Joint models of M/EEG and behavior to understand *cognition*

Unlocking New Horizons in Cognitive Modeling
with Simulation-Based Inference 2026

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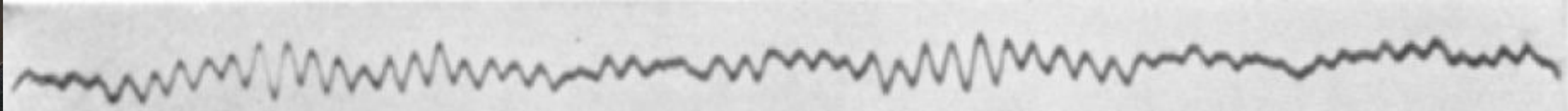
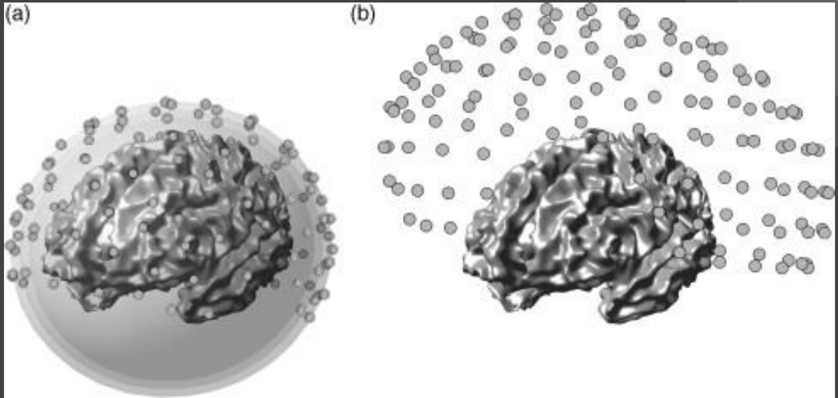
EEG



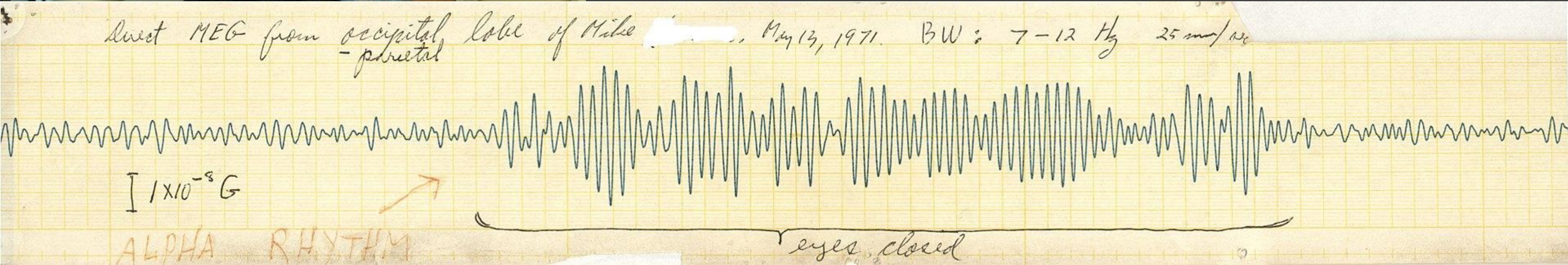
EEG

- **Electro-encephalo** *(Greek: "brain")*-**graphy (EEG)** is the measurement of the electric potentials on the **scalp** surface generated **(in part)** by neural activity originating from the brain

MEG



(a)
(b)



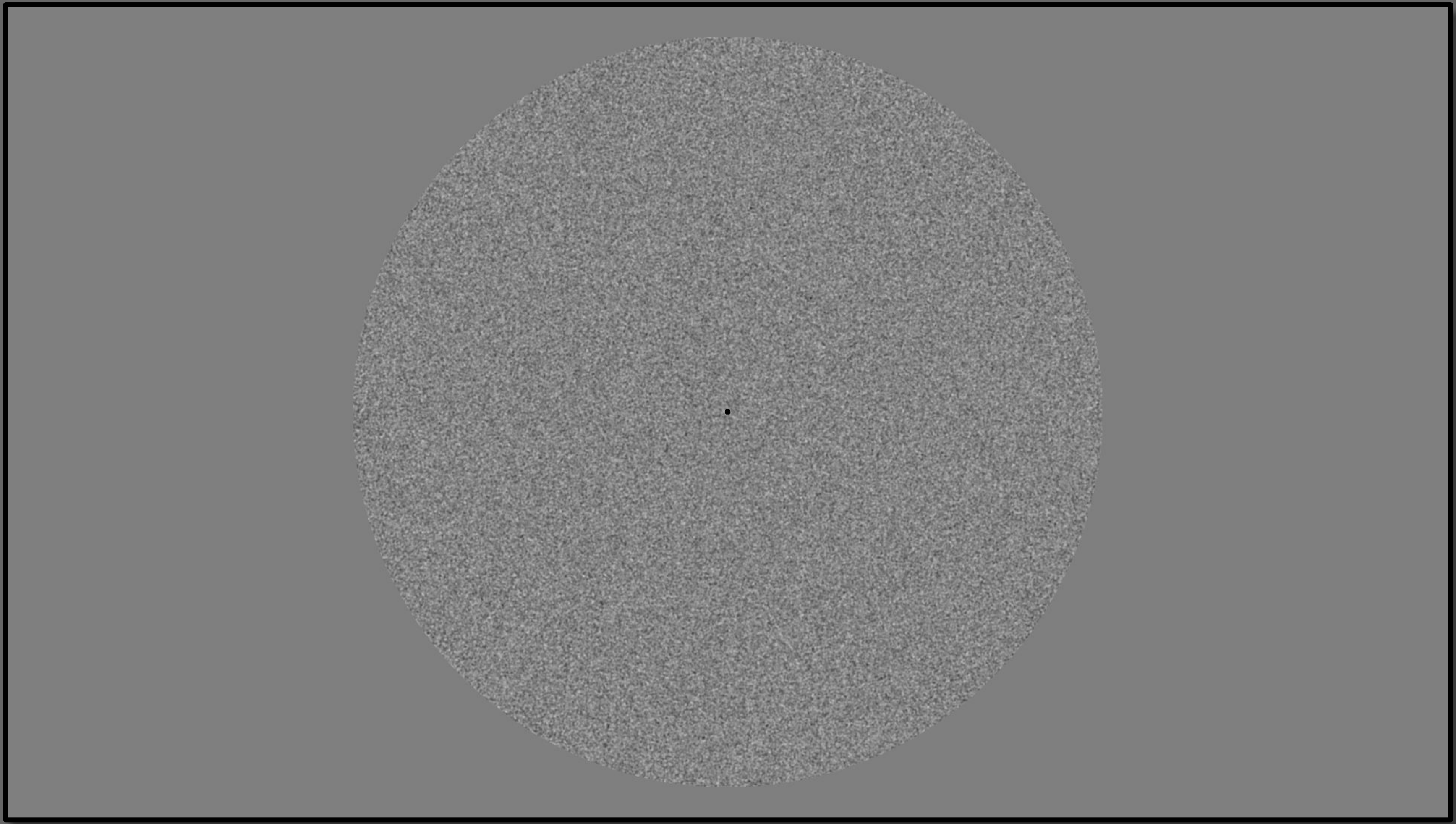
Direct MEG from occipital lobe of Mike
- parietal
May 13, 1971. BW: 7 - 12 Hz 25 mm/se
1 X10^-8 G
ALPHA RHYTHM
eyes closed

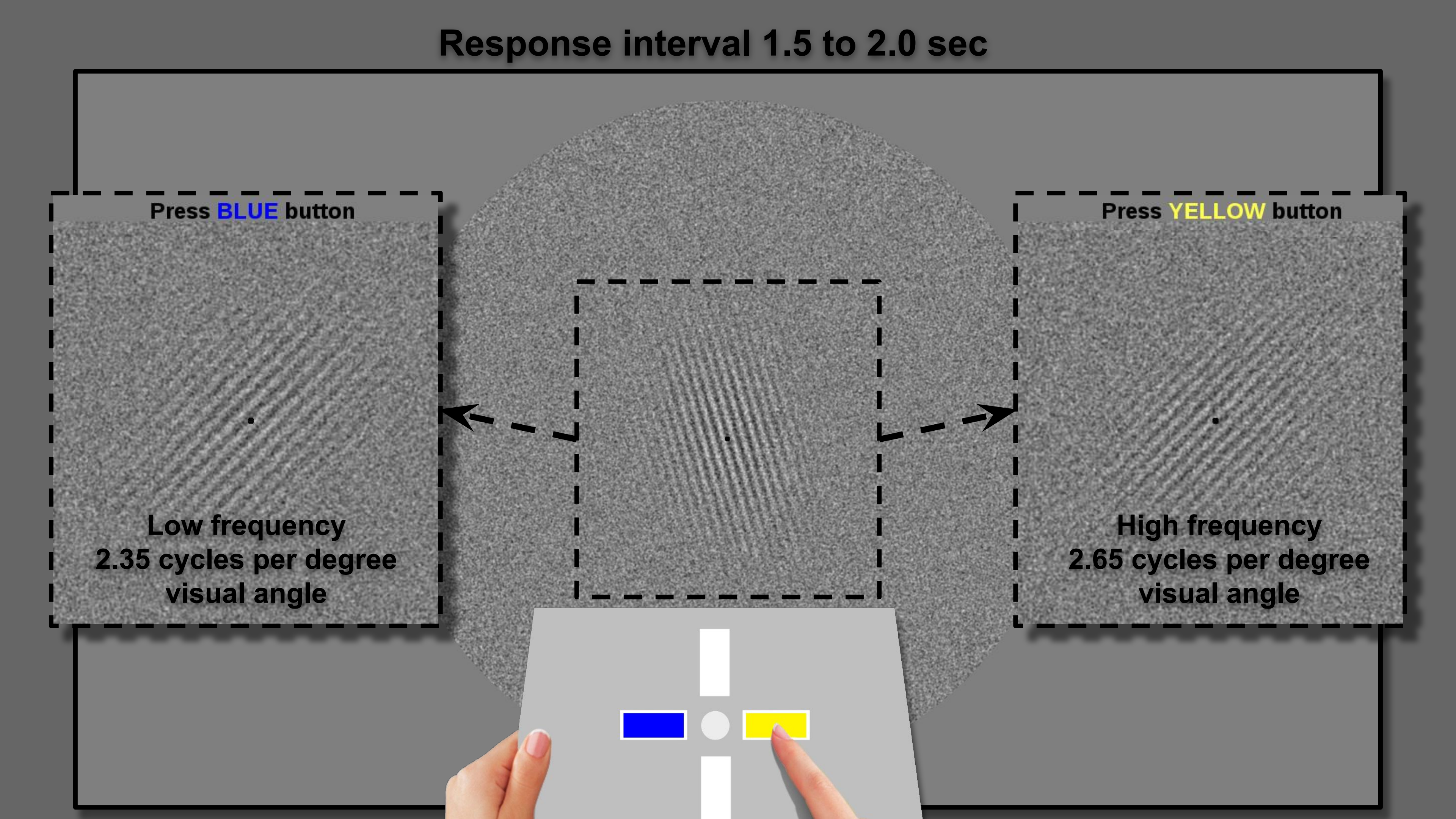
MEG

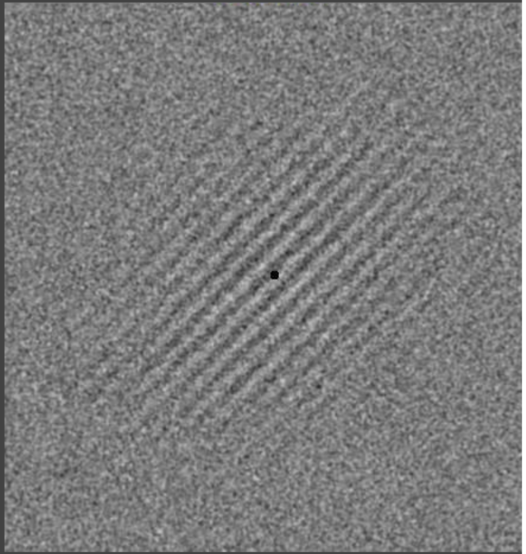
- **Magneto-encephalo** *(Greek: "brain")*-**graphy (MEG)** is the measurement of the **magnetic fields** produced by electrical currents generated **(in part)** by neural activity originating from the brain

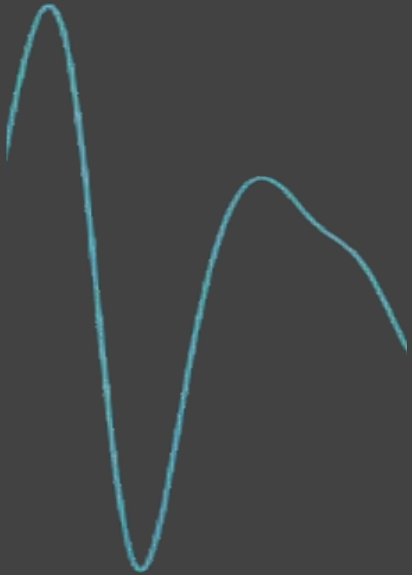
E Boto *et al. Nature* **555**, 657–661 (2018) doi:10.1038/nature26147

Cue interval 0.5 to 1.0 sec

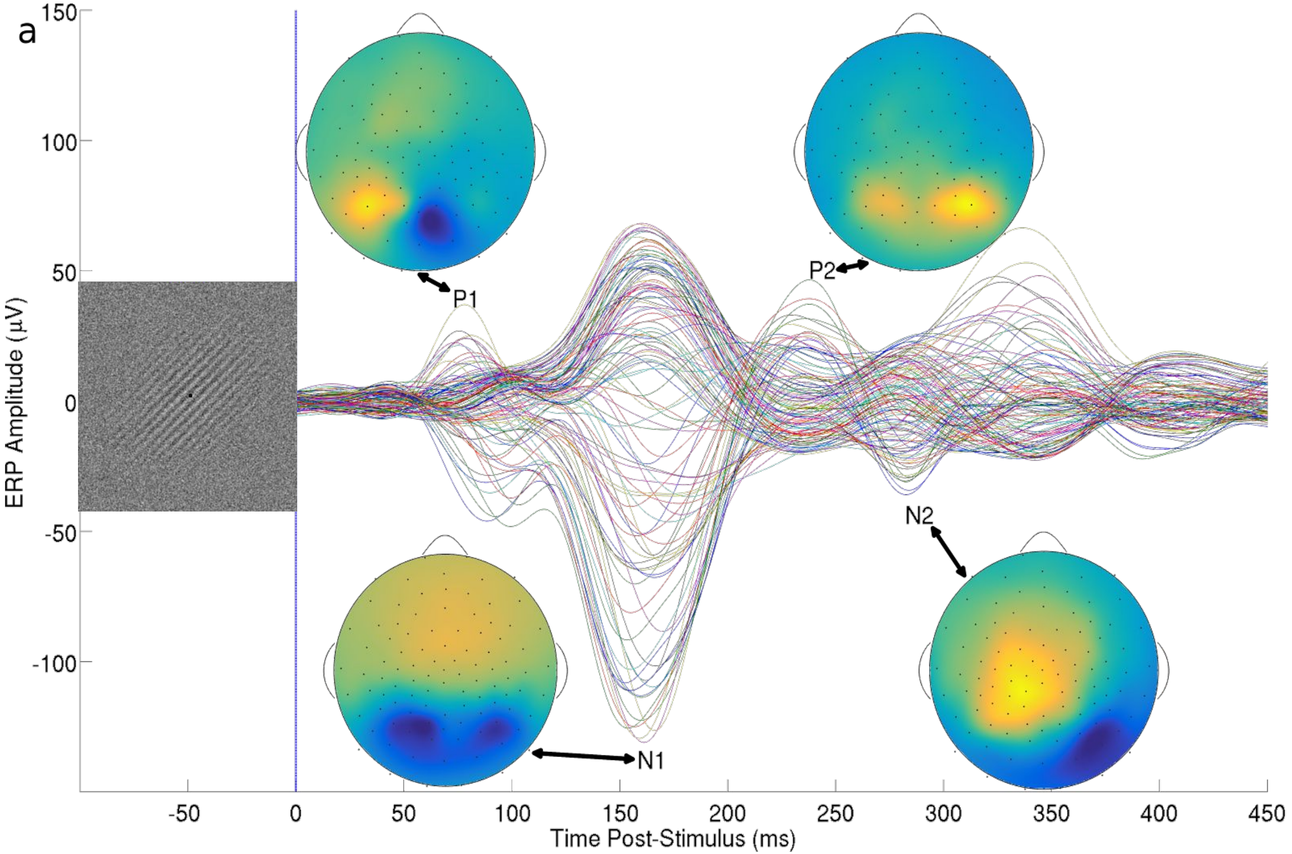



Response interval 1.5 to 2.0 sec
Press BLUE button
Low frequency
2.35 cycles per degree
visual angle
Press YELLOW button
High frequency
2.65 cycles per degree
visual angle





Event-Related Potentials (ERPs)



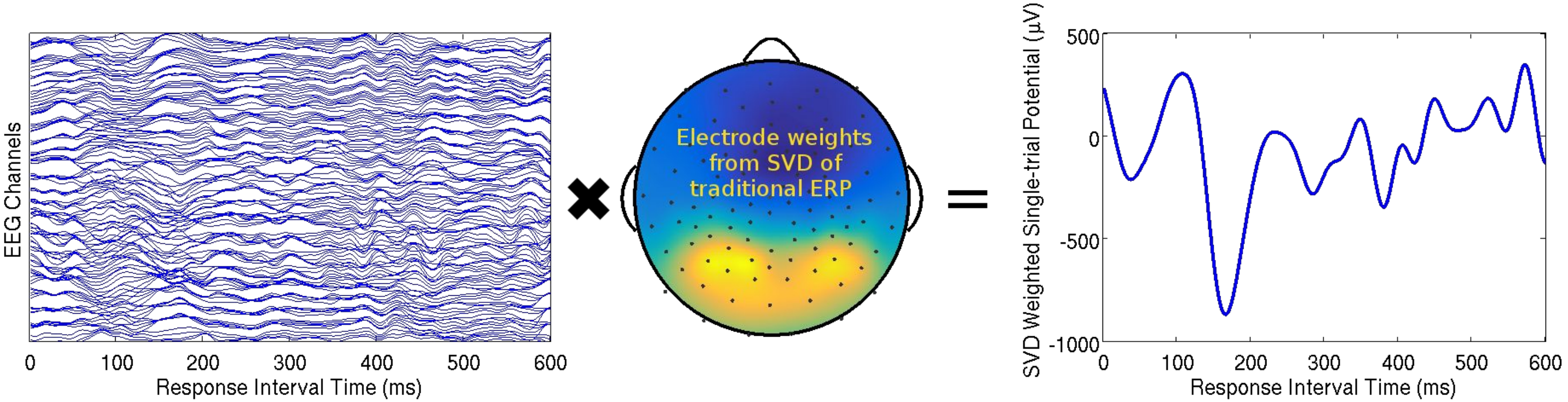
$$\mu(t) = \frac{1}{K}\sum_{k=1}^{K} V_k(t)$$

The time-varying mean over K trials of EEG following an experimental stimulus.

Nunez, M. D. , Nunez, P. L., & Srinivasan, R. (2016) Electroencephalography (EEG), neurophysics, experimental methods, and signal processing

Single-trial ERPs with Singular Value Decomposition (SVD)

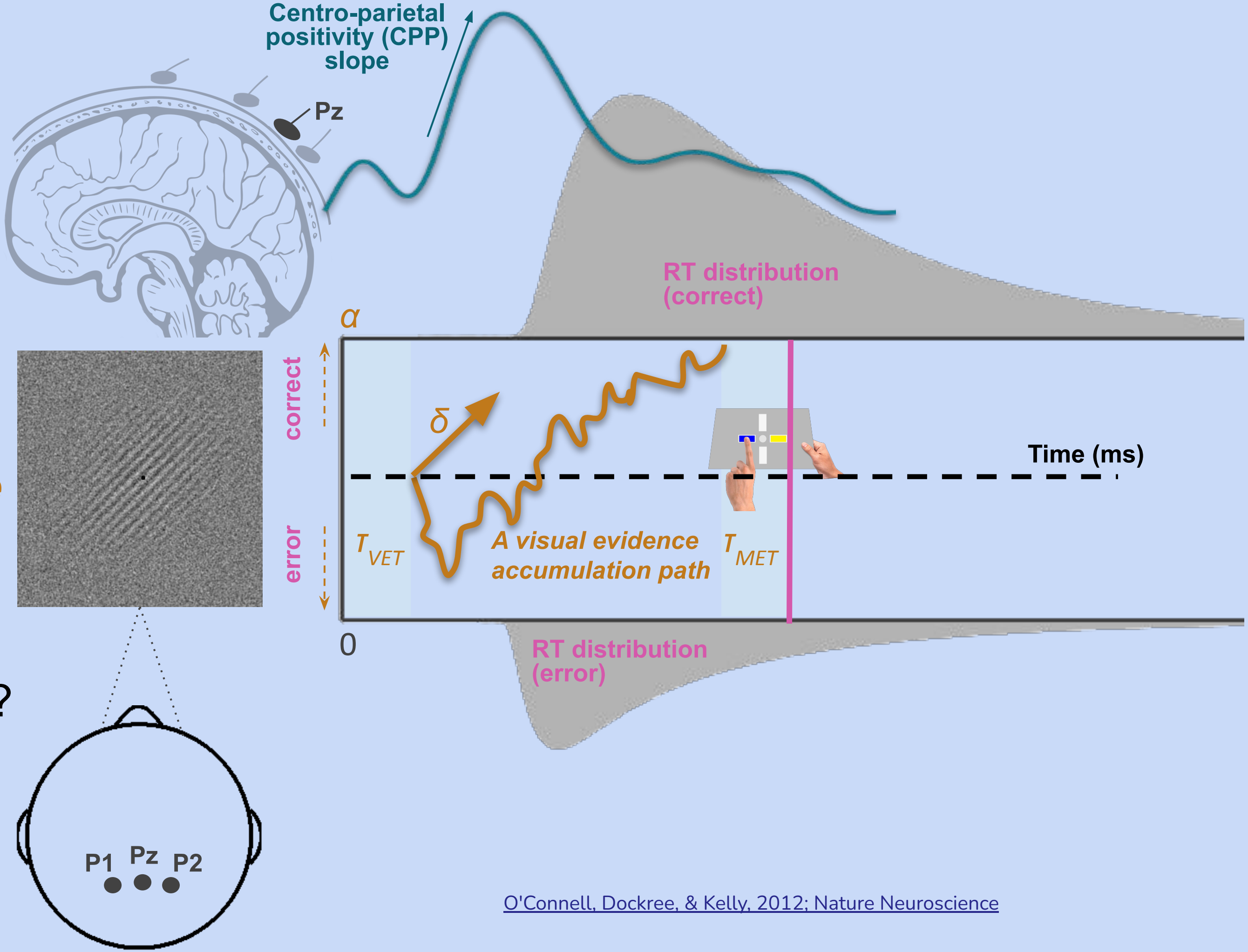
Essentially: Principal Component Analysis (PCA) on traditional ERP data with resultant channel weights applied on each trial



[Click here for example Python script]()
(simple SVD method starting line 189)

[Nunez, M. D. , Vandekerckhove, J., & Srinivasan, R. (2017). How attention influences perceptual decision making: Single-trial EEG correlates of drift-diffusion model parameters.]()

Do the **centro-parietal positivity (CPP) slopes** reflect ***visual evidence accumulation paths*** that describe **response times**?



O'Connell, Dockree, & Kelly, 2012; Nature Neuroscience

Behavior Research Methods
https://doi.org/10.3758/s13428-023-02331-x

ORIGINAL MANUSCRIPT

A tutorial on fitting joint models of M/EEG and behavior to understand cognition

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Accepted: 21 December 2023

Abstract
We present motivation and practical steps necessary to find parameter estimates of joint models of behavior and neural electrophysiological data. This tutorial is written for researchers wishing to build joint models of human behavior and scalp and intracranial electroencephalographic (EEG) or magnetoencephalographic (MEG) data, and more specifically those researchers who seek to understand human cognition. Although these techniques could easily be applied to animal models, the focus of this tutorial is on human participants. Joint modeling of M/EEG and behavior requires some knowledge of existing computational and cognitive theories, M/EEG artifact correction, M/EEG analysis techniques, cognitive modeling, and programming for statistical modeling implementation. This paper seeks to give an introduction to these techniques as they apply to estimating parameters from neurocognitive models of M/EEG and human behavior, and to evaluate model results and compare models. Due to our research and knowledge on the subject matter, our examples in this paper will focus on testing specific hypotheses in human decision-making theory. However, most of the motivation and discussion of this paper applies across many modeling procedures and applications. We provide Python (and linked R) code examples in the tutorial and appendix. Readers are encouraged to try the exercises at the end of the document.

Keywords Computational modeling · Cognitive modeling · Electroencephalography (EEG) · Magnetoencephalography (MEG) · Psychology · Neuroscience

Paper link

How to jointly model Brain and Behavior?

Z_i

Single-trial ERPs

X_i

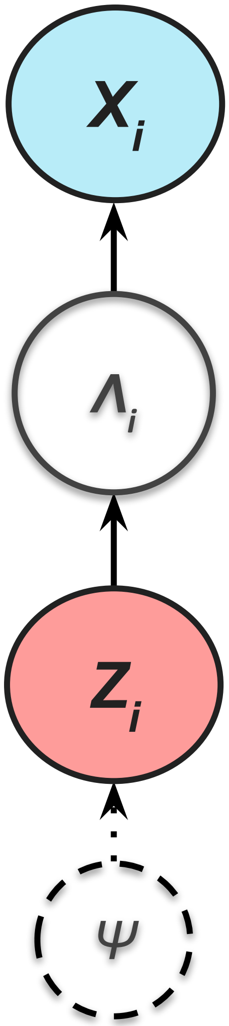
Choice-RTs

Λ_i

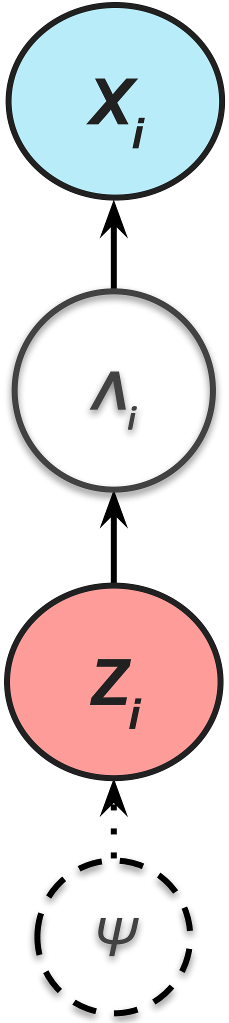
DDM params.

α distance between boundaries
τ non-decision time (VET + MET)
δ_i single-trial drift rate
β relative start point

Ghaderi-Kangavari, Rad, Nunez. 2023; Computational Brain & Behavior



Directional Joint Models

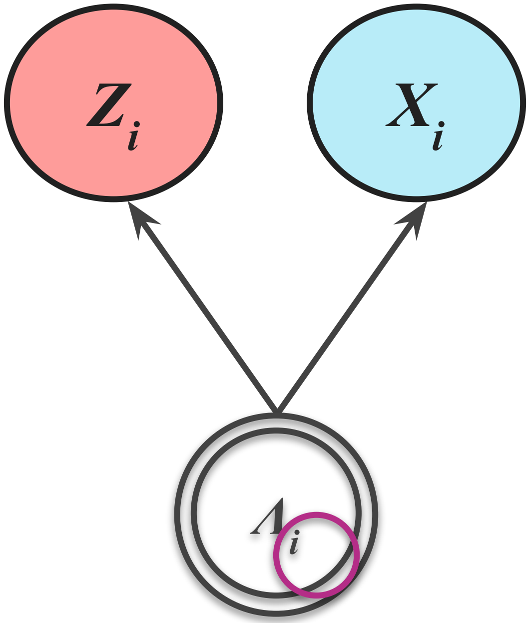


$$x_i \sim DDM(\alpha, \tau, \delta_i, \beta)$$

$$\delta_i \sim N(\lambda z_i + b, \eta^2)$$

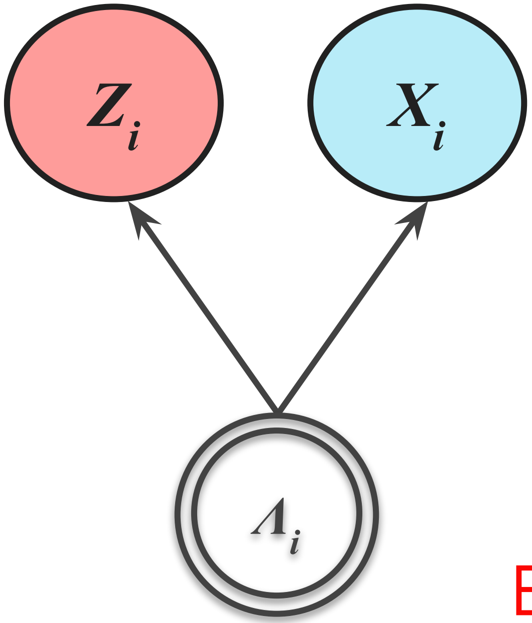
$$z_i \sim N(\mu_z, \sigma_z^2)$$

Brain measures are independent variables with dependent cognitive parameters that describe Behavior on every trial



Single-trial Integrative Models

Ghaderi-Kangavari, Rad, Nunez. 2023; Computational Brain & Behavior



$$x_i \sim DDM(\alpha, \tau, \delta_i, \beta)$$

$$\delta_i \sim N(\mu_\delta, \eta_\delta^2)$$

$$z_i \sim N(\gamma\delta_i, \sigma^2)$$

Brain measures and Behavior are both dependent on cognitive parameters

But which model is better?

Qualitative differences

Directional Joint

$$x_i \sim DDM(\alpha, \tau, \delta_i, \beta)$$

$$\delta_i \sim N(\lambda z_i + b, \eta^2)$$

$$z_i \sim N(\mu_z, \sigma_z^2)$$

- Identifiable
- Assumes *noiseless* neural data
- Literature-established
- Multiple fitting procedures available

Single-trial Integrative

$$x_i \sim DDM(\alpha, \tau, \delta_i, \beta)$$

$$\delta_i \sim N(\mu_\delta, \eta_\delta^2)$$

$$z_i \sim N(\gamma\delta_i, \sigma^2)$$

- Identifiability issues
- Appropriately accounts for noise
- New and unestablished
- Only one tested fitting procedure

NPE in BayesFlow (**tutorial at 4pm!**)

Quantitative differences

PDF of our CCN 2026 poster

Bruny Krijgsman
PhD candidate at Erasmus University Rotterdam

Further reading

Original integrative modeling paper

Good directed modeling example

More lab info on https://www.michaeldnunez.com

Thanks for listening!