

# Neurochaos Learning



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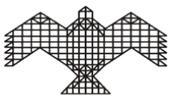
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**02 Sept. 2021**

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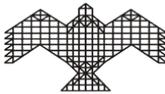
Associate Professor

Consciousness Studies Programme  
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# Outline

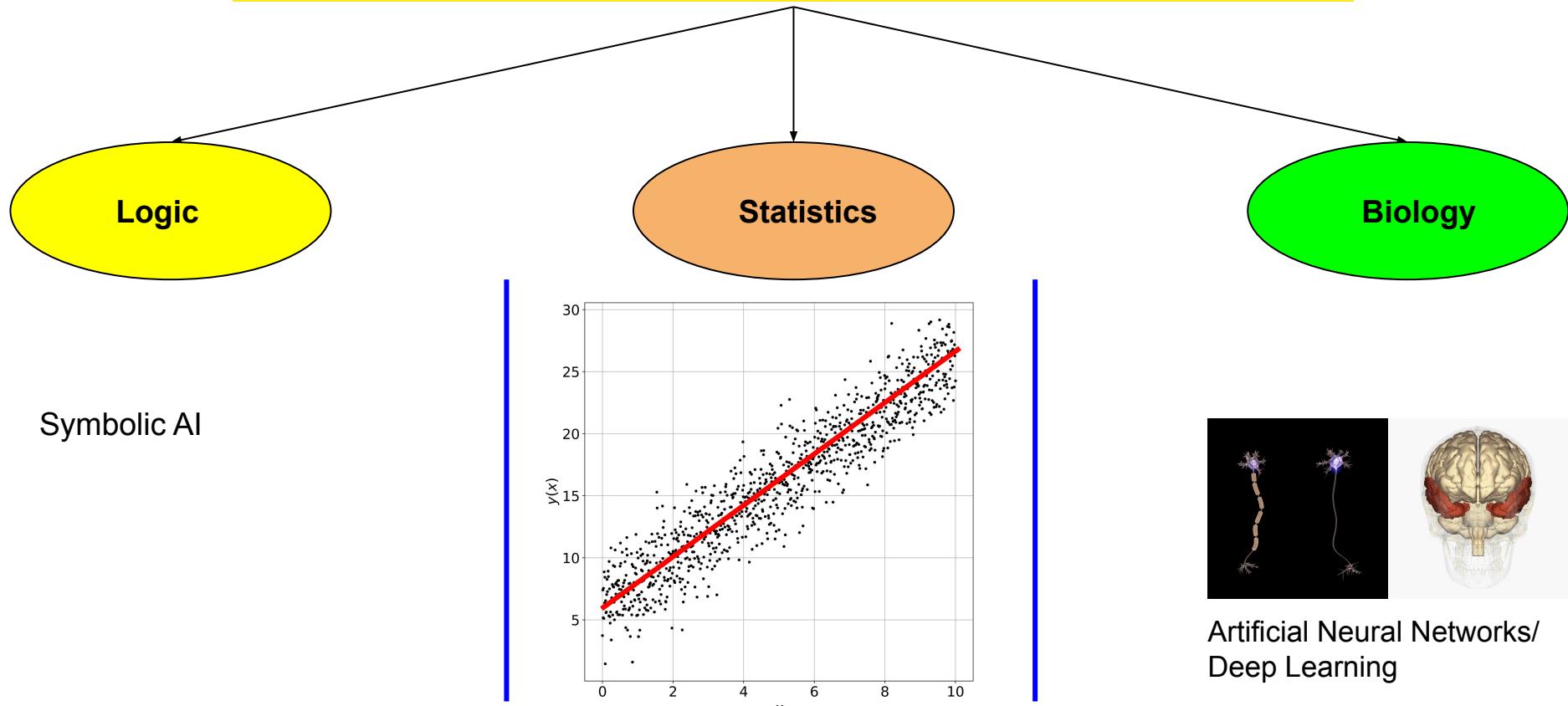
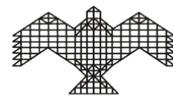
- Part I: Neurochaos Learning
- Part II: Role of Noise in Neurochaos Learning



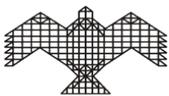
# Artificial Intelligence

- Chess Playing Machine
- Speech Recognition system
- GPS Navigation
- Virtual Assistance
- Machine Translation
- Facial Recognition
- Self Driving Car
- Medical Diagnosis
- Industrial Robotics

# Artificial Intelligence: An Anarchy of Methods\*



- Reference: Lehman, Joel, Jeff Clune, and Sebastian Risi. "An anarchy of methods: Current trends in how intelligence is abstracted in ai." *IEEE Intelligent Systems* 29.6 (2014): 56-62.
- Prof. Melanie Mitchell's Talk: <https://www.youtube.com/watch?v=NMUqvhuDZtQ>



# Brain: The Ultimate Machine

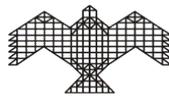


- High complexity (non-linear)
- Very high neural noise and interference
- Very low SNR: -29 dB to -20 dB\*
- Neural signal multiplexing†
- Low power “neural computation” (~12.6 Watts\*\*)
- How does it work? No idea!

\*Ref: G. Czanner et al., Measuring the signal-to-noise ratio of a neuron, PNAS 112 (23), 2015

†Ref: M L R Meister et al., Signal multiplexing and single-neuron computations in Lateral Intraparietal Area during decision-making, J. Neurosci. 33 (6), 2013

\*\*Ref: Scientific American, 18 July 2012



# Neuroscience Inspired AI



- Rich source of inspiration for new types of algorithms and architectures, independent and complementary to the mathematical and logic based methods.
- Neuroscience can provide a validation of AI techniques that already exists.

## Neuroscience-Inspired Artificial Intelligence

Demis Hassabis,<sup>1,2,\*</sup> Dharshan Kumaran,<sup>1,3</sup> Christopher Summerfield,<sup>1,4</sup> and Matthew Botvinick<sup>1,2</sup>

<sup>1</sup>DeepMind, 5 New Street Square, London, UK

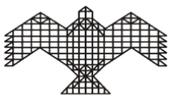
<sup>2</sup>Gatsby Computational Neuroscience Unit, 25 Howland Street, London, UK

<sup>3</sup>Institute of Cognitive Neuroscience, University College London, 17 Queen Square, London, UK

<sup>4</sup>Department of Experimental Psychology, University of Oxford, Oxford, UK

\*Correspondence: [dhcontact@google.com](mailto:dhcontact@google.com)

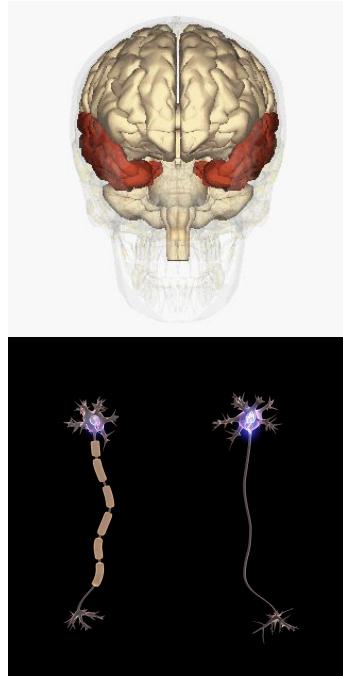
<http://dx.doi.org/10.1016/j.neuron.2017.06.011>

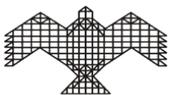


# Reinvestigate the current learning algorithms

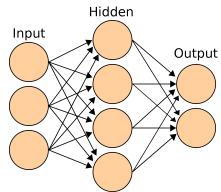
- Brain science is still in *Faraday Stage* [1]
- Brain has ~86 billion neurons [2]
- Complex network of neurons
- Neurons are inherently **non-linear** & found to exhibit **Chaos**
- ***Current AI only loosely inspired from the brain***

1. Ramachandran, Vilayanur S., Sandra Blakeslee, and Neil Shah. *Phantoms in the brain: Probing the mysteries of the human mind.* 1998.
2. Azevedo, Frederico AC, et al. "Equal numbers of neuronal and nonneuronal cells make the human brain an isometrically scaled-up primate brain." *Journal of Comparative Neurology* 513.5 (2009): 532-541.





# Artificial vs. Biological Neural Networks



## Research and Development Gap



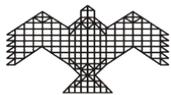
<b><i>Artificial Neural Networks (ANN)</i></b>	<b><i>Biological Neural Networks</i></b>
Linearity + Non-linear activation.	<b>Non-linearity at the neuronal level. [3, 4]</b>
Current deep learning architectures does not exhibit chaotic behaviour at the neuronal level for classification.	<b>Exhibits different behaviours - from periodic to chaotic at different spatiotemporal scales.</b>
Not robust to noise.	Robust to noise and interference.
Need huge amount of training data.	<b>Learning from limited samples.</b>

3. Faure, Philippe, and Henri Korn. "Is there chaos in the brain? I. Concepts of nonlinear dynamics and methods of investigation."

*Comptes Rendus de l'Académie des Sciences-Series III-Sciences de la Vie* 324.9 (2001): 773-793.

4. Korn, Henri, and Philippe Faure. "Is there chaos in the brain? II. Experimental evidence and related models." *Comptes rendus biologies* 326.9 (2003):

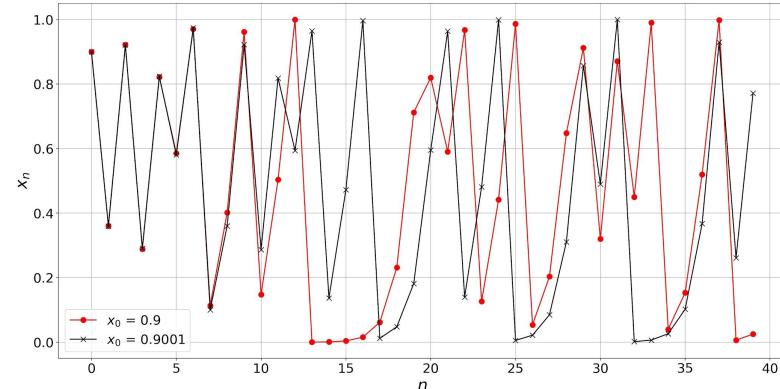
787-840.



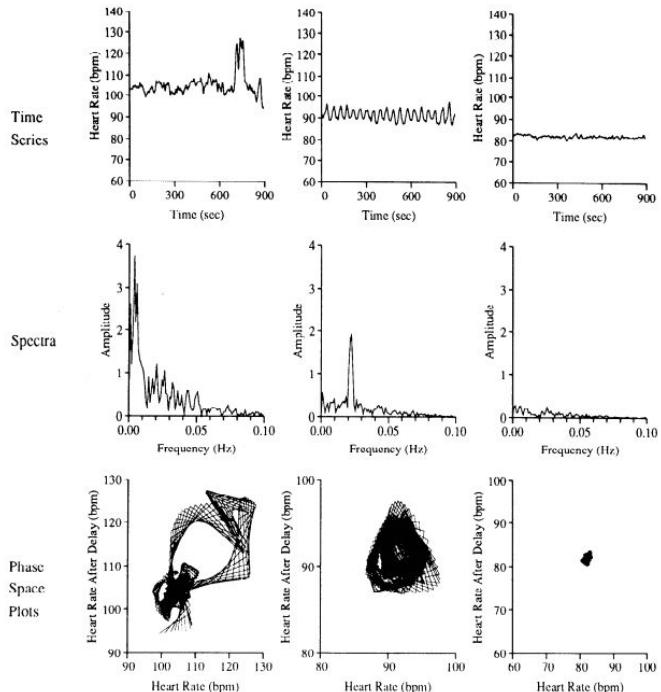
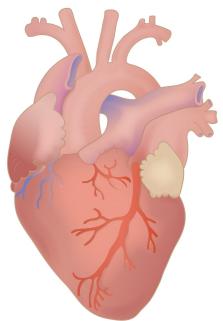
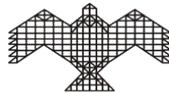
# Chaos

- Deterministic, yet unpredictable
- Bounded, non-linear, iterations
- Looks/feels like Randomness, but has rich structure and order
- Sensitive dependence on initial value (Butterfly Effect)
- Periodic, quasi-periodic and non-periodic solutions/trajectories
- Topological Transitivity

$$x_n = 4x_{n-1}(1 - x_{n-1})$$



# Healthy Heart is Chaotic

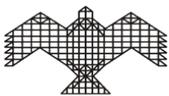


**FIGURE 3.** Heart rate dynamics. Normal sinus rhythm in healthy subjects (*left*) shows complex variability with a broad spectrum and a phase space plot consistent with a strange (chaotic) attractor. Patients with heart disease may show altered dynamics, sometimes with oscillatory sinus rhythm heart rate dynamics (*middle*) or an overall loss of sinus variability (*right*). With the oscillatory pattern, spectrum shows a sharp peak, and phase space plot shows a more periodic attractor, with trajectories rotating about a central hub. With the flat pattern, spectrum shows an overall loss of power, and phase space plot is more reminiscent of a fixed-point attractor. (Adapted from Goldberger et al. (9).)

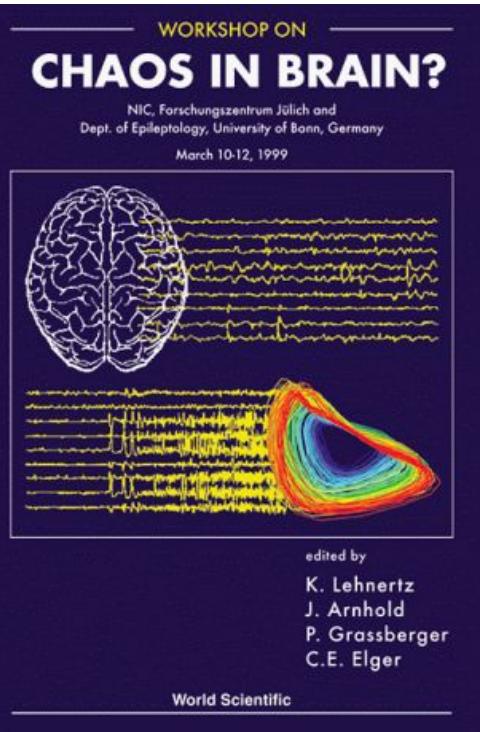
## Is the Normal Heartbeat Chaotic or Homeostatic?

Ary L. Goldberger

DOI: [10.1152/physiologyonline.1991.6.2.87](https://doi.org/10.1152/physiologyonline.1991.6.2.87)



# Chaos in the Brain



Comptes Rendus de l'Académie des Sciences - Series III - Sciences de la Vie  
Volume 324, Issue 9, September 2001, Pages 773-793

Is there chaos in the brain? I. Concepts of nonlinear dynamics and methods of investigation

Pierre Buser  
Philippe Faure, Henri Korn  

Comptes Rendus Biologies  
Volume 326, Issue 9, September 2003, Pages 787-840

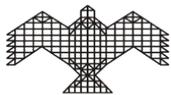
Neurosciences

Is there chaos in the brain? II. Experimental evidence and related models

Presented by Pierre Buser  
Henri Korn  , Philippe Faure  

## “Neuro-Chaos” \*

- Chaos – empirically found at all levels of hierarchy in the brain.
- Single and coupled neurons
- Neuronal attractors in information processing, perception and memory
- Chaos – as a neuronal code.



# Neurochaos Learning Architectures

AIP Chaos: An Interdisciplinary Journal of Nonlinear Science

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## ChaosNet: A chaos based artificial neural network architecture for classification

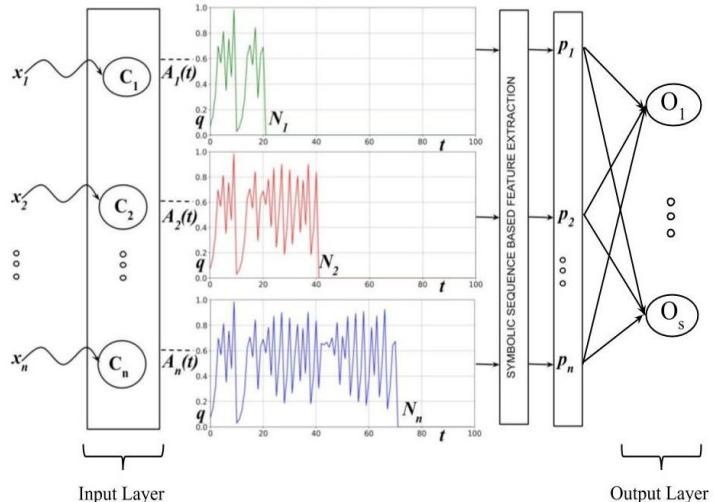
Cite as: Chaos 29, 113125 (2019); doi: 10.1063/1.5120831

Submitted: 21 July 2019 Accepted: 4 November 2019

Published Online: 20 November 2019

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Harikrishnan Nelliappallil Balakrishnan,<sup>1,a)</sup> Aditi Kathpalia,<sup>1,b)</sup> Snehanshu Saha,<sup>2,c)</sup> and Nithin Nagaraj<sup>1,d)</sup>



Conferences > 2020 International Conference... [?](#)

## ChaosFEX +ML

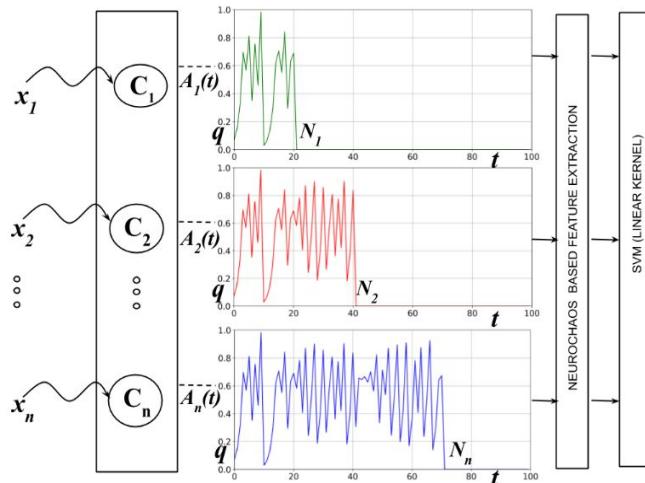
### Neurochaos Inspired Hybrid Machine Learning Architecture for Classification

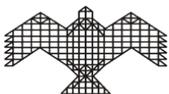
Publisher: IEEE

[Cite This](#)

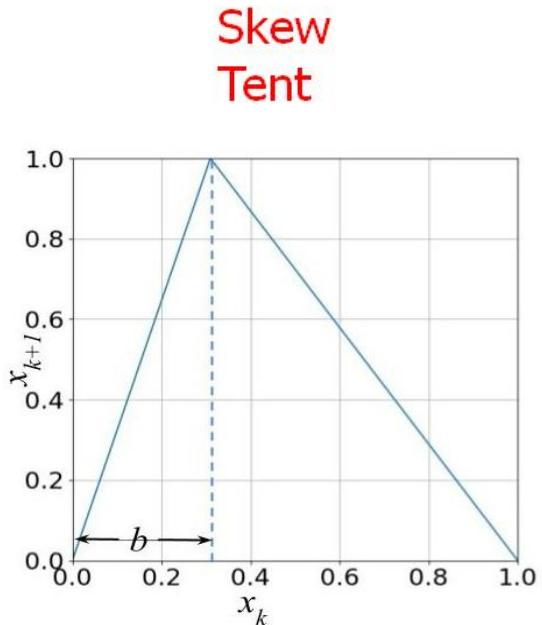
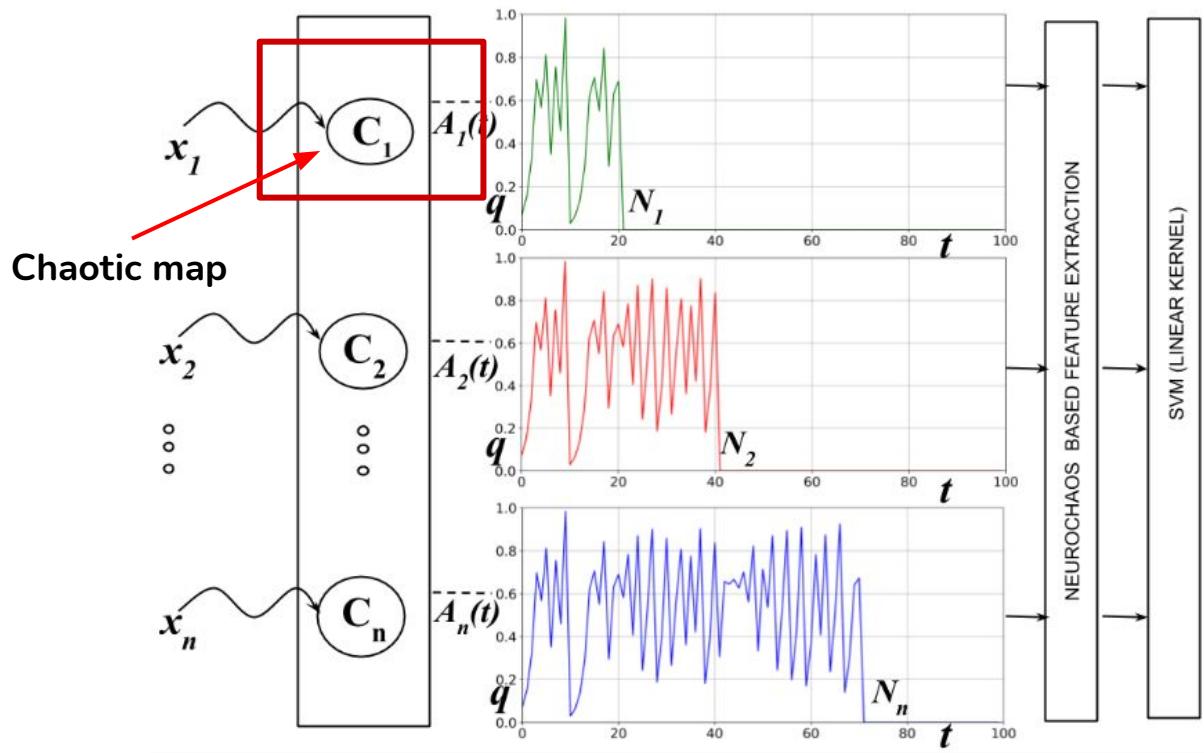
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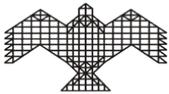
N.B. Harikrishnan ; Nithin Nagaraj [All Authors](#)





# Neurochaos Learning (NL)

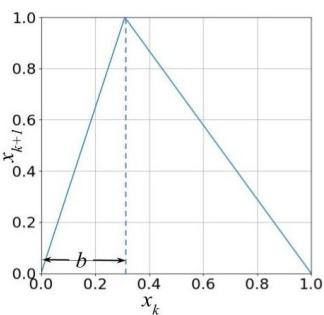
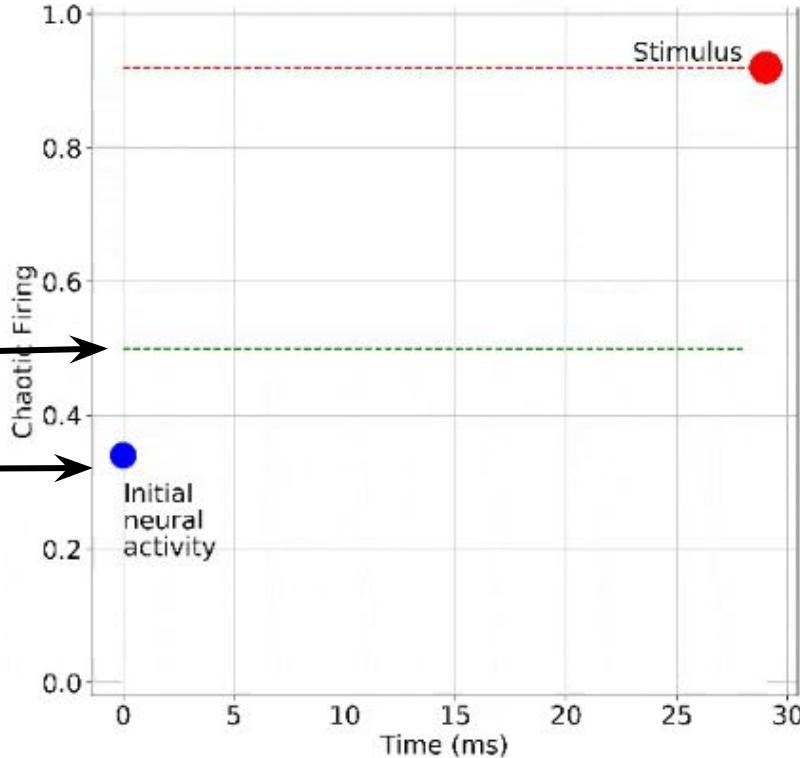




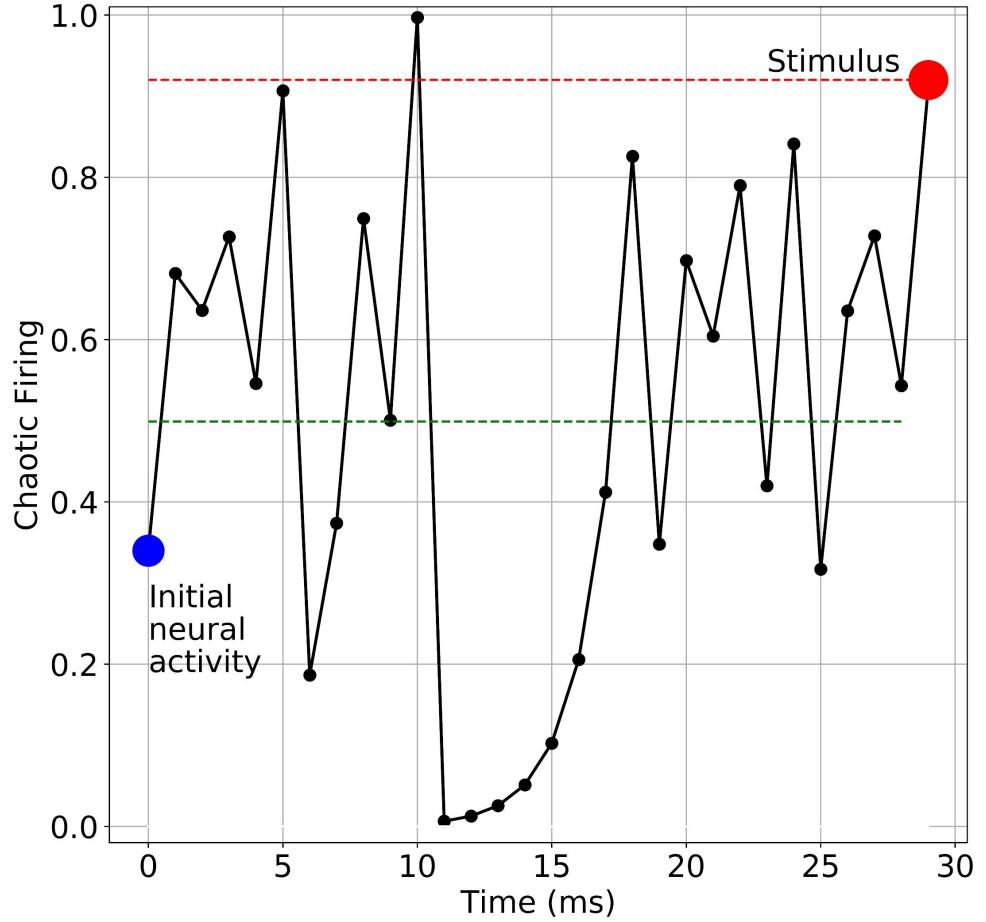
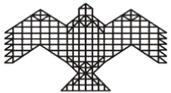
# Neuron for NL

$b = 0.499$

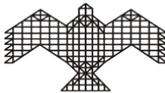
$q = 0.34$



- Initial neural activity ( $q$ ) = **0.34**
- Stimulus = **0.92**
- Discrimination Threshold ( $b$ ) = **0.499**
- Epsilon (Noise Intensity) = **0.01**
- **We extract the following features:**
  - **Firing Time**
  - **Firing Rate**
  - **Energy of chaotic trajectory.**
  - **Entropy of the symbolic sequence of the chaotic trajectory**



- We extract the following features:
  - Firing Time
  - Firing Rate
  - Energy of chaotic trajectory.
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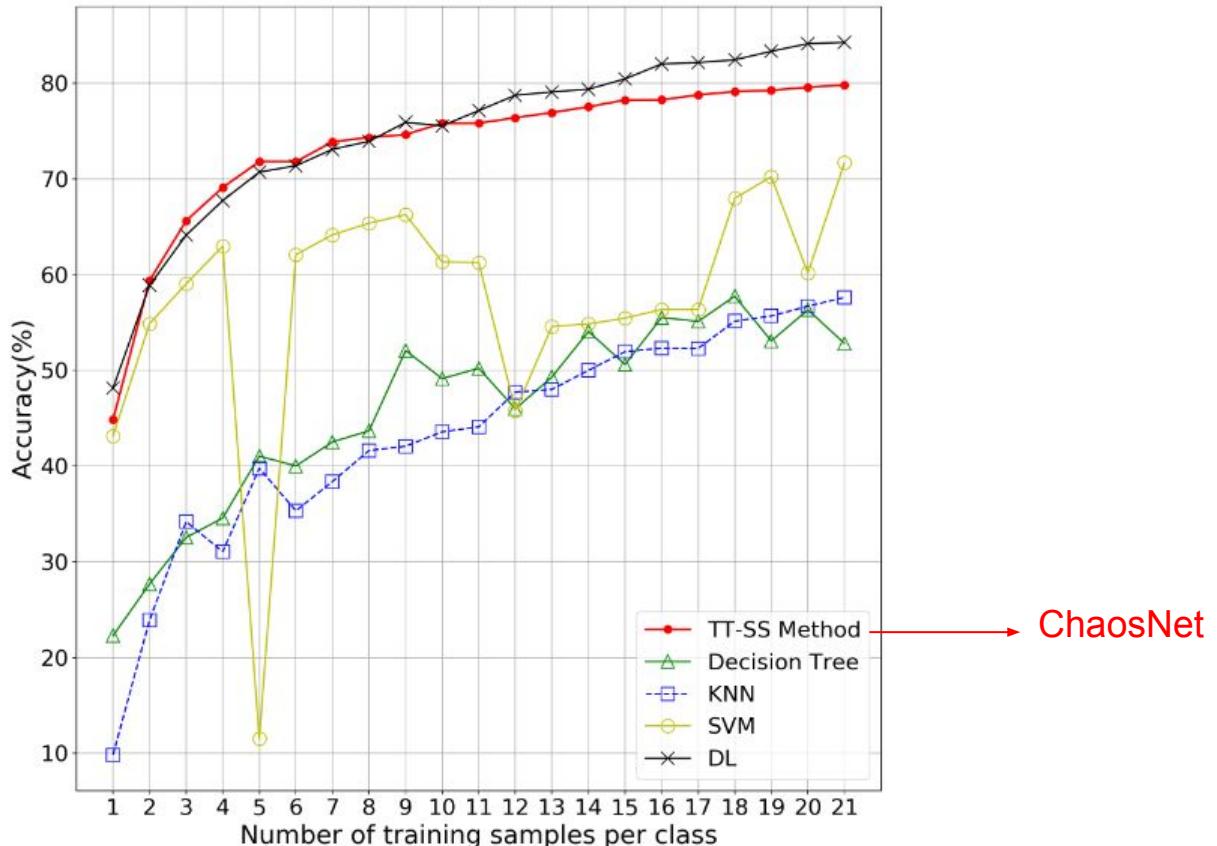
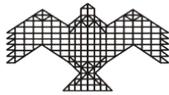
# Chaotic Neural Trace Features Fed to Classifiers

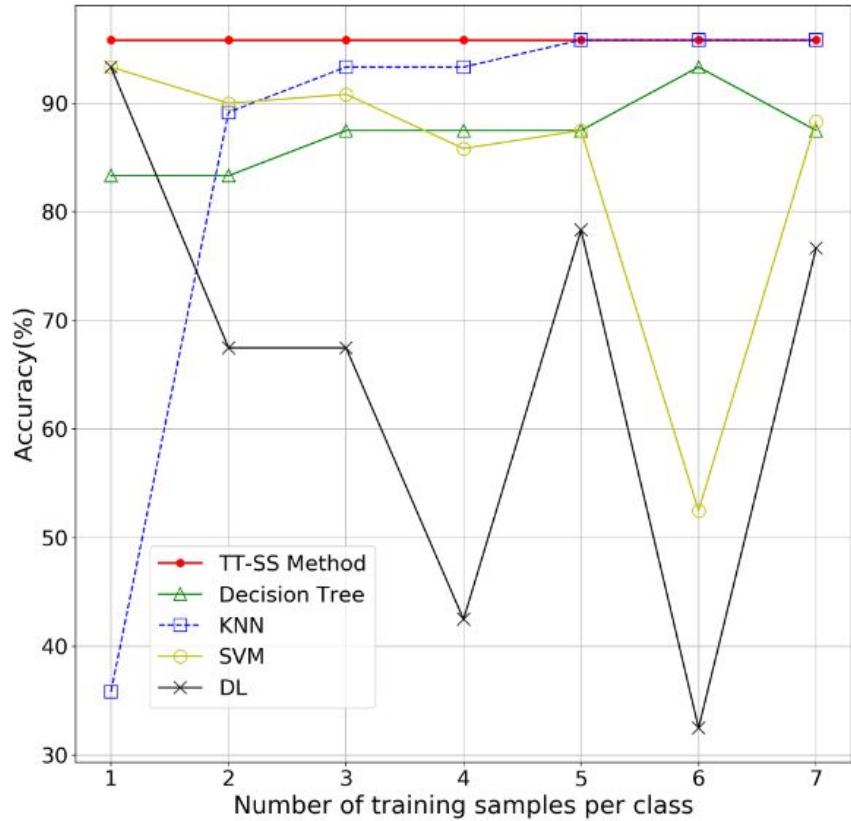
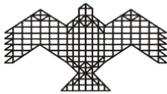
Three Flavors of NL:

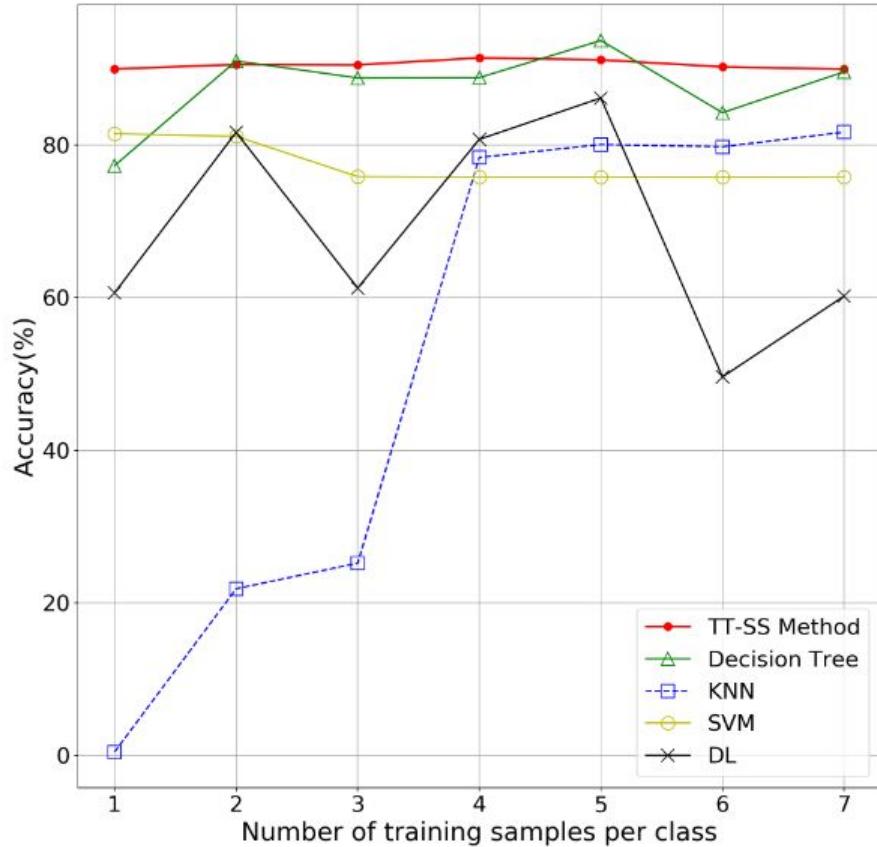
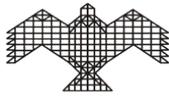
1. ChaosNet: Simple classifier based on mean representation vectors and a cosine similarity measure
2. ChaosFEX + SVM: Chaotic neural trace features are passed to a SVM with linear kernel classifier
3. ChaosFEX + ML/DL: Pass features to ML or DL or your-favorite-classifier!

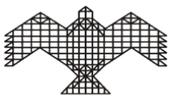
Tested on:

- MNIST
- Iris
- Exoplanets
- Intrusion detection
- Spoken digit
- SARS-CoV-2

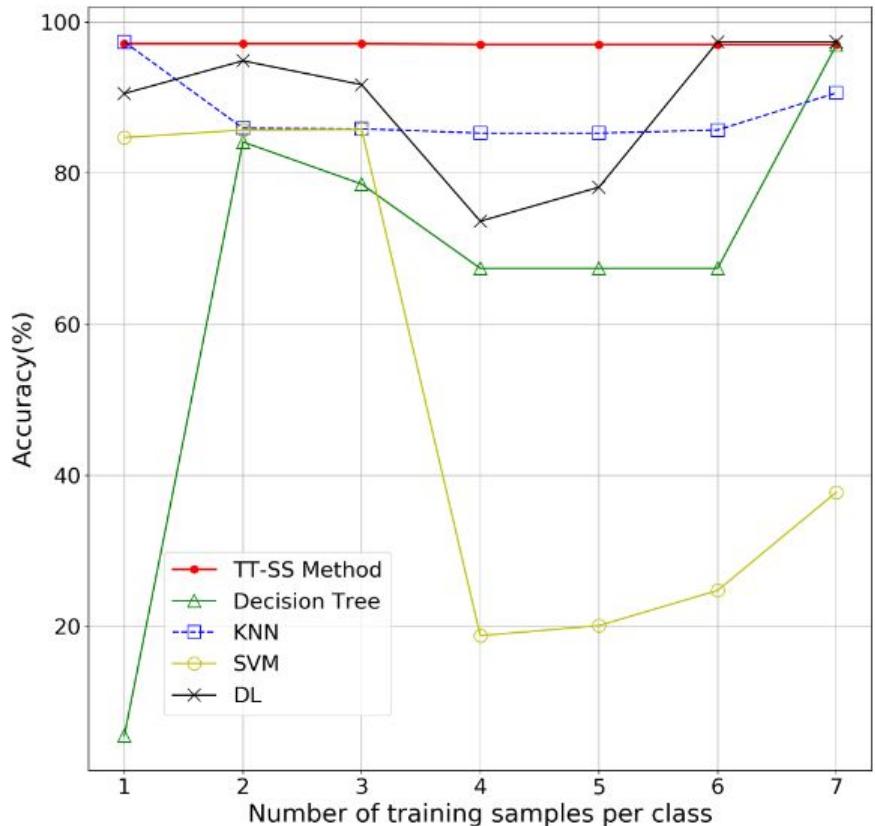


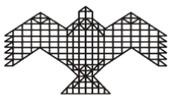






# Exoplanet





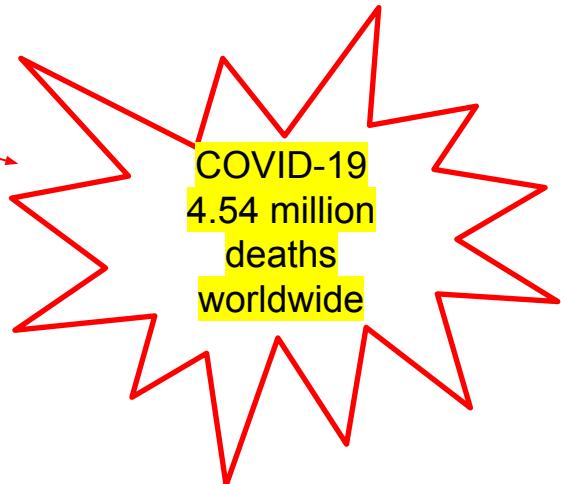
# SARS-CoV-2 Genome Classification

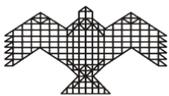
- SARS-CoV-2 vs. SARS-CoV-1: We report an average macro F1-score > 0.99 with just one sample for training (averaged across 1000 independent random trials)

Data	Genome	No. of samples
Class-0	SARS-CoV-2	4498
Class-1	SARS-CoV-1	101

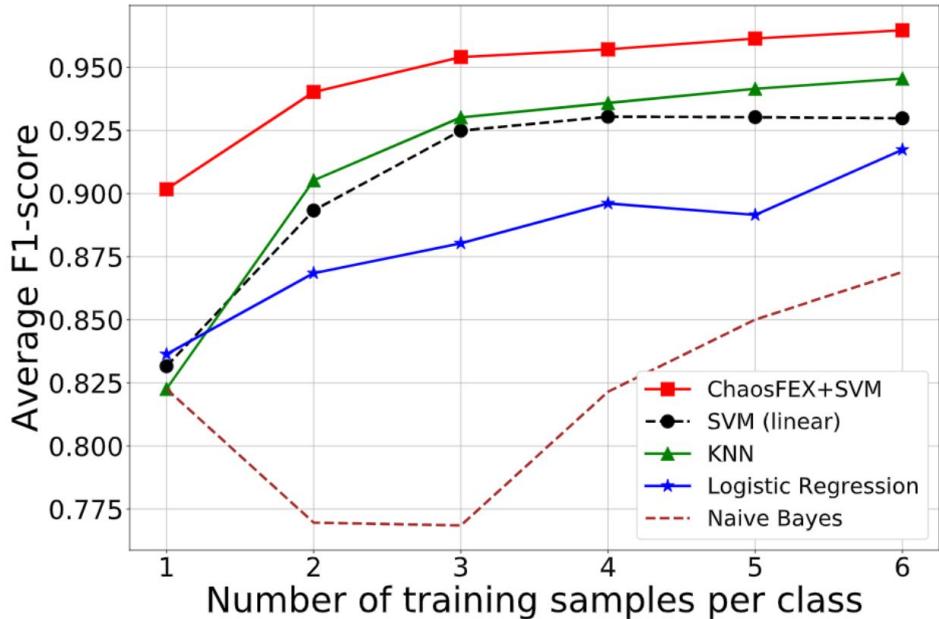
- Multi-class classification: SARS-CoV-2 vs. Other Coronaviruses

- Class-0: SARS-CoV-2 (66 samples).
- Class-1: MERS-CoV (240 samples).
- Class-2: HCoV-OC43 (132 samples), HCoV-229E (22 samples), HCoV-4408 (2 samples), HCoV-EMC (6 samples).
- Class-3: HCoV-NL63 (58 samples), HCoV-HKU1 (17 samples).
- Class-4: SARS-CoV (7 samples), SARS-CoV P2 (1 sample), SARS-CoV HKU-39849 (1 sample), SARS-CoV GDH-BJH01 (1 sample).

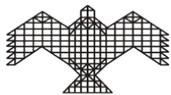




# Multiclass Classification



- With just **6 sequences** for training (per class) NL (ChaosFEX+SVM) algorithm reports an avg. F1-score **> 95%**
- These sequences potentially contain unique signature of the virus.
- Accurate classification of newly sequenced viral isolates using a classifier trained on smaller number of known sequences.
- Beginning of an outbreak!**



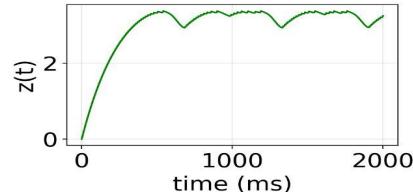
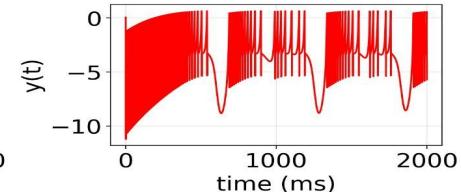
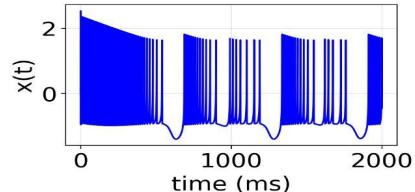
# Some Theoretical Results

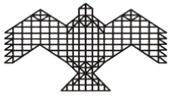
- Memory encoding (lossless/lossy) - 2019
- XOR – 2012
- Universal Approximation Theorem (a single layer of GLS neurons) – 2019

Can we use spiking-bursting neurons in NL?

- ✓ YES, (Neuromorphic Computing?)

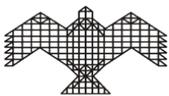
$$\begin{aligned}\frac{dx}{dt} &= y - ax^3 + bx^2 - z + I, \\ \frac{dy}{dt} &= c - dx^2 - y, \\ \frac{dz}{dt} &= r(s(x - x_1) - z).\end{aligned}$$





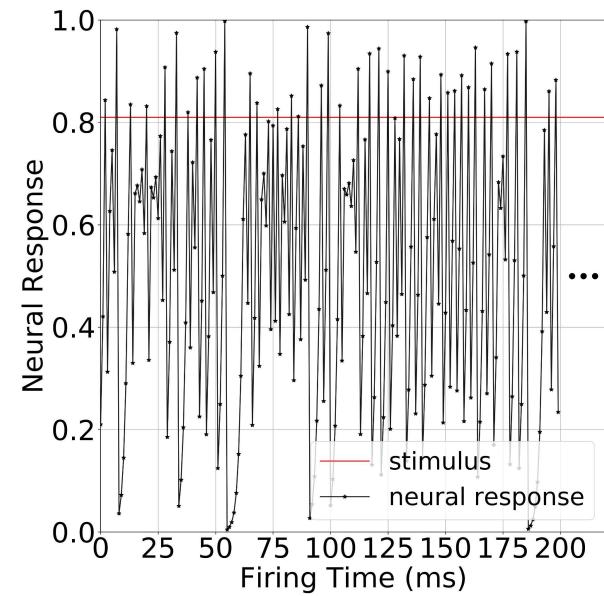
## Part II: The Role of Noise in Neurochaos Learning

( $q$ ,  $b$ ,  $\epsilon$ )

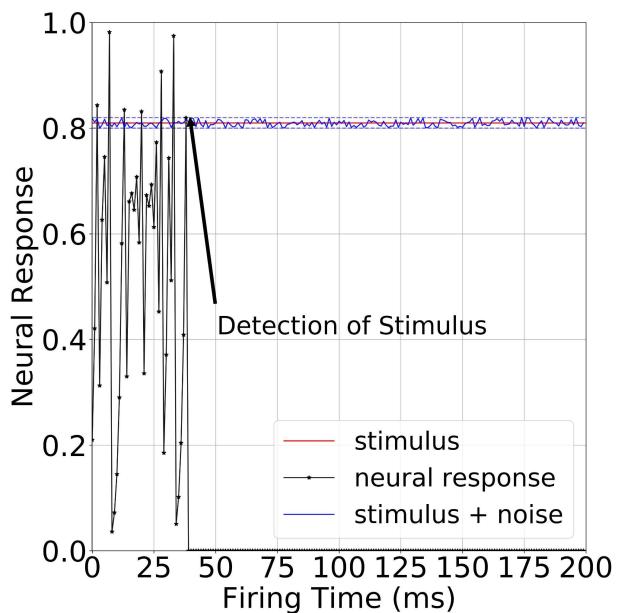


# Interpretation in terms of Noise

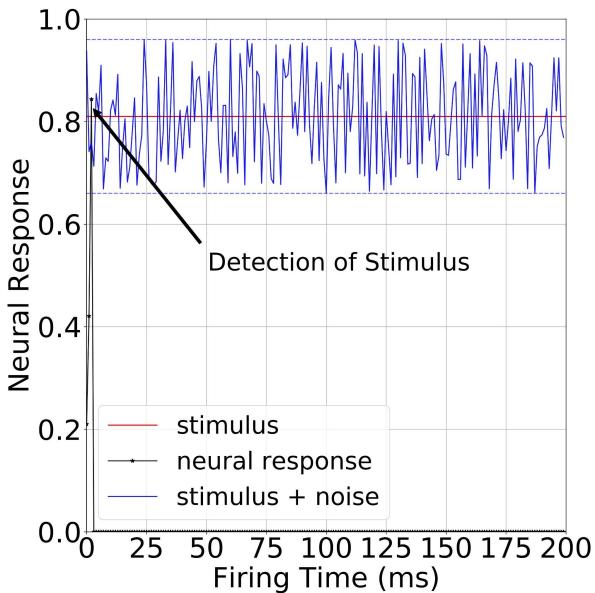
Zero Noise

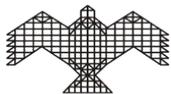


Intermediate Noise

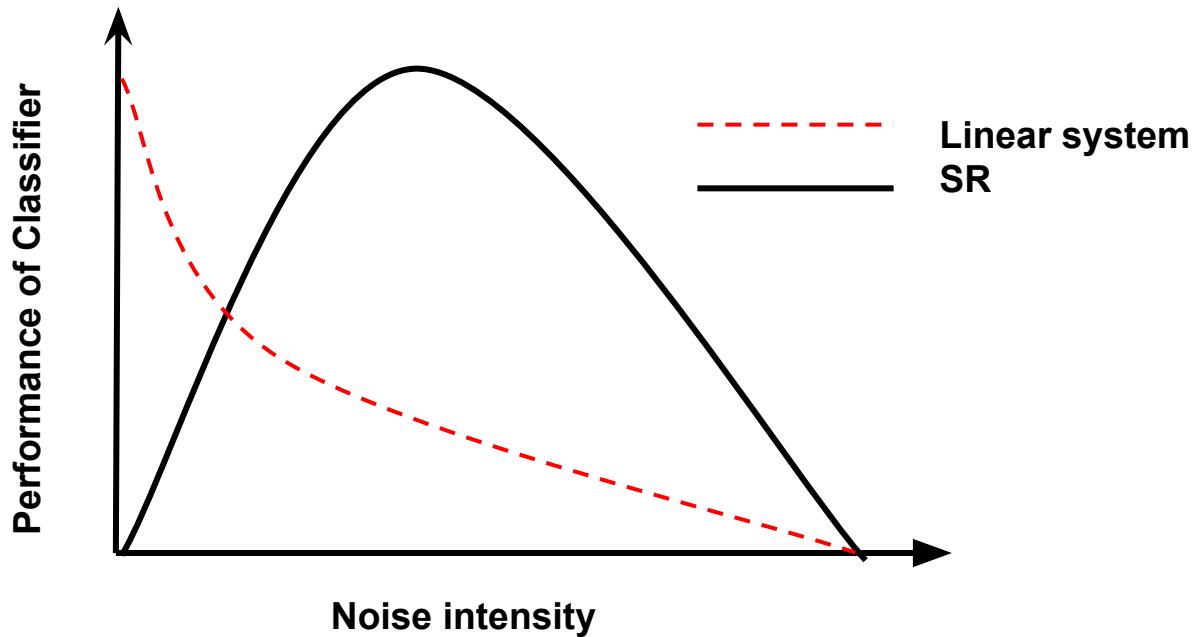


High Noise





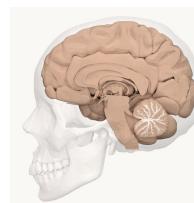
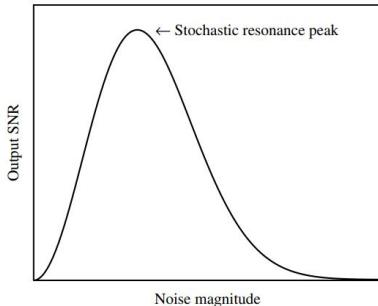
For a given non-linearity, what is the optimum noise required for the NL to learn a decision boundary of a classification task?



# What is SR?

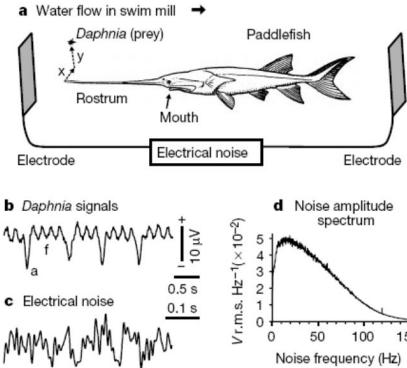


**Definition of SR:** A phenomenon where the *presence of internal noise or external input noise* in a *nonlinear system* provides a *better system response* to a certain input signal than in the absence of noise. (Ref: McDonnell, M. D., Stocks, N. G., Pearce, C. E., & Abbott, D. (2008). Stochastic resonance. *stre.*)



SR has already found a direct application for efficient encoding of auditory information used in cochlear implants[\*].

- Experimental evidence of SR in Crayfish mechanosensory neurons [\*\*].
- Behavioural SR in Paddlefish [\*\*\*].



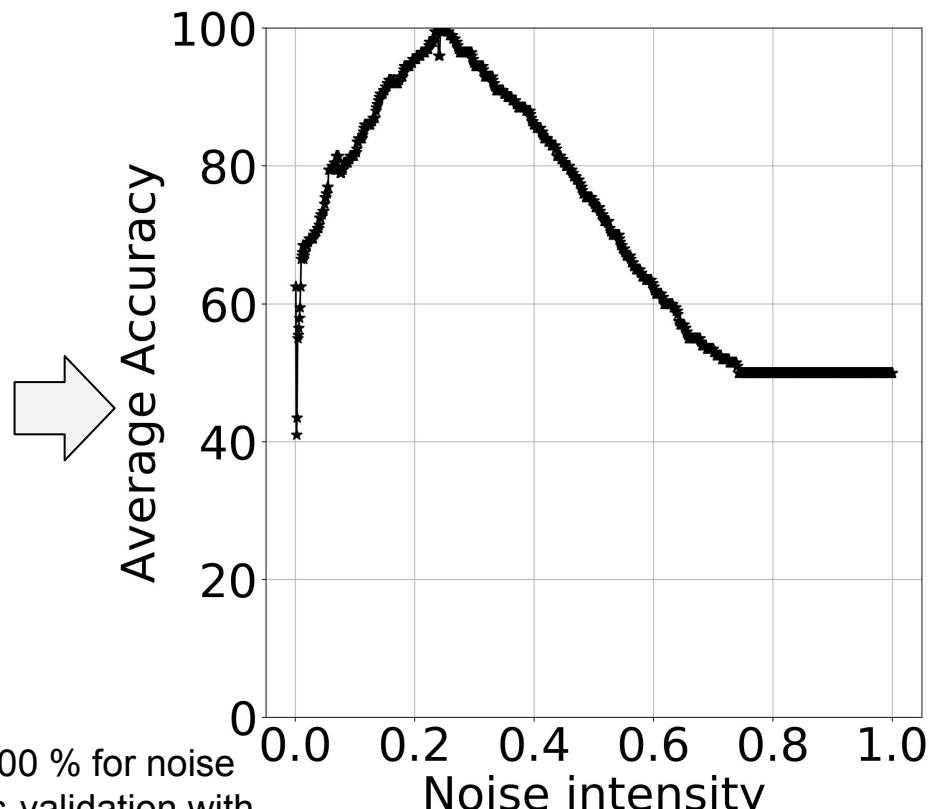
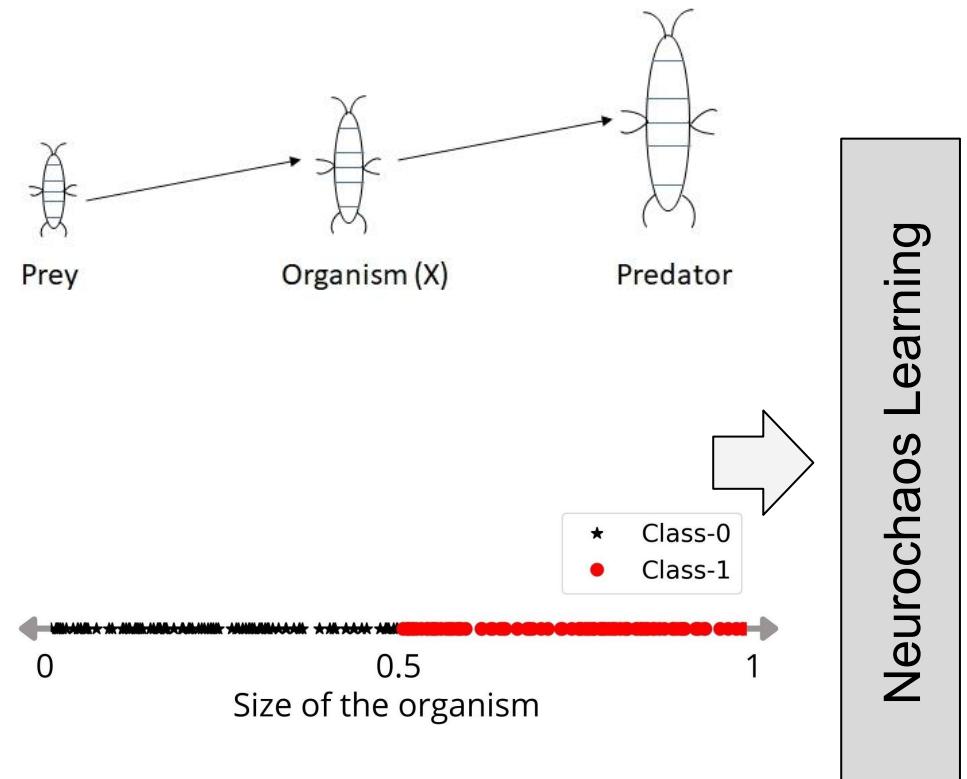
[\*]. Morse, Robert P., and Edward F. Evans. "Enhancement of vowel coding for cochlear implants by addition of noise." *Nature medicine* 2.8 (1996): 928-932.

[\*\*] Douglass, John K., et al. "Noise enhancement of information transfer in crayfish mechanoreceptors by stochastic resonance." *Nature* 365.6444 (1993): 337-340.

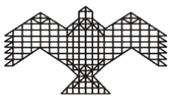
[\*\*\*] Russell, David F., Lon A. Wilkens, and Frank Moss. "Use of behavioural stochastic resonance by paddle fish for feeding." *Nature* 402.6759 (1999): 291-294.



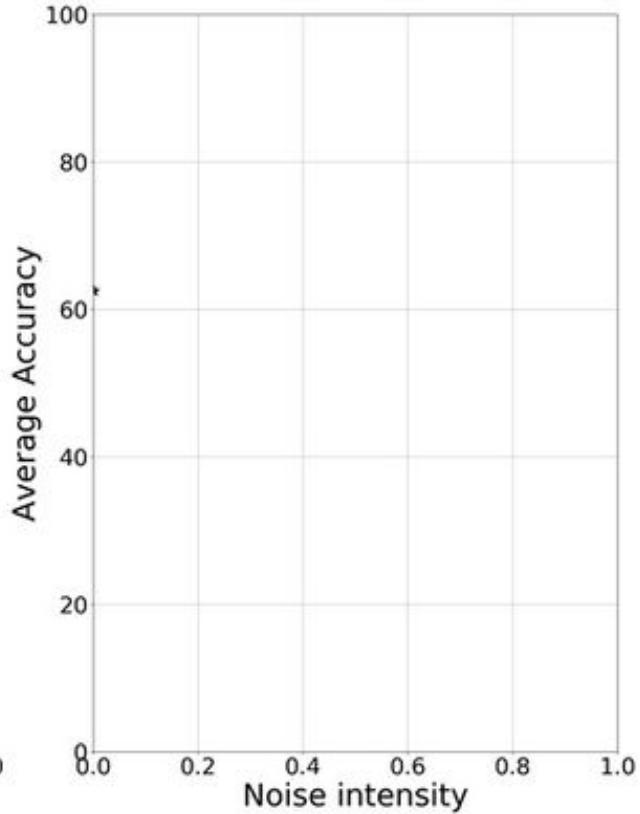
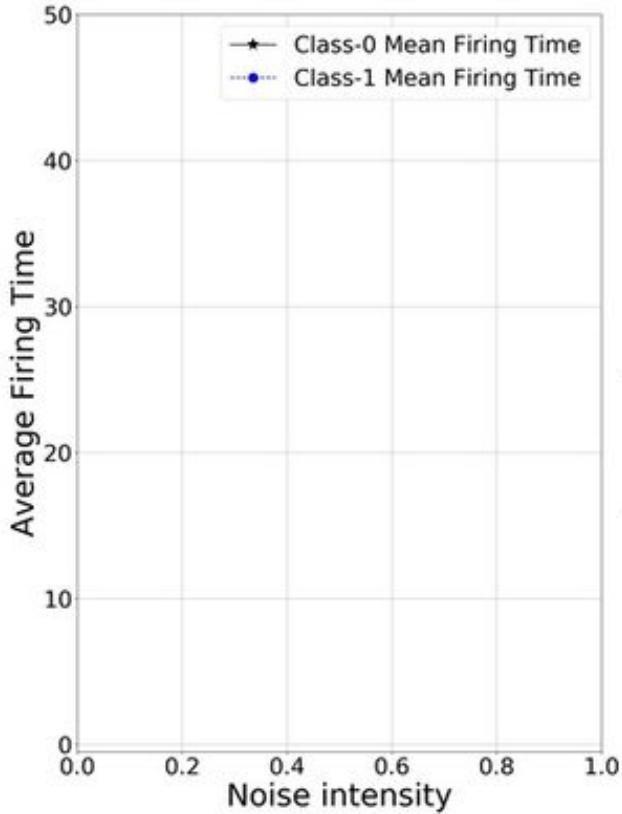
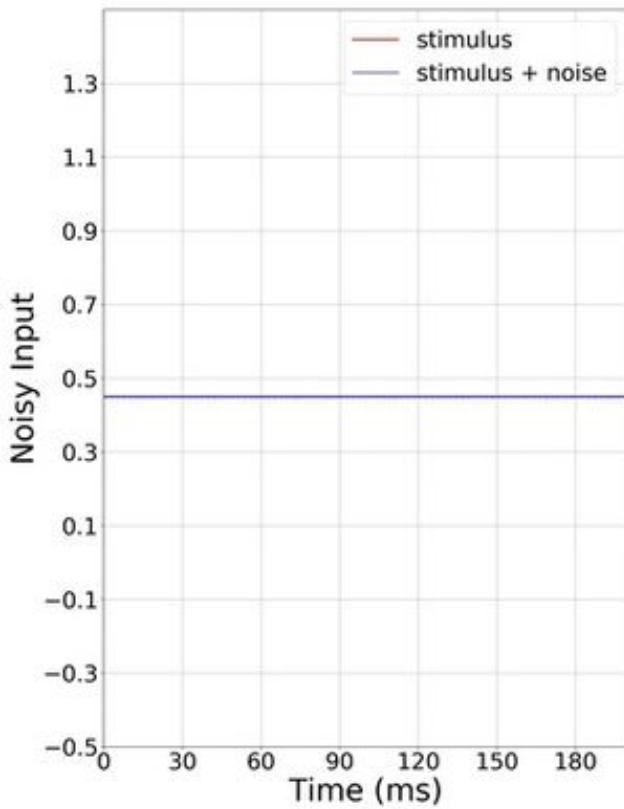
# A simple experiment to demonstrate SR in NL



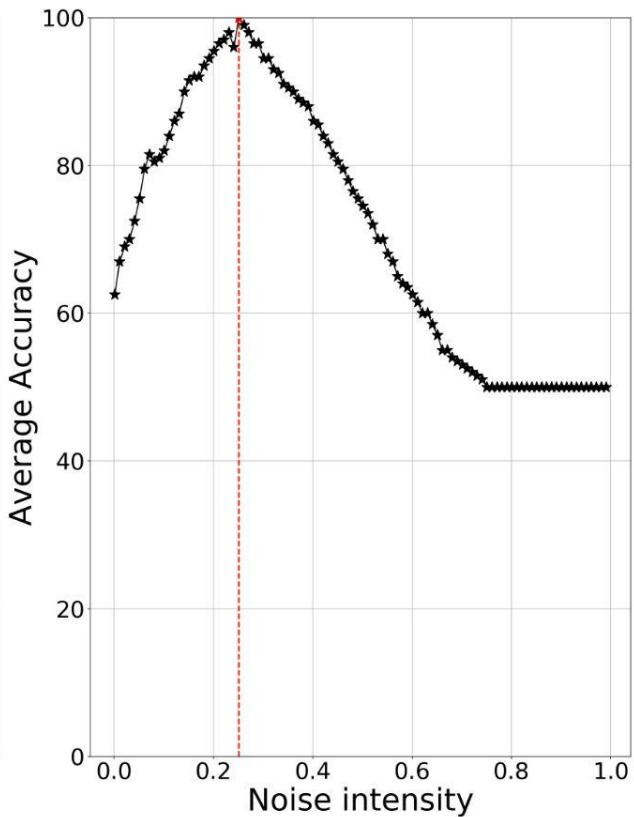
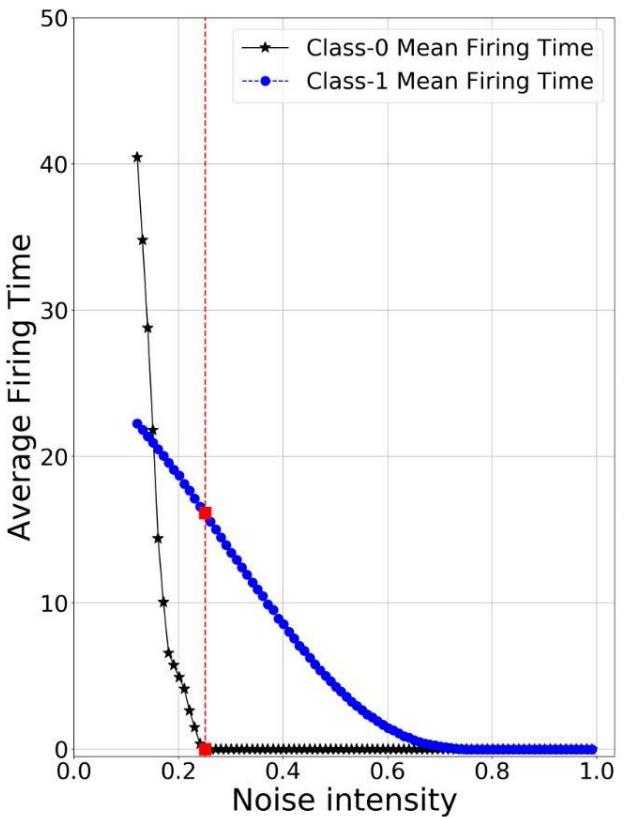
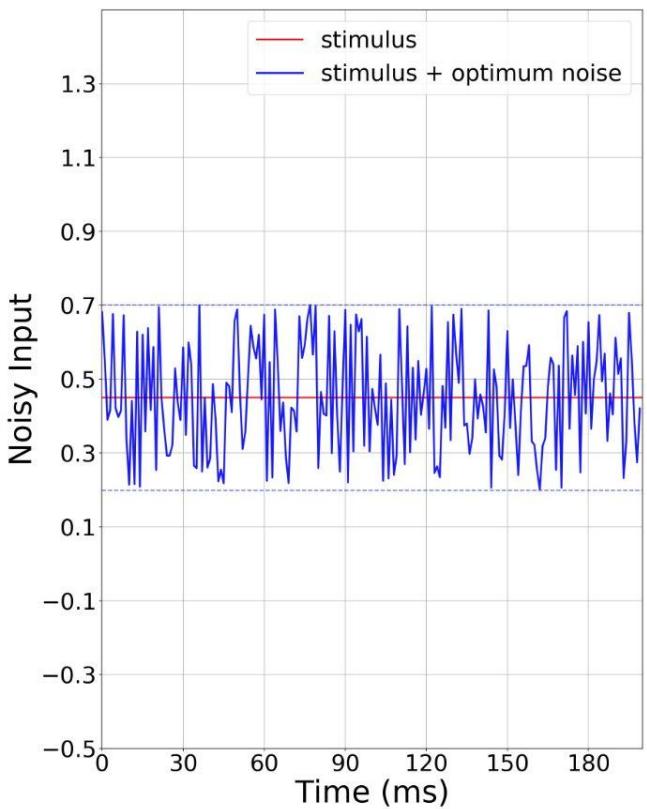
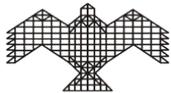
For  $q = 0.25$ ,  $b = 0.96$ , we report an average accuracy of 100 % for noise intensities ranging from 0.248 to 0.253 in the five fold cross-validation with 80 instances per each class.

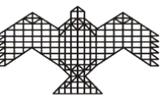


# Visual Representation of SR in NL

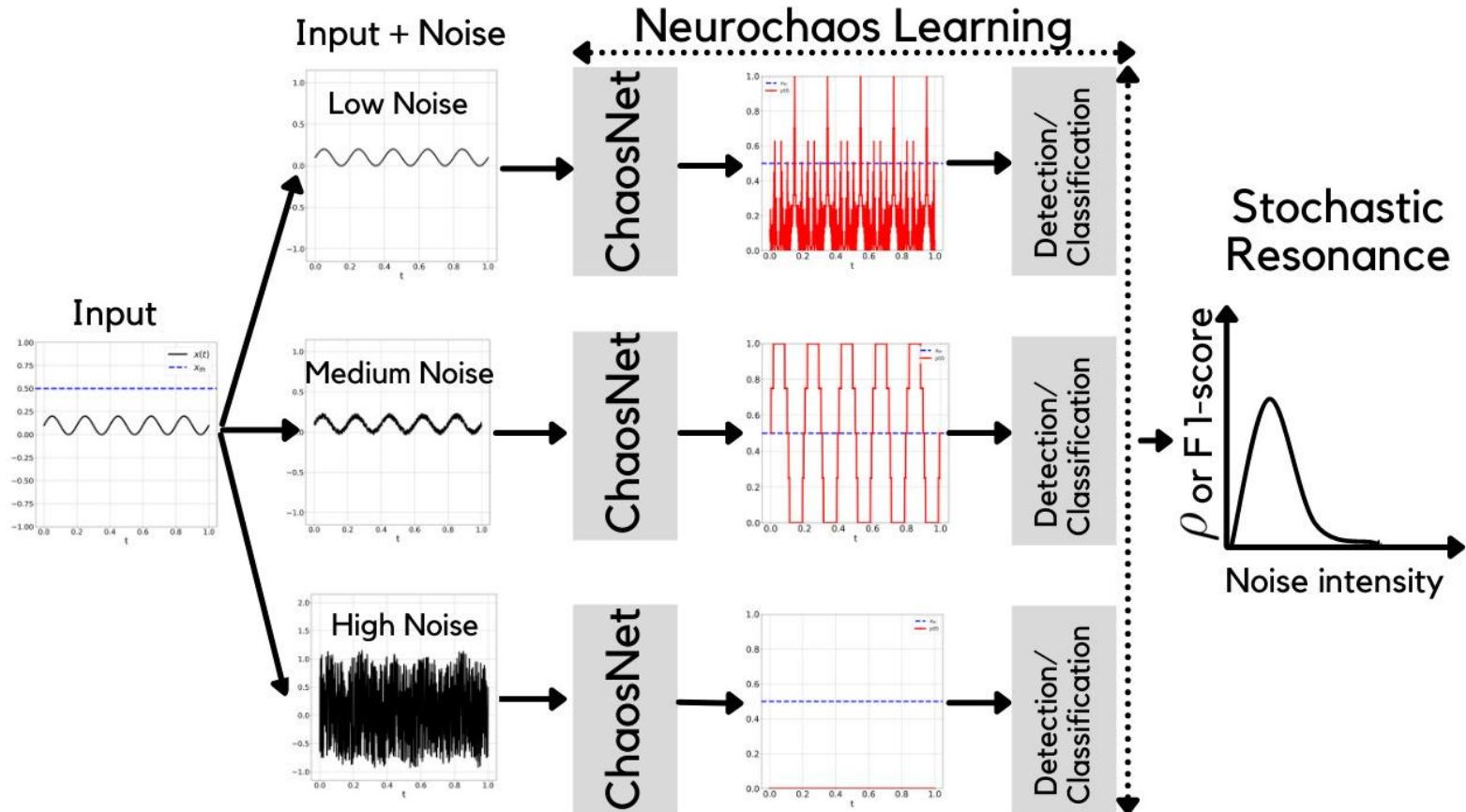


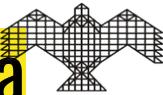
# Optimum Noise $\rightarrow$ Optimum Firing Time $\rightarrow$ Best Accuracy





# General Architecture





# Application of SR in NL for Spoken Digit Classification Data



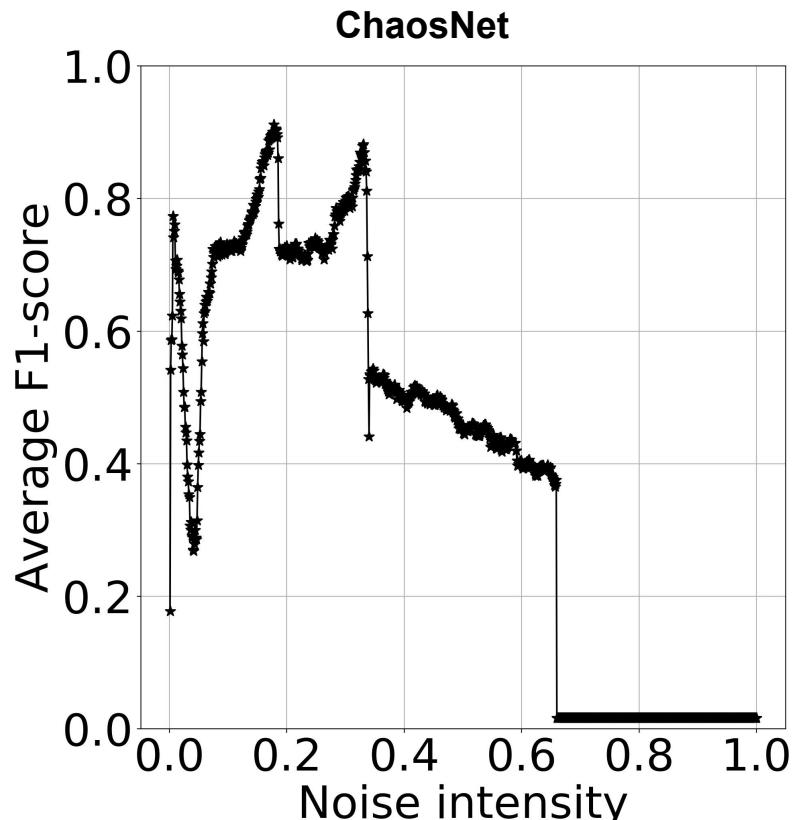
O, 1, 2, 3..., 9

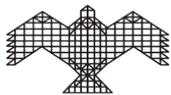
Jackson

Ten class classification

- Sampling Rate - 8KHz
- We took 2753 samples.
- Fourier Pre-processing
- Edge Applications

The noise intensity was varied from 0.001 to 1.0 in steps of 0.001. For  $q = 0.34$ ,  $b = 0.499$  and a **noise intensity = 0.178**, we get a maximum macro average **F1-score = 0.911** in five fold cross-validation.





# ChaosFEX+SVM on Spoken Digit Classification Data

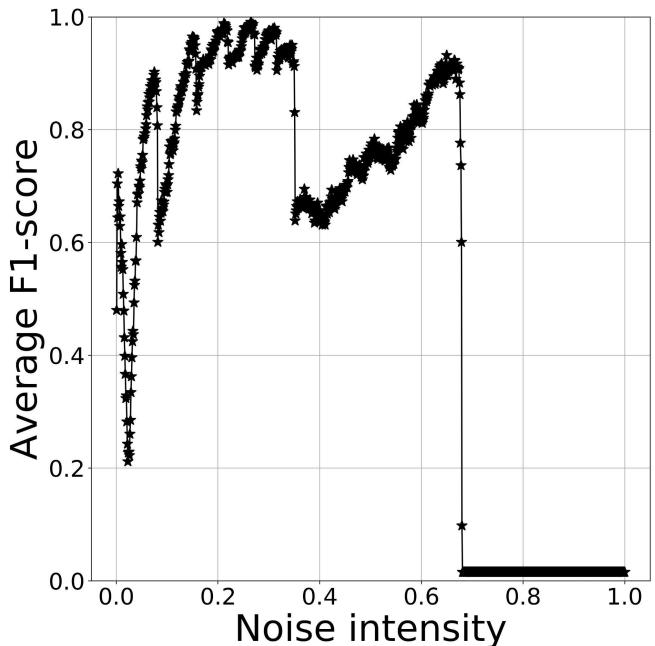


0, 1, 2, 3..., 9

Jackson

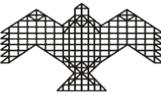
Ten class classification

- Sampling Rate - 8KHz
- We took 2753 samples.
- Fourier Pre-processing
- Edge Applications

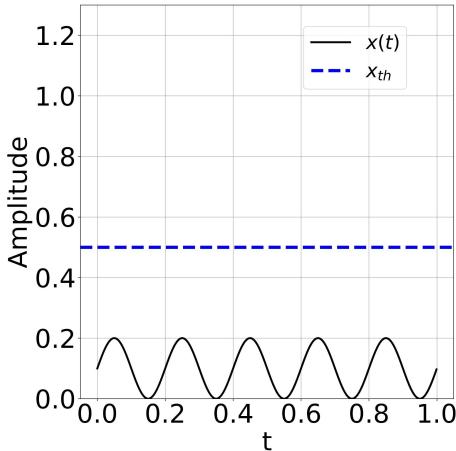


**ChaosFEX+SVM on spoken digit data:** We took 40 data instances per each class (10 class classification). We then performed a five fold cross validation with  $q = 0.68$ ,  $b = 0.09$  and noise intensity ranging from 0.001 to 1 with a step size of 0.001. For a **noise intensity of 0.265** we obtained an **average macro F1-score = 0.991** in five fold cross-validation.

# Application of NL in Signal Detection

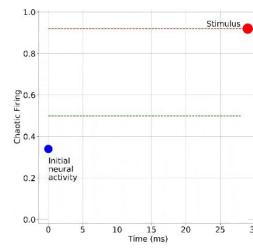


Subthreshold signal

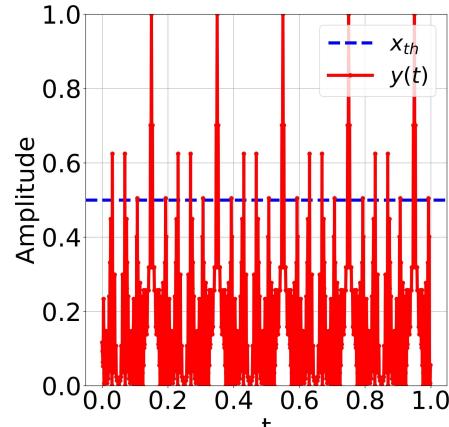


$$x(t) = \frac{A(\sin(2\pi 5t) + 1)}{2}$$

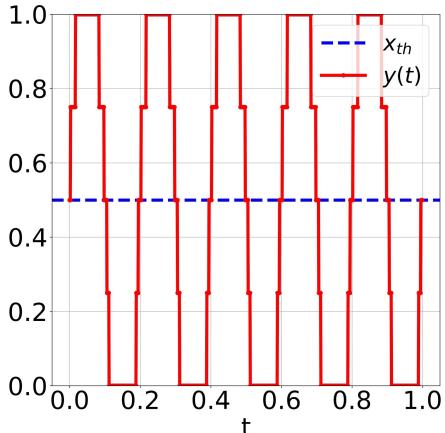
$$A = 0.2$$



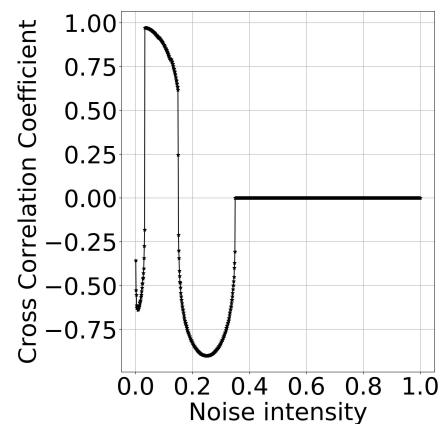
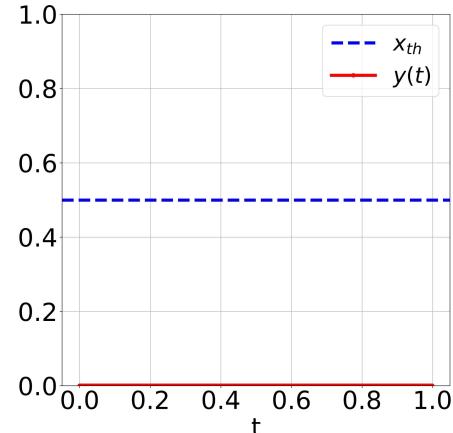
Low Noise



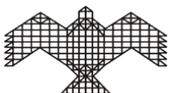
Medium Noise



High Noise

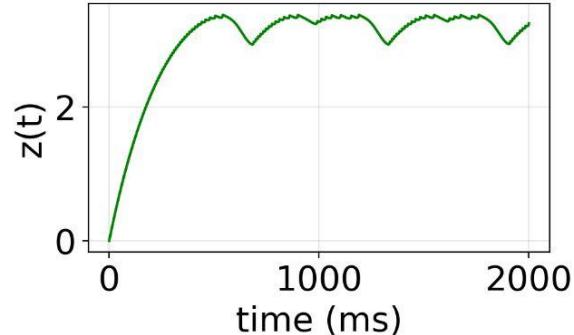
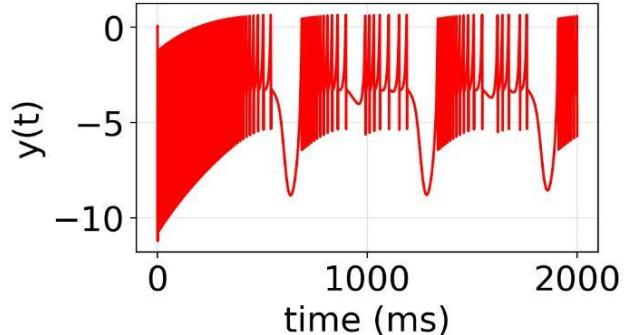
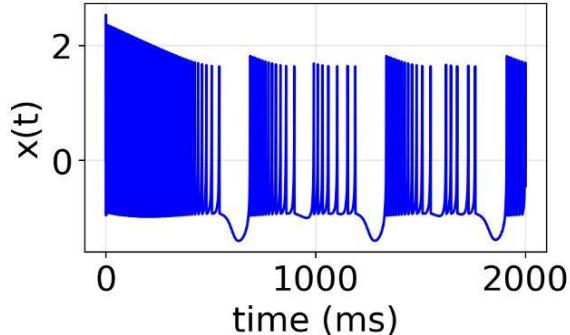


For an intermediate amount of noise intensity, namely = 0.033, q = 0.35 and b = 0.65, we get a maximum cross correlation coefficient of 0.971.



# Hindmarsh Rose Neuronal Model in NL

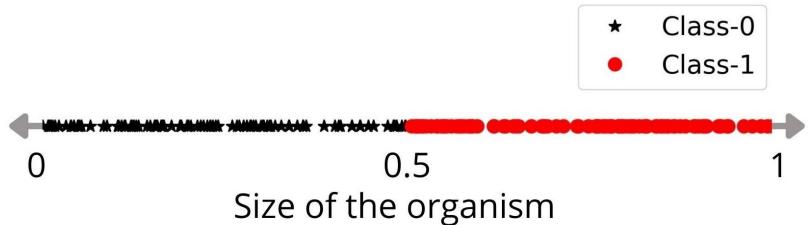
$$\begin{aligned}\frac{dx}{dt} &= y - ax^3 + bx^2 - z + I, \\ \frac{dy}{dt} &= c - dx^2 - y, \\ \frac{dz}{dt} &= r(s(x - x_1) - z).\end{aligned}$$



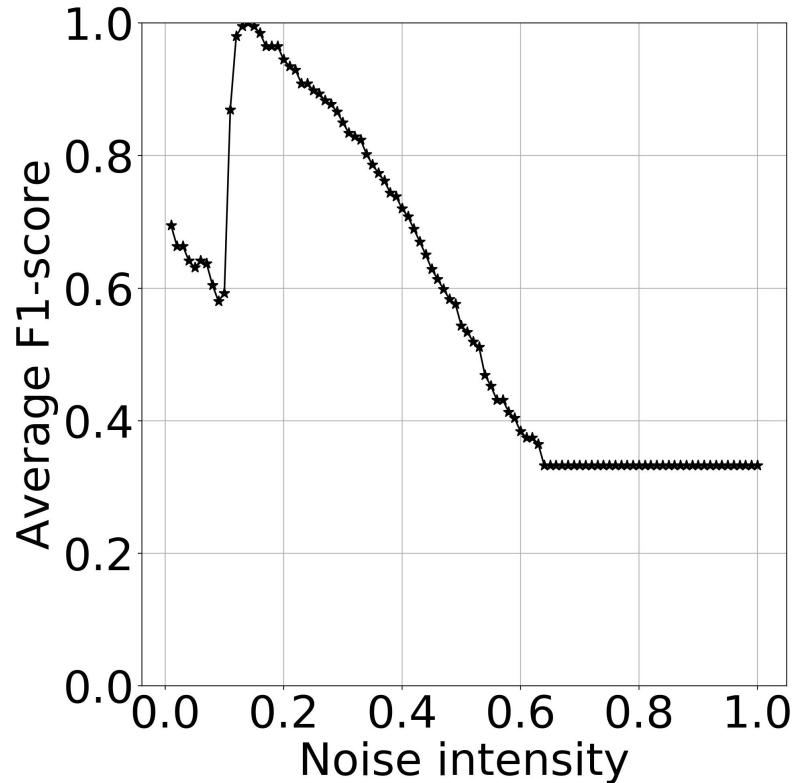
The parameters of the system are set to the following values:  
 $a = 1$ ,  $b = 3$ ,  $c = 1$ ,  $d = 5$ ,  $x_1 = -1.6$ . The values of  $I$ ,  $r$  and  $s$  are critical in controlling the behaviour of the system.  
We choose  $I = 3.28$ ,  $r = 0.0021$ , and  $s=4$  which makes the Hindmarsh Rose model exhibit **chaotic behaviour**.

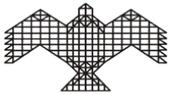


# Application of Hindmarsh Rose Model in NL (Classification)



For a **noise intensity = 0.14**, we get an **average macro F1-score = 1.0** for the five fold cross-validation with 80 data instances per class-0 and class-1.





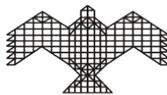
# Conclusions

- Chaos ubiquitous in the brain (“Neurochaos”)
- We propose a **Neurochaos Learning (NL) architecture**
- State-of-the-art performance in ‘low training sample’ regime
- **No backpropagation**, very few hyperparameters ( $q$ ,  $b$ , noise level  $\epsilon$ ), continual learning possible
- Noise and Chaos interact in NL to produce **Stochastic Resonance**

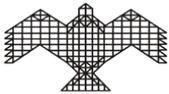
## Going forward

- **Low SNR machine learning** (how are our brains doing this?)
- Heterogeneous neurons in NL
- Enrich AI with Non-linear Physics and Neuroscience (closer to mimicking the Brain!)
- Neuromorphic computing, Edge Applications, Few-shot learning, Continual learning

# Publications



1. **Journal Publication:** Harikrishnan N. B., and Nithin Nagaraj. "When noise meets chaos: Stochastic resonance in Neurochaos Learning." *Neural Networks* (2021), DOI:<https://doi.org/10.1016/j.neunet.2021.06.025>.
2. **Journal Publication:** - Harikrishnan N. B., Aditi Kathpalia, Snehanshu Saha, and Nithin Nagaraj. "ChaosNet: A chaos based artificial neural network architecture for classification." *Chaos: An Interdisciplinary Journal of Nonlinear Science* 29, no. 11 (2019): 113125, DOI: <https://doi.org/10.1063/1.5120831>.
3. **Conference Proceedings:** Harikrishnan, N. B., and Nithin Nagaraj. "A novel chaos theory inspired neuronal architecture." In 2019 *Global Conference for Advancement in Technology (GCAT)*, pp. 1-6. IEEE, 2019, DOI: [10.1109/GCAT47503.2019.8978360](https://doi.org/10.1109/GCAT47503.2019.8978360).
4. **Conference Proceedings:** - Harikrishnan, N. B., and Nithin Nagaraj. "Neurochaos Inspired Hybrid Machine Learning Architecture for Classification." 2020 *International Conference on Signal Processing and Communications (SPCOM)*. IEEE, 2020, DOI: [10.1109/SPCOM50965.2020.9179632](https://doi.org/10.1109/SPCOM50965.2020.9179632).
5. **Journal Submission:** - Submitted a manuscript titled "A Neurochaos Learning Architecture For Genome Classification" (with Dr. Pranay SY and Dr. Nithin Nagaraj as co-authors) to "[Special Issue on Computer Vision, Big Data and AI Research in Combating COVID-19](#)" on 22 June 2021.



# Research on NL by other groups

- Continual Learning / Stream Learning:

Laleh, Touraj, et al. "Chaotic Continual Learning." ICML 2020 Workshop LifelongML, (2020).

- Deep ChaosNet:

Chen, Huafeng, et al. "Deep ChaosNet for Action Recognition in Videos." Complexity 2021 (2021).

Please try out NL (available for free download and use)

*ChaosFEX:* <https://github.com/pranaysy/ChaosFEX>

*ChaosFEX+SVM:* [https://github.com/HarikrishnanNB/genome\\_classification](https://github.com/HarikrishnanNB/genome_classification)

*SR in NL:* [https://github.com/HarikrishnanNB/stochastic\\_resonance\\_and\\_nl](https://github.com/HarikrishnanNB/stochastic_resonance_and_nl)

I thank



Dr. Nithin Nagaraj



Dr. Aditi Kathpalia



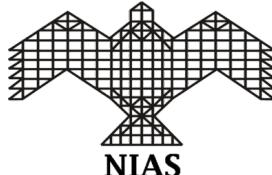
Dr. Snehanshu Saha



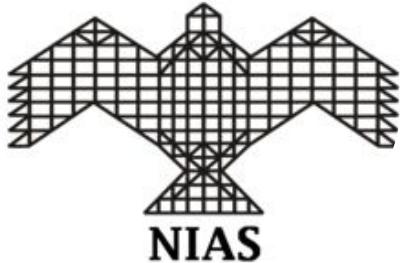
Dr. Pranay SY (MBBS)



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(EMR/2016/005687)



# Thank You

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