

**A TRIBUTE TO
ANTONIO GALVES
(1947/2023)**

THE STATISTICIAN BRAIN

Claudia D. Vargas

Institute of Biophysics Carlos Chagas Filho

Federal University of Rio de Janeiro

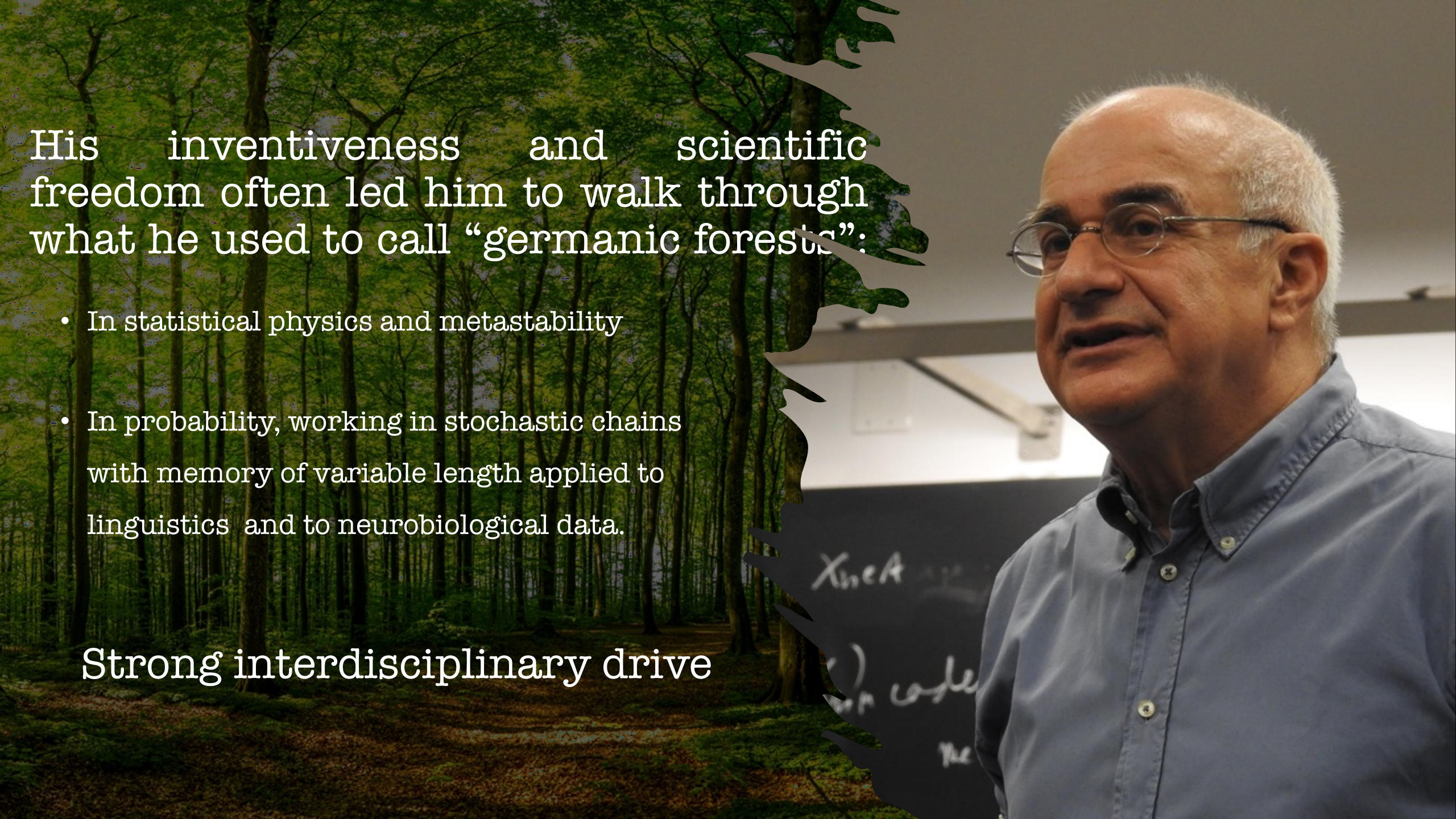
CO-PI of the CEPID NeuroMat

Pictures were taken from https://commons.wikimedia.org/wiki/Category:NeuroMat_events

BIOGRAPHY

- Jefferson Antonio Galves was born in São Paulo in June 18th, 1947. His parents, Antonio and Odette Galves, were descendants of Iberic immigrants. Proud of his origins, he spoke fluently French, Italian and Spanish.
- He graduated in mathematics in 1968, completed a master's degree in statistics (1972) and a doctorate thesis in the same area (1978). In 1974, at the Pierre and Marie Curie University - Paris VI, in France, he obtained a "Diplôme approfondi" in statistics.
- He became a professor at USP in 1969, when mathematics was still taught at the now extinct Faculty of Philosophy, Sciences and Letters. He became then professor at the Institute of Mathematics and Statistics (IME) in 1970, until retiring in 2022 as Full Professor.
- He was coordinator of the Center for Research Support in Mathematics, Computing, Language and Brain (MaCLinC-USP), and of the Center for Research, Innovation and Dissemination in Neuromathematics (NeuroMat).
- Galves was married to French linguist Charlotte Chambelland Galves, from the State University of Campinas (Unicamp). He had two daughters, Sophia and Julia, and a son, Miguel.
- Since 1996, he was a member of the Brazilian Academy of Sciences.
- In 2007, Galves received with great joy from President Lula the Grand Cross of the National Order of Scientific Merit.

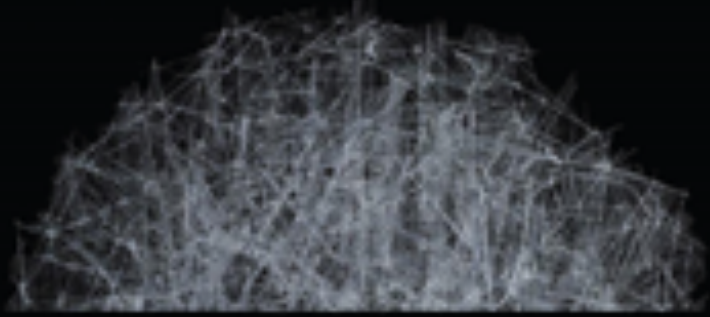




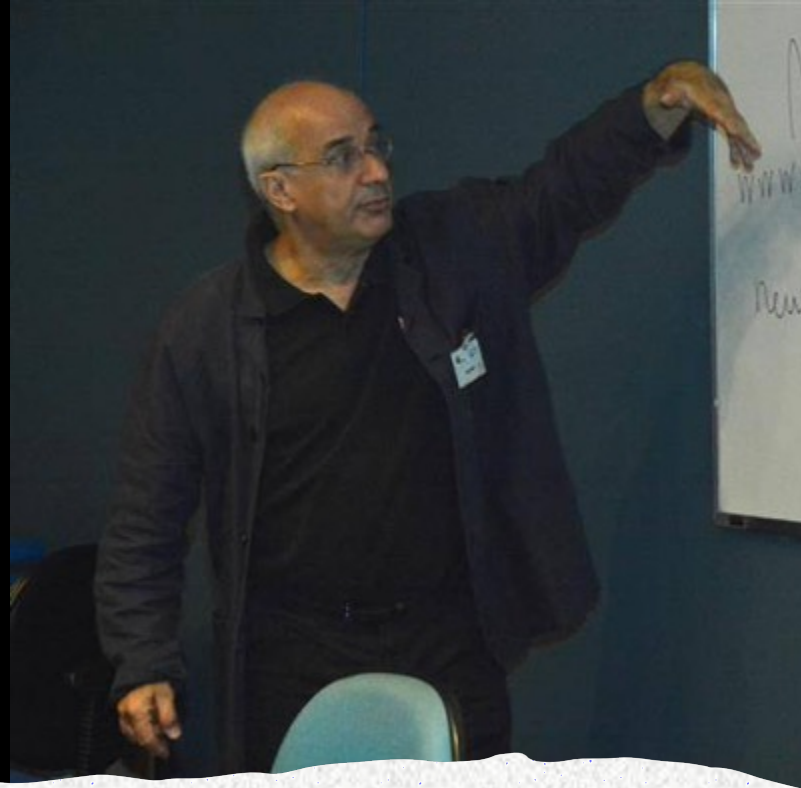
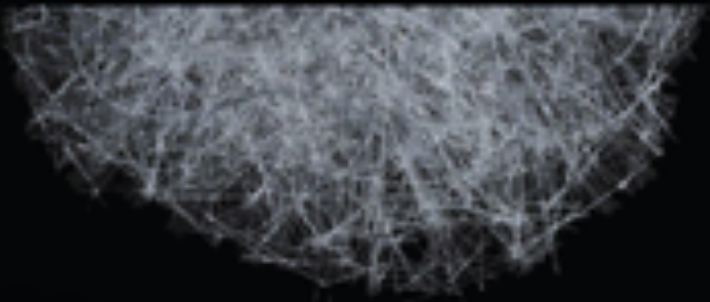
His inventiveness and scientific freedom often led him to walk through what he used to call “germanic forests”:

- In statistical physics and metastability
- In probability, working in stochastic chains with memory of variable length applied to linguistics and to neurobiological data.

Strong interdisciplinary drive

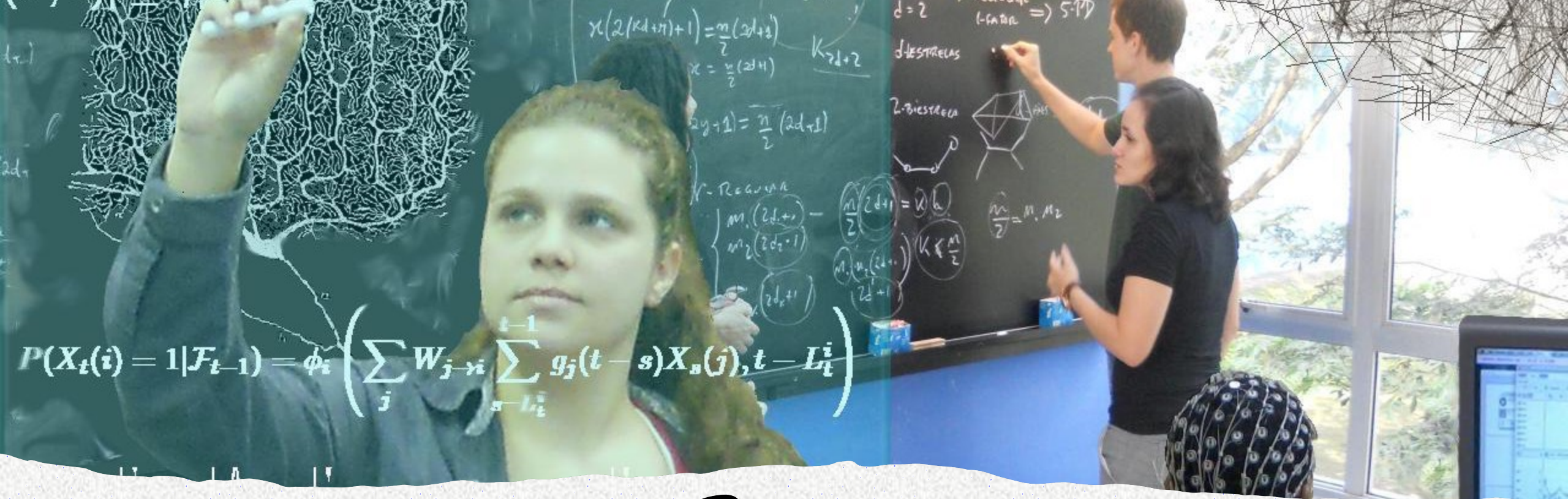


NeuroMat



Coordinator of the the Research, Innovation and Dissemination Center for Neuromathematics (RIDC NeuroMat), funded by FAPESP (2013-2023)

<https://neuromat.numec.prp.usp.br/>



- “A center of mathematics whose mission is to develop the new mathematics needed to construct a Theory of the Brain accounting for the experimental data gathered by neuroscience research”.

A photograph of an older man with white hair and glasses, wearing a light blue short-sleeved shirt and dark trousers, standing in profile and writing on a chalkboard. The chalkboard is filled with mathematical notations in white chalk, including $X_n \in A = \{$, (τ, p) , p , τ_n , and $F($. The scene is dimly lit, with a warm light source from the right illuminating the man's face and arm.

NeuroMat Main Research Lines

-
- Stochastic modeling of nets of spiking neurons
 - The Statistician Brain

Predicting means anticipating outcomes

“Unconscious inference”, by Helmholtz (1821 - 1894)



The Helmholtz' heritage

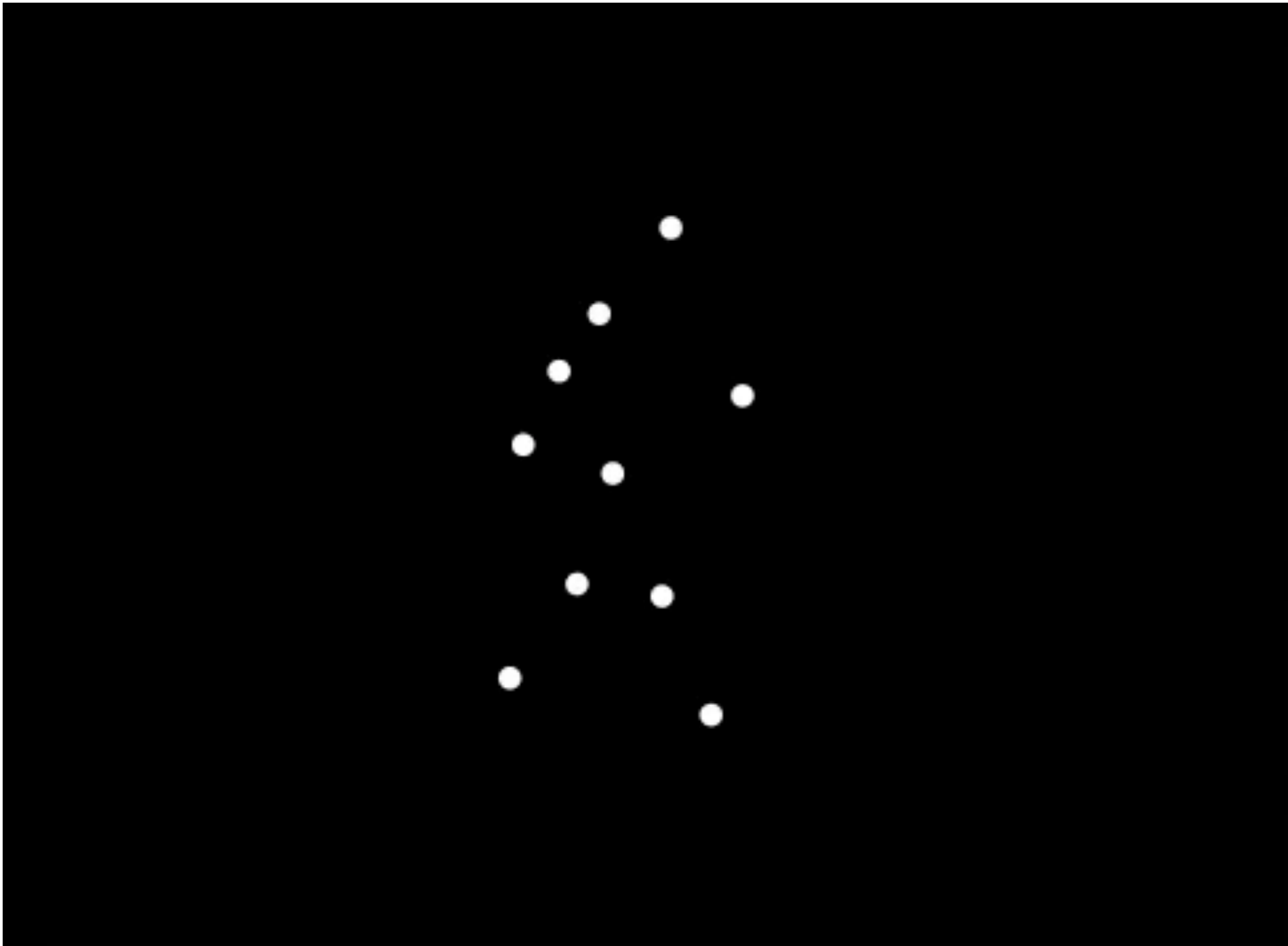
*Kawato et al., 1987; Jordan and Rumelhart, 1992; Jordan, 1995;
Wolpert et al., 1995; Miall and Wolpert, 1996; Wolpert, 1997; Shadmehr et
al., 1994, Friston et al., 2015, Deahene et al., 2014 and others.*

... Does the brain “infer” or assign probabilistic models to sequences of stimuli so as it learns how to act in the world?

How to approach this question experimentally?



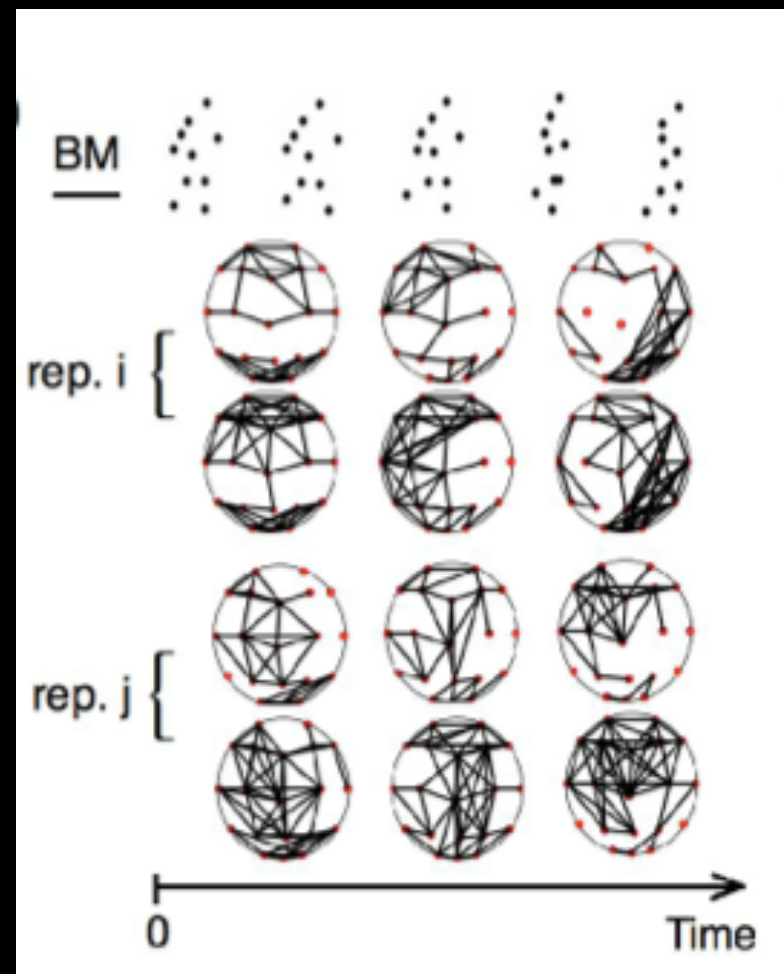
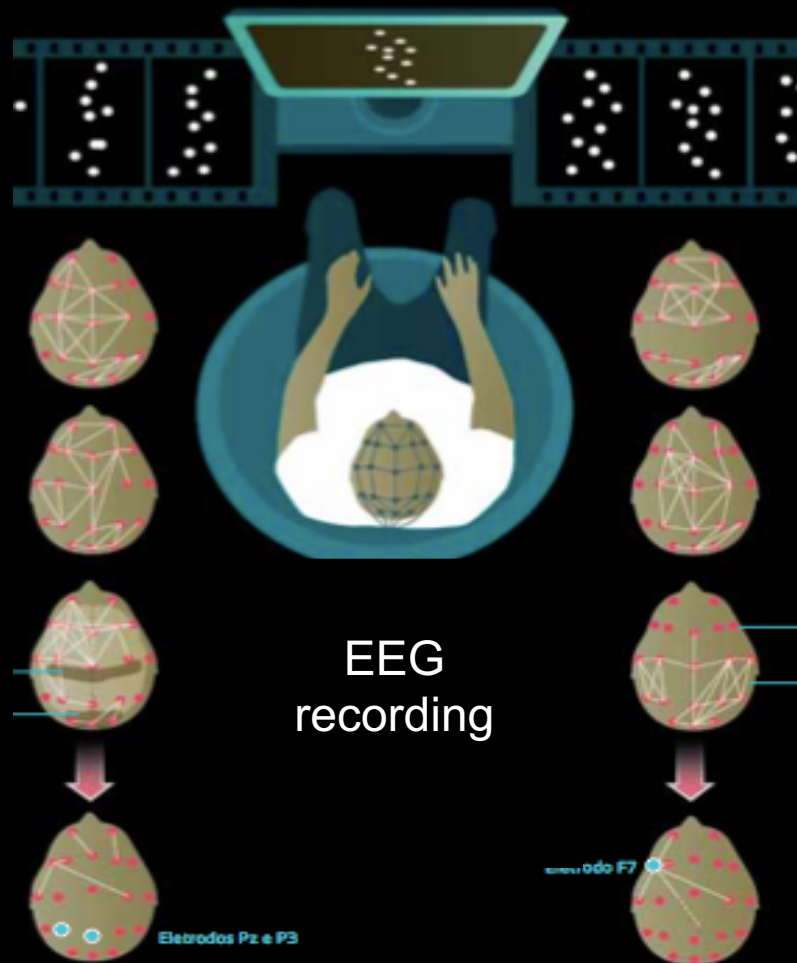
Fabiana Murer, world championship in pole vault

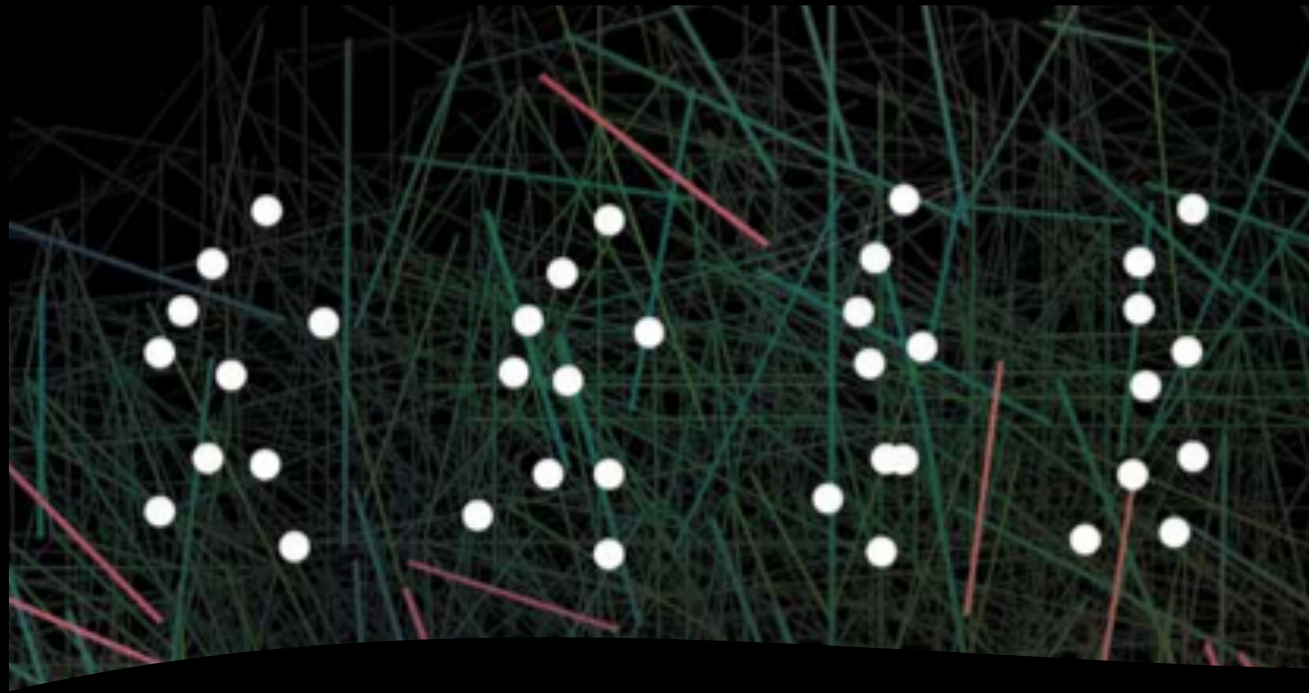


Biological Motion Coding in the Brain: Analysis of Visually Driven EEG Functional Networks

Daniel Fraiman^{1,2}, Ghislain Saunier^{3,4}, Eduardo F. Martins³, Claudia D. Vargas^{3*}

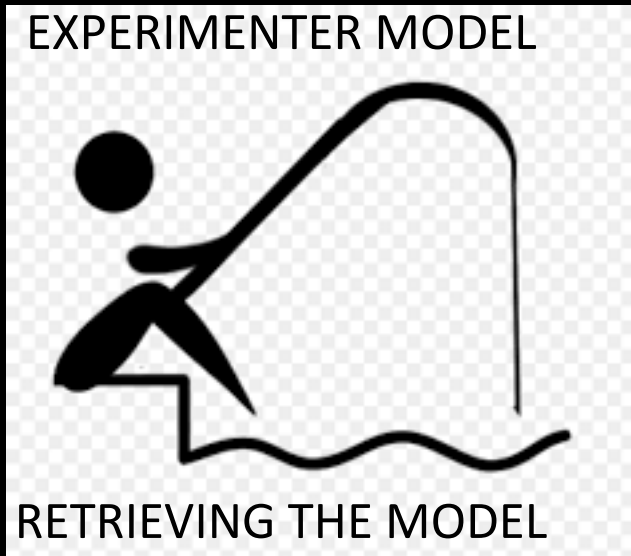
Graphs of interaction





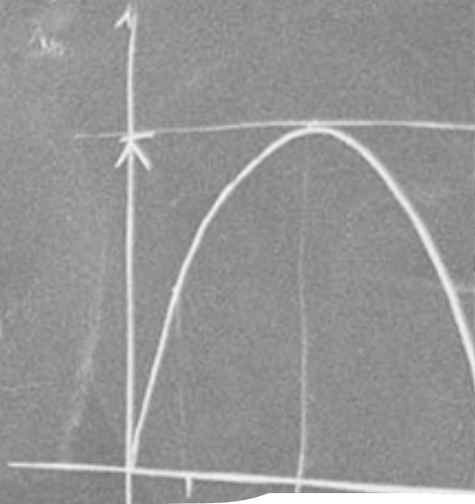
Open questions

- **HOW TO EXTRACT FROM BRAIN SIGNALS THE VERY STRUCTURE OF A SEQUENCE OF EVENTS?**
- **HOW TO ESTABLISH A FORMAL RELATIONSHIP BETWEEN THIS SEQUENCE OF EVENTS AND THE RECORDED SIGNALS?**





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



Universal Data Compression

JORMA RISSANEN

A data compression algorithm is described which is applicable to long strings generated by a "finitely generated" source. The algorithm achieves an optimum per symbol length without prior knowledge of the source. Sources may be viewed as a generalization of Markov chains. Moreover, the algorithm does not require a number of bits much larger than that needed to describe the source parameters.

1. INTRODUCTION

Universal data compression algorithms were first proposed for coding strings, generated by independent sources, with asymptotically optimum mean

data compression system. The concept of universal compressibility, the algorithm, and the limitations of the algorithm in a natural setting are discussed in Rissanen's Section II.

The main results in Sections III and V. After having introduced the algorithm and Lempel's universal algorithm, the importance of the algorithm is discussed.

A Universal data compression system

Jorma Rissanen, 1983

Context tree models: a class of stochastic models capable of compressing any sequence of symbols generated by a source

OPEN

Retrieving the structure of probabilistic sequences of auditory stimuli from EEG data

Noslen Hernández¹, Aline Duarte¹, Guilherme Ost², Ricardo Fraiman³, Antonio Galves¹ & Claudia D. Vargas⁴✉



Hand Claps

Strong beat 2 211211211211211211211211

Weak beat 1 211210211211211201210211

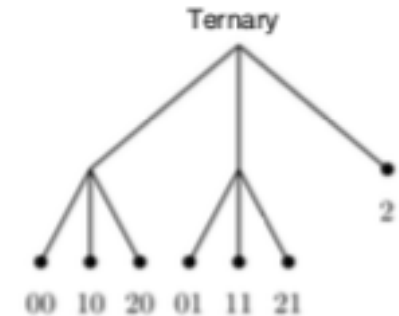
Silent unit 0

Replace symbol 1 by 0 with a probability E

(A) Sequence of auditory units



(B) Probabilistic Context Trees

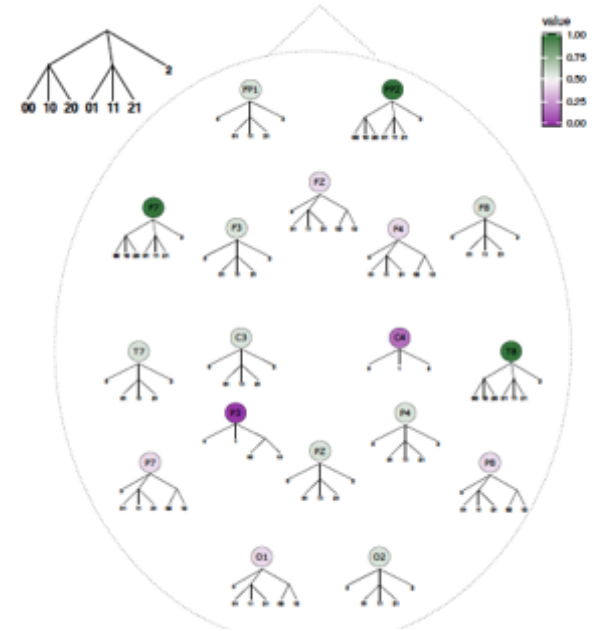


context w	P(0 w)	P(1 w)	P(2 w)
2	0.2	0.8	0
21	0.2	0.8	0
11	0	0	1
01	0	0	1
20	0.2	0.8	0
10	0	0	1
00	0	0	1

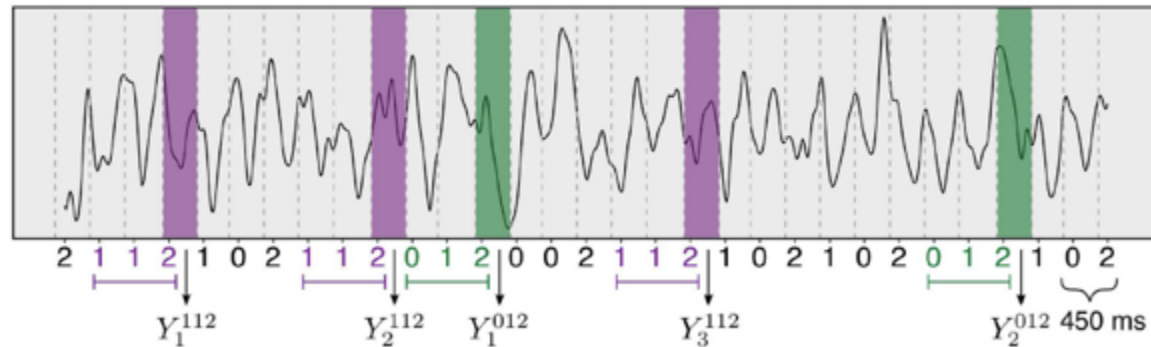
OPEN

Retrieving the structure of probabilistic sequences of auditory stimuli from EEG data

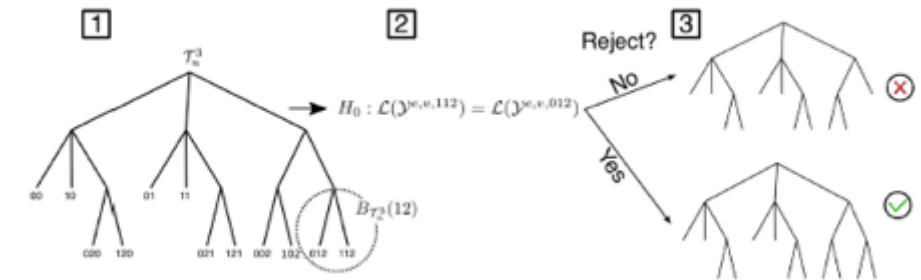
Noslen Hernández¹, Aline Duarte¹, Guilherme Ost², Ricardo Fraiman³, Antonio Galves¹ & Claudia D. Vargas⁴✉



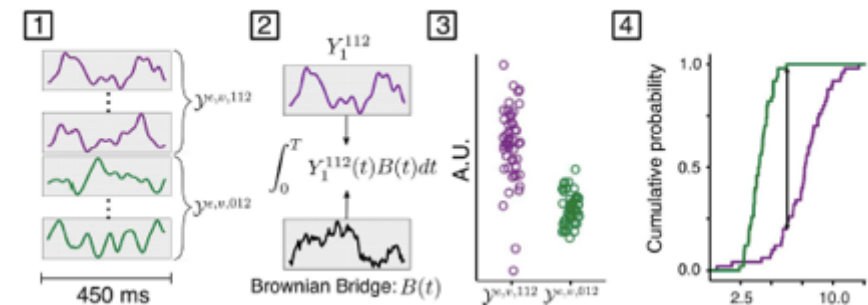
(A) Segmenting EEG according to stimuli

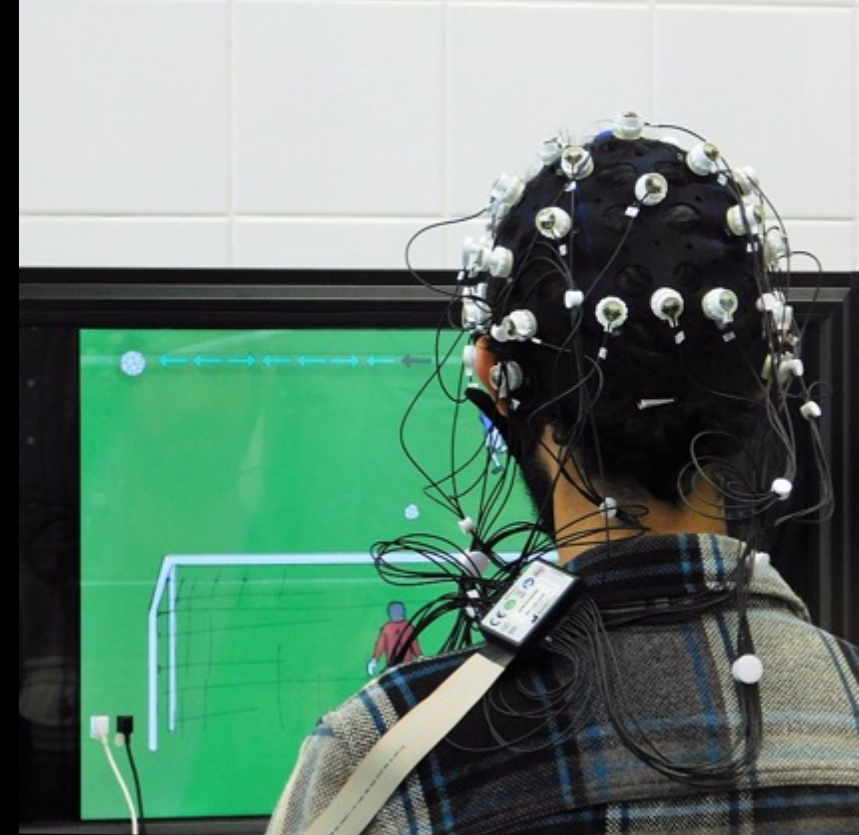


(B) Context tree pruning procedure



(C) Projective method to test the equality of laws of EEG segments





The Goalkeeper game

The dilemma of the goalkeeper at the penalty kick

Noslen Hernández¹, Antonio Galves², Jesus Garcia³, Marcos Dimas Gubitoso², and Claudia D. Vargas^{4,*}

Goalkeeper Game: A New Assessment Tool for Prediction of Gait Performance Under Complex Condition in People With Parkinson's Disease

Rafael B. Stern¹, Matheus Silva d'Alencar², Yanina L. Uscap³, Marco D. Gubitoso⁴, Antonio C. Roque⁵, André F. Helene³ and Maria Elisa Pimentel Piemonte^{2*}

WHAT COMES NEXT? RESPONSE TIME IS AFFECTED BY MISPREDICTION IN A STOCHASTIC GAME

Paulo Roberto Cabral-Passos¹, Jesus Enrique Garcia², Antonio Galves³, and Claudia D. Vargas^{4,*}

The dilemma of the goalkeeper at the penalty kick

Noslen Hernández¹, Antonio Galves², Jesus Garcia³, Marcos Dimas Gubitoso², and Claudia D. Vargas^{4,*}



Noslen Hernandez



Antonio Galves



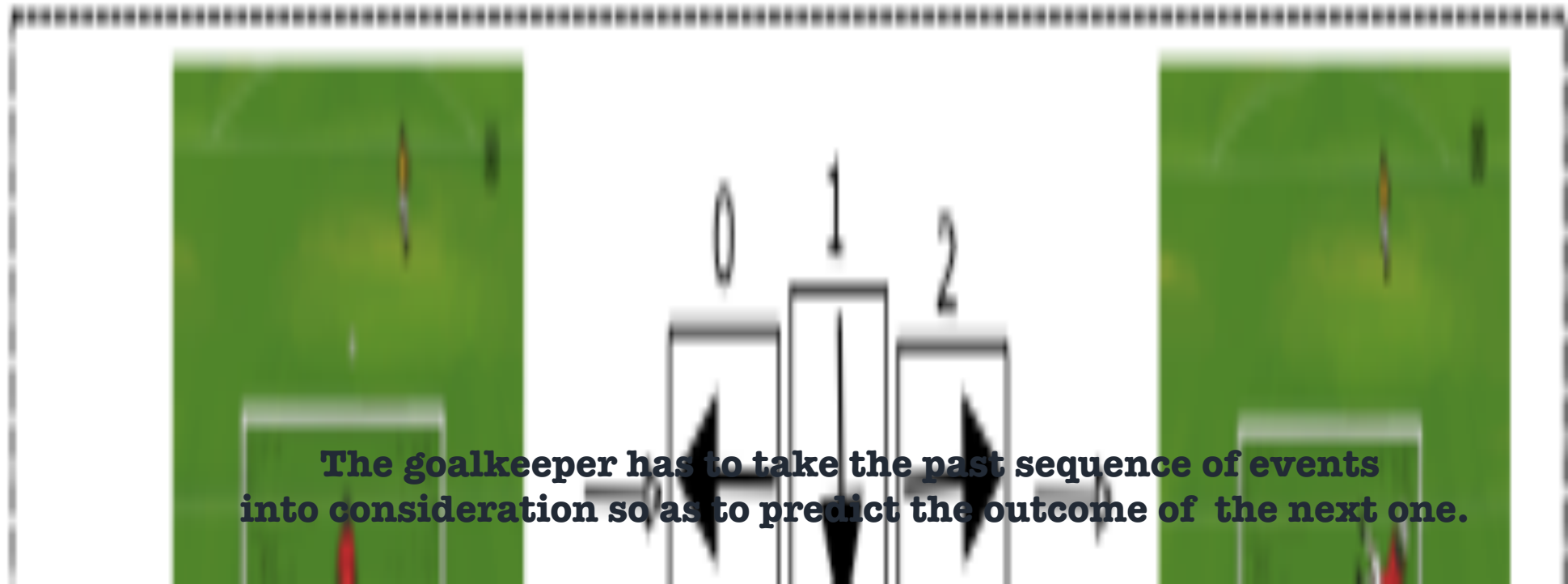
Jesus Garcia



Marcos Gubitoso



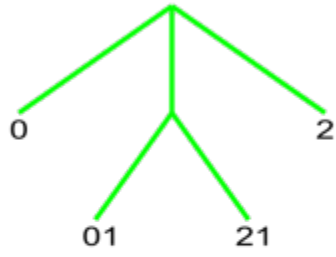
Modeling the learning process of a goalkeeper while he/she tries to guess successive choices displayed by the Game.



(<https://game.numec.prp.usp.br/>).

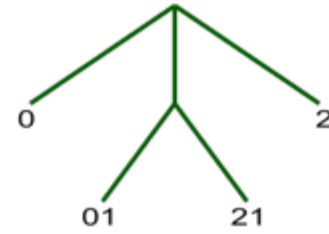
Which features dictate the context trees learning difficulty?

Entropy (H)



$$H = 0.65$$

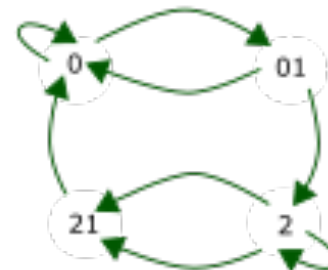
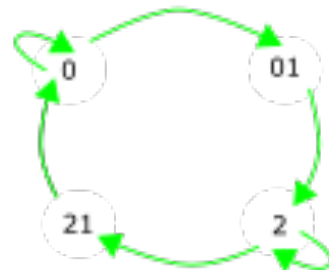
τ_1^k		$p_1^k(\cdot w)$		
		0	1	2
Context (w)	0	0.75	0.25	0
	01	0	0	1
	21	1	0	0
	2	0	0.25	0.75



$$H = 0.81$$

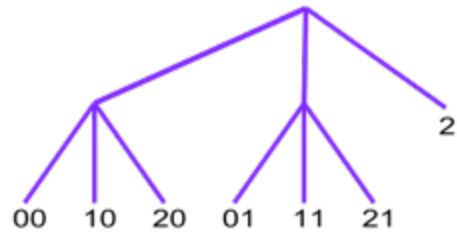
τ_2^k		$p_2^k(\cdot w)$		
		0	1	2
Context (w)	0	0.75	0.25	0
	01	0.25	0	0.75
	21	0.75	0	0.25
	2	0	0.25	0.75

2 2 2 2 2 2 1 0 0 1 2 2 2 2 2 1 0 0 0 0 0 0 1 2 2 2 2 1 0 0
 2 2 2 1 0 0 1 0 0 1 2 2 2 2 2 1 0 0 0 0 0 0 1 2 2 2 2 1 2 1



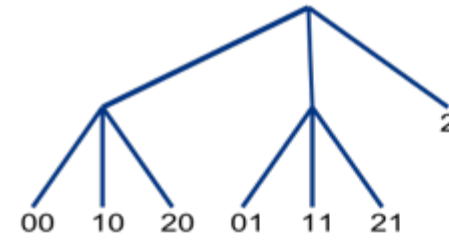
Which features dictate the context trees learning difficulty?

Periodicity



$H = 0.54$

τ_3^k		$p_3^k(\cdot w)$		
		0	1	2
Context (w)	00	0	0	1
	10	0	0	1
	20	0.25	0.75	0
	01	0	0	1
	11	0	0	1
	21	0.25	0.75	0
	2	0.25	0.75	0

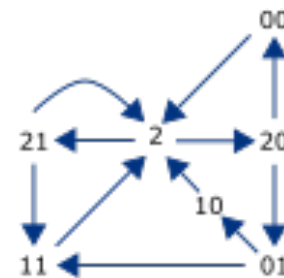
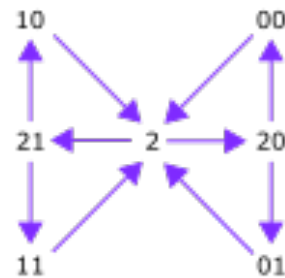


$H = 0.56$

τ_4^k		$p_4^k(\cdot w)$		
		0	1	2
Context (w)	00	0	0	1
	10	0	0	1
	20	0.25	0.75	0
	01	0.25	0.75	0
	11	0	0	1
	21	0	0	1
	2	0.75	0.25	0

2 1 1 2 1 1 2 0 1 2 1 0 2 1 1 2 1 1 2 1 1 2 0 1 2 0 0 2

0 1 1 2 0 1 1 2 0 1 1 2 0 1 1 2 0 1 1 2 1 2 1 2 1 2 0 1



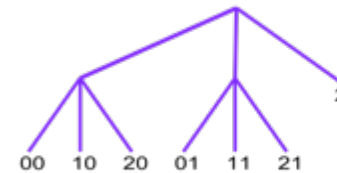
Is it true that

- 1) The context tree model with higher entropy would be more difficult to learn as compared with that of lower entropy?
- 2) The context tree model that displays a periodic structure would be easier to learn?
- 3) Augmenting the number of contexts would increase the learning difficulty?



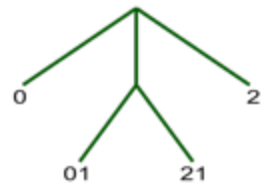
$$H = 0.65$$

τ_1^k		$p_1^k(\cdot w)$		
		0	1	2
Context (w)	0	0.75	0.25	0
	01	0	0	1
	21	1	0	0
	2	0	0.25	0.75



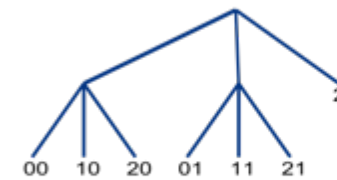
$$H = 0.54$$

τ_3^k		$p_3^k(\cdot w)$		
		0	1	2
Context (w)	00	0	0	1
	10	0	0	1
	20	0.25	0.75	0
	01	0	0	1
	11	0	0	1
	21	0.25	0.75	0
	2	0.25	0.75	0



$$H = 0.81$$

τ_2^k		$p_2^k(\cdot w)$		
		0	1	2
Context (w)	0	0.75	0.25	0
	01	0.25	0	0.75
	21	0.75	0	0.25
	2	0	0.25	0.75



$$H = 0.56$$

τ_4^k		$p_4^k(\cdot w)$		
		0	1	2
Context (w)	00	0	0	1
	10	0	0	1
	20	0.25	0.75	0
	01	0.25	0.75	0
	11	0	0	1
	21	0	0	1
	2	0.75	0.25	0

Time evolution of the performance per context tree: raw data

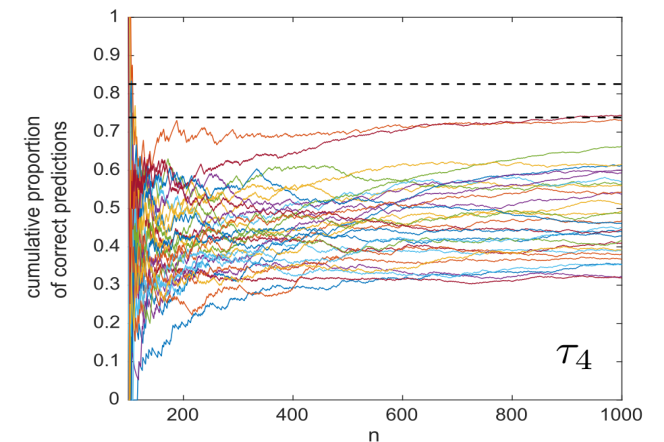
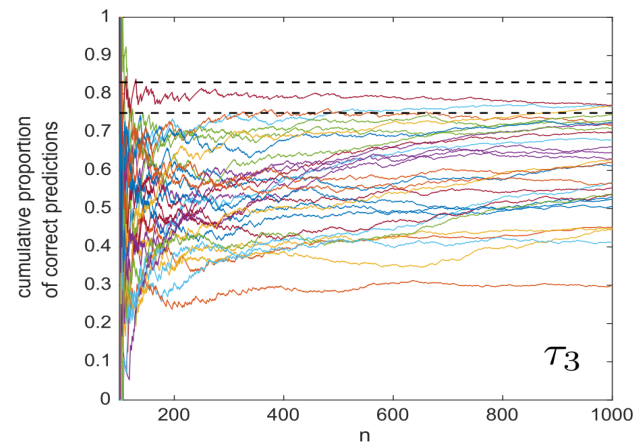
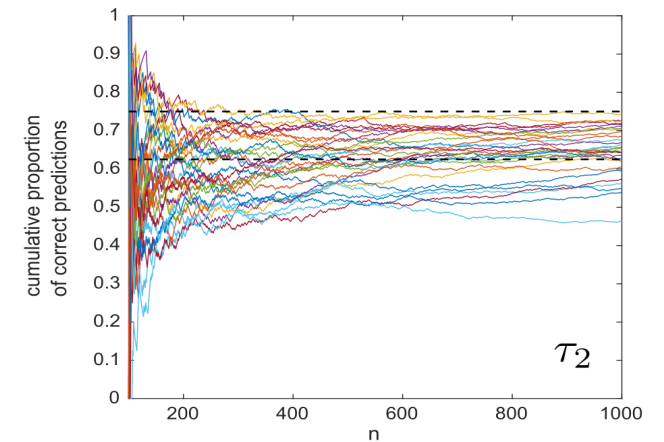
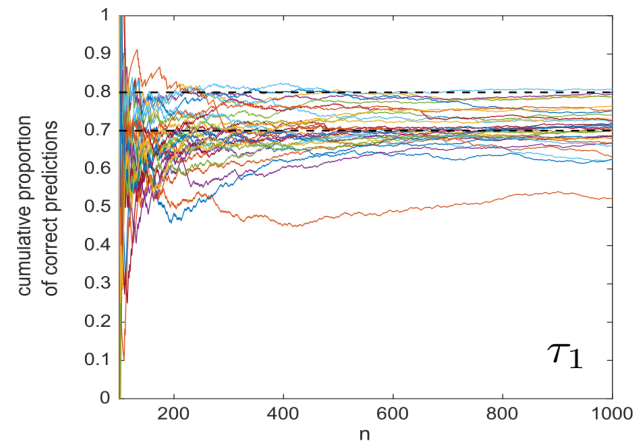
Data collection

122 participants were recruited (60 females).

Each participant played a thousand trials of one out of the four context trees.

Data collection was performed remotely during the COVID 19 pandemics and response choices were stored for posterior analysis.

Cumulative proportion of correct predictions across trials

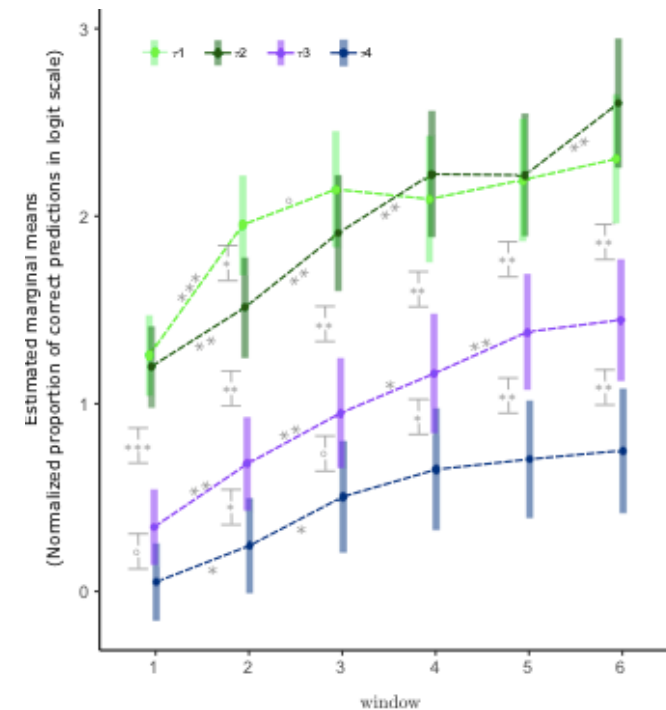
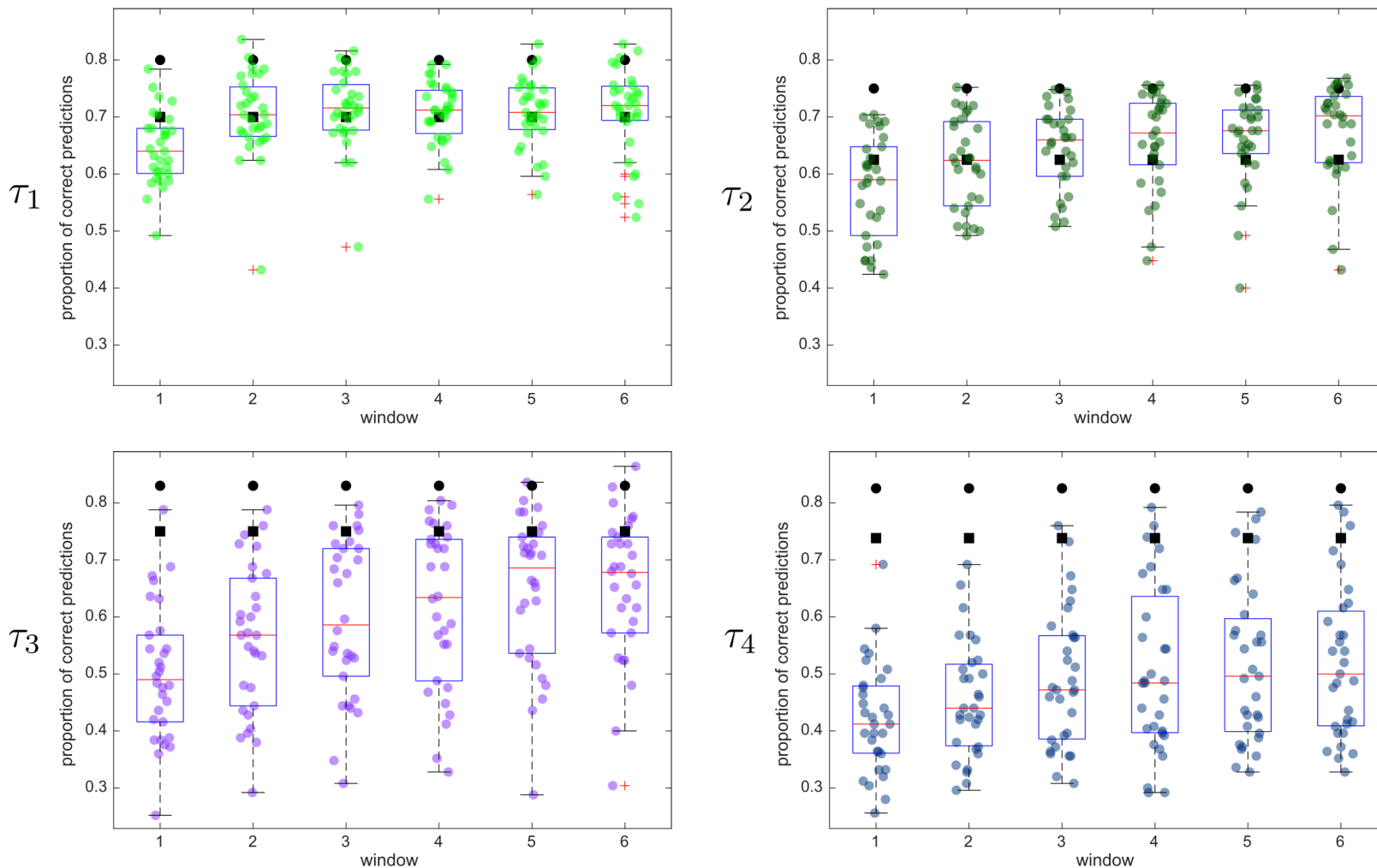


Maximizing: the participant would always choose the outcome with higher probability

Matching: the participant would try to emulate the selection procedure used to generate the sequence

Time evolution of the performance per context tree: windows of analysis

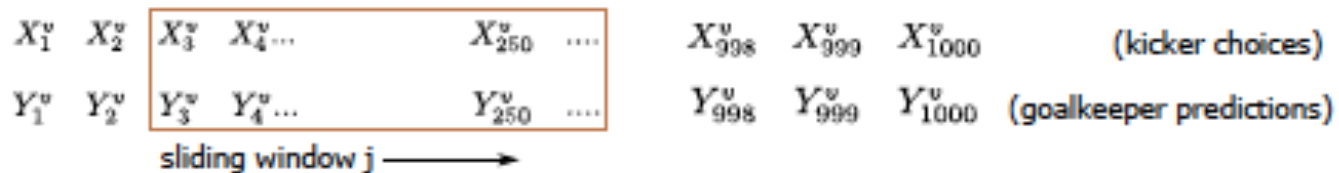
(B) Distributions of the proportion of correct predictions per time window



Two way mixed ANOVA indicated differences across Windows and between context trees.

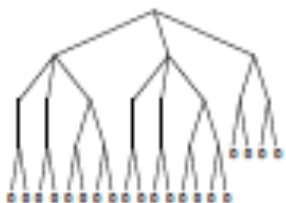
Estimating a context tree per window of analysis per goalkeeper

(A) Sequence of kicker choices and the corresponding sequence of goalkeeper predictions for a given participant v

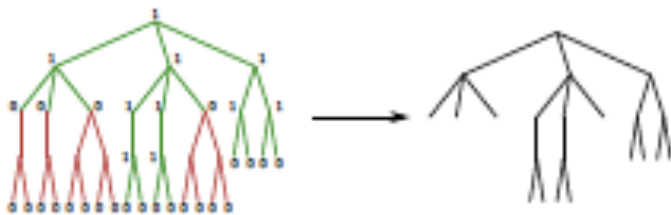


(B) Context tree estimation inside one window

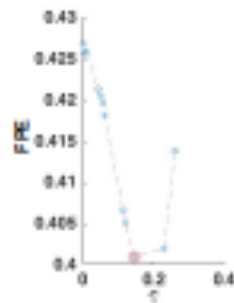
1 Admissible context tree of maximal height 4 (\mathcal{T}_n^4)



2 Pruning based on indicators

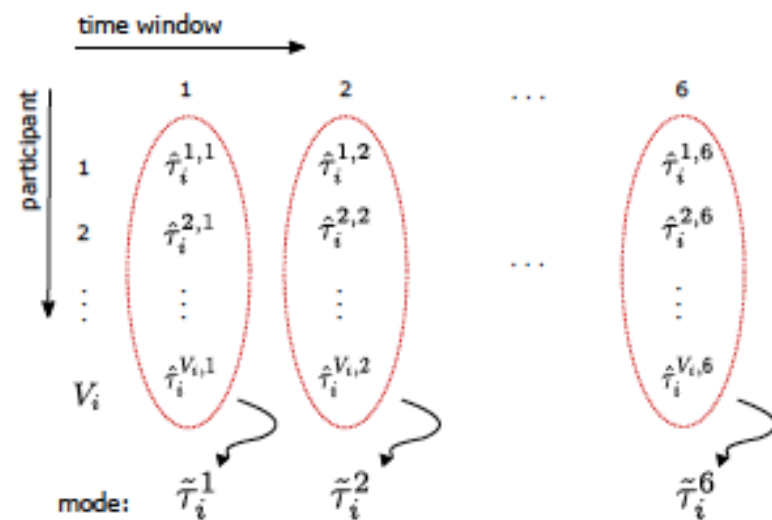


3 Selection of the penalty constant (c) value



$(\hat{\tau}_i^{v,j}, \hat{q}_i^{v,j})$

(C) Mode Context tree



Time evolution of context tree learning

Window of analysis



Highlights

Context trees τ_1 and τ_2 are identified as early as in the first window of analysis.

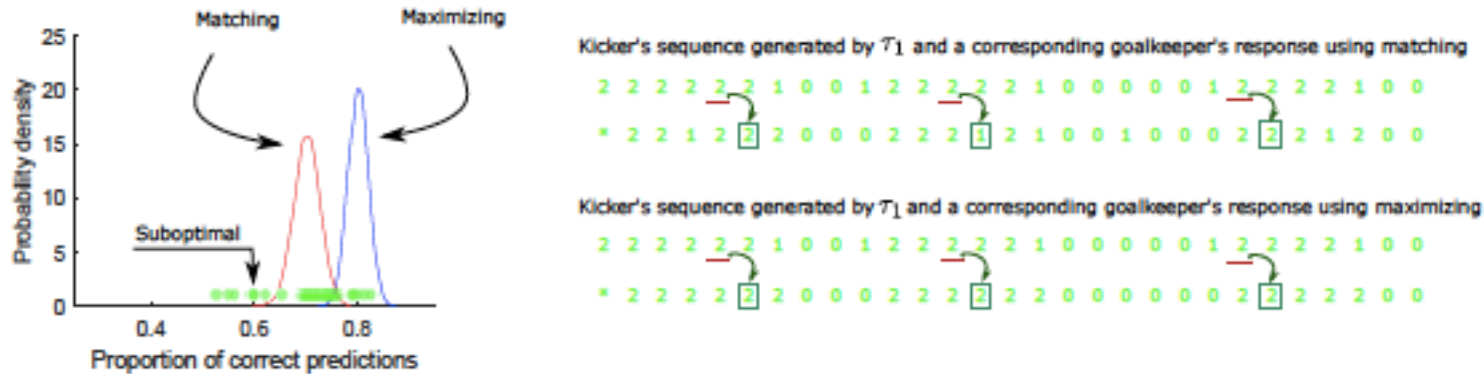
For context tree τ_3 , the mode context tree of the goalkeeper matches that of the kicker from the third window of analysis on.

For context tree τ_4 , the mode context tree of the goalkeeper matches that of the kicker from the fourth window of analysis on.

High fluctuations in the proportion of leaves identified for context trees τ_3 and τ_4 suggest that participants keep trying to guess throughout time.

Proportion of correct predictions x number of correct contexts

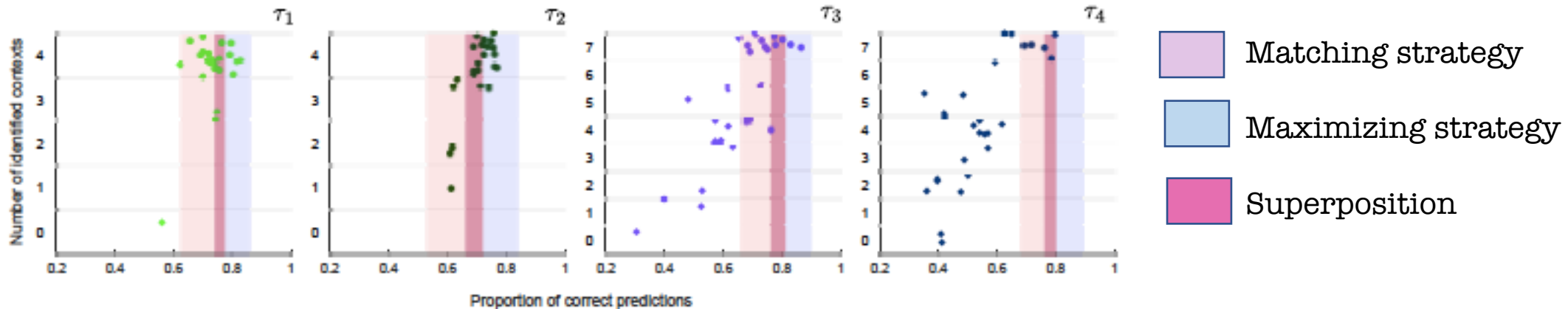
(A) Estimation of the density of each strategy



Matching : the goalkeeper would try to emulate the selection procedure used to generate the sequence

Maximizing: the goalkeeper would always choose the outcome with higher probability

(C) Context identification under each strategy per context tree model



1) While most goalkeepers of context trees 1 and 2 achieve the matching and the maximizing strategies, much less goalkeepers achieve these strategies for context trees 3 and 4.

2) To achieve a strategy, the goalkeeper must first learn the contexts.

In conclusion,

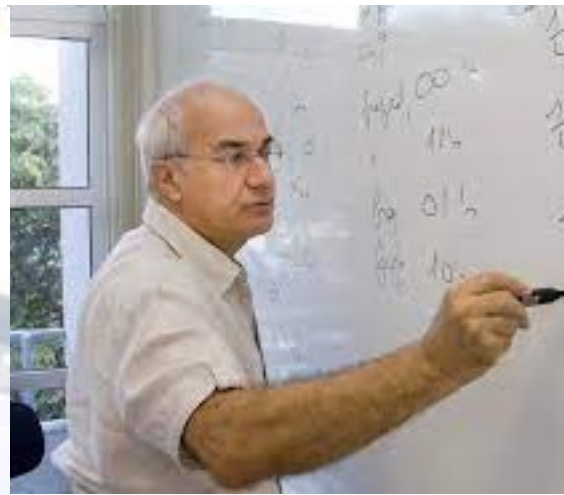
- Our results show that entropy alone does not give an accurate indication of the learning difficulty across context tree models.
- Furthermore, **breaking up the periodic structure** of a stochastic sequence of events makes it much more difficult to learn.
- In learning structures sequences of stochastic events, one must first learn the contexts and then choose a strategy to keep going.

OPEN Response times are affected by mispredictions in a stochastic game

Paulo Roberto Cabral-Passos¹, Antonio Galves², Jesus Enrique Garcia³ & Claudia D. Vargas^{4,5}



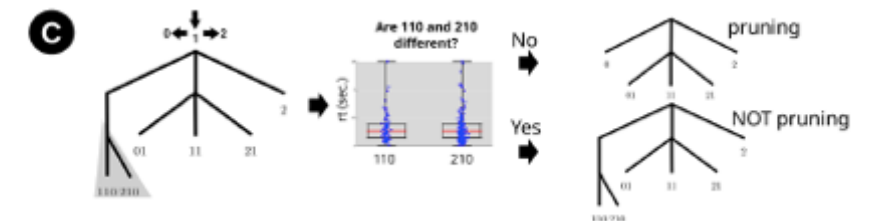
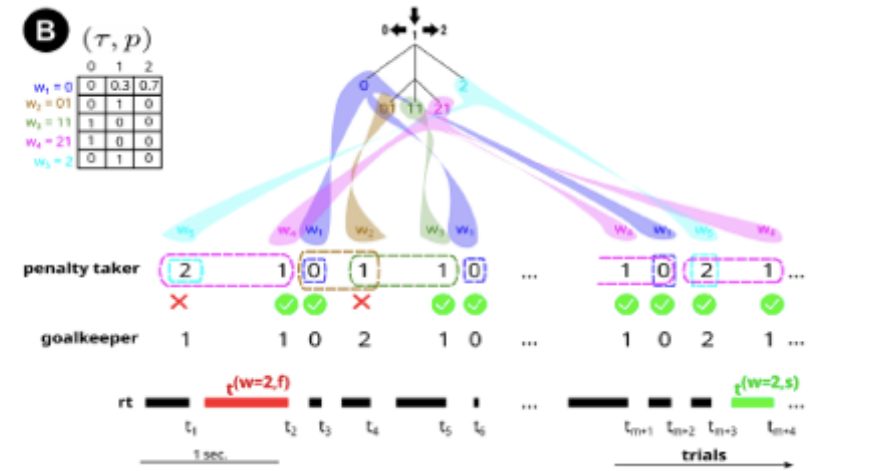
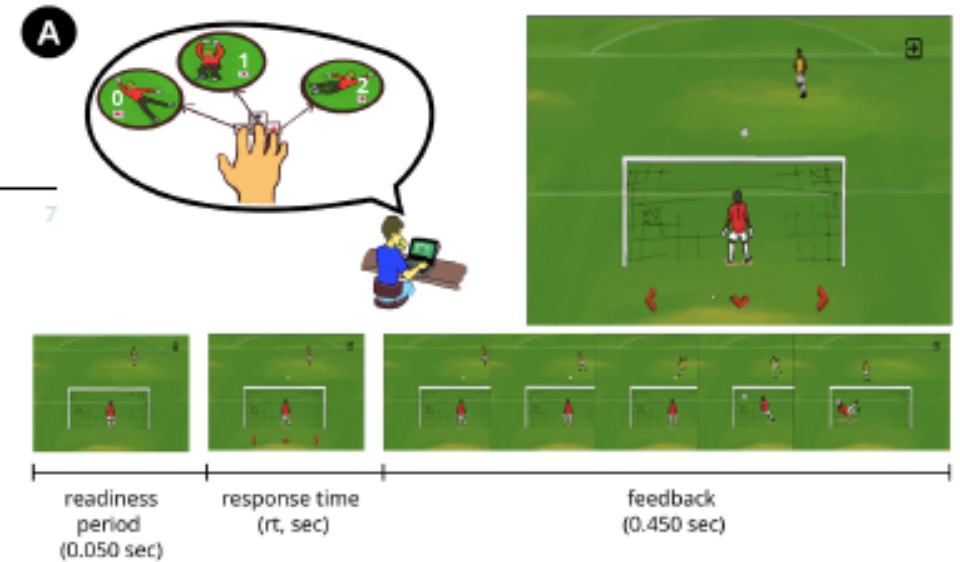
Paulo Passos



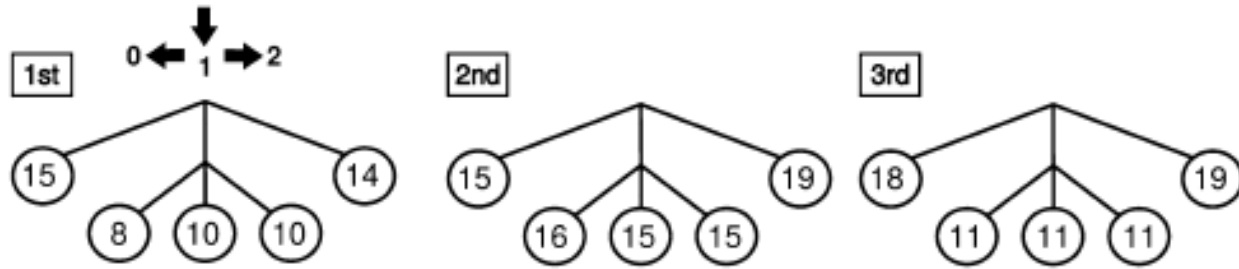
Antonio Galves



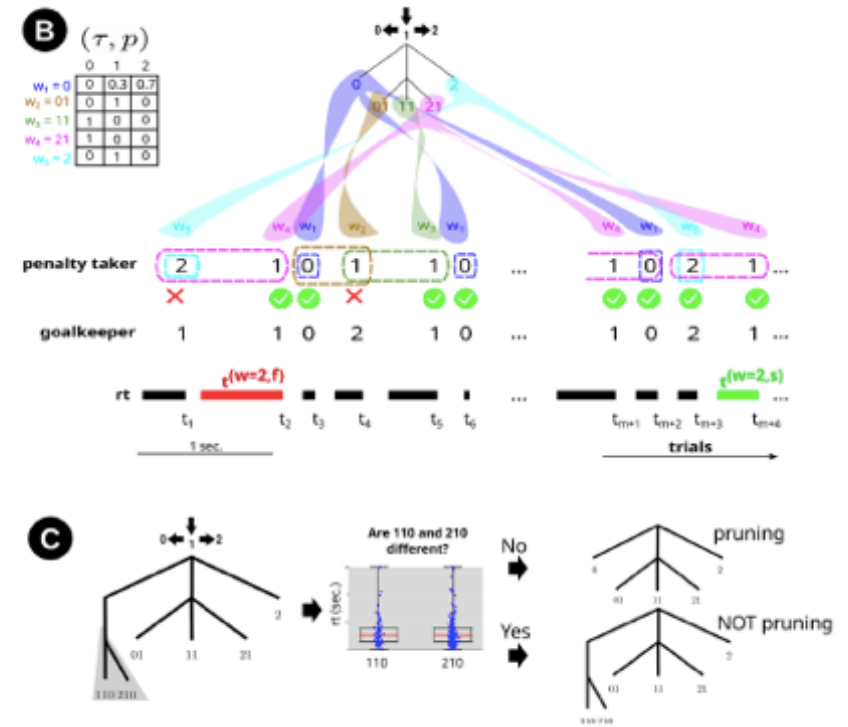
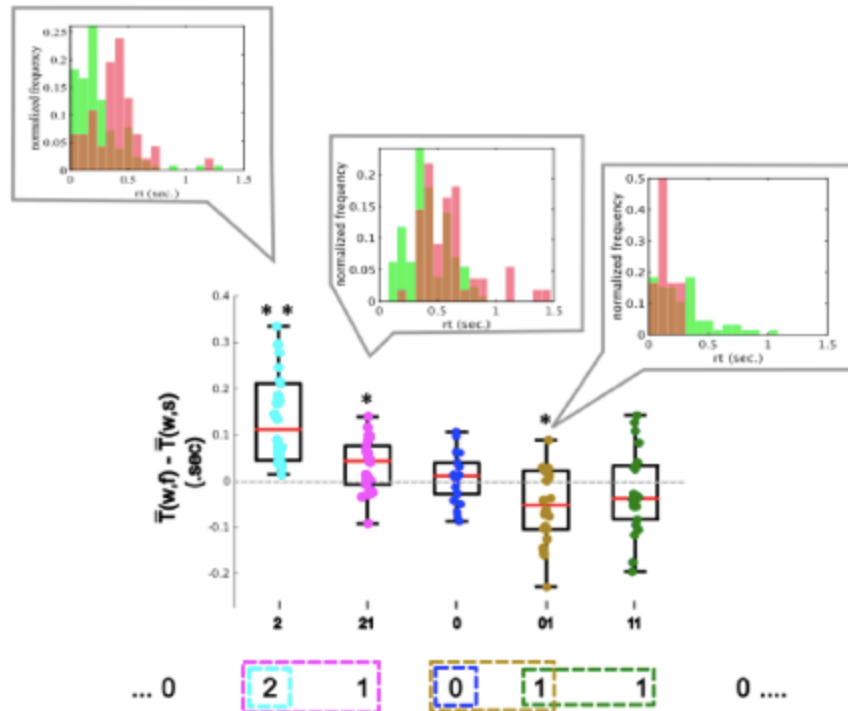
Jesus Garcia



Retrieving context tree models from response times per epoch



1) A lower number of goalkeepers have correctly identified the contexts 01, 11 and 21 at the third window of analysis.



2) Slower response times occur after incorrect x correct responses for contexts 2 and 21; the inverse occurs for context 01.

In conclusion II,

- Our results show that entropy alone does not give an accurate indication of the learning difficulty across context tree models.
- Furthermore, breaking up the periodic structure of a stochastic sequence of events makes it much more difficult to learn.
- In learning structures sequences of stochastic events, one must first learn the contexts and then choose a strategy to keep going
- In stochastic sequence learning, response times are affected by the result of previous choices .

Work in progress...

EVALUATING THE PREDICTIVE CAPACITY OF INDIVIDUALS WITH TRAUMATIC BRACHIAL PLEXUS INJURY USING THE GOALKEEPER GAME

Bia L. Ramalho, Pedro R. Pinheiro, Paulo R.C. Passos, Vinicius V. Maria , Antonio Galves,
Claudia D. Vargas



Scientific dissemination “directly from the battlefield”

<https://neuromat.numec.prp.usp.br/>

- **Podcasts, radiocasts**
- **Dissemination texts**
- **Booklets**
- **videos**



With Eduardo Vicente, from <https://podcast.numec.prp.usp.br/>

The Statistician Brain, with the Parece Cinema team, 2014

<https://www.youtube.com/watch?v=WbJa27ksUjY>





- With Christophe Pouzat and Marcus Diesmann, Pablo Ferrari, Leo Cohen

Antonio Galves was a very cultivated and humanistic fellow.
Also, a warm and cherishing person.

We miss him so much.