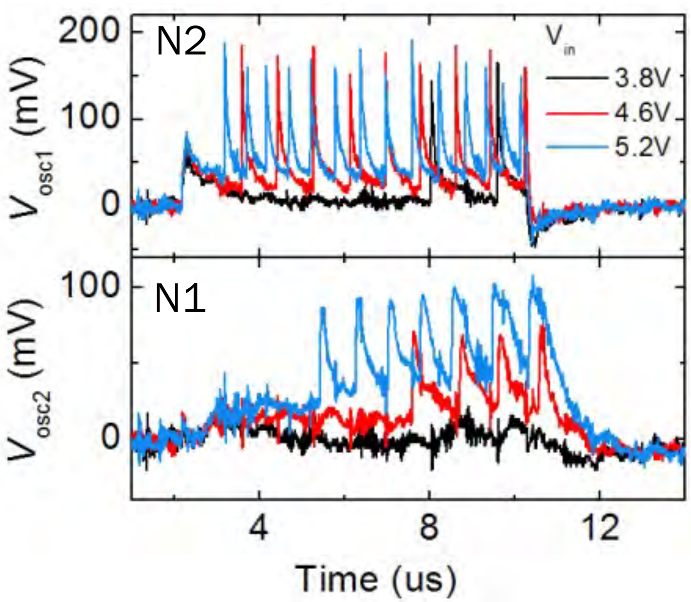



*H. Lim, Sci. Rep. 2015, 5, 09776.*

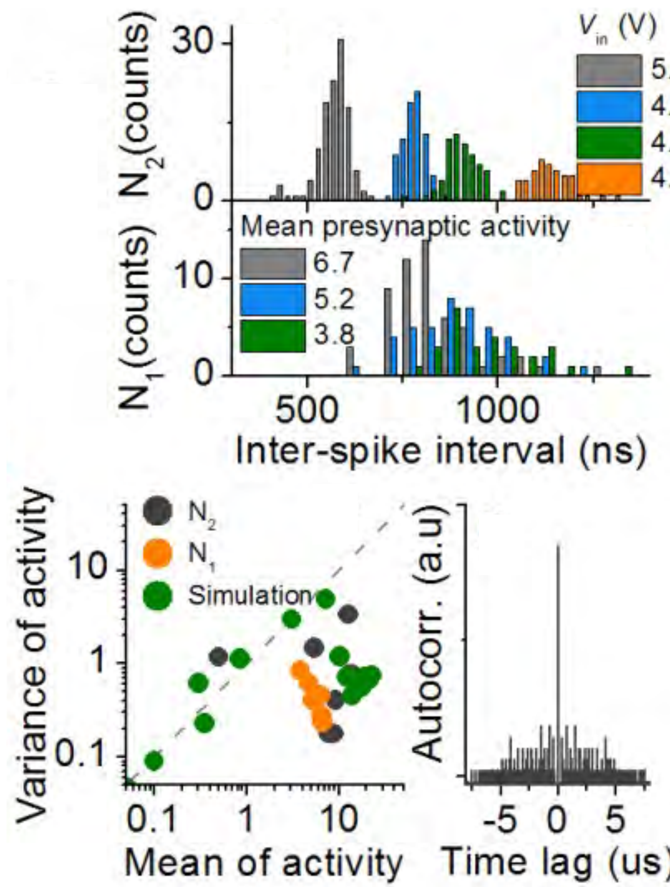
# ROLIF neurons in connection and noise

- Synaptic transmission and signal amplification




- Random Poisson noise




*H. Lim, et al., unpublished results*

# Are we bothering neurons too much?

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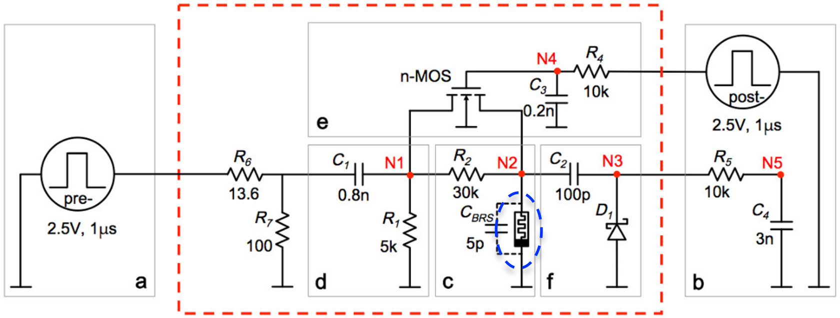
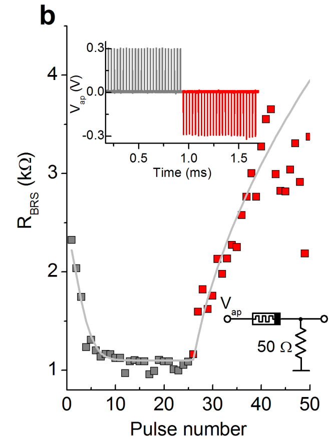
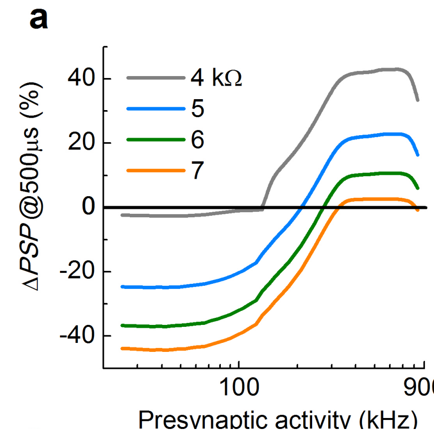
- Artificial synaptic (excitatory) circuit

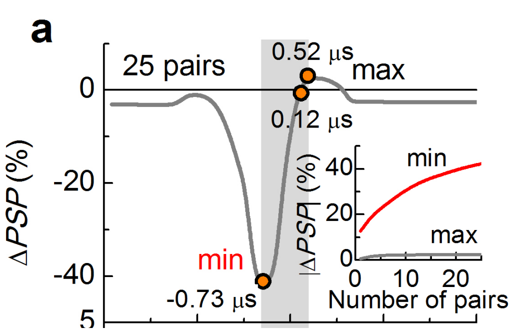



*Vladimir et al., Nanoscale 2014, 6, 15151.*

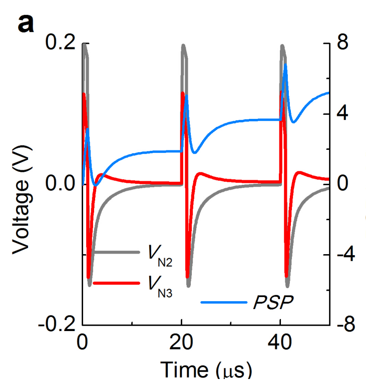


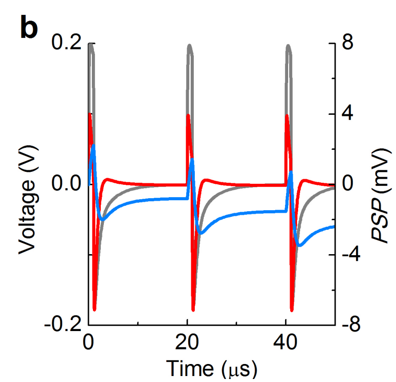

Activity encoding




Spikes' temporal order encoding




Excitatory synapse




Inhibitory synapse

Should synapses represent analogue information?

# Summary and outlook

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- Feasible neuronal behaviour of the ROLIF neuron is in sight.
  - Analogue information encoding (gain function)
  - Signal amplification using op-amps
  - Random Poisson noise

- Synaptic transmission through an artificial synapse is successfully seen.

- Optimization of threshold switching behaviour should be underpinned; particularly, the endurance and switching voltage.

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Thank you for your attention!

# For your information

IOP Publishing — Reports on Progress in Physics
Rep. Prog. Phys. **75** (2012) 076502 (31pp) doi:10.1088/0034-4885/75/7/076502

## Emerging memories: resistive switching mechanisms and current status

**Doo Seok Jeong[1,6], Reji Thomas[2,6], R S Katiyar[2], J F Scott[3], H Kohlstedt[4], A Petraru[4] and Cheol Seong Hwang[5]**

*Rep. Prog. Phys.* ***2012**, 75, 076502.*

RSC Advances — RSC Publishing
REVIEW
View Article Online
View Journal
Cite this: DOI: 10.1039/c2ra22507g

## Towards artificial neurons and synapses: a materials point of view

Doo Seok Jeong,*[a] Inho Kim,[a] Martin Ziegler[b] and Hermann Kohlstedt[b]

*RSC Advances* ***2013**, 3, 3169.*

# Leaky integrate-and-fire neuron