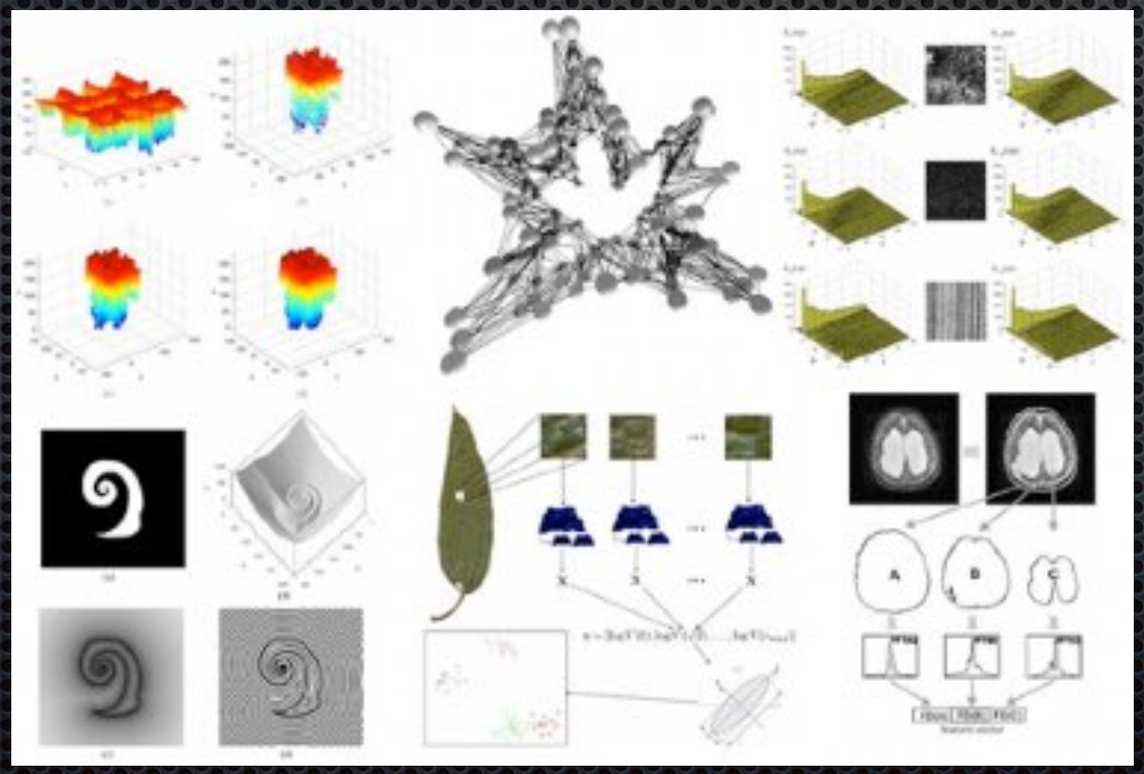
Complex Systems and Artificial Intelligence: Theory and Applications

Prof. Dr. Odemir M. Bruno

Scientific Computing Group
São Carlos Institute of Physics
University of São Paulo - Brazil

Scientific Computing Group

http://scg.ifsc.usp.br



SCG - USP

Artificial Intelligence

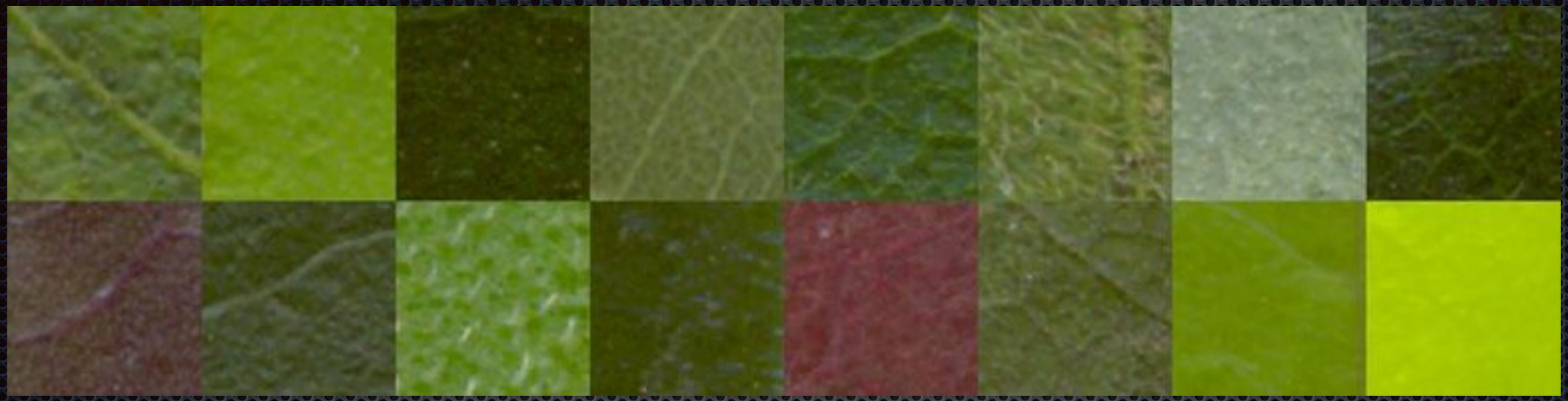
Complex Systems

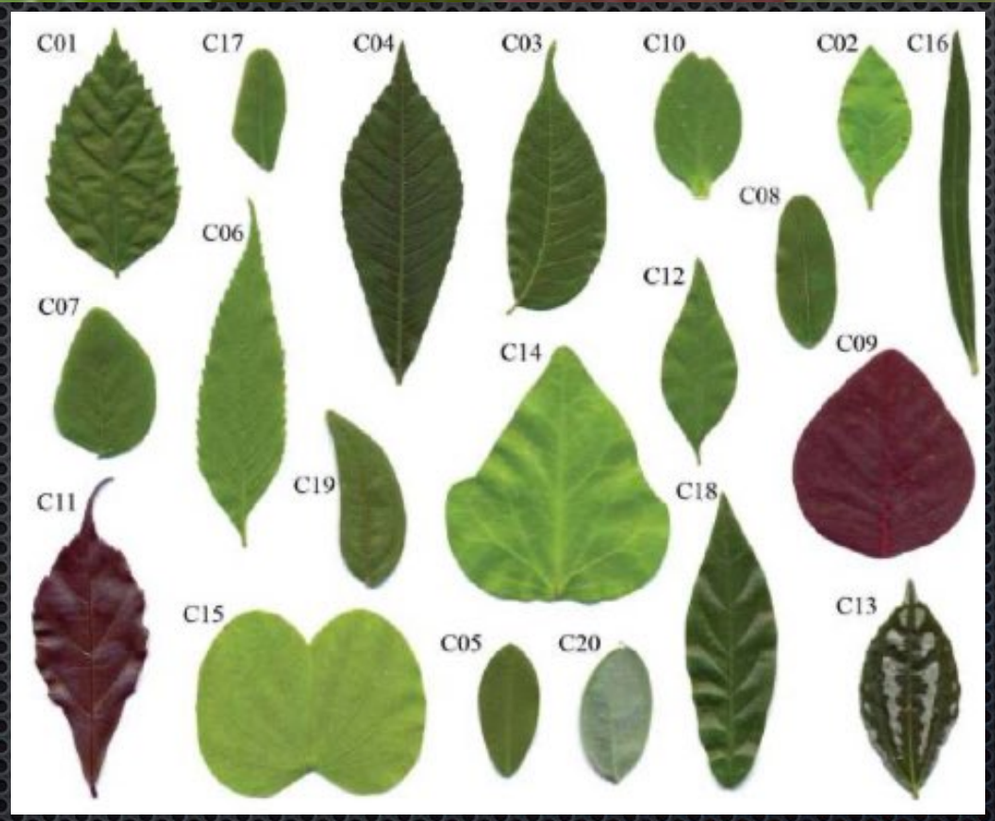
Big Data

Data Science

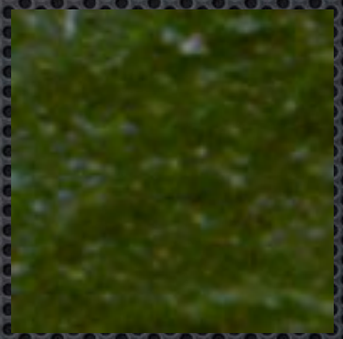
Texture and complex patterns

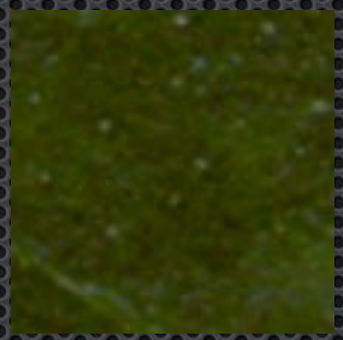
1200tex - benchmark dataset

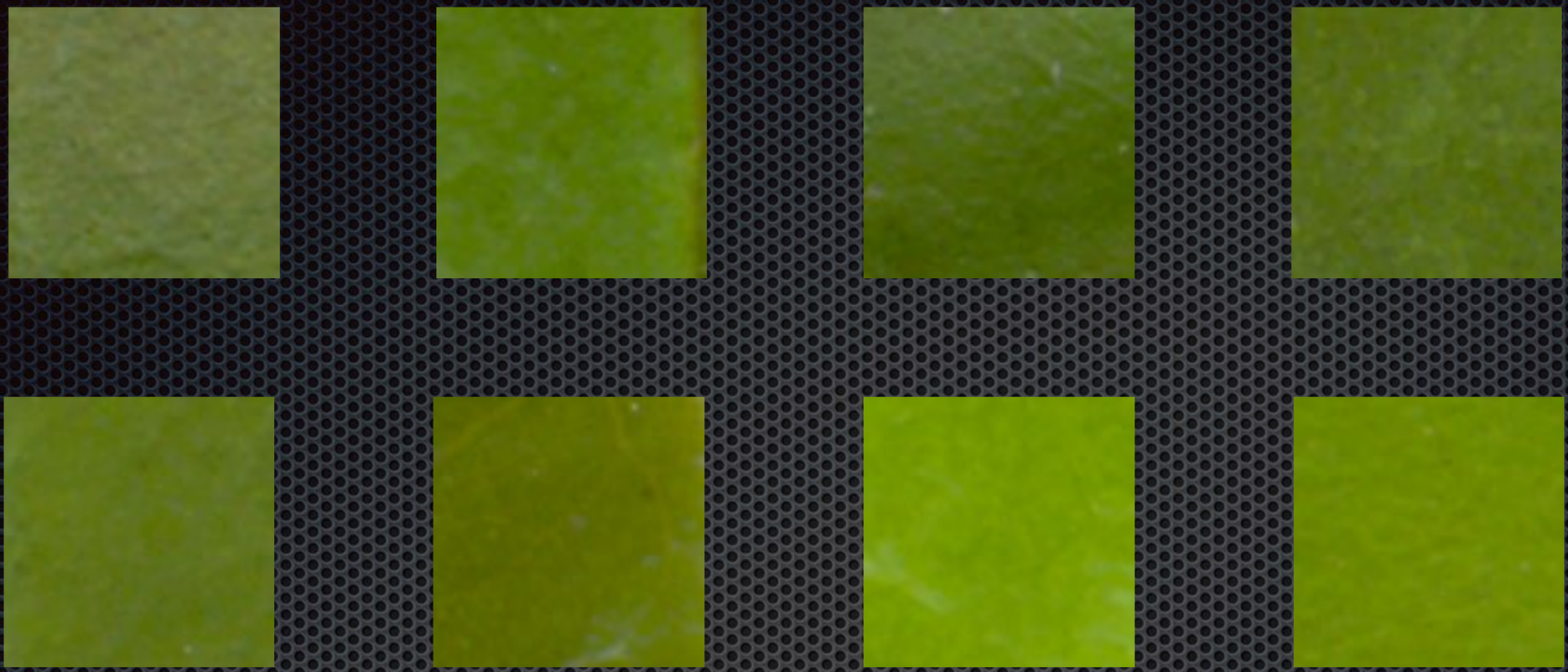


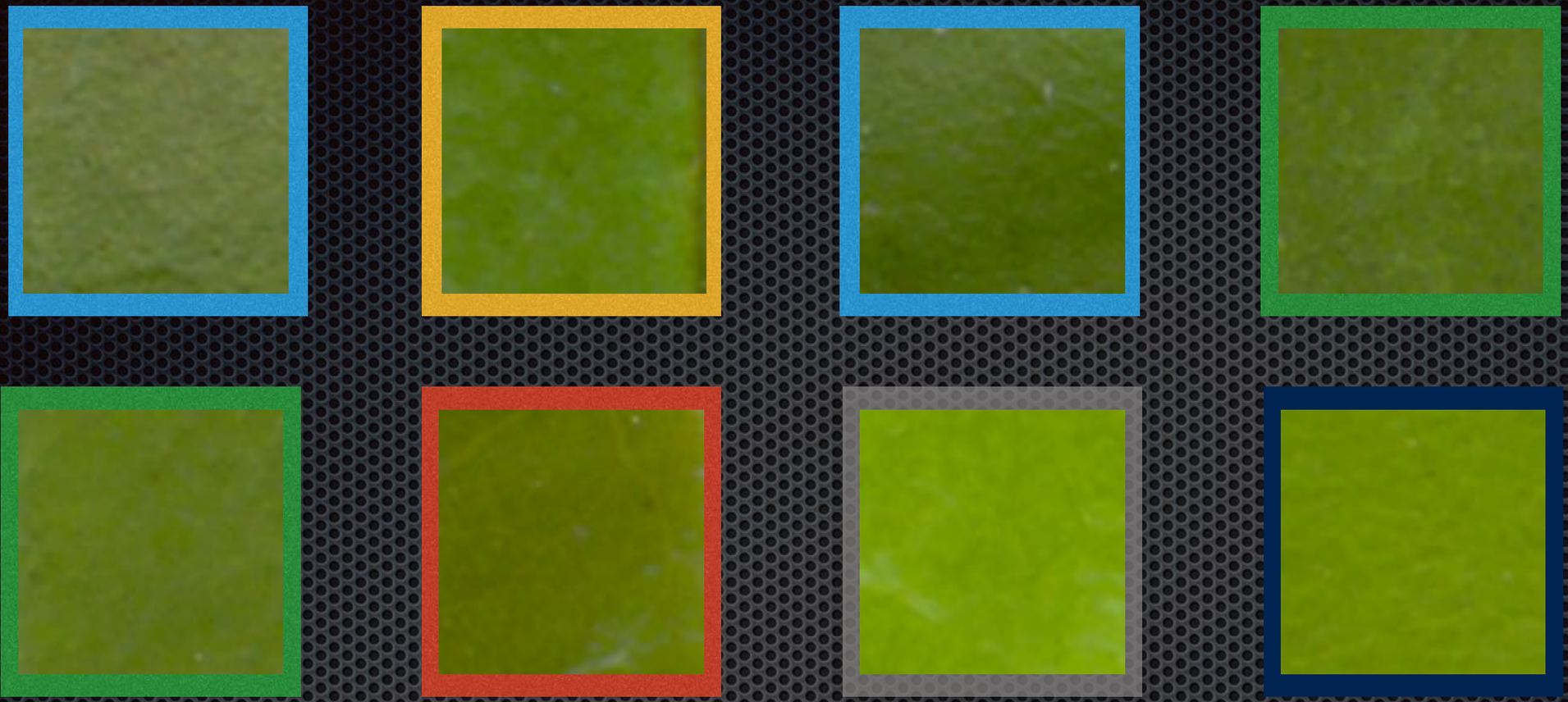


http://scg.ifsc.usp.br/dataset/1200Tex.php

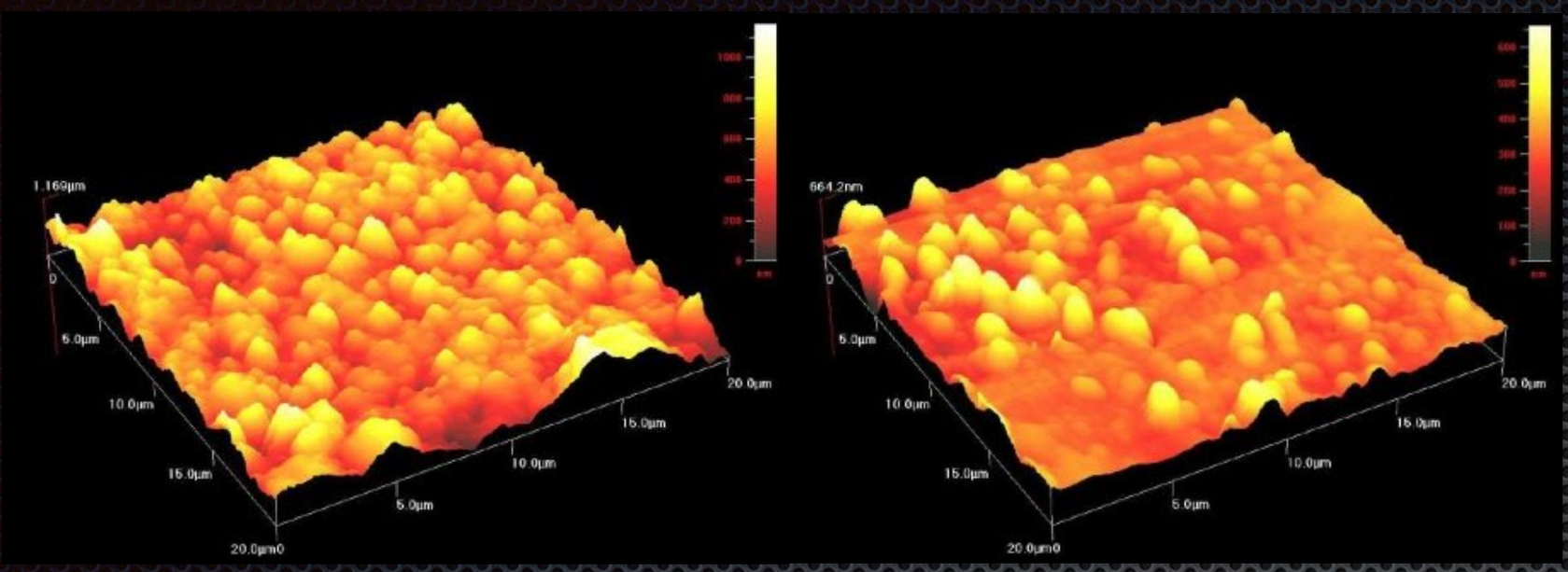








Humans have been surpassed by machines in recognizing texture and complex patterns.


1.169µm
0
5.0µm
10.0µm
15.0µm
20.0µm0
5.0µm
10.0µm
15.0µm
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5.0µm
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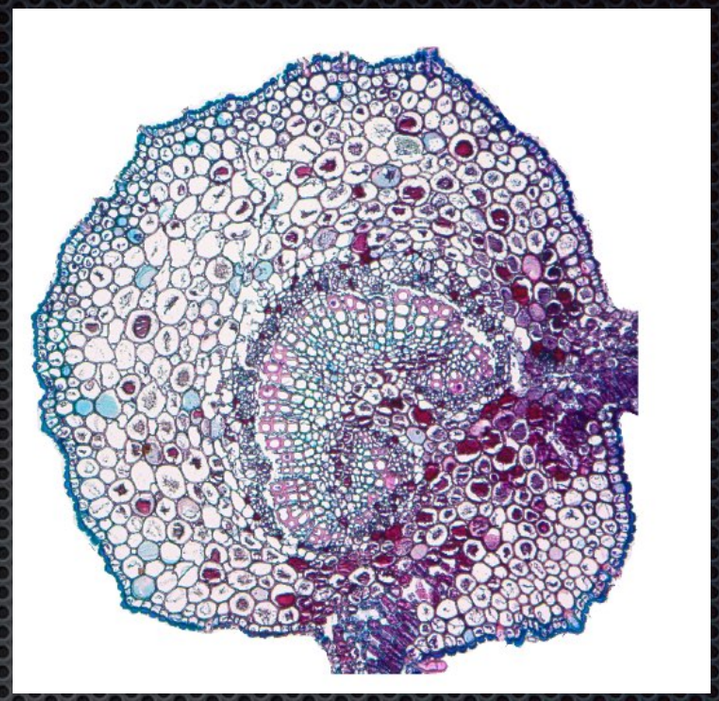
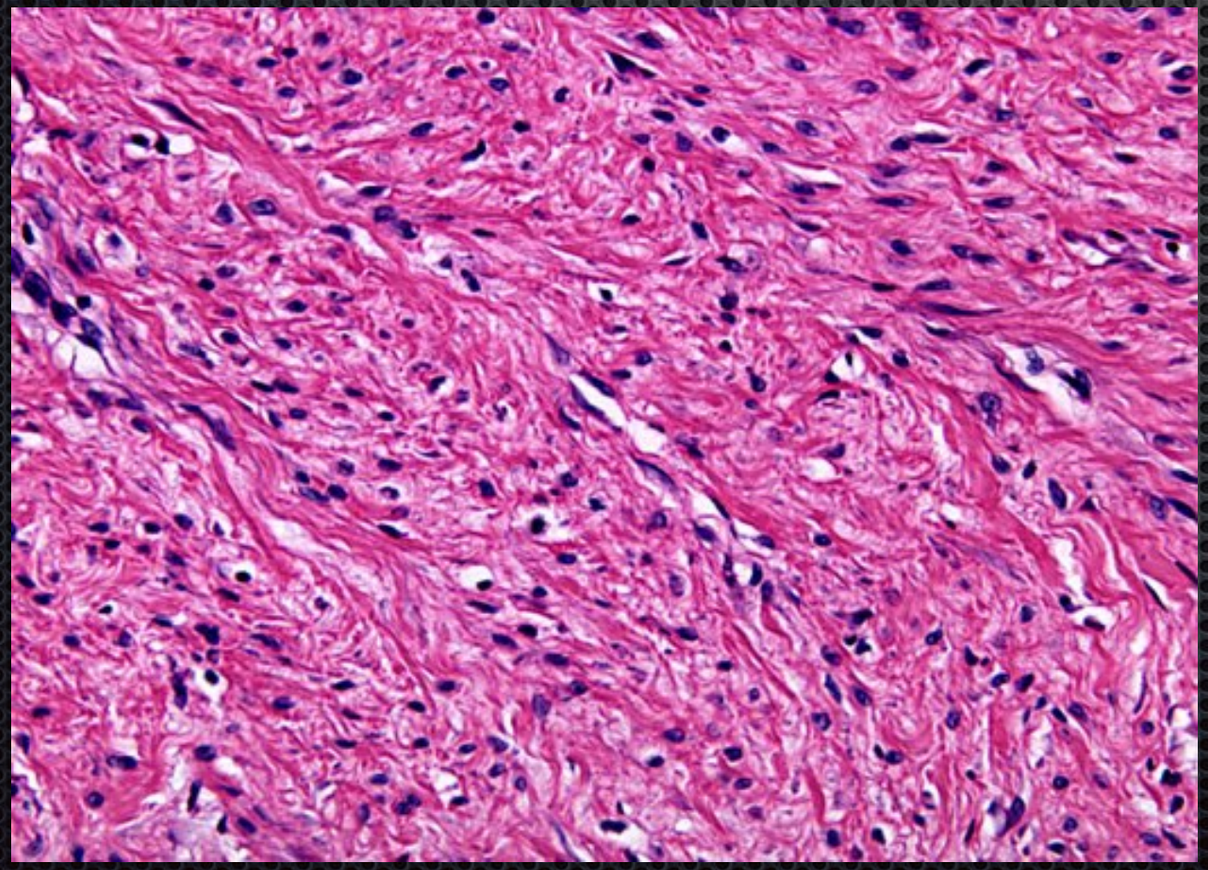
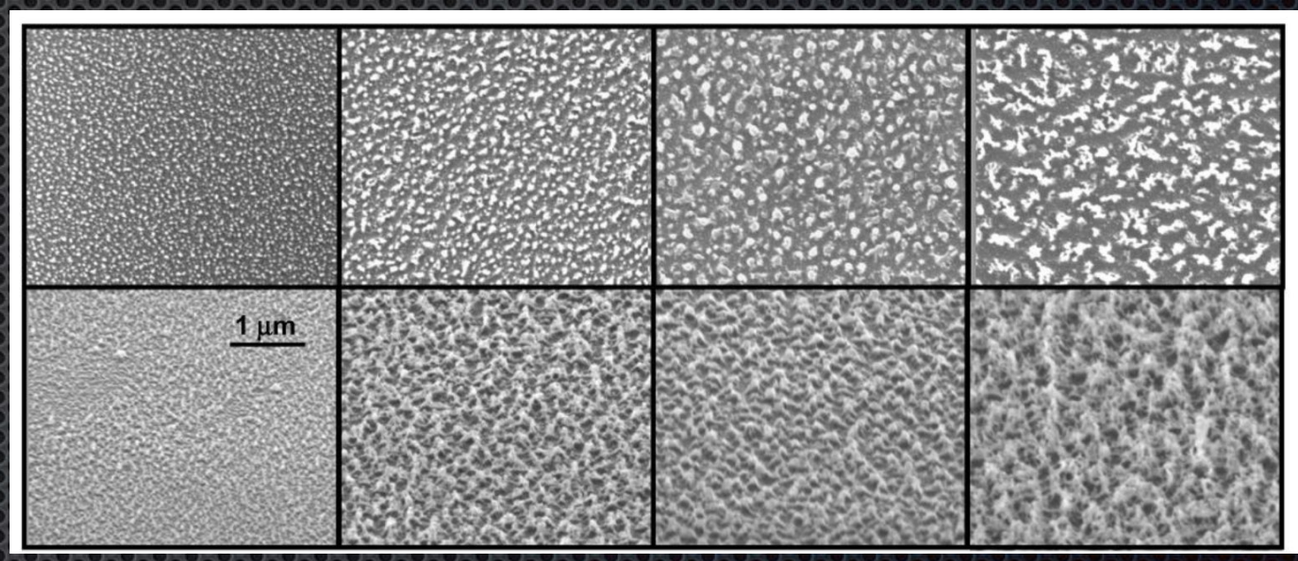
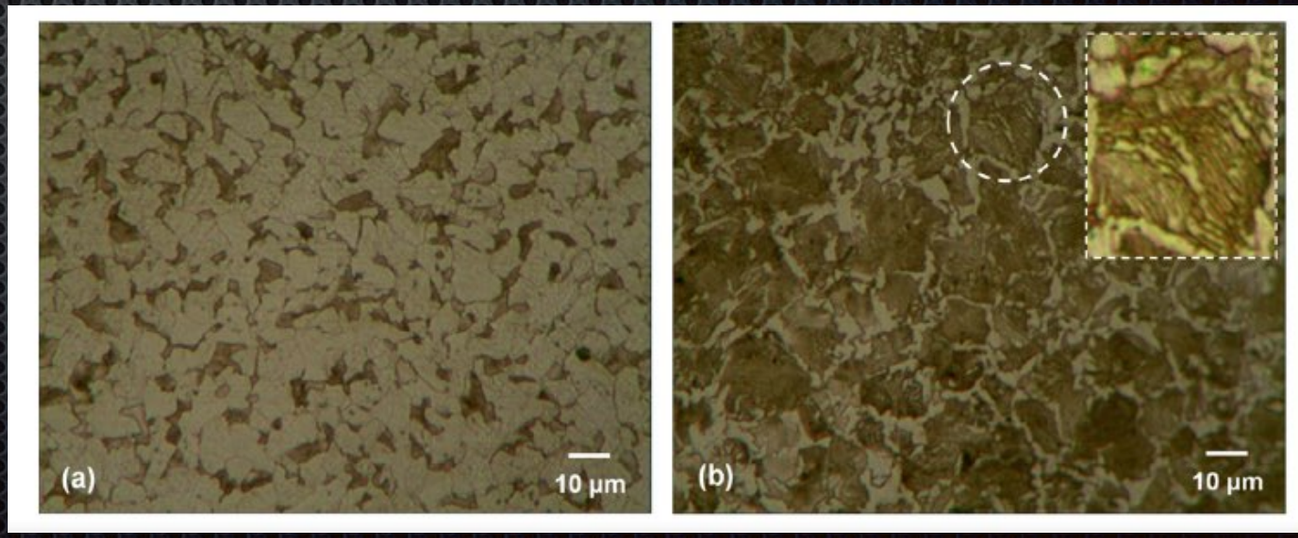
20.0µm0
5.0µm
10.0µm
15.0µm
20.0µm






1 µm


(a)
10 µm
(b)
10 µm

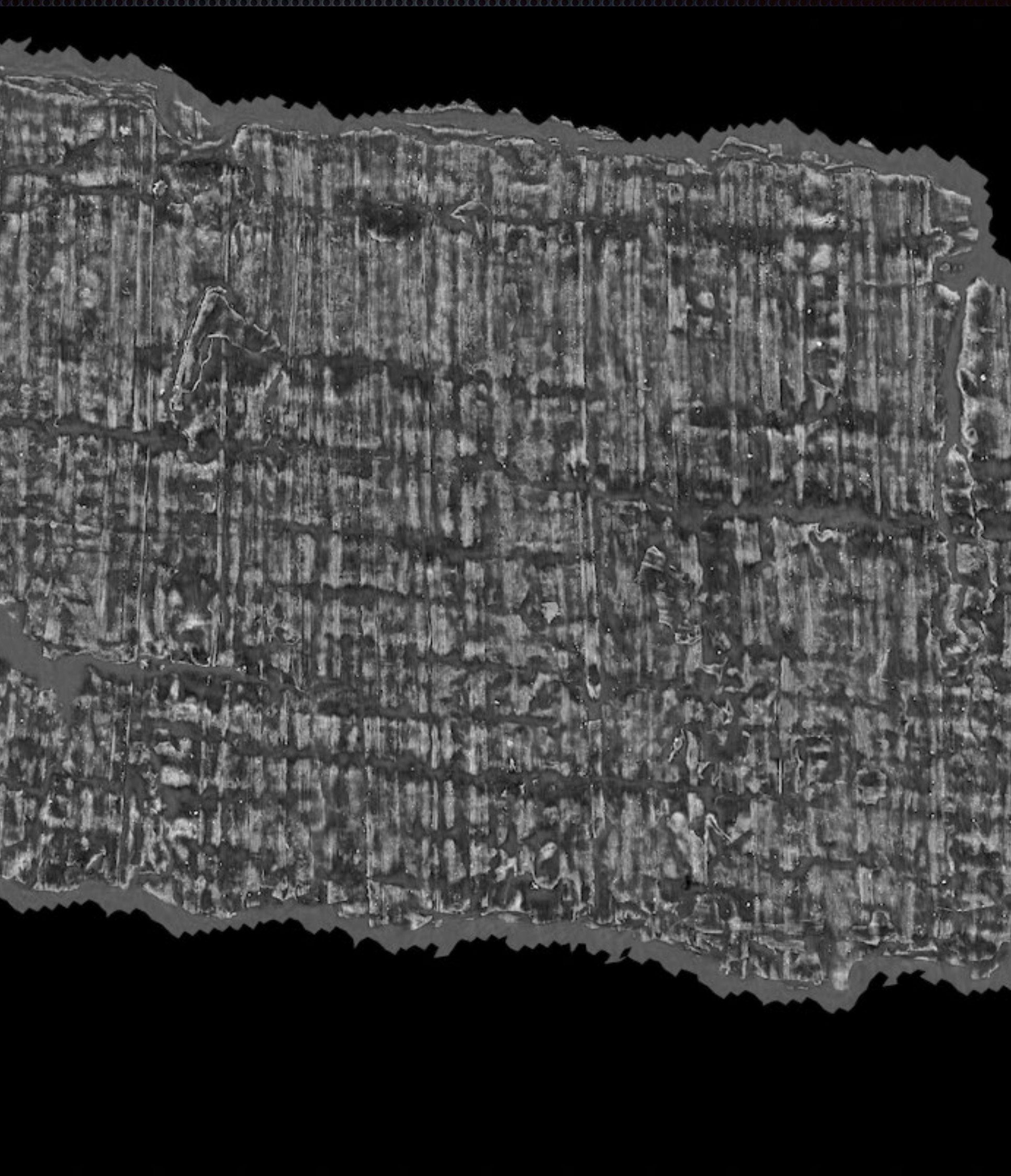
Vesuvius Challenge

Reading images of carbonized papyrus dating back almost 2000 years.

impossible ???

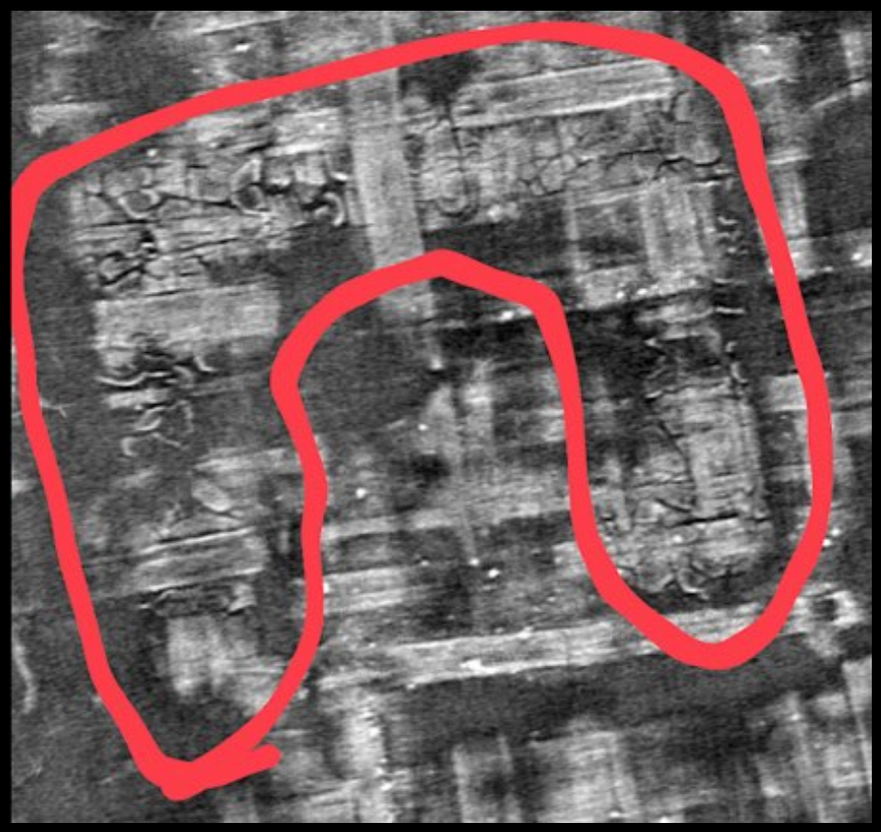
TARE
KEENOX

Papiro Nº 10
Preso per svolgersi da D. Carlo Orazi in giugno 1865
Pezzo I
Comforti



Ink mark

In the figure, we can see the letter π emerging from the crackles.



Vesuvius Challenge

Runner-up for the award.

Elian Rafael Dal Prá, Sean Johnson, **Leonardo Scabini**, Raí Fernando Dal Prá, João Vitor Brentigani Torezan, Daniel Baldin Franceschini, Bruno Pereira Kellm, Marcelo Soccol Gris, e **Odemir Martinez Bruno**.

IFSC USP

Vesuvius Challenge
1003
Date
2/5/2024
$50,000
Nat Friedman
Signature
123456789 1001

Vesuvius Challenge

1003

Elian Rafael Dal Prá, Sean Johnson, Leonardo Scabini, Raí Fernando Dal Prá, João Vitor Brentigani Torezan, Daniel Baldin Franceschini, Bruno Pereira Kellm, Marcelo Soccol Gris, and Odemir Martinez Bruno

Pay to the order of

2/5/2024

Date

$ $50,000

2023 Grand Prize Runner Up

Memo

Nat Friedman

Signature

12112490 123456789 1001

Deep learning

Enhancing deep learning for specific visual attributes

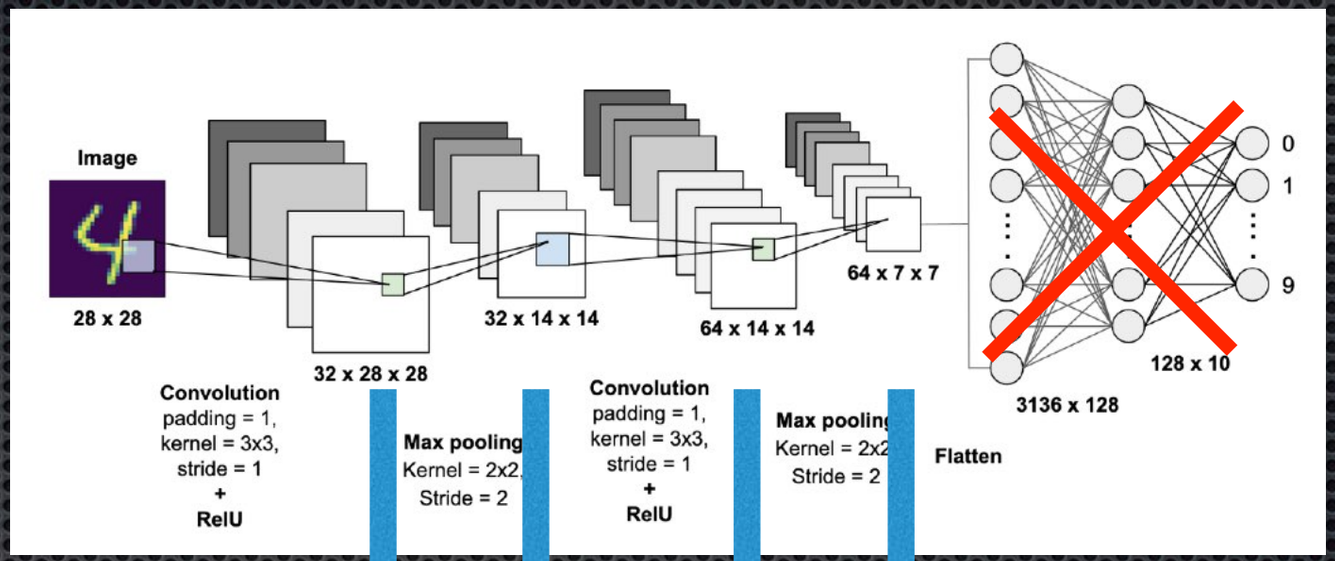
14M images organised in 21,000 groups.

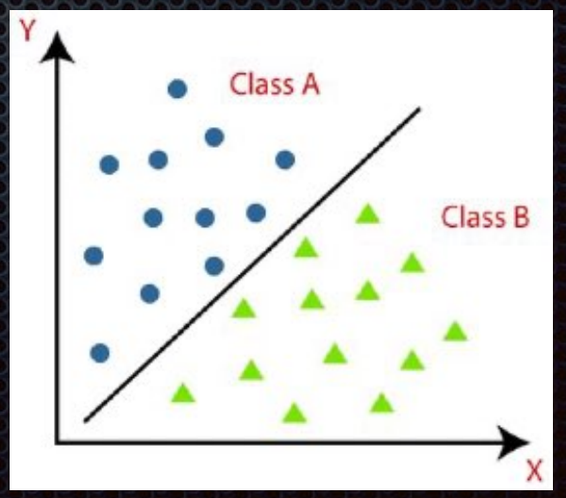
- general
- not specific for specific visual attributes or problem

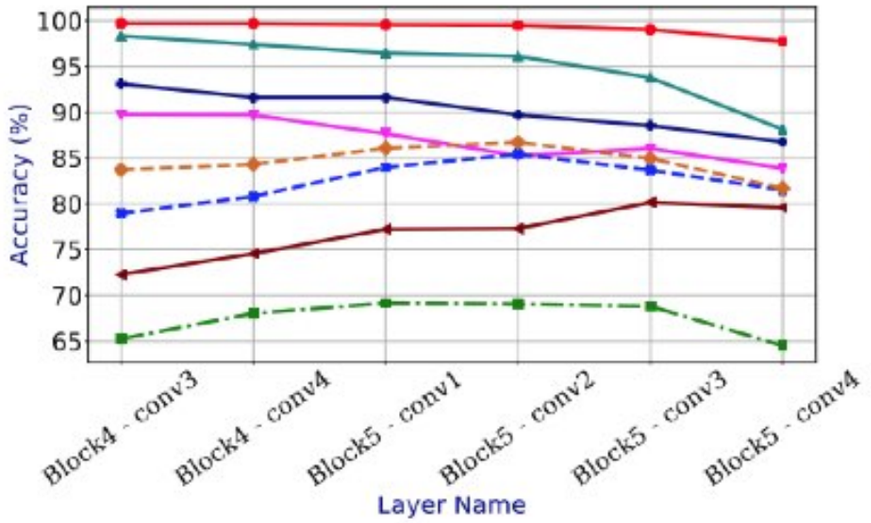
Information Sciences
Volume 555, May 2021, Pages 260-279

Analysis of activation maps through global pooling measurements for texture classification

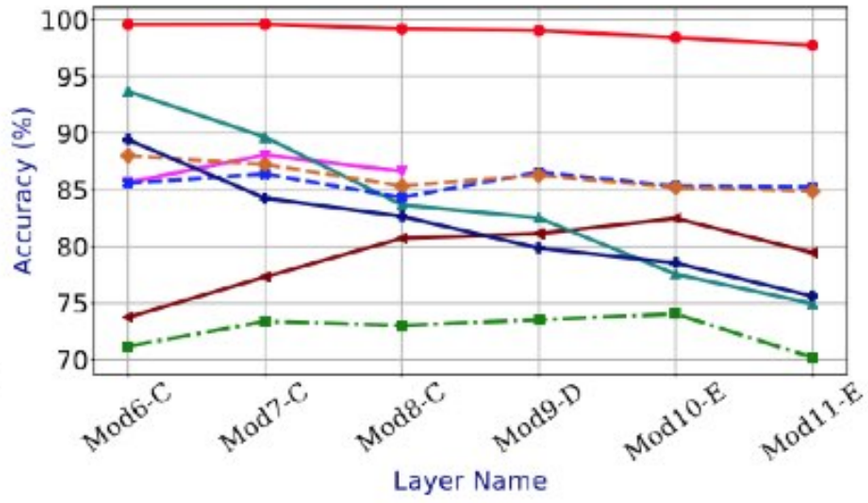
Rayner H. M. Condori [a, b], Odemir M. Bruno [b, a]



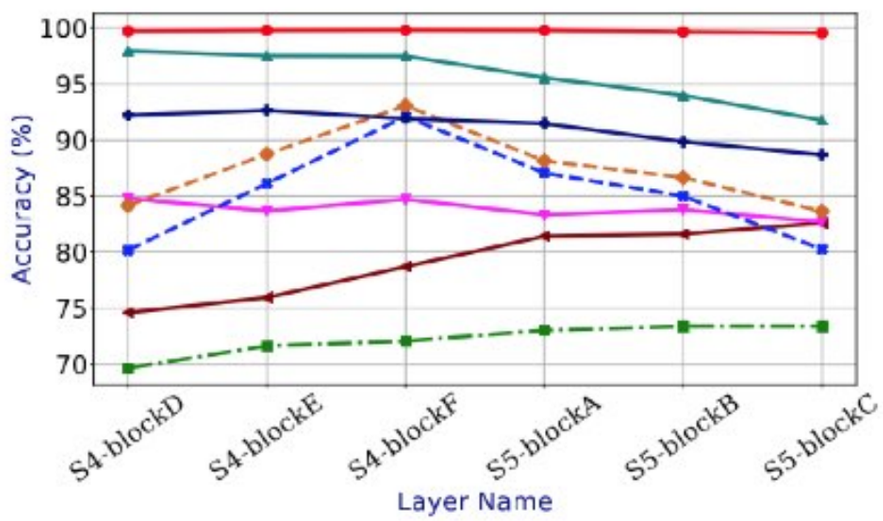


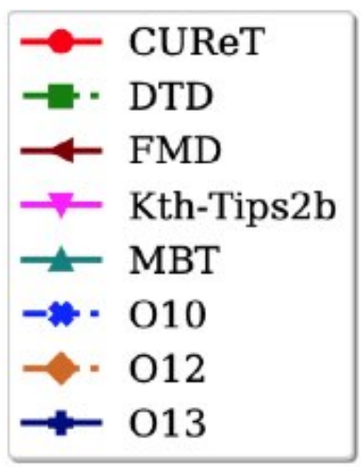


(a) BN-VGG-19



(b) Inception-V3





(c) ResNet-50

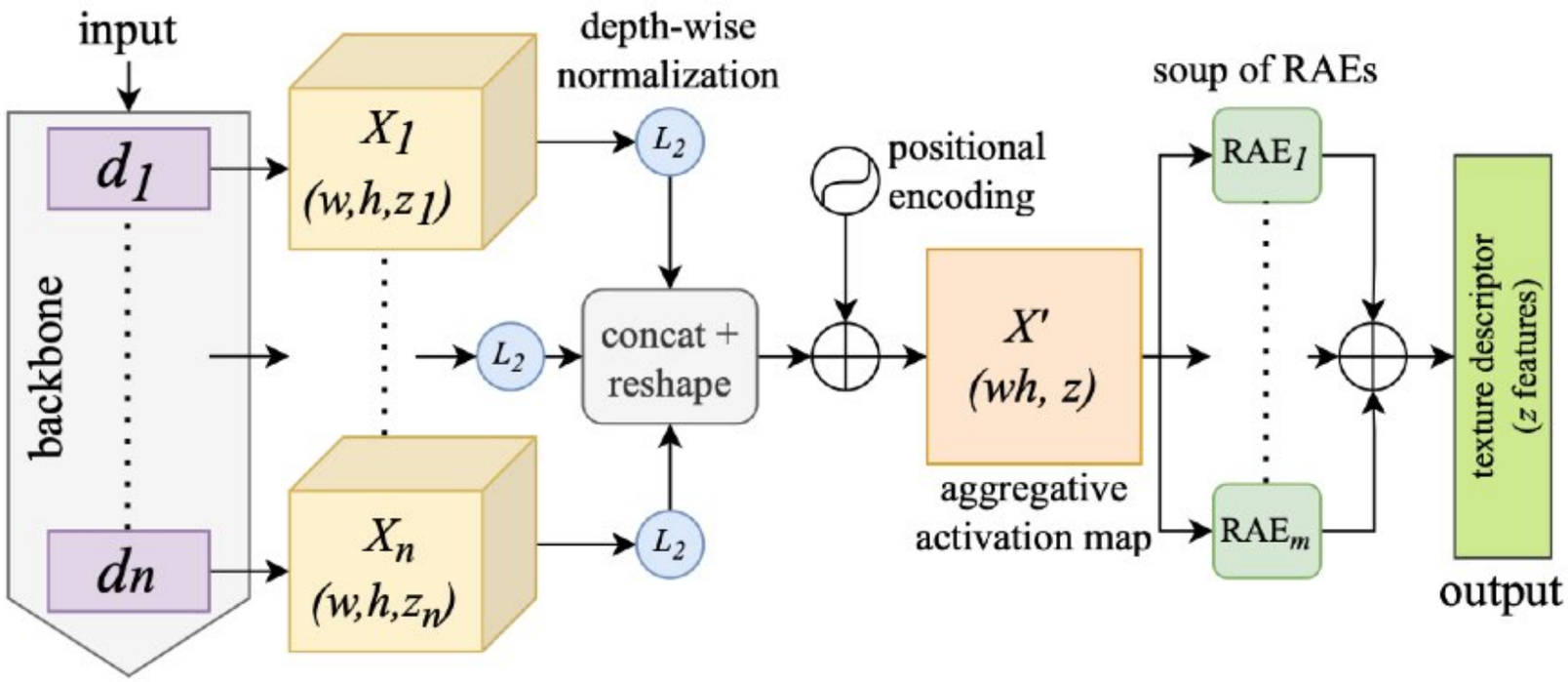
Advantages:

- No need large datasets for training - statistical classifier
- Fast and better results

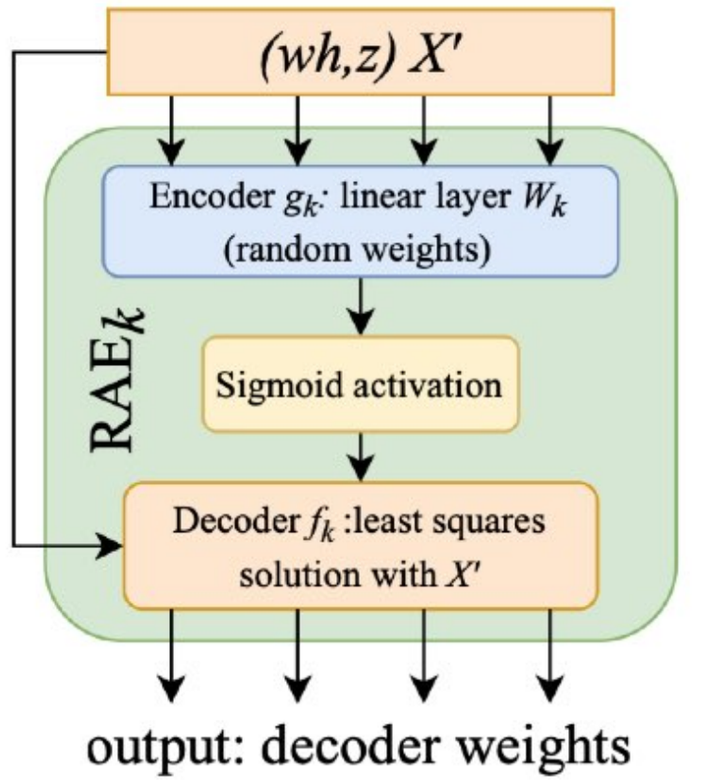
Pattern Recognition
Volume 143, November 2023, 109802

RADAM: Texture recognition through randomized aggregated encoding of deep activation maps

Leonardo Scabini [a b], Kallil M. Zielinski [a], Lucas C. Ribas [c], Wesley N. Gonçalves [d], Bernard De Baets [b], Odemir M. Bruno [a]



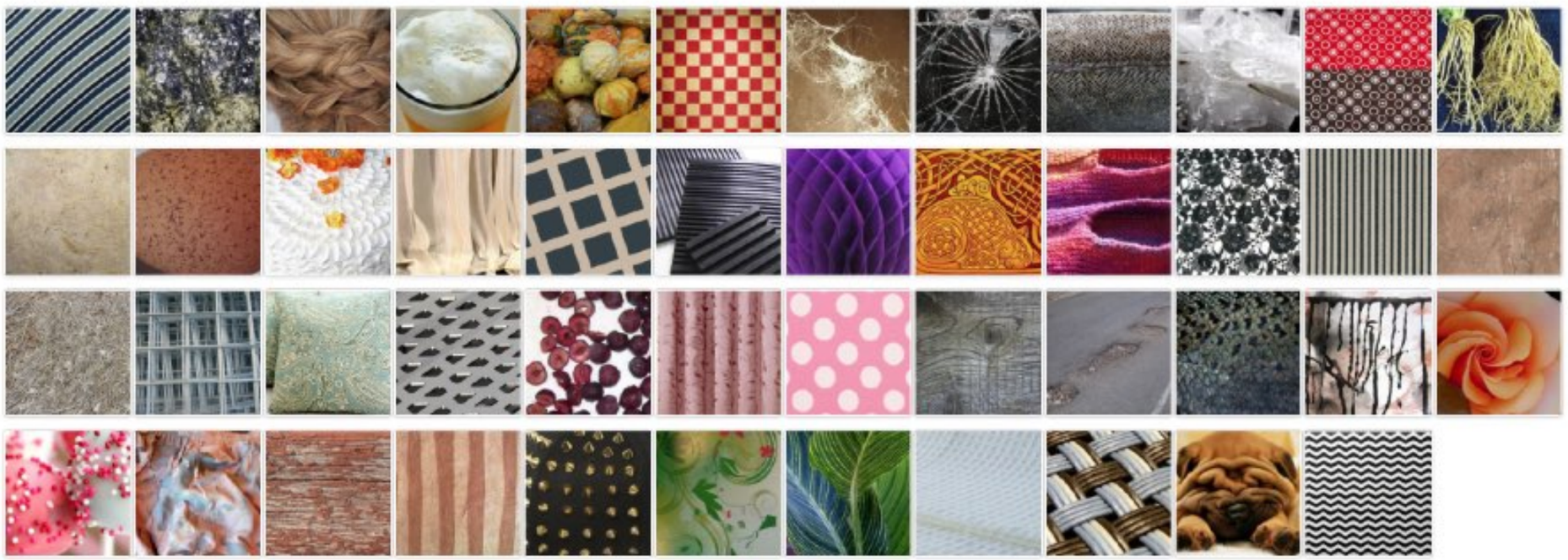
(a) The proposed feature encoding module (RADAM).



(b) Randomized Auto-encoder (RAE).

Papers With Code

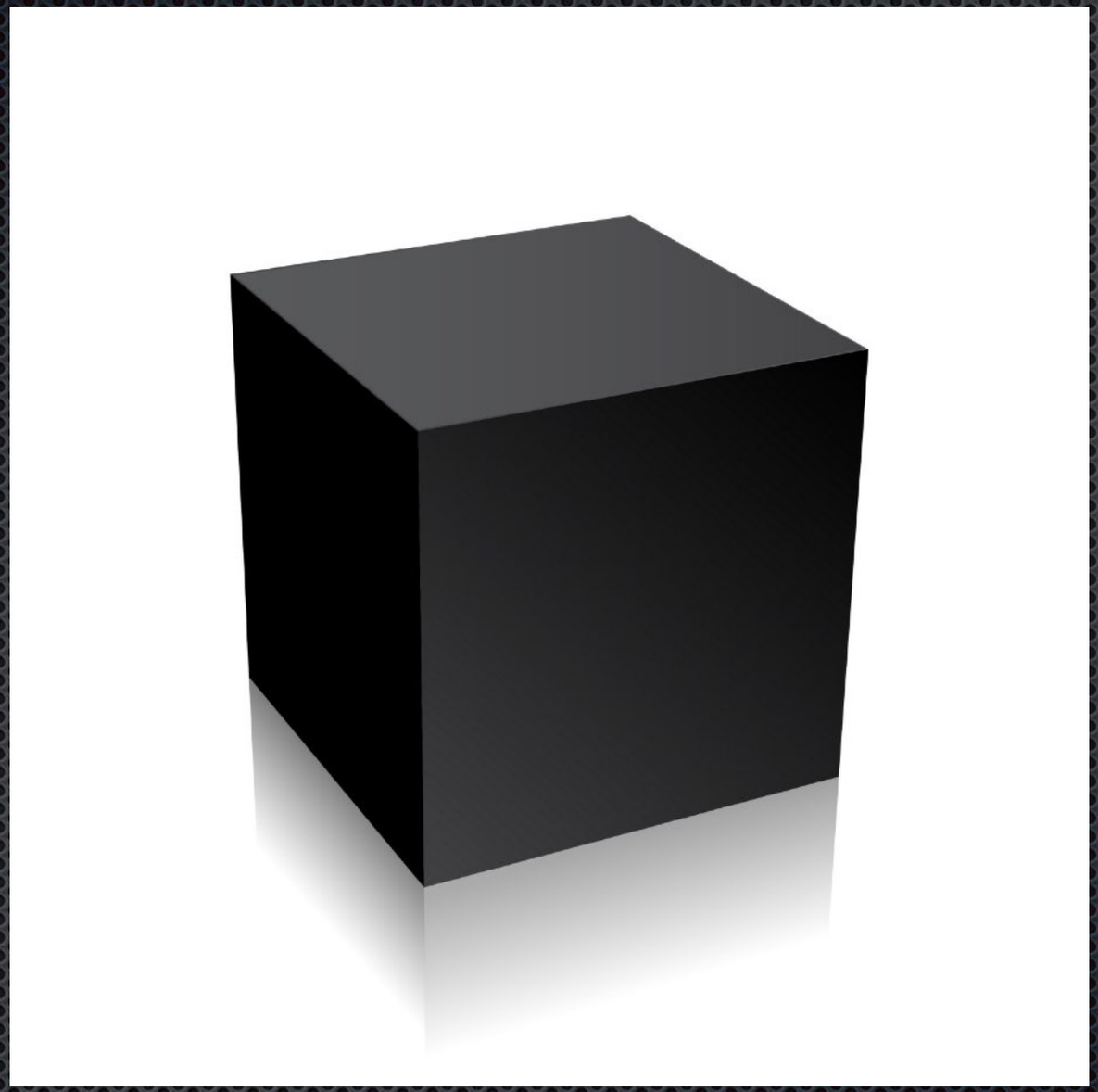
Describable Textures Dataset (DTD)



Ranked as the best in literature from March 2023 to May 2024

Deep learning

opening the black box



Physica A: Statistical Mechanics and its Applications
Volume 615, 1 April 2023, 128585

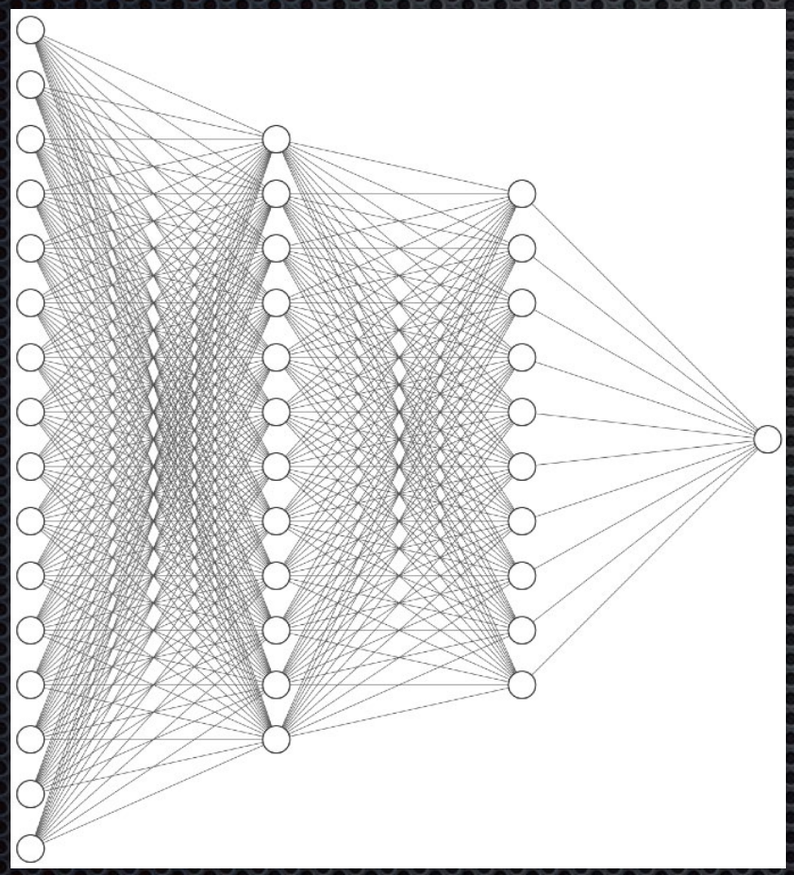
Structure and performance of fully connected neural networks: Emerging complex network properties

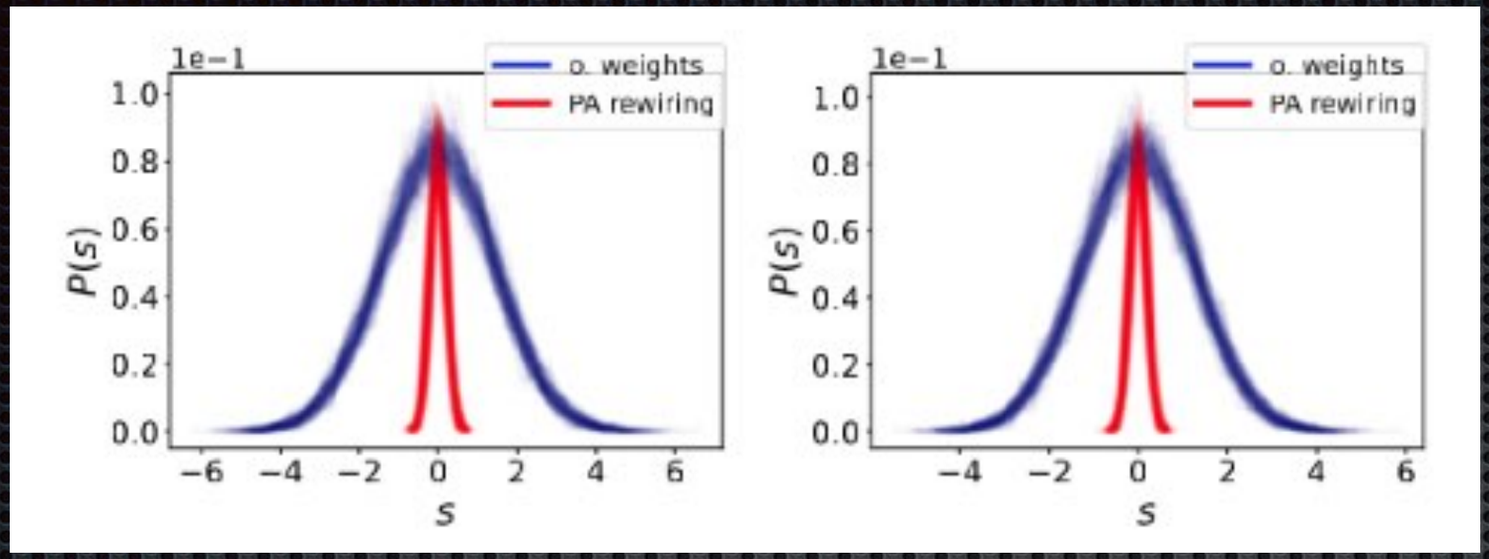
Leonardo F.S. Scabini, Odemir M. Bruno

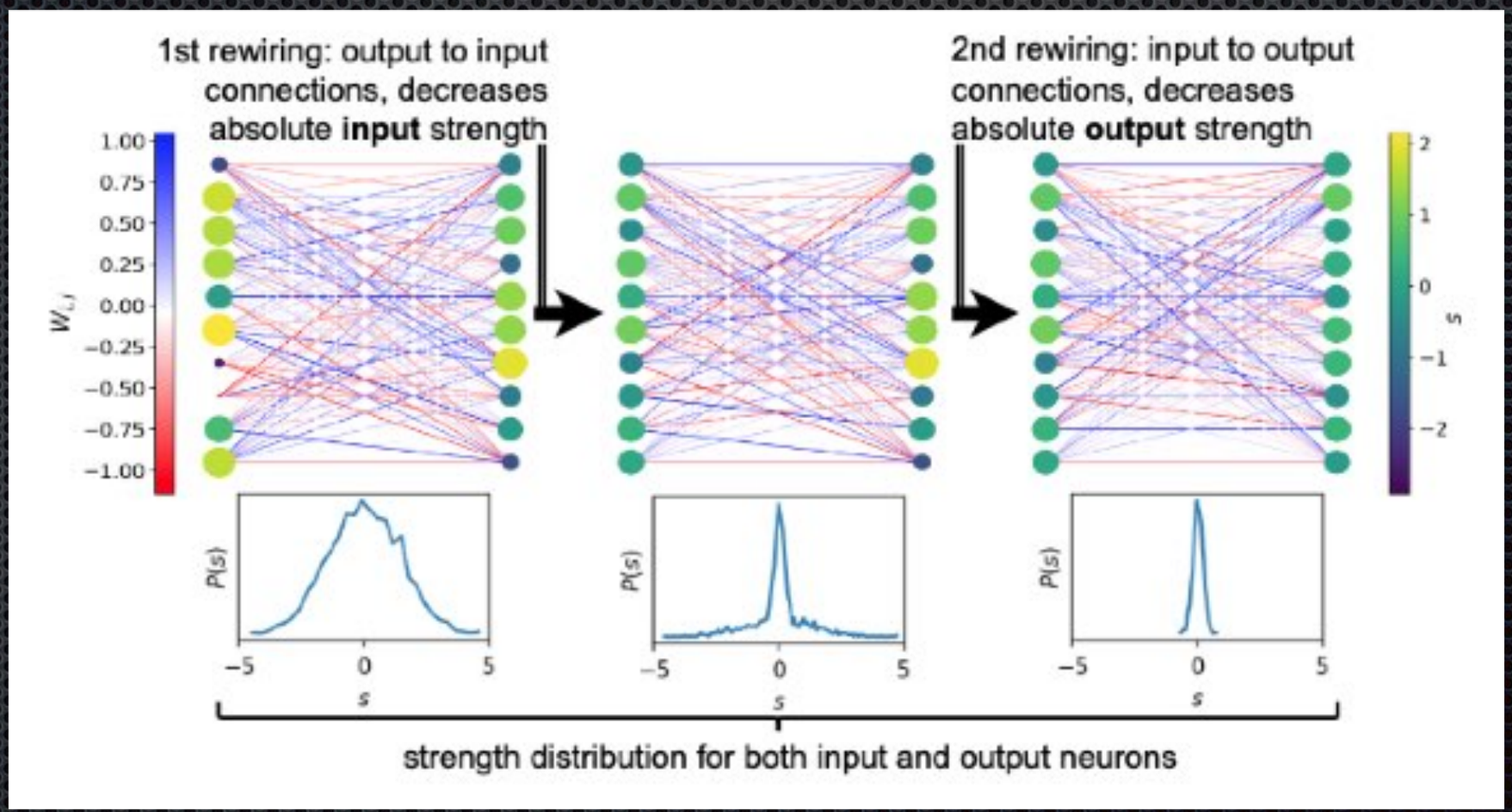
Neurocomputing
Volume 599, 28 September 2024, 128130

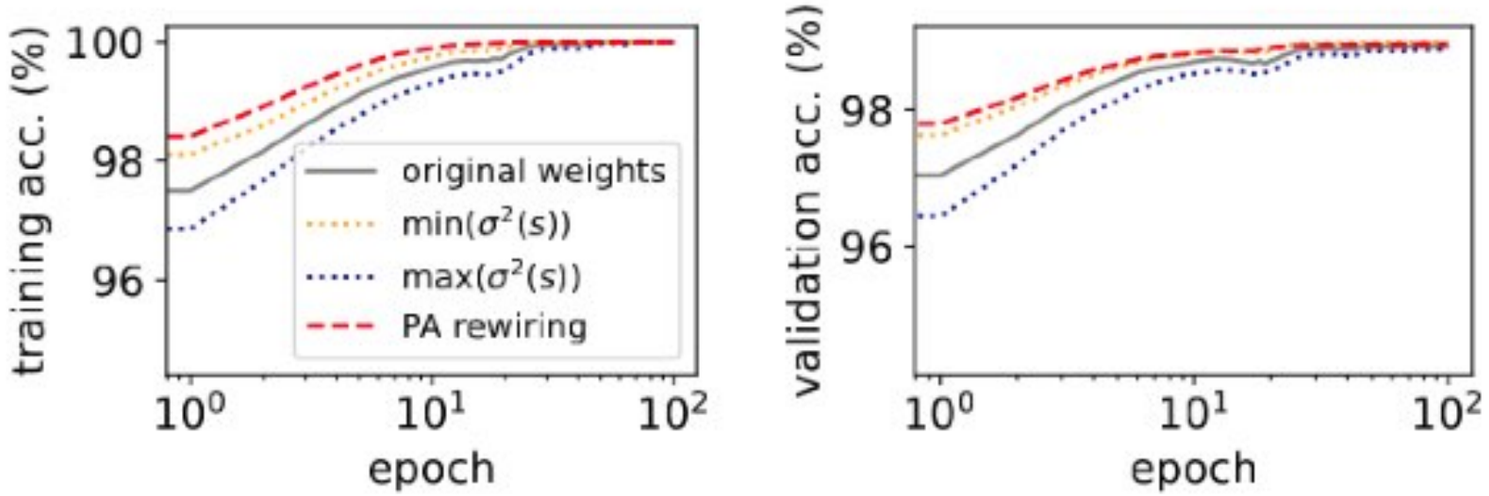
Improving deep neural network random initialization through neuronal rewiring

Leonardo Scabini [a b], Bernard De Baets [b], Odemir M. Bruno [a]

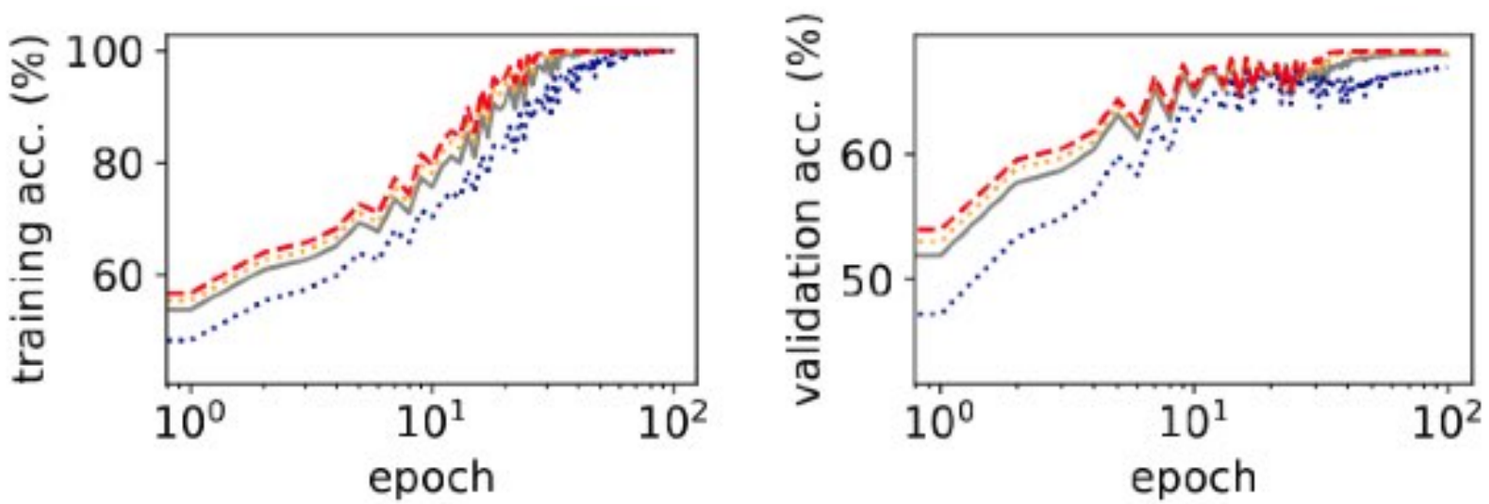



1e−1
o. weights
PA rewiring
P(s)
s
1e−1
o. weights
PA rewiring
P(s)
s


1st rewiring: output to input connections, decreases absolute input strength
2nd rewiring: input to output connections, decreases absolute output strength
W_{ij}
s
P(s)
s
strength distribution for both input and output neurons



(a) MNIST



(b) CIFAR10

What if we don’t need to train the network?

Without any training.
No transfer learning.

International Conference on Image Analysis and Processing

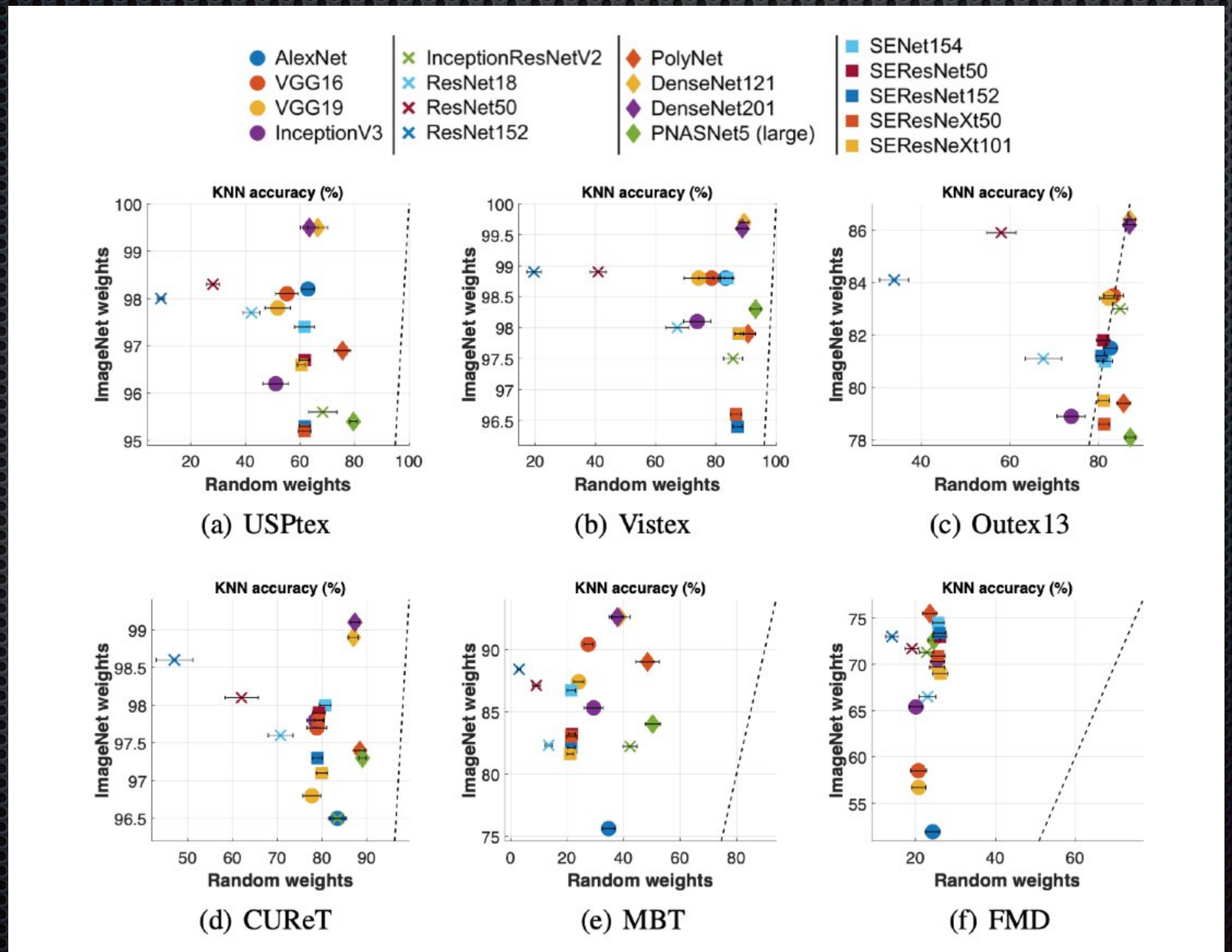
↳ ICIAP 2019: **Image Analysis and Processing – ICIAP 2019** pp 192–202 | Cite as

Evaluating Deep Convolutional Neural Networks as Texture Feature Extractors

Leonardo F. S. Scabini ✉, Rayner H. M. Condori, Lucas C. Ribas & Odemir M. Bruno

Conference paper | First Online: 02 September 2019

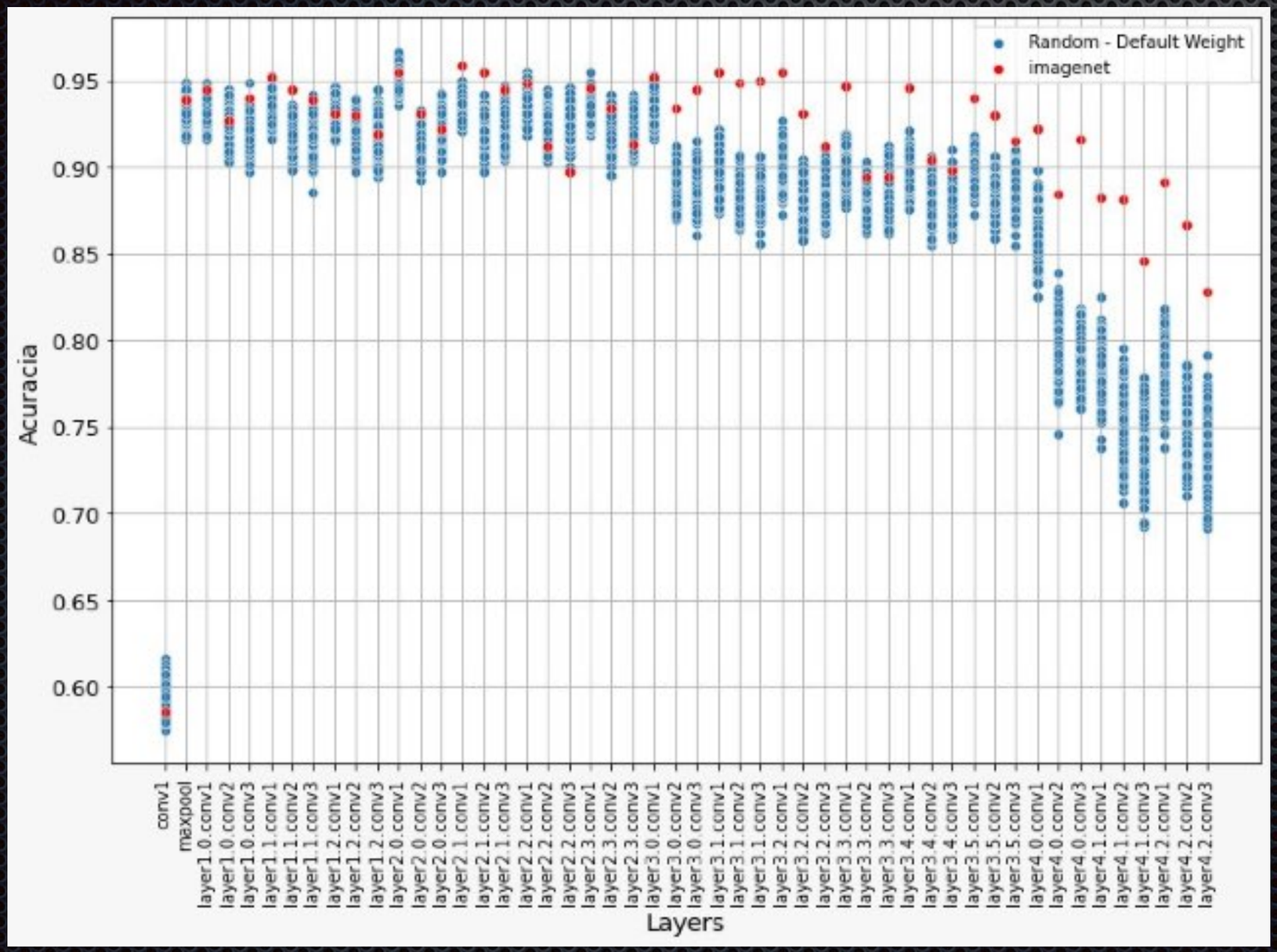
1547 Accesses

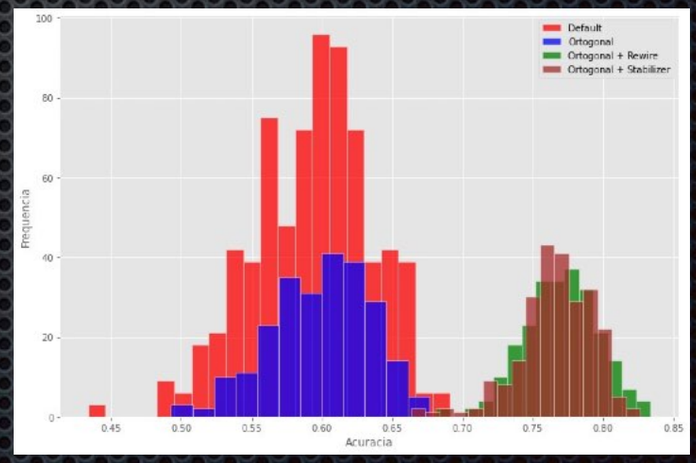


(a) USPtex (b) Vistex (c) Outex13

(d) CUReT (e) MBT (f) FMD

Current work: re-wiring and finding best random initializer automatically



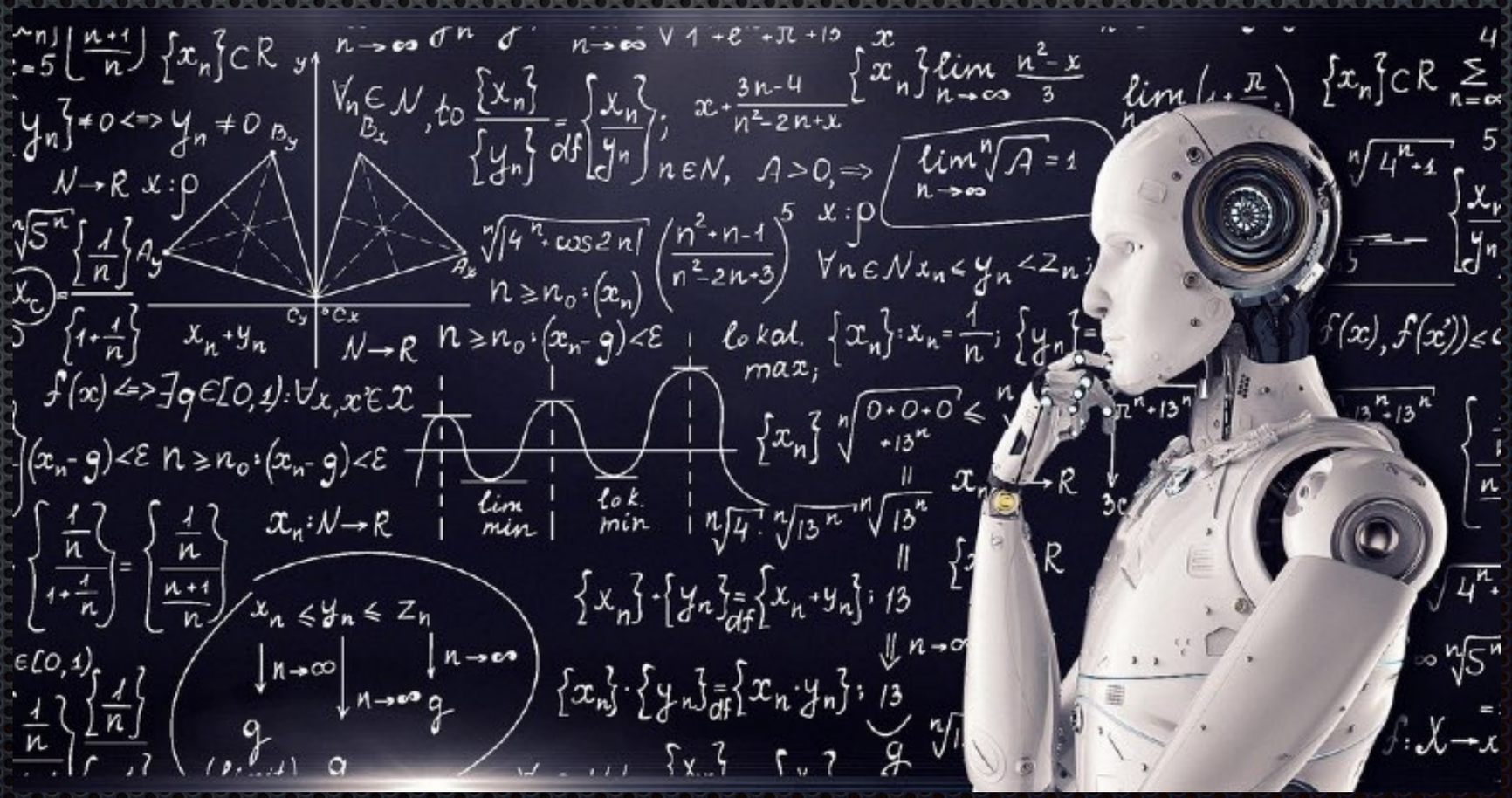


Advantages:

- No need large datasets for training - statistical classifier
- No training, no imagenet
- Light and fast
- Lab for finding new DL architectures and backbones

AI applied to Complex Systems

Chaos theory



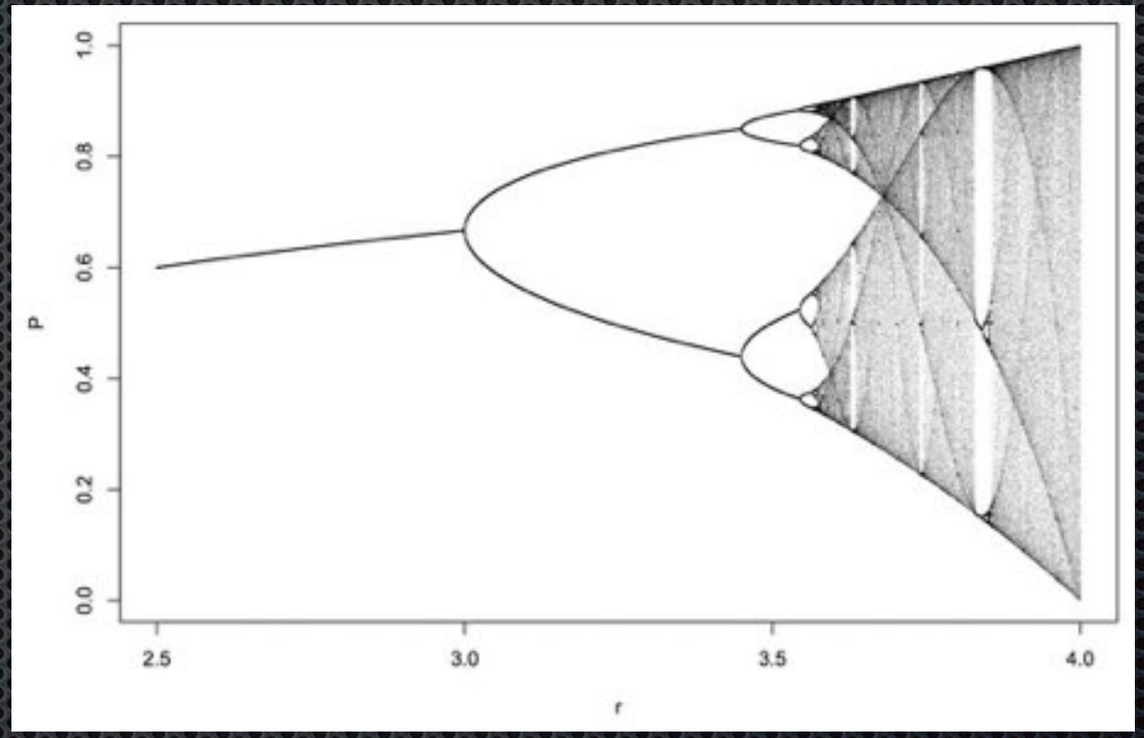
Chaos theory –

Is chaos really unpredictable?

Chaos, Solitons & Fractals
Volume 192, March 2025, 116034

Forecasting chaotic time series: Comparative performance of LSTM-based and Transformer-based neural network

João Valle, Odemir Martinez Bruno

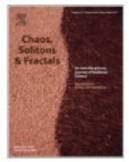


$$x_{n+1} = r x_n (1 - x_n)$$

ELSEVIER

Chaos, Solitons & Fractals

Volume 161, August 2022, 112296



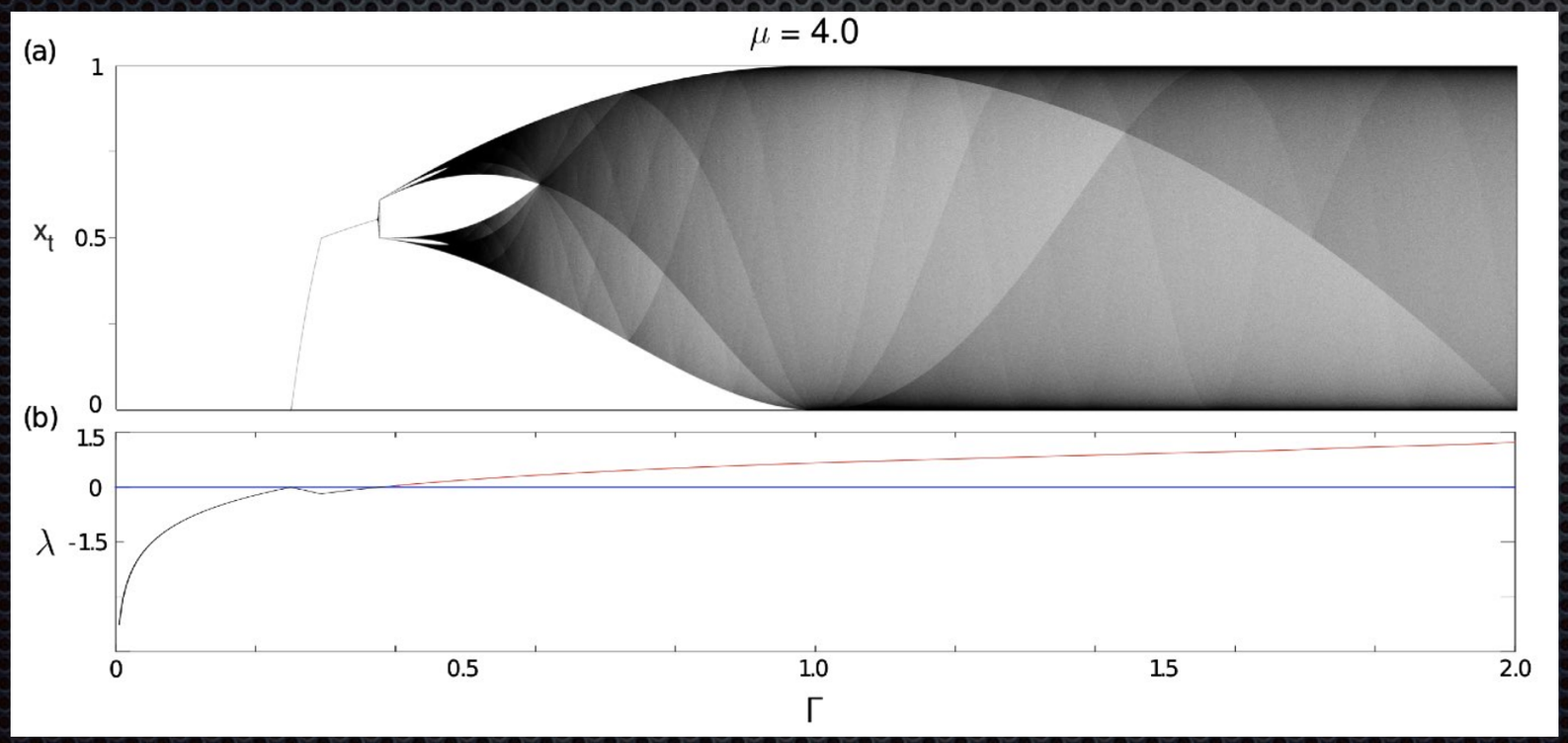
Chaotical PRNG based on composition of logistic and tent maps using deep-zoom

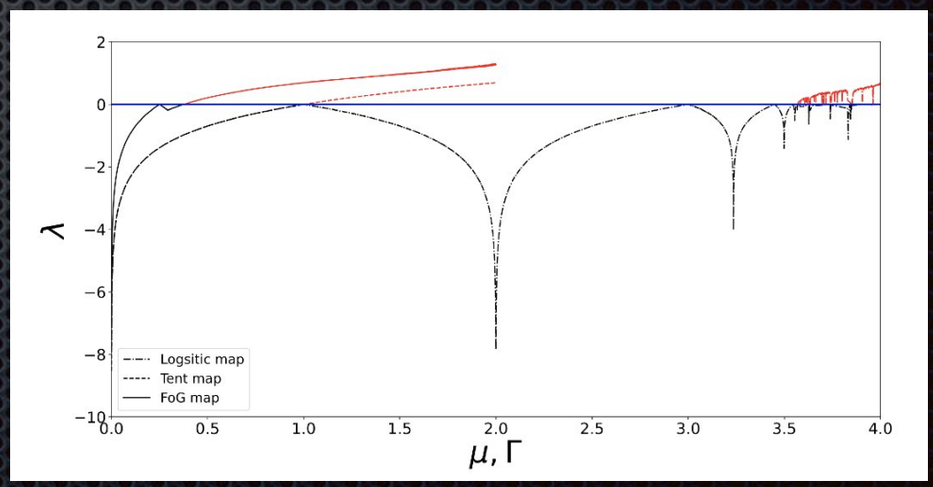
João Valle [a], Jeaneth Machicao [a b c], Odemir M. Bruno [a 1]

$$f(x_t) = x_{t+1} = \mu x_t(1 - x_t)\,,$$

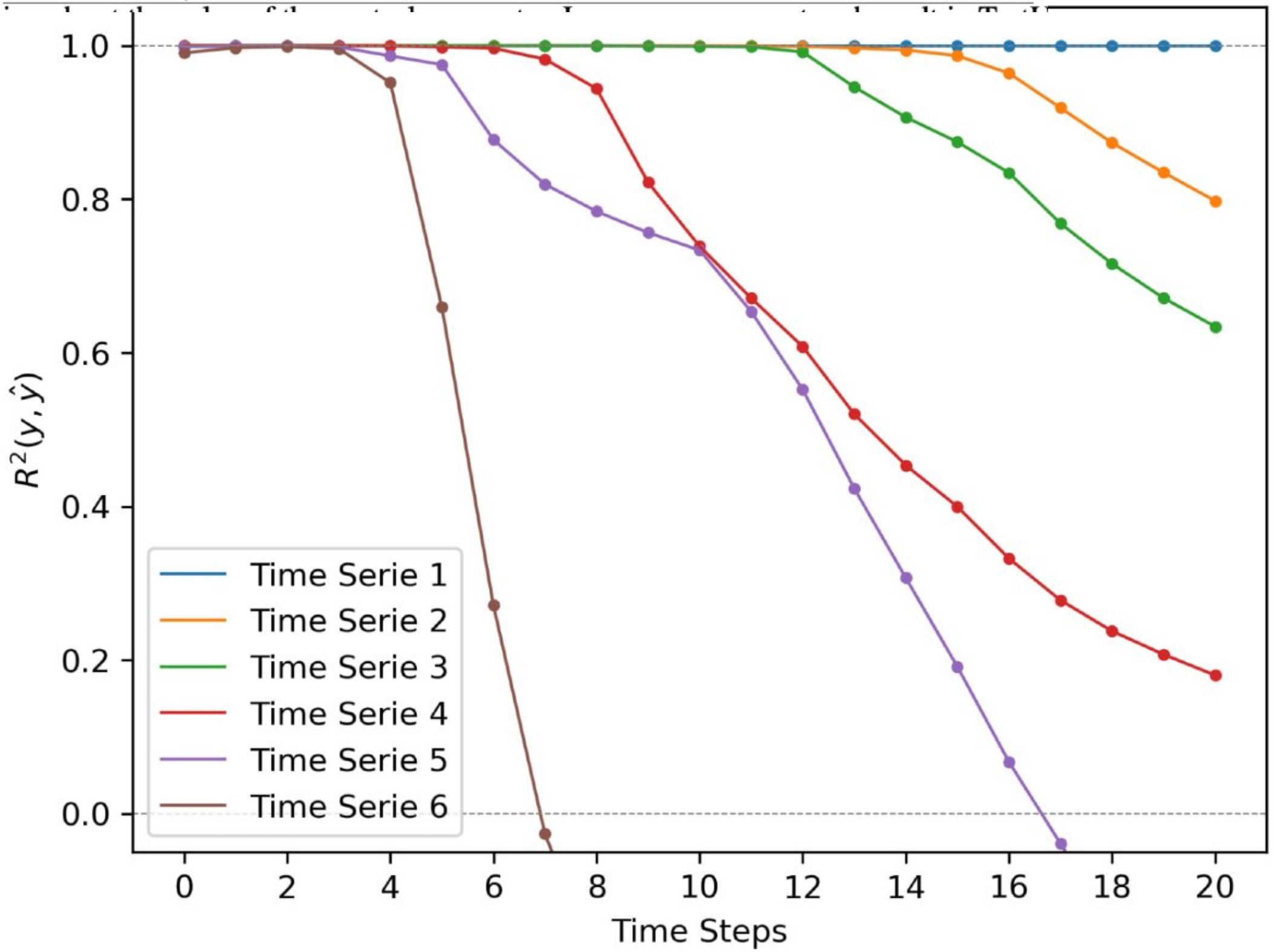
$$g(x_t) = x_{t+1} = \begin{cases} \Gamma x_t, & \text{if } x_t < \frac{1}{2} \\ \Gamma(1 - x_t), & \text{if } x_t \geq \frac{1}{2}\,, \end{cases}$$

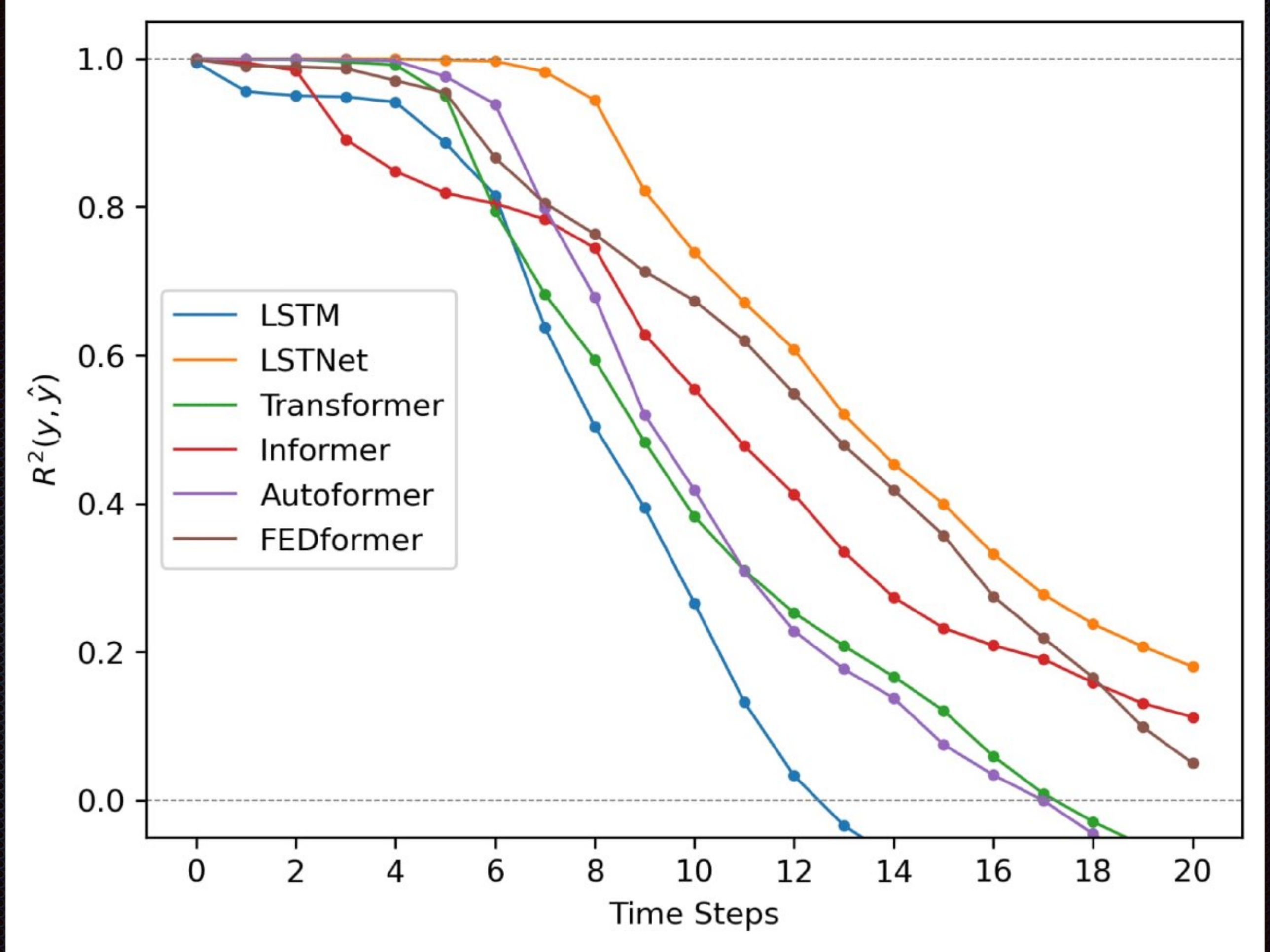
$$(f \circ g)(x_{t+1}) = \begin{cases} \mu\Gamma x_t(1 - \Gamma x_t), & \text{if } x_t < \frac{1}{2} \\ \mu\Gamma(1 - x_t)[1 - \Gamma(1 - x_t)], & \text{if } x_t \geq \frac{1}{2} \end{cases}$$





	Control parameter	Lyapunov exponent (λ)	Tests passed in TestU01 [%]
Time Series 1	$\mu = 3.854$	0.019	-
Time Series 2	$\mu = 3.874$	0.456	23.1
Time Series 3	$\mu = 4.0$	0.693	26.8
Time Series 4	$\mu = 3.999$ and $\Gamma = 1.323$	0.856	28.4
Time Series 5	$\mu = 3.999$ and $\Gamma = 1.686$	1.051	31.1
Time Series 6	$\mu = 3.999$ and $\Gamma = 1.989$	1.253	33.9




1.0
0.8
0.6
0.4
0.2
0.0
$R^2(y, \hat{y})$
LSTM
LSTNet
Transformer
Informer
Autoformer
FEDformer
0
2
4
6
8
10
12
14
16
18
20
Time Steps

Chaos theory – Can ergodicity be grasped?

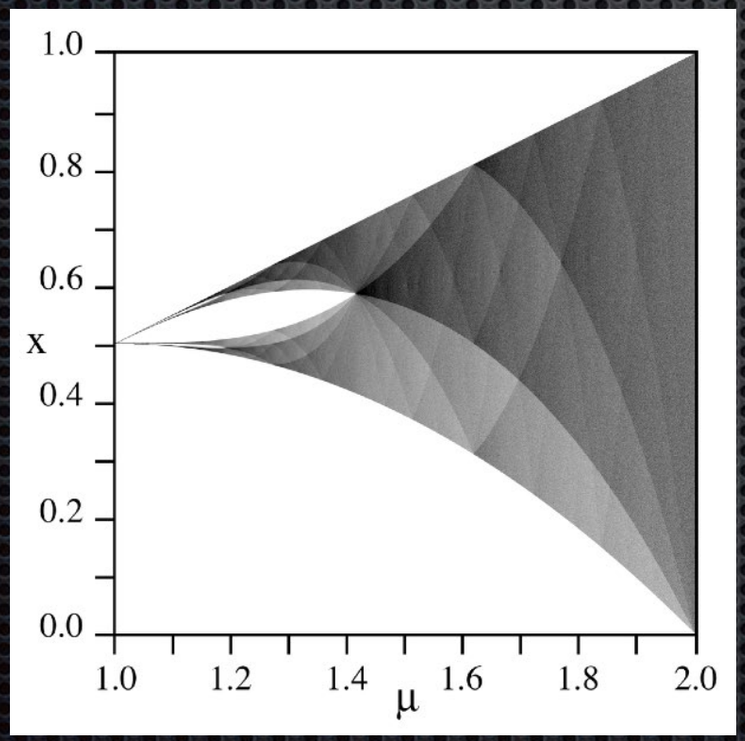
to appear

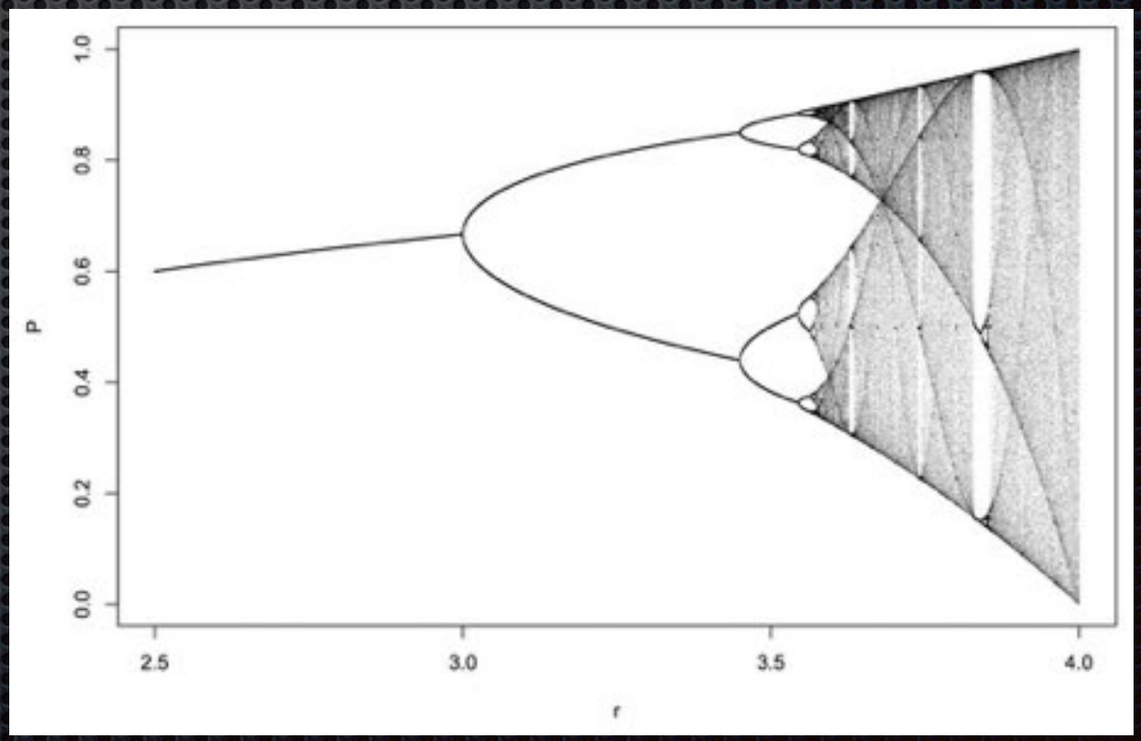
Learning the ergodicity of chaotic systems with generative adversarial networks

João Valle[a,b], Bernard De Baets[b], Odemir M. Bruno[a,*]

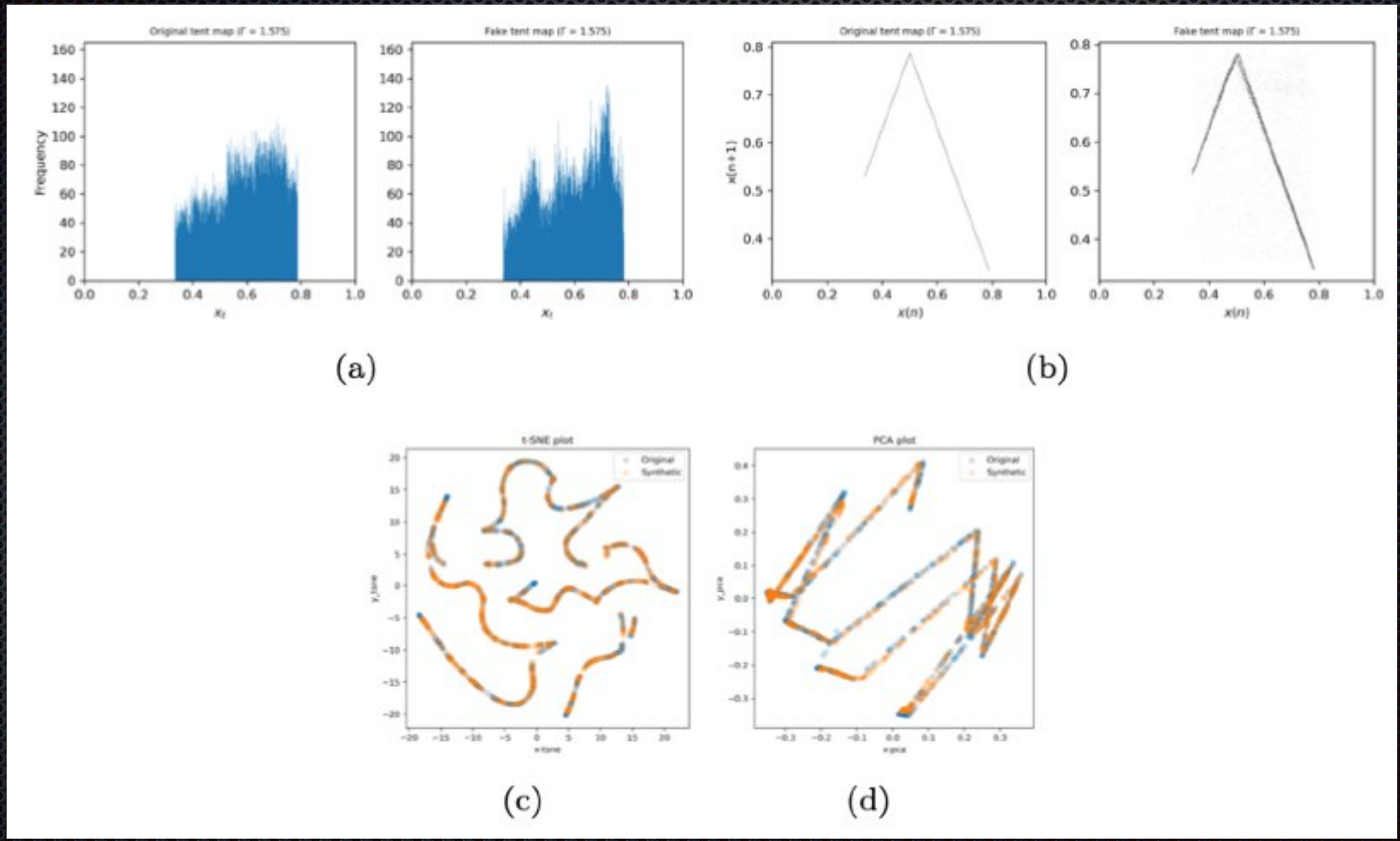
[a]*Scientific Computing Group, São Carlos Institute of Physics, University of São Paulo, USP, PO Box 369, 13560-970, São Carlos, SP, Brazil*

[b]*KERMIT, Department of Data Analysis and Mathematical Modelling, Ghent University, Coupure links 653, postal code 9000, Ghent, Belgium*

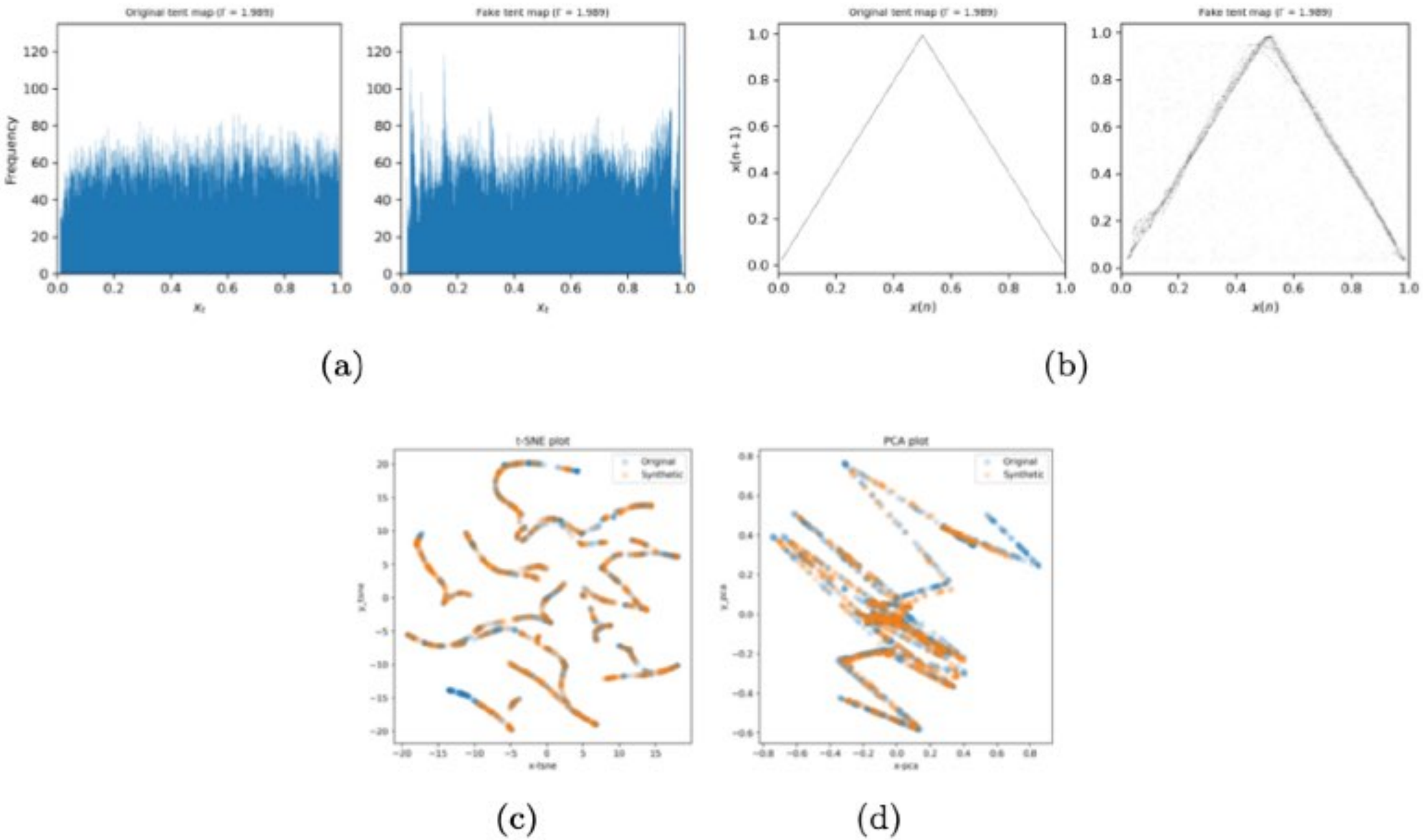


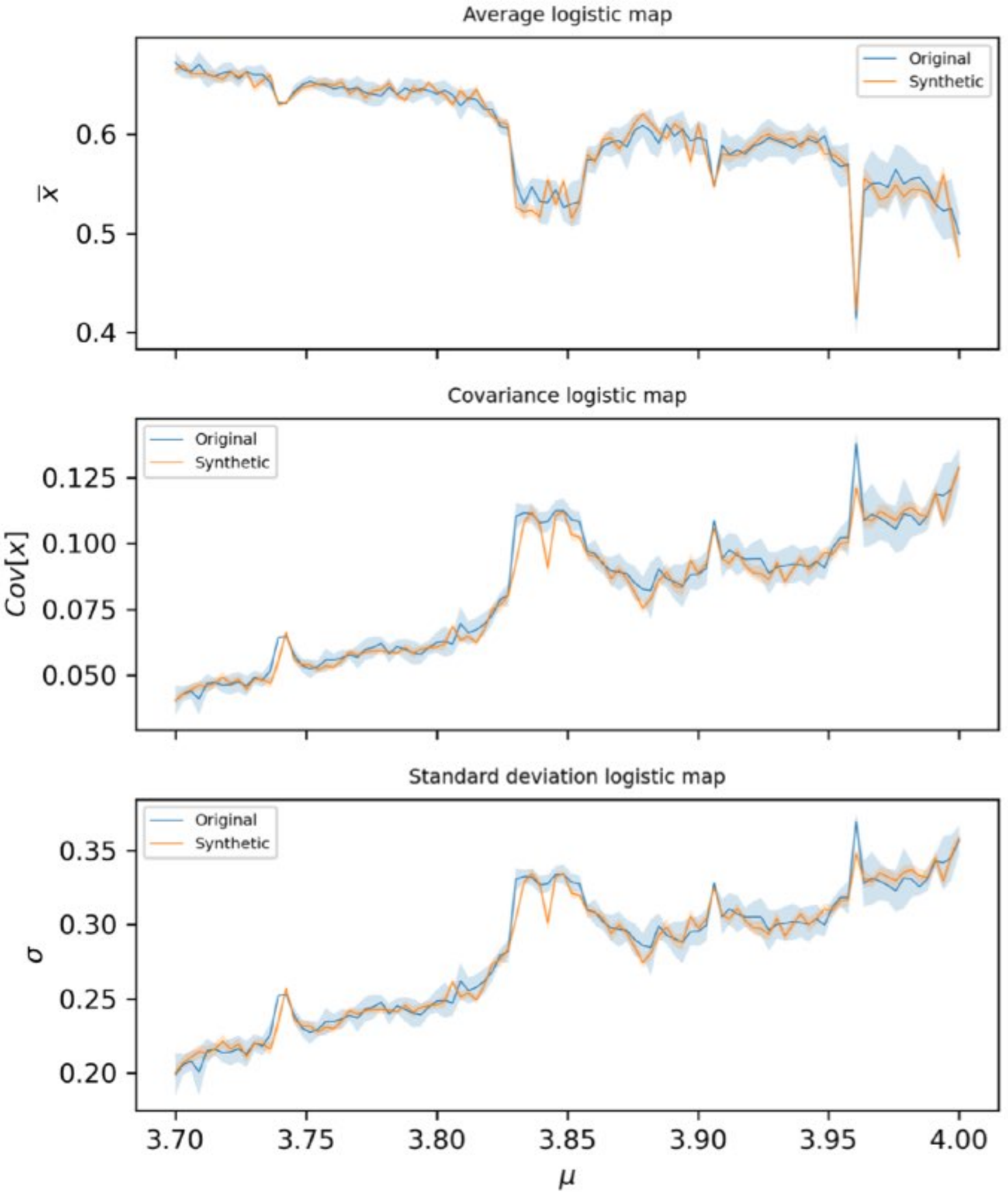


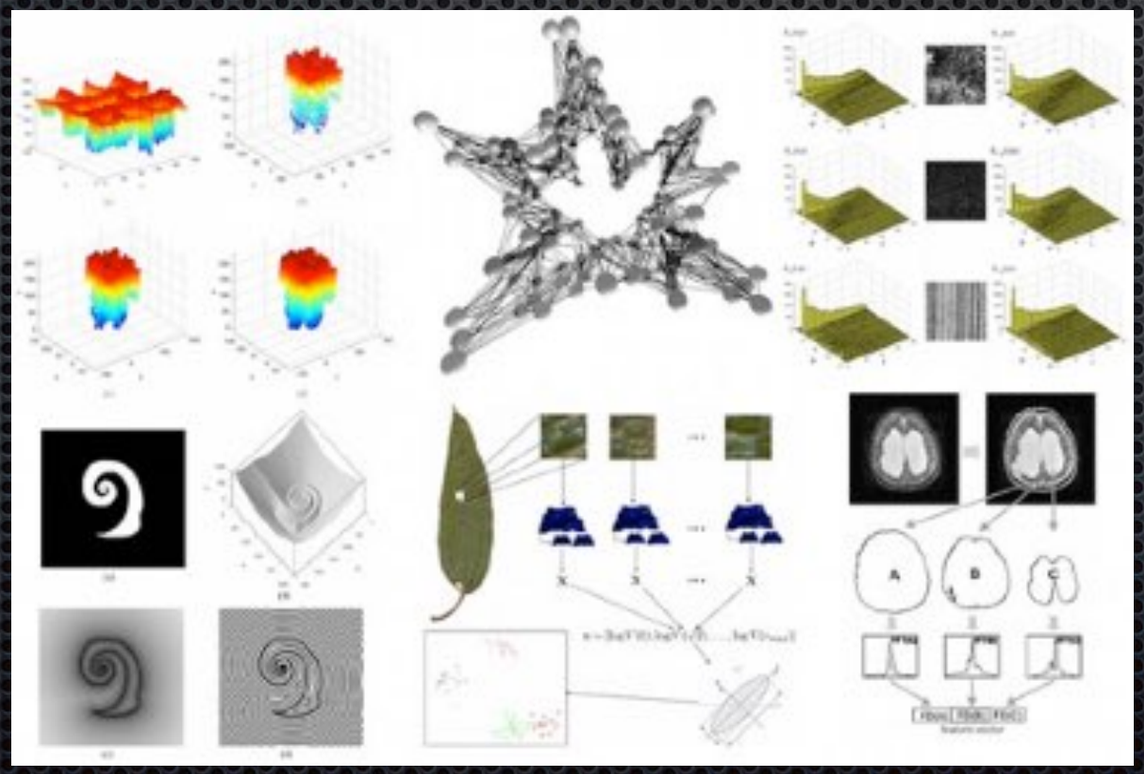
tent map : u = 1.575



tent map : u = 1.989




Average logistic map
Original
Synthetic
0.6
0.5
0.4
x
Covariance logistic map
Original
Synthetic
0.125
0.100
0.075
0.050
Cov[x]
Standard deviation logistic map
Original
Synthetic
0.35
0.30
0.25
0.20
σ
3.70
3.75
3.80
3.85
3.90
3.95
4.00
μ

Scientific Computing Group

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