한국음악지각인지학회 [KSMPC] 여름학교 | September 7, 2024

SESSION 3 – MUSIC & BRAIN

Linearized Encoding Modeling: 음악지각의 예측적 분석방법론

Seung-Goo Kim [김승구]

Research Group Neurocognition of Music and Language, Max Planck Institute for Empirical Aesthetics, Frankfurt am Main, Germany
[음악과 언어의 신경인지 연구그룹, 막스플랑크 경험미학 연구소, 프랑크푸르트 암 마인, 독일]

Session plan

Session-3: Music and the Brain

From	To	Contents	Dur
15:15	15:25	강연자 소개, 세션 구조 소개	10m
15:25	15:55	**Introduction: Naturalistic Stimuli for Music Research**	30m
15:55	16:10	**Motivations (WHYs)**	15m
16:10	16:15	Short break	5m
16:15	16:55	**Methods (HOWs)**	40m
16:55	17:05	Long break	10m
17:05	18:15	**Hands-on (MATLAB Online)**	1h 10m
		SUM	*3h*

🤔: 이 사람은 누구지?

Seung-Goo Kim

- Originally from Seoul, South Korea
- First name: Seung-Goo 승구[/sɯŋgu/](勝九)
- Family name: Kim 김[/gim/](金)
- And very into 🧠🎶🤖

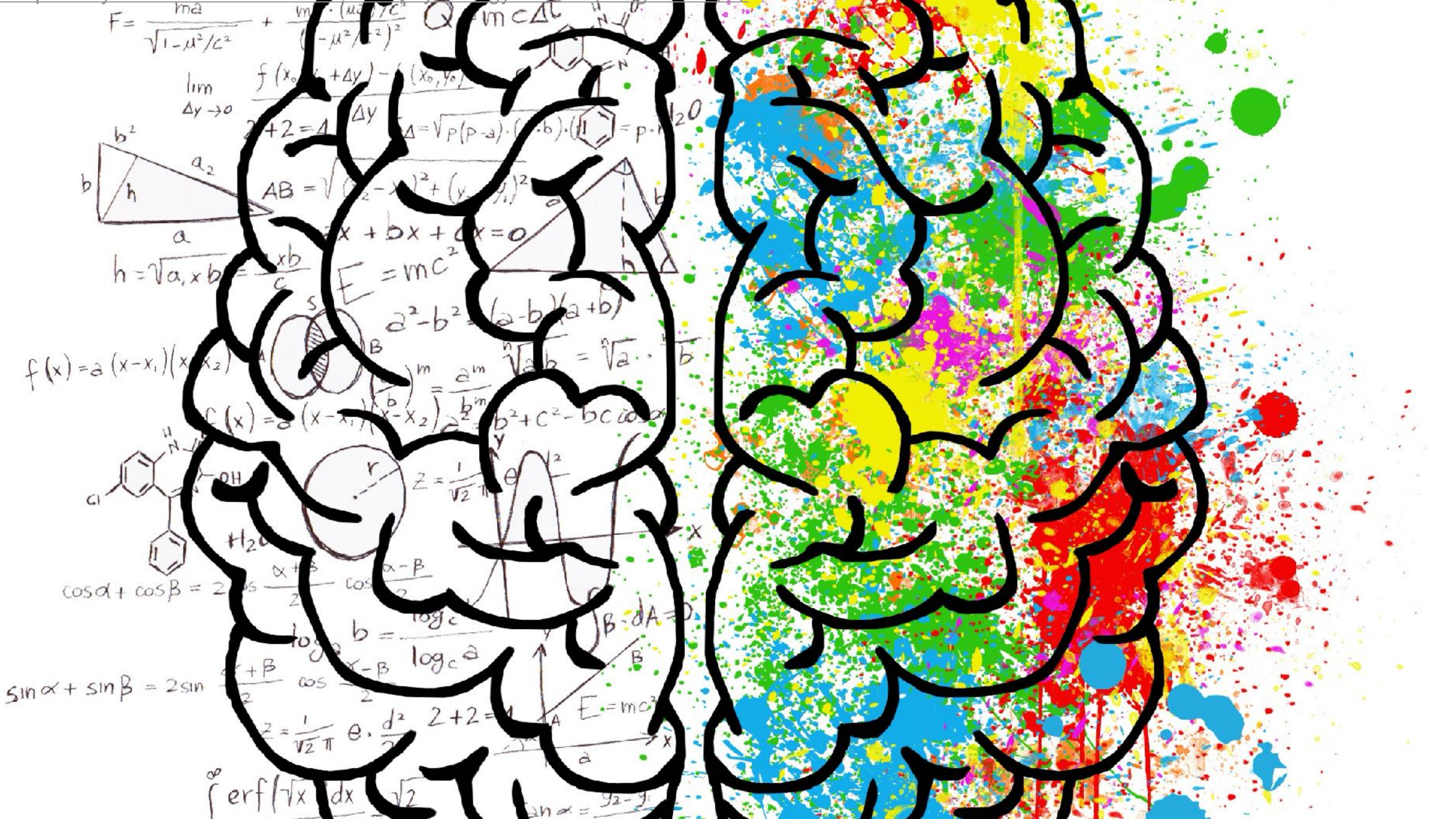
2016, Leipzig

2019, Jeju


SCORE<1> HI-SCORE SCORE<2>
0990 0000
3
CREDIT 05
BRIGHTNESS
CONTRAST
VERTICAL
POWER
ENTER
SHIFT
DEL
SPACE INVADERS


Scream Tracker V3.21
Copyright (C) 1993,1994 Sami Tammilehto
Song Armani Showers
Instrument 01: (C) Edge / EMF 1994
Order 000/010
Pattern 00
Row 00
Channel 01
File armani.s3m (S3M)
Chord none
C.Tempo 7D
C.Speed 06
Baseoctave 3
FreeMem: 281K
FreeEMS: 31280K
FreeGUS: 1018K
ESC ..... Main Menu
F10 ..... Quick-Help
CTRL-Q .. Quit to DOS
F1..F4 .. Edit Screen
CTRL-L .. Load Module
F5/F8 ... Play / Stop
Pattern Editor (F2)
01: L1
02: R1
03: L2
04: R2
05: L3
00 E-3 01 01 S85 ^^. .. .. .00 ^^. .. .. .00 ^^. .. .. S8B ^^. .. .. .00
01 A-3 .. 01 GAF ... . .00 ... . .00 ... . .00 00
02 B-3 .. 02 G00 ... . .00 ... . .00 E-3 01 01 .00 00
03 E-3 .. 02 G00 ... . .00 ... . .00 A-3 .. .. GAF 00
04 B-3 .. 03 G00 ... . .00 ... . .00 B-3 .. .. G00 00
05 C-4 .. 03 G00 ... . .00 ... . .00 E-3 .. .. G00 00
06 E-3 .. 04 G00 ... . .00 ... . .00 B-3 .. .. G00 00
07 D-4 .. 05 G00 ... . .00 ... . .00 C-4 .. .. G00 00
08 E-3 .. 05 G00 ... . .00 ... . .00 E-3 .. .. G00 00
09 A-3 .. 06 G00 ... . .00 ... . .00 D-4 .. .. G00 00
10 B-3 .. 06 G00 ... . .00 ... . .00 E-3 .. .. G00 00
11 E-3 .. 07 G00 ... . .00 ... . .00 A-3 .. .. G00 00
12 B-3 .. 07 G00 ... . .00 ... . .00 B-3 .. .. G00 00
13 C-4 .. 08 G00 ... . .00 ... . .00 E-3 .. .. G00 00
14 E-3 .. 09 G00 ... . .00 ... . .00 B-3 .. .. G00 00
15 E-4 .. 09 G00 ... . .00 ... . .00 C-4 .. 02 G00 00
16 E-3 .. 10 G00 E-4 01 00 S8F ... . .00 E-3 .. .. G00 00
17 A-3 .. 10 G00 ... . .00 ... . .00 E-4 .. .. G00 00
18 B-3 .. 11 G00 ... . .00 ... . .00 E-3 .. .. G00 00
19 E-3 .. 11 G00 ... .. 01 .00 ... . .00 A-3 .. .. G00 00
20 B-3 .. 12 G00 ... . .00 ... . .00 B-3 .. 03 G00 00
21 C-4 .. 13 G00 ... . .00 ... . .00 E-3 .. .. G00 00
22 E-3 .. 13 G00 ... .. 02 .00 ... . .00 B-3 .. .. G00 00
23 D-4 .. 14 G00 ... . .00 ... . .00 C-4 .. .. G00 00
24 E-3 .. 14 G00 ... .. 03 .00 ... . .00 E-3 .. .. G00 00
25 A-3 .. 15 G00 ... . .00 ... . .00 D-4 .. .. G00 00
26 B-3 .. 15 G00 ... . .00 ... . .00 E-3 .. .. G00 00
27 E-3 .. 16 G00 ... .. 04 .00 ... . .00 A-3 .. .. G00 00
28 B-3 .. 17 G00 ... . .00 ... . .00 B-3 .. .. G00 00

https://pixabay.com/illustrations/brain-mind-psychology-idea-drawing-2062057/



Education & Training (1)

- 선화예고 작곡전공
- 문학학사: 연세대 심리학 및 경제학 이중전공
- 이학석사: 서울대 인지과학협동과정 (MEG for music)
- 2012-2017, PhD in Psychology: Max Planck Institute for Human Cognitive and Brain Sciences & University of Leipzig, Leipzig [라이프치히, 독일] (s/fMRI for music)

2017, Leipzig

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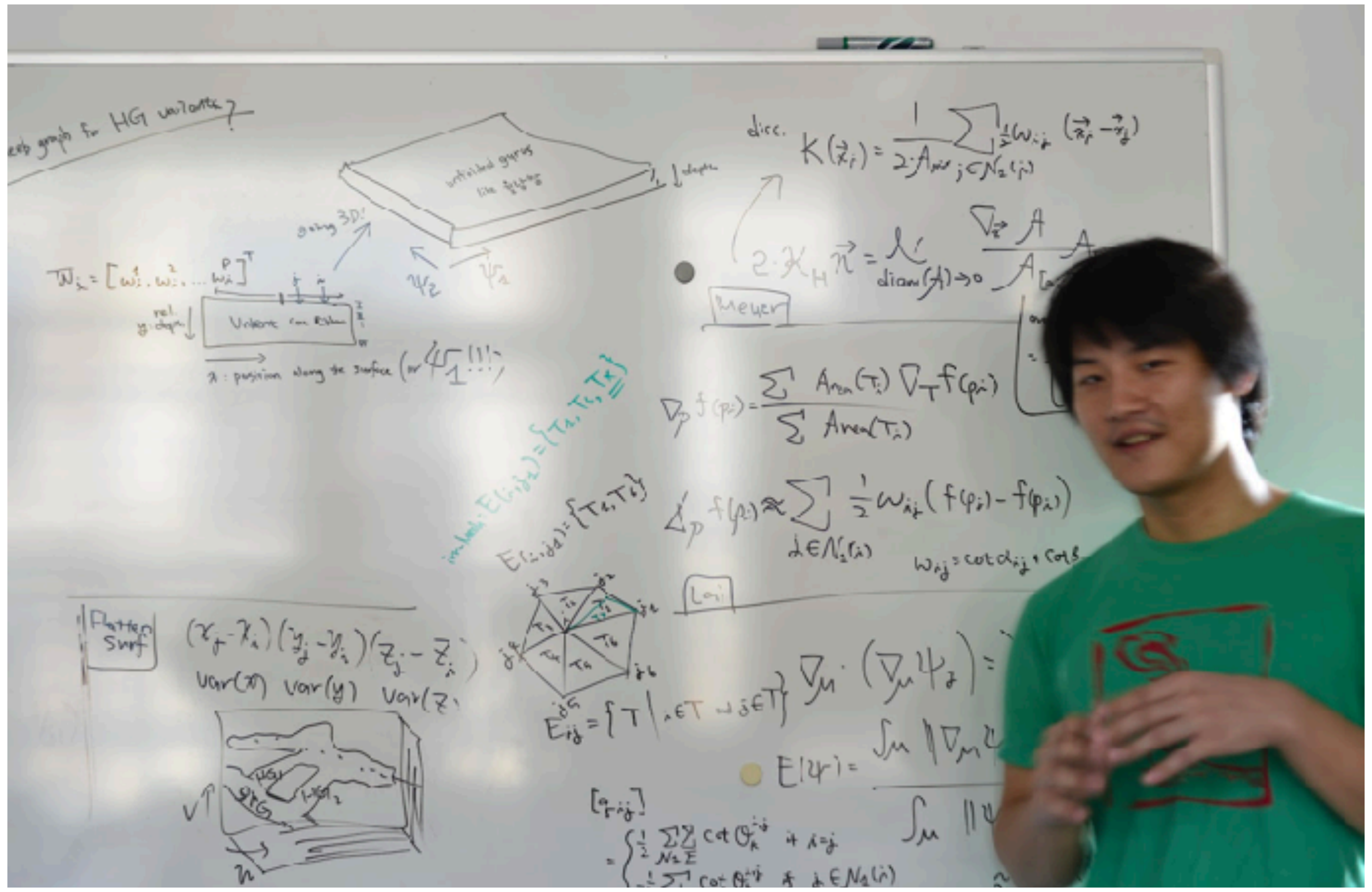
From Wilhelm Wundt's the first ever experimental psychology lab!

2017, Leipzig

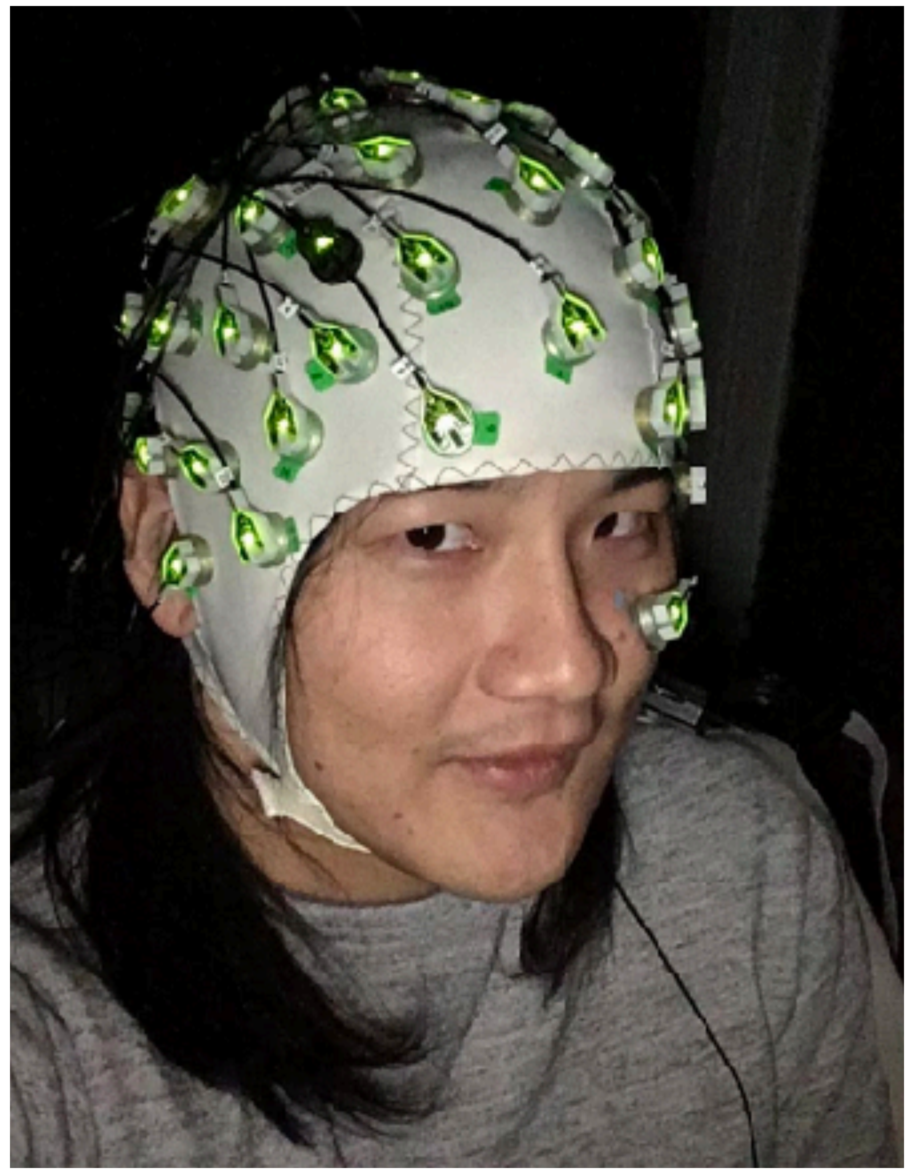
2017, Leipzig

Education & Training (2)

- 2017–2018, Postdoc, Cambridge University, UK [캠브리지, 영국] (s/fMRI for psychiatry)
- 2018–2021, Postdoc, Duke University, NC, USA [노스캐롤라이나, 미국] (M/EEG, fMRI for speech)
- 2021–, **Research Scientist, Max Planck Institute for Empirical Aesthetics, Frankfurt am Main** [프랑크프루트, 독일] (fMRI for music)



2013, Leipzig



2018, Durham, NC

Max Planck Society [Max-Planck-Gesellschaft]

- 84 institutes and research facilities across Germany for emerging fields of science
- 31 Nobel laureates
- Two Korean directors as of 2023

Prof. Sarah M. Kang, Ph.D.

Director at the Max Planck Institute for Meteorology, Hamburg (previously worked at the Ulsan National Institute of Science and Technology, South Korea)

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MAX PLANCK INSTITUTE
FOR EMPIRICAL AESTHETICS
ND CARREE


Harmony in the pianist's brain
Playing without sound
Listening
L R
z=26
z=41
z=56
z=-3
z=12
(C) Max Planck Institute for Empirical Aesthetics


SCHÖN

https://ae.mpg.de/en.html

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Creating and Experiencing

The Max Planck Institute for Empirical Aesthetics (MPIEA) investigates why and how people create art and how they perform, experience, and evaluate it. The Institute's focus is on music, but we also engage with other performing arts such as dance and film.

https://ae.mpg.de/en/career/jobs.html

MAX PLANCK INSTITUTE FOR EMPIRICAL AESTHETICS

Jobs

The Max Planck Institute for Empirical Aesthetics offers excellent career opportunities in both research and non-research-oriented areas. In accordance with Max Planck Society policy, we aim to increase the proportion of women in fields where they are underrepresented and therefore urge women in particular to apply. We are also committed to hiring more people with disabilities and expressly encourage applications from disabled persons.

- Information on data protection for job applicants

PhD Position to Investigate Phenotypic and Genetic Relations between Substance Use, Mental Health, and Creative Engagement

limited to 36 months | fulltime

Bewerbungsschluss: 08.09.2024

Research Software Engineer in the Department of Cognitive Neuropsychology

permanent position | fulltime

Bewerbungsschluss: 30.09.2024

Career

- Jobs
- Internships
- Master's Theses
- Equal opportunity
- Information on Data Protection for Job Applicants

CONTACT

Mara Schmitt

Human Resources
+49 69 8300479-507
Email

Please do not send applications via email. Use the
- applicant management system

🤔: 뭘 배우는 거지?

Overview of the session

음악지각의 예측적 분석방법론

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- **Introduction:** Why do we need a predictive analysis for music research?

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- **🙄: 그런데 왜 슬라이드는 영어고 말은 판교 사투리지?** English is currently the lingua franca of science & engineering.

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- 😡: **그리고 왜 MALTAB을 쓰지? ${다른 언어}가 훨씬 좋은데!** (1) Killer-apps in the neuroscience field. (2) You need to learn everything anyway (3) Some of us (including myself) are already using it.

Is Python a language of Open Science?

ANACONDA

Permanent Link:

Summary: Anaconda is a Python distribution featuring the package manager *conda*. According to their terms of service it cannot be used at the institute without a license.

Can I use Anaconda at the institute?

No.

According to their terms of service we (the Max Planck Society (MPS)) are not allowed to use "Anaconda's offerings" for free as we have more than 200 employees and there is no exception for research facilities. Since the MPS has no licenses for Anaconda you are not allowed to use it. To prevent license violations we are blocking connections to Anaconda's package repository.

ANACONDA®

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```
Last login: Fri Sep  6 09:54:44 on ttys003
seung-goo.kim@PCX0152:~
$ rm -rf anaconda3
seung-goo.kim@PCX0152:~
$ 
```

What is "Open Science"?

Not just an ideology but a pragmatic practice!

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- **Values**: Transparency, Collaboration, Accessibility, Reusability, Sustainability

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Richard Stallman (circa 2002)

St. IGNUcius, the Church of EMACS (2012)

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  - **Cybersocialism**: "Californian Ideology" or the Hacker culture (e.g., GNU manifesto [1983/1985])
  - **Reproducibility crisis**: ~40% psychology studies did not replicated (OSC, 2015, *Science*).

Richard Stallman (circa 2002)

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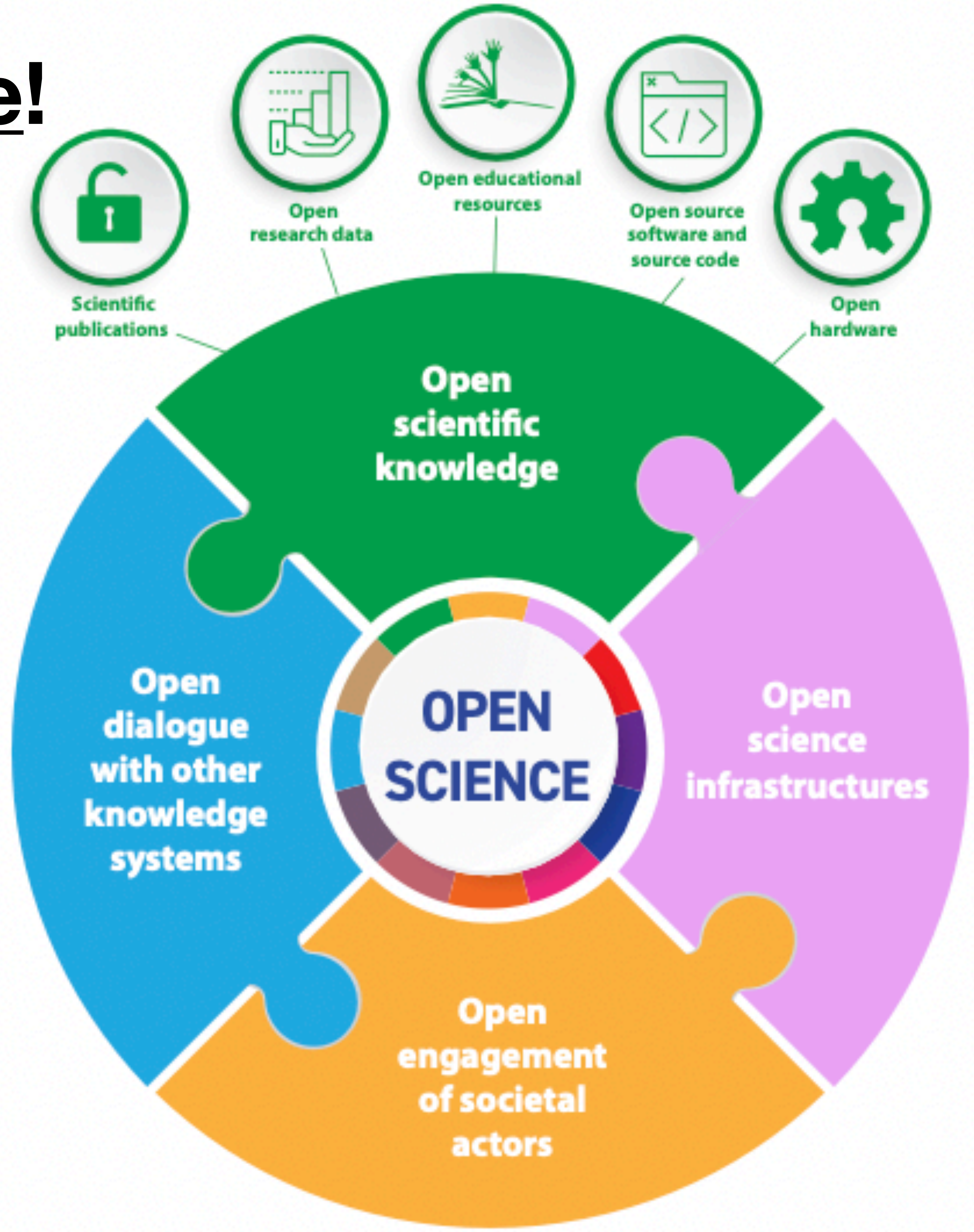
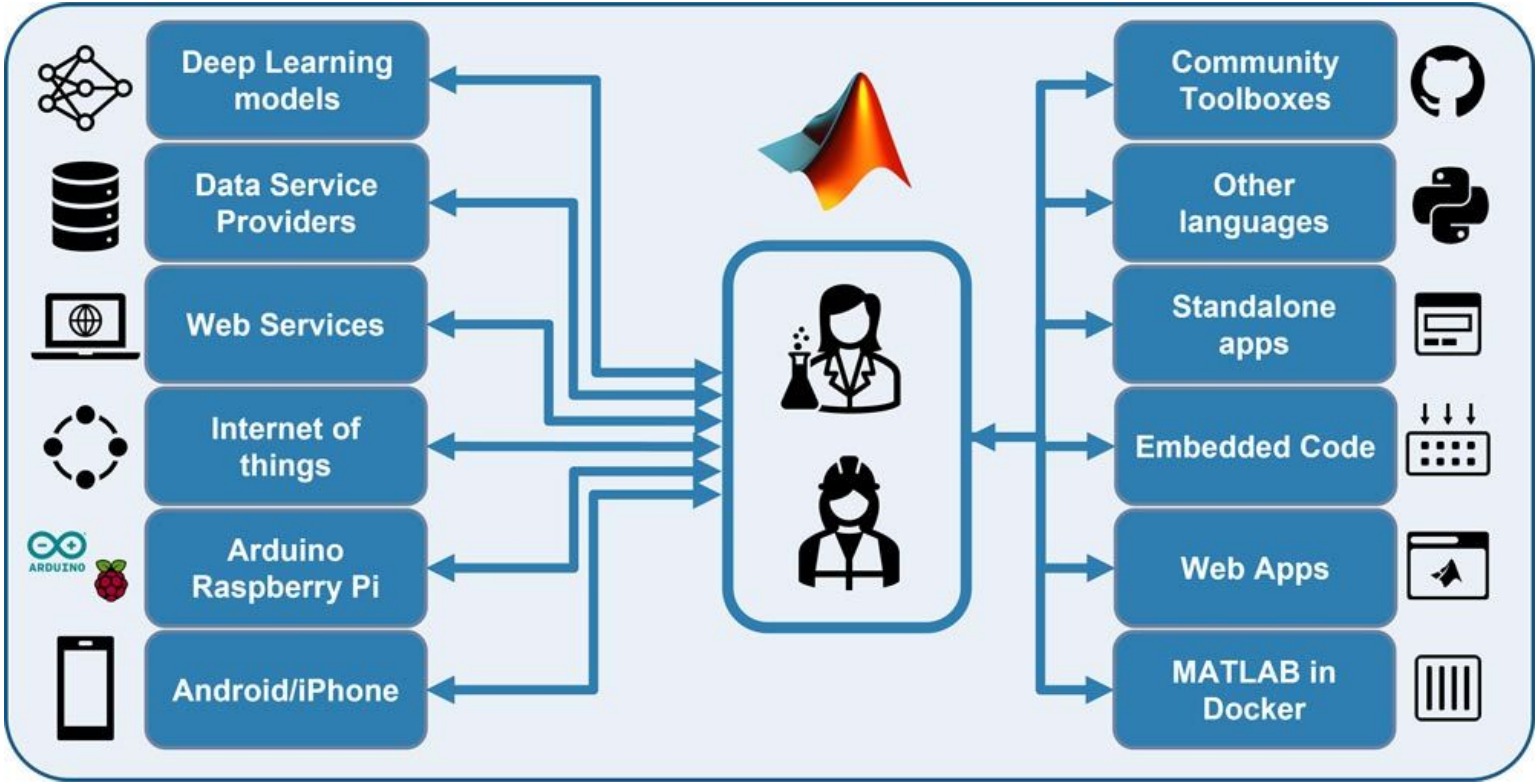


UNESCO, 2022, *Recommendation on Open Science*.

MATLAB for Open Science?

At least they know it sells for now...



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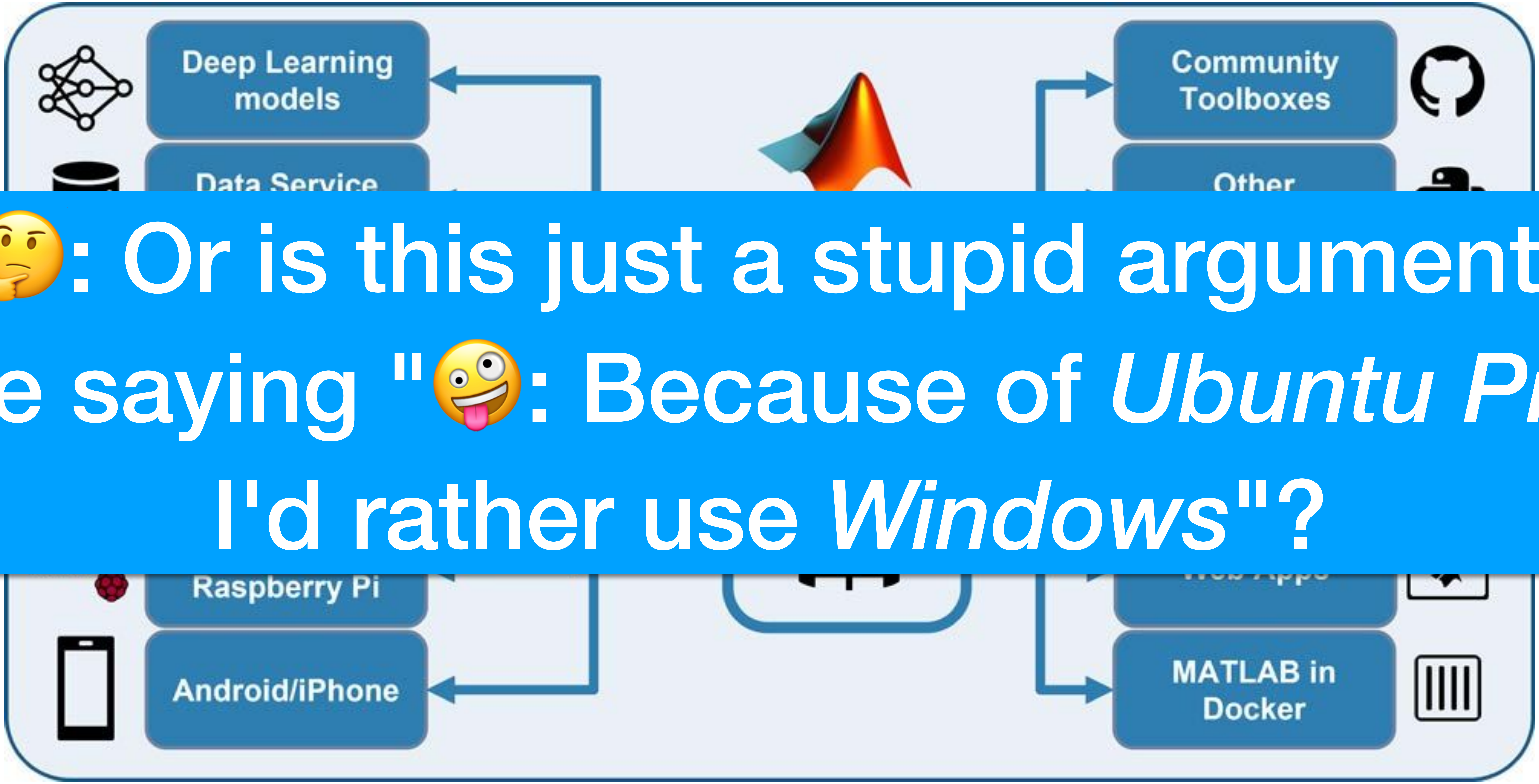


🤔: Or is this just a stupid argument, like saying "🤪: Because of *Ubuntu Pro*, I'd rather use *Windows*"?

Anyway it feels like a punch in the face...

"Don't be evil" my a$$...

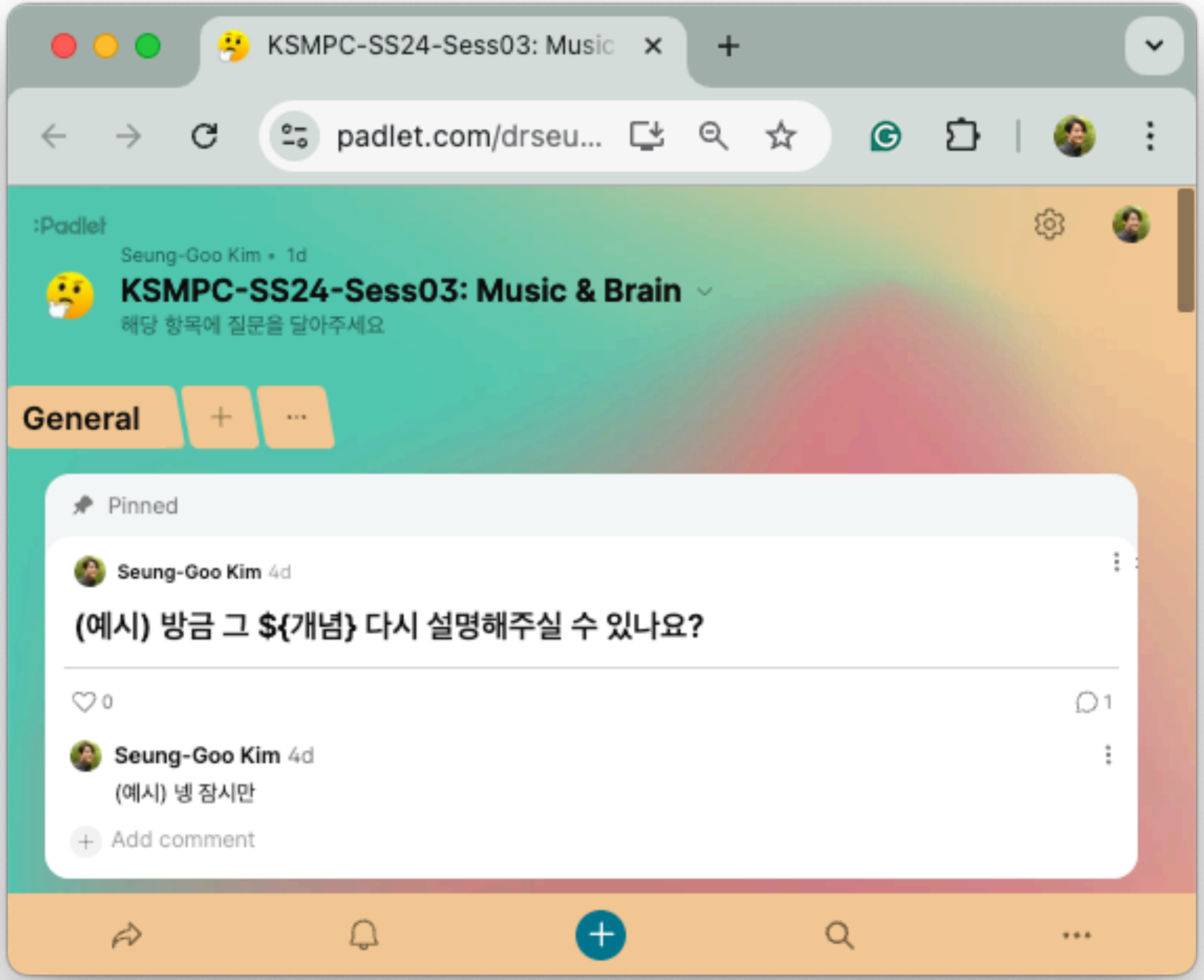
- Even in non-ML fields, Python (and R) has been popularized due to the "greater cause" of Open Science.
- Now it dominates the academia, and it's not free anymore?
- But another wisdom: "*If you're not paying for the product, then <u>you are the product</u>.*" (Tristan Harris)

How to communicate

Use Padlet board!

How to communicate

Use Padlet board!



My first question: what is your programming language?

Go back to SESSION PLAN

Introduction:
Naturalistic Stimuli for Music Research

Introduction:
Naturalistic Stimuli for Music Research

🤔: But what do you mean by "naturalistic"?

https://voxpopulisphere.com/2015/11/01/audio-what-ancient-greek-music-actually-sounded-like/

How does music evoke emotions *via* the brain?

Neuroscientific view

Music

How does music evoke emotions *via* the brain?

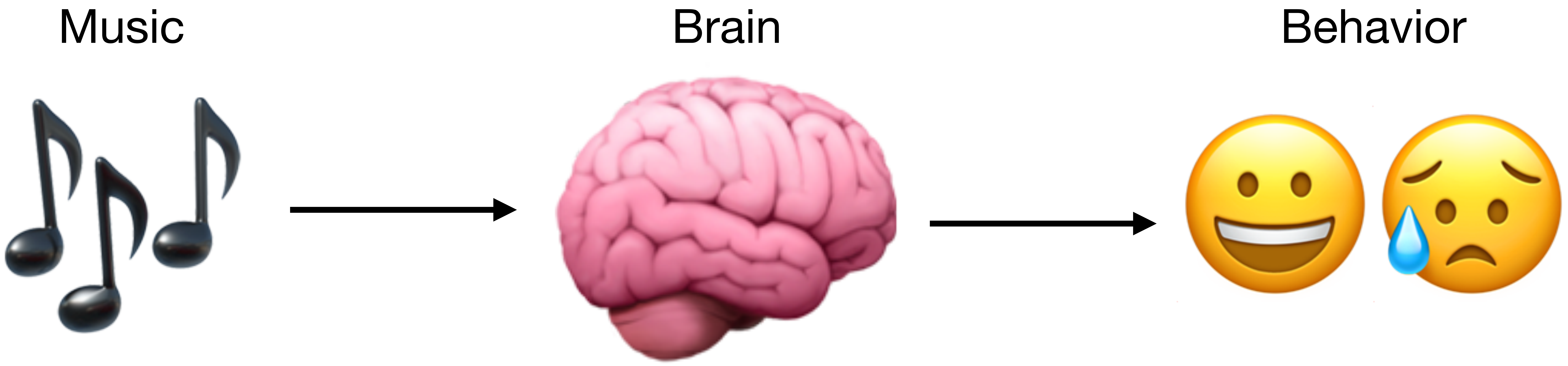
Neuroscientific view

Music

Brain

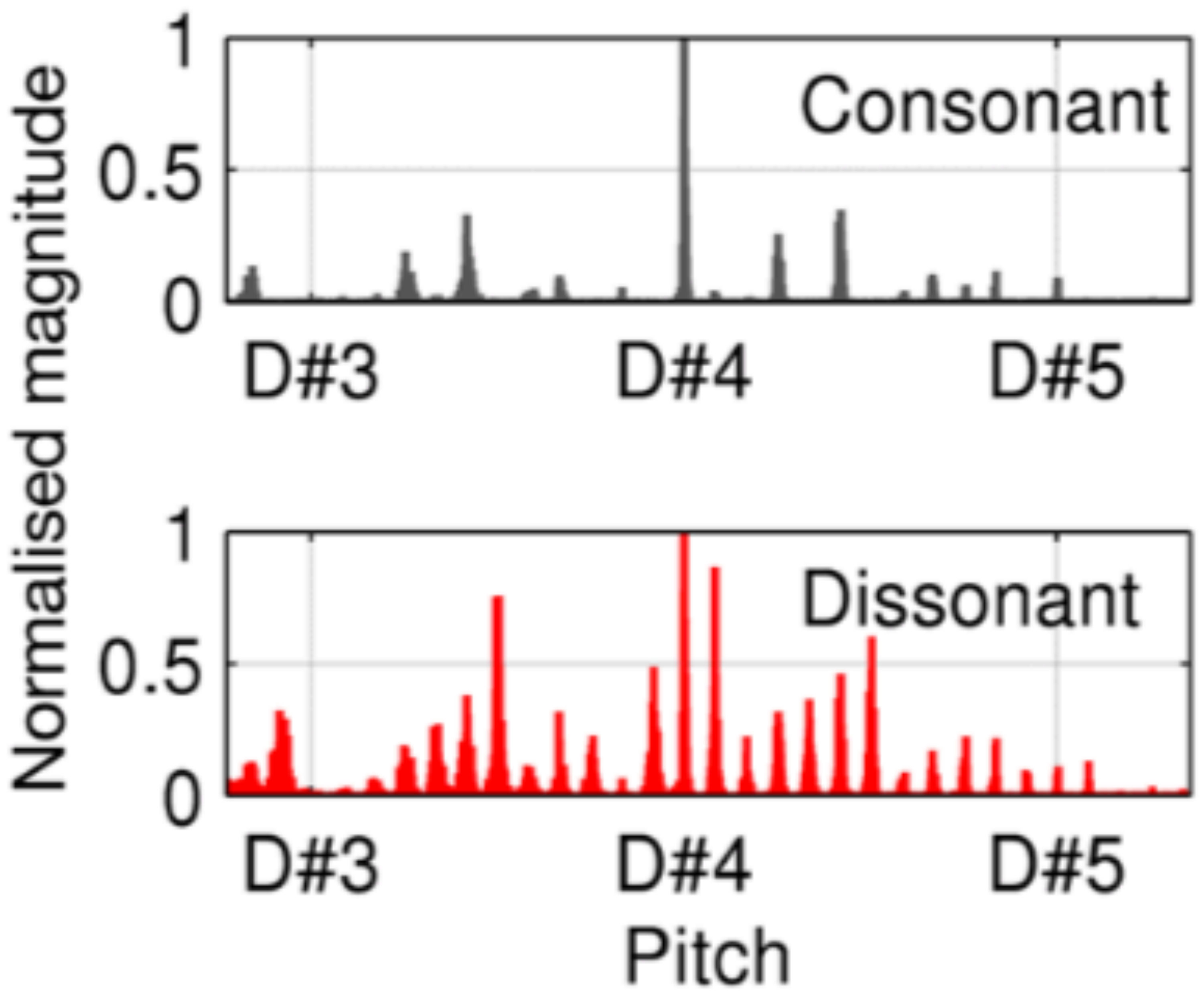
How does music evoke emotions *via* the brain?

Neuroscientific view



Traditional approach: music vs. "non-music"

Music 🎶

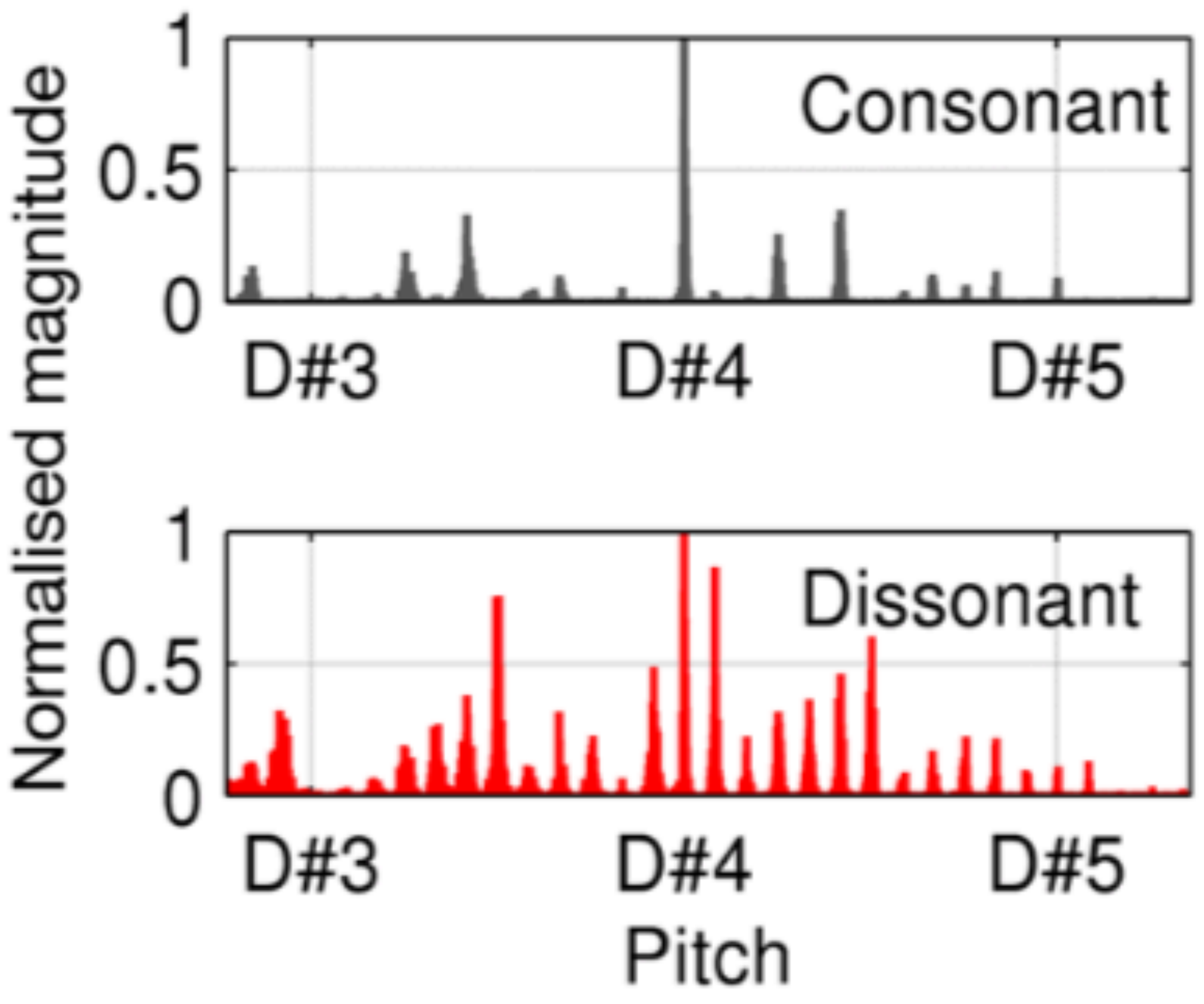


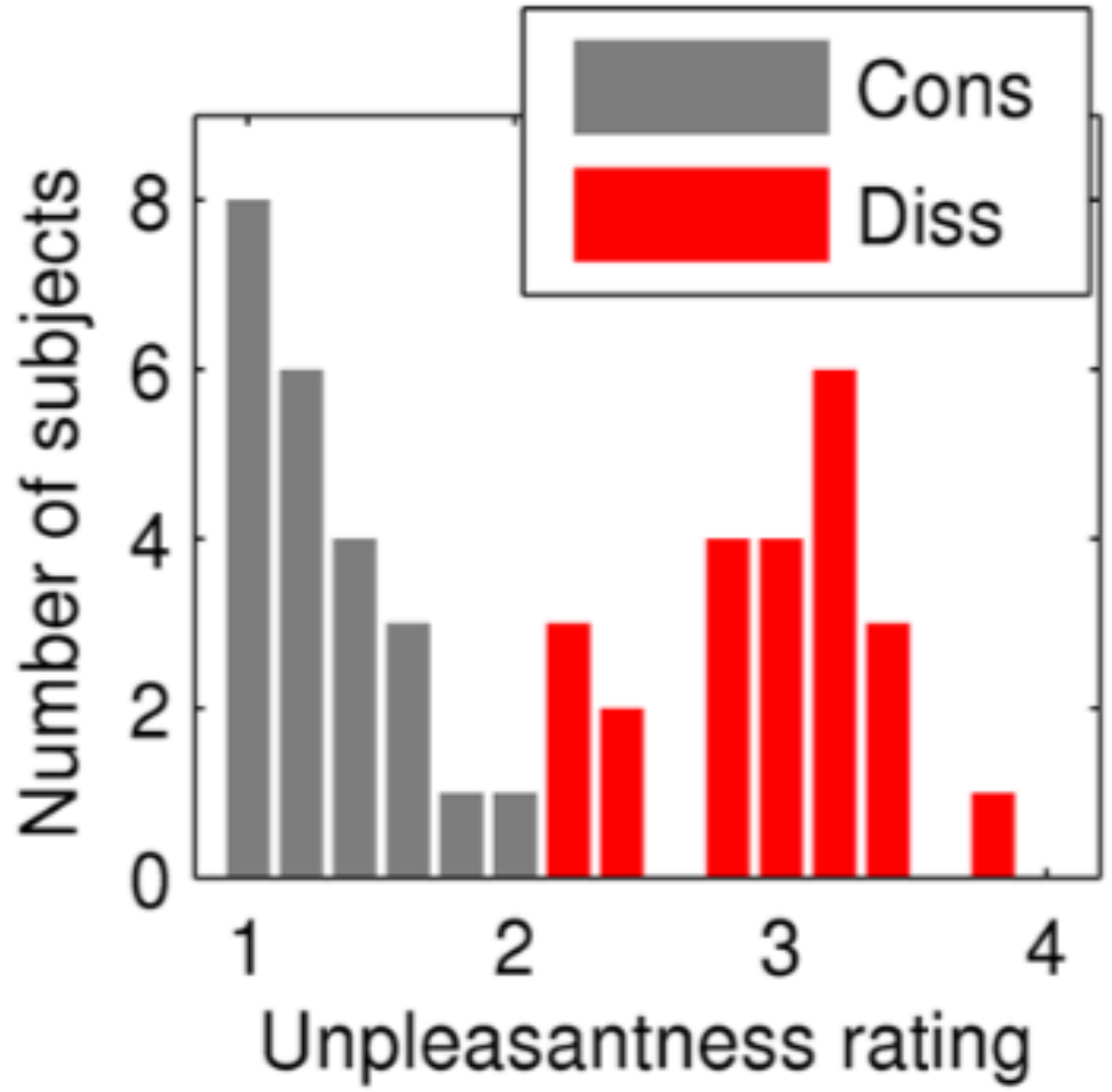
stimuli per condition = 20, stimulus duration = 30 s, # subjects = 23 (25.9 yo; 13 F)

Kim et al., 2017, *Sci Rep.*

Traditional approach: music vs. "non-music"

Music 🎶 ⟶ 😀😥 Behavior





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Kim et al., 2017, *Sci Rep.*

SOUND DEMO: J. S. Bach Prelude No.3 in C# major (BWV 848), consonant & dissonant

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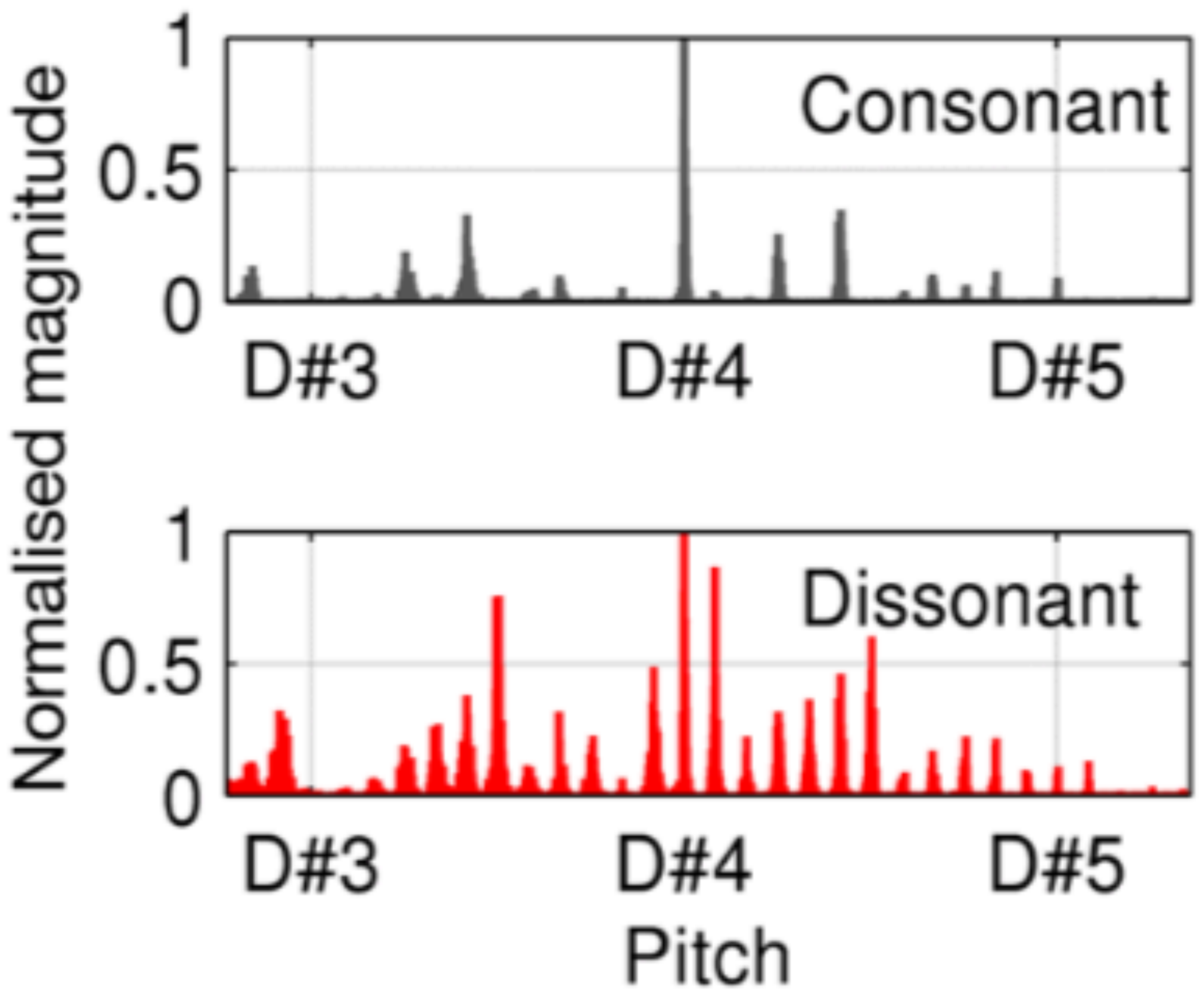
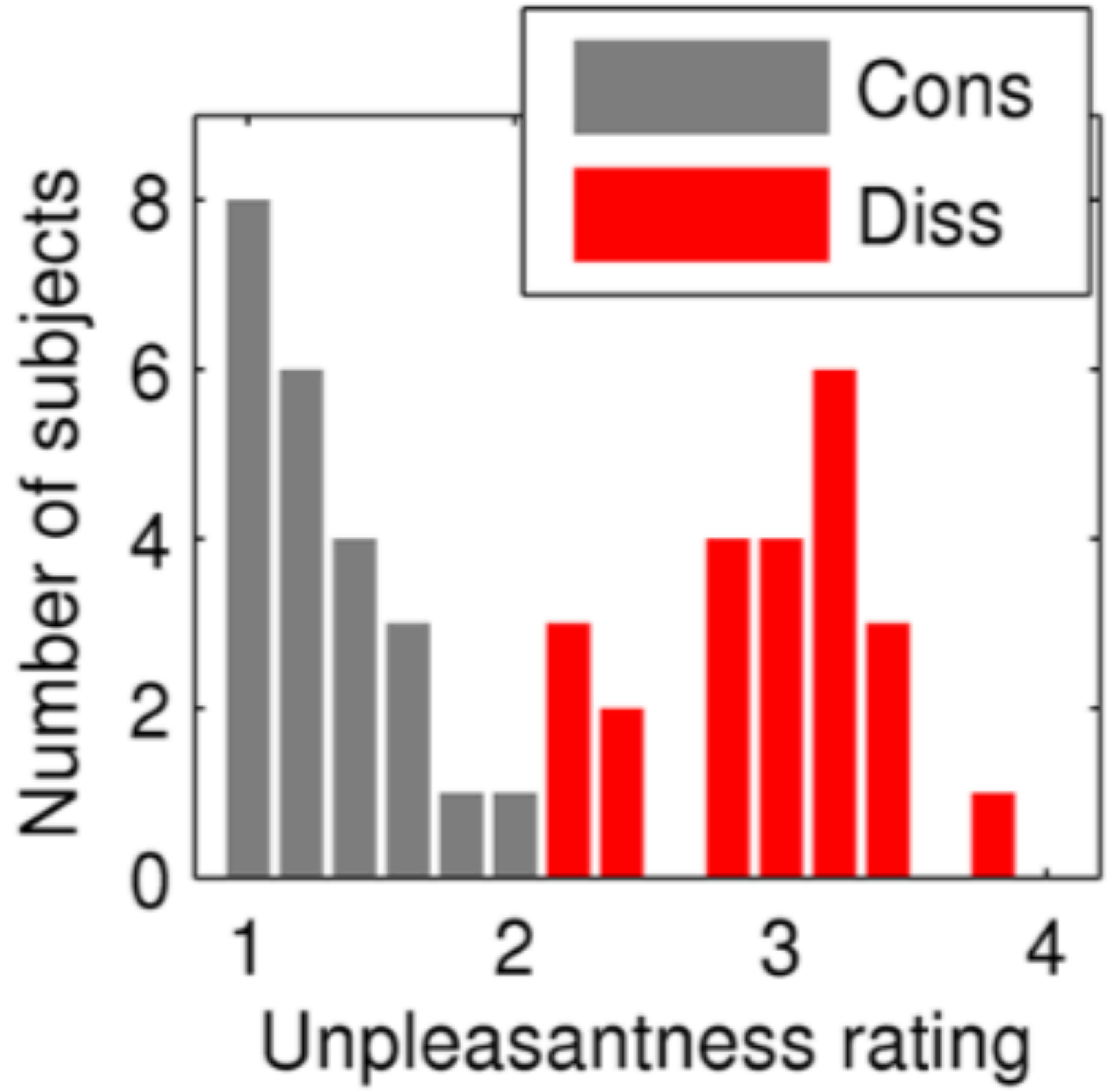
Music 🎶 ⟶ 😀😥 Behavior





“Dissonant” stimuli were rated more unpleasant.

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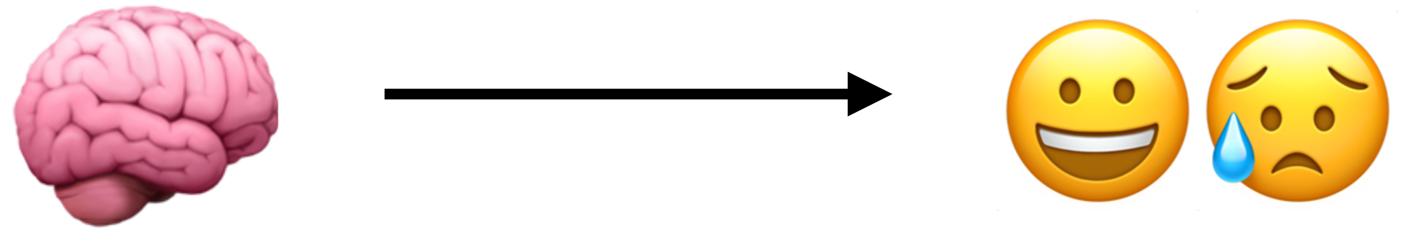

$$\Delta BOLD = \beta_0 + \beta_1 \Delta Rating + error$$

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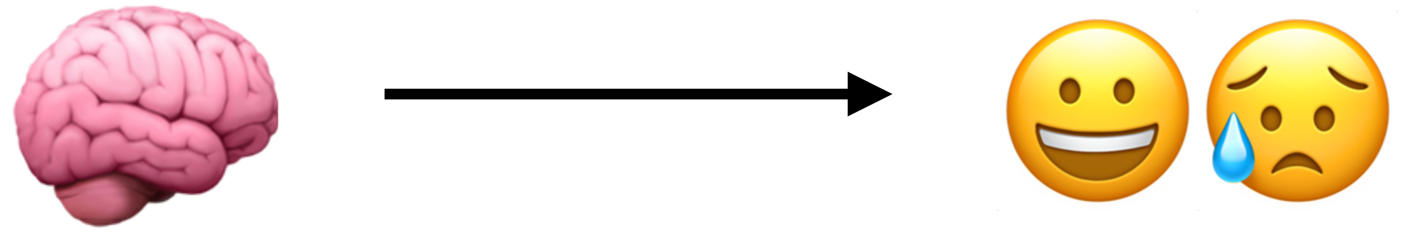

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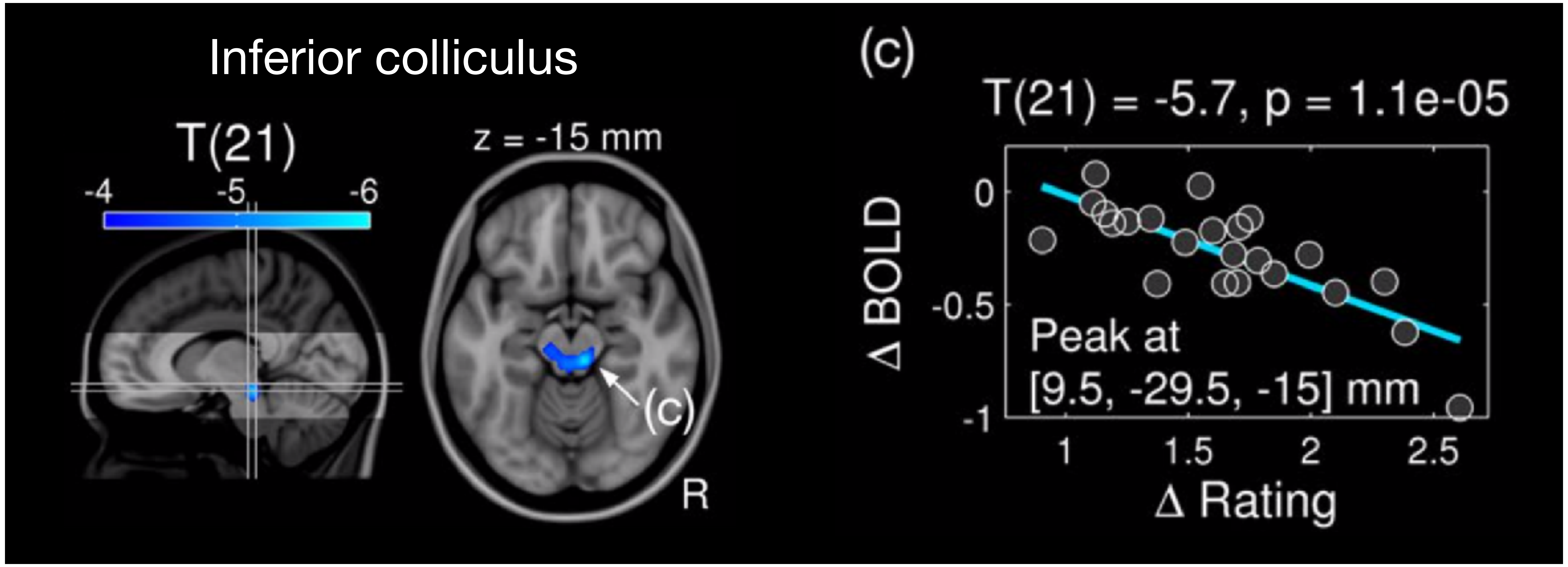

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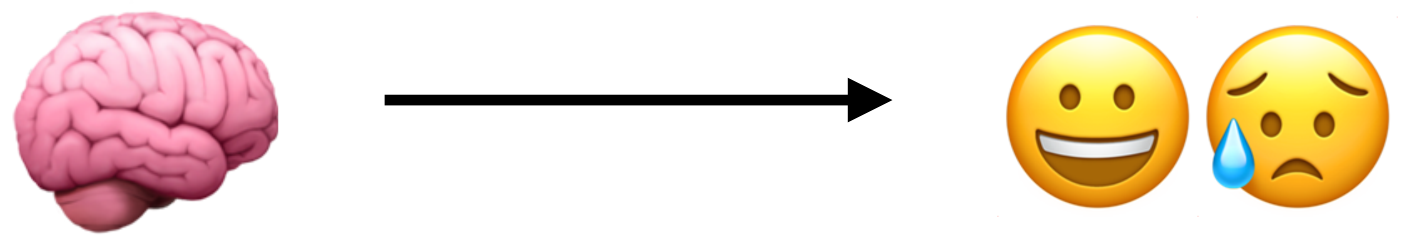
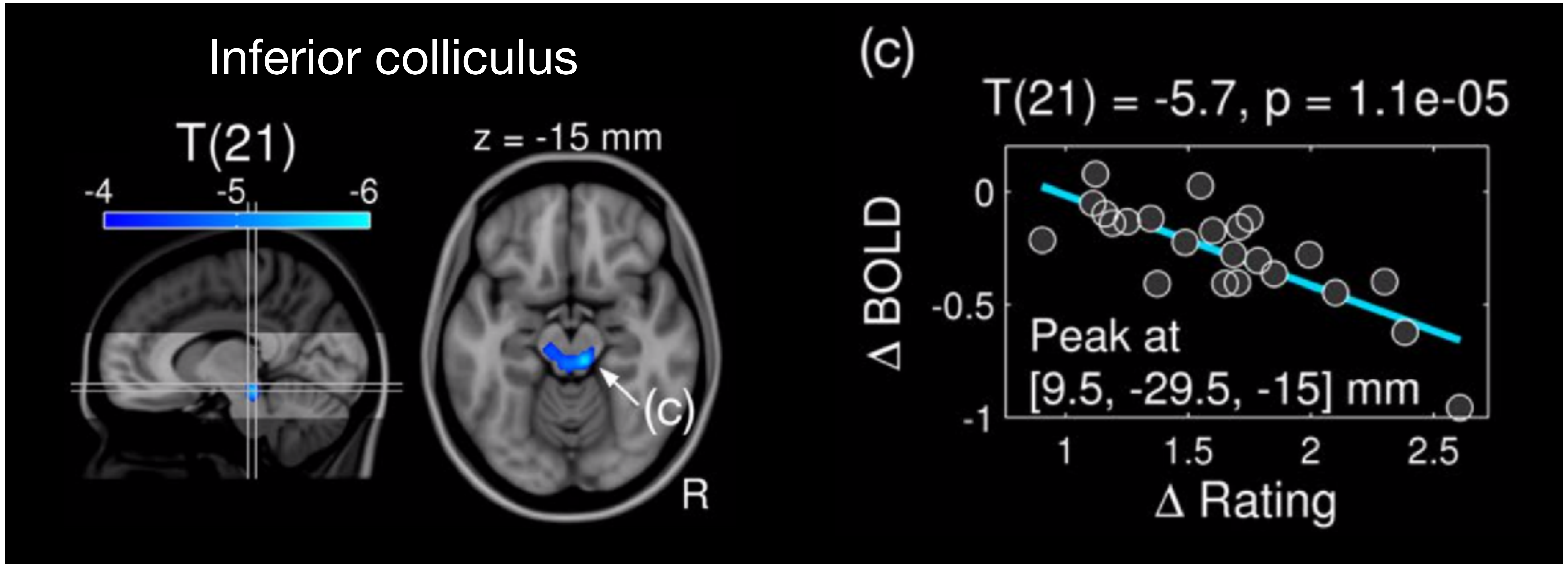


$$\Delta BOLD = \beta_0 + \beta_1 \Delta Rating + error$$



BOLD activation in the inferior colliculus (IC) decreased more in individuals who rated dissonant versions worse.

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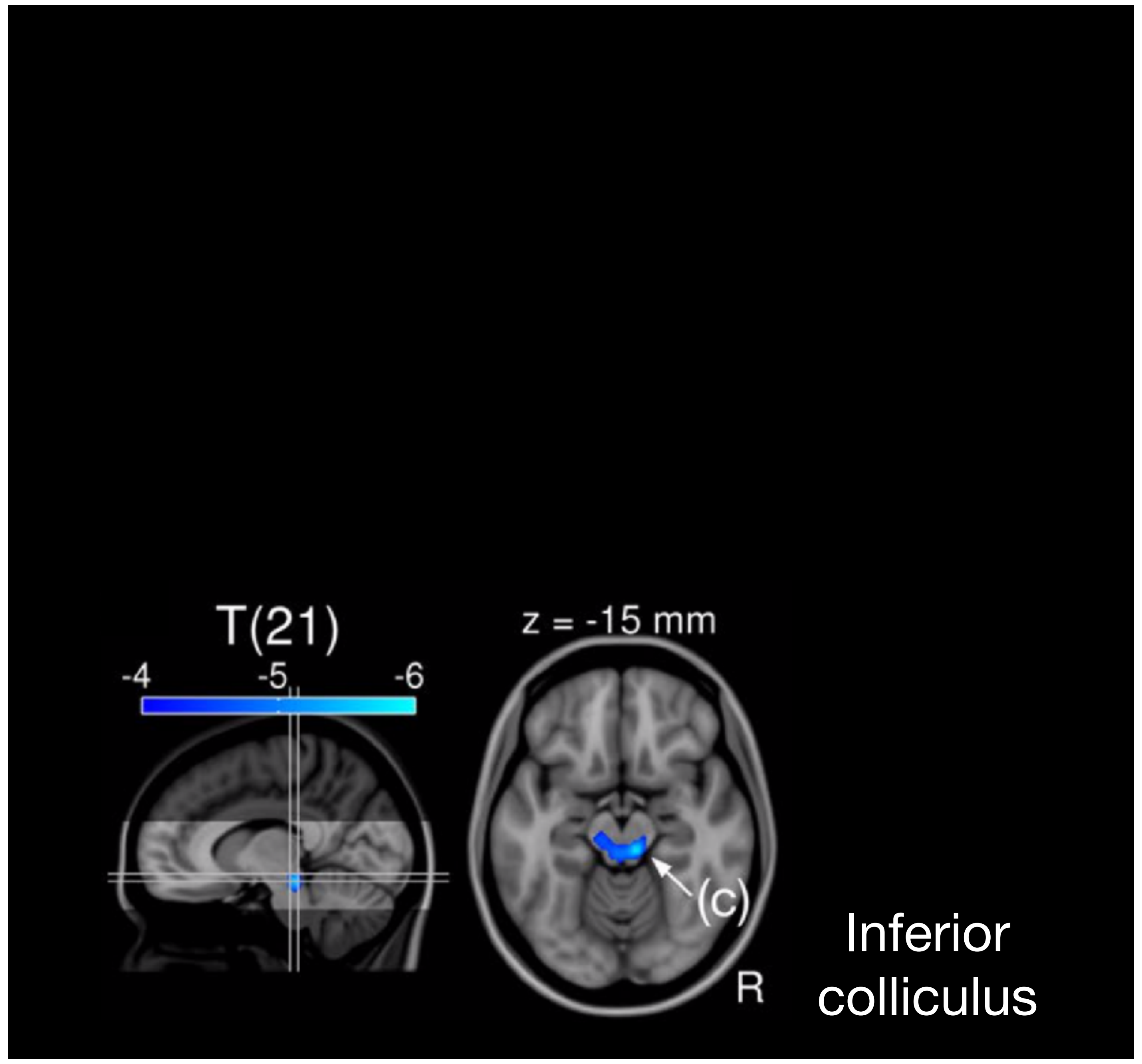
Traditional approach: music vs. "non-music"

Psycho-Physiological Interaction (PPI)



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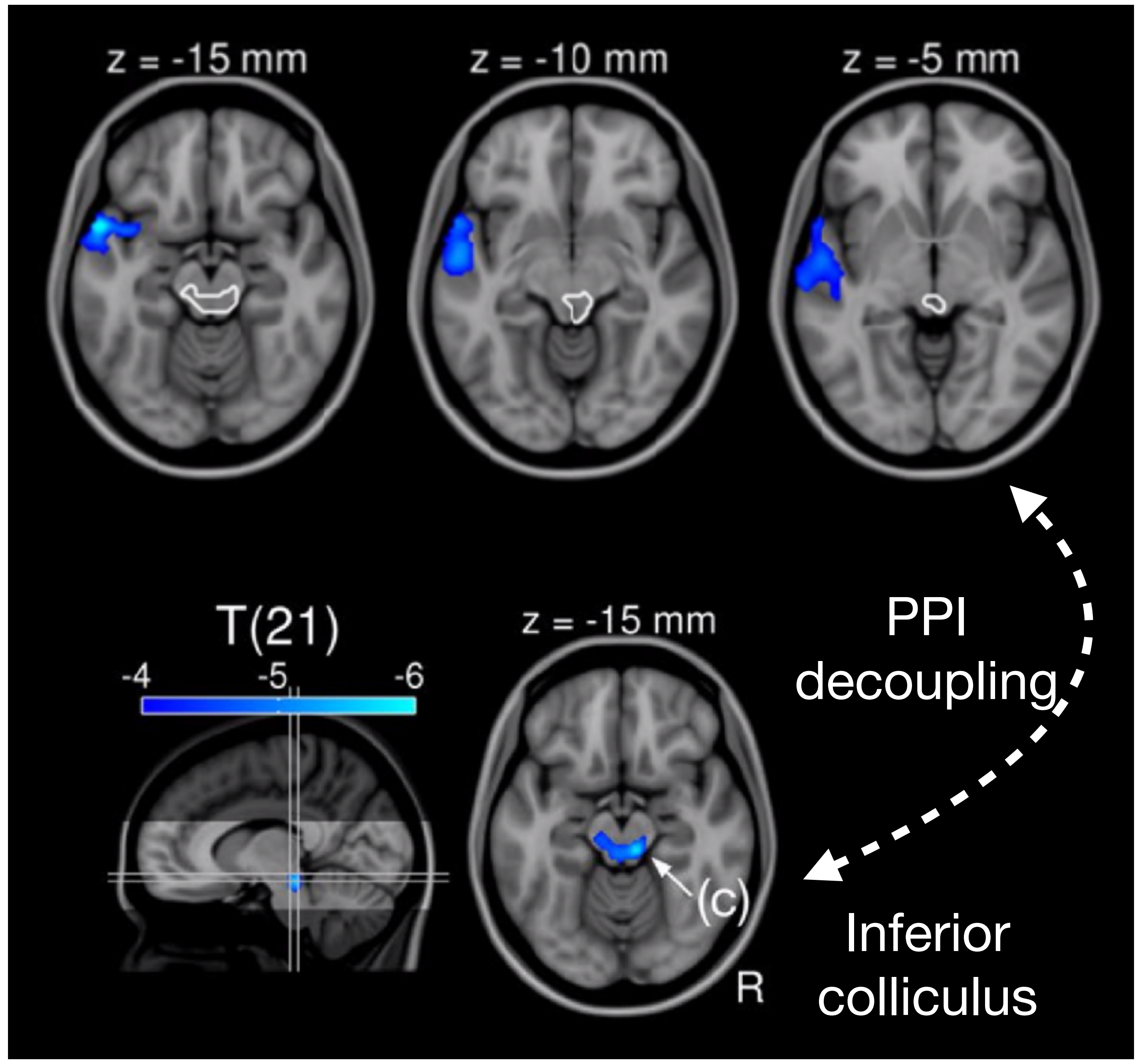

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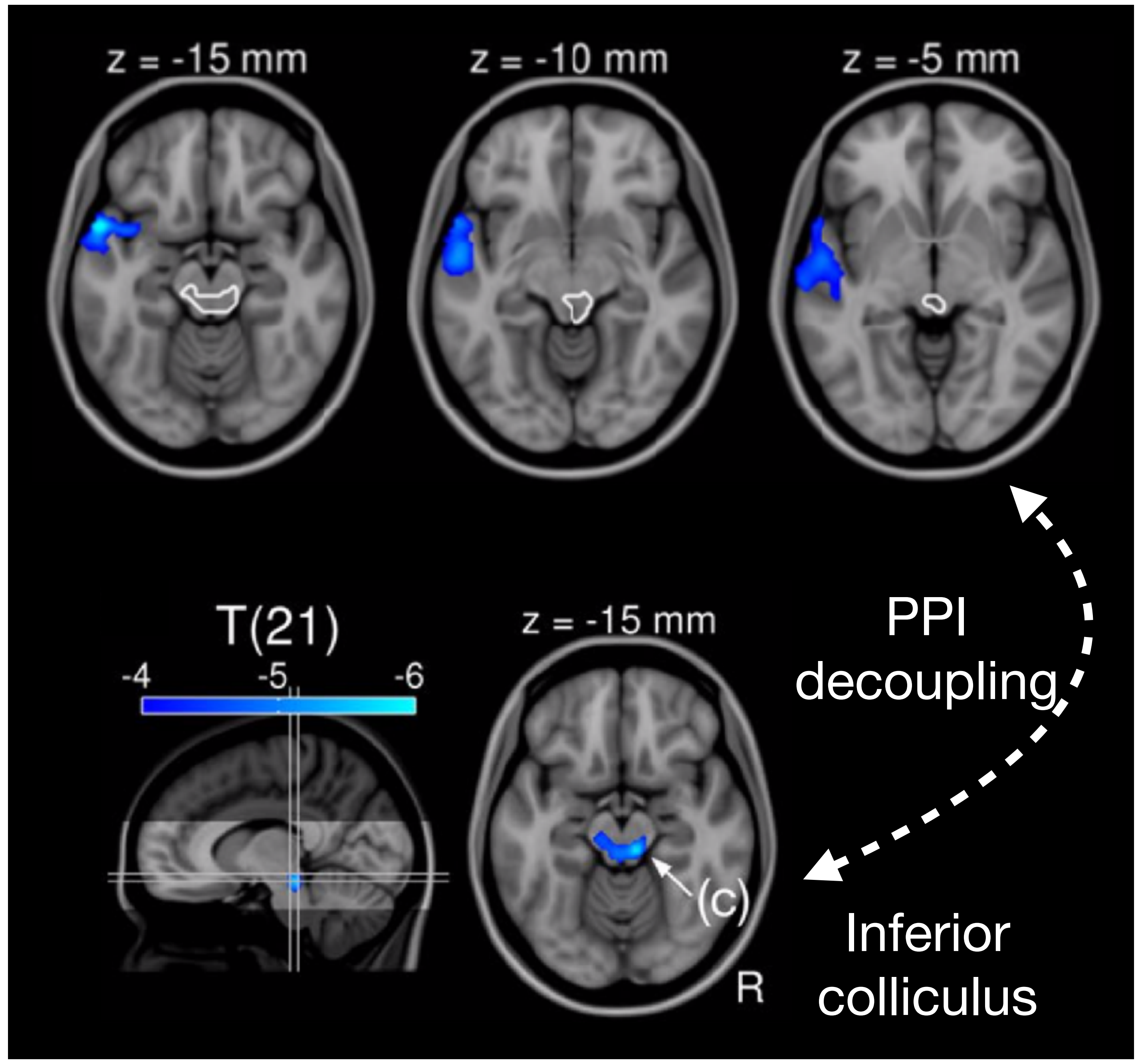
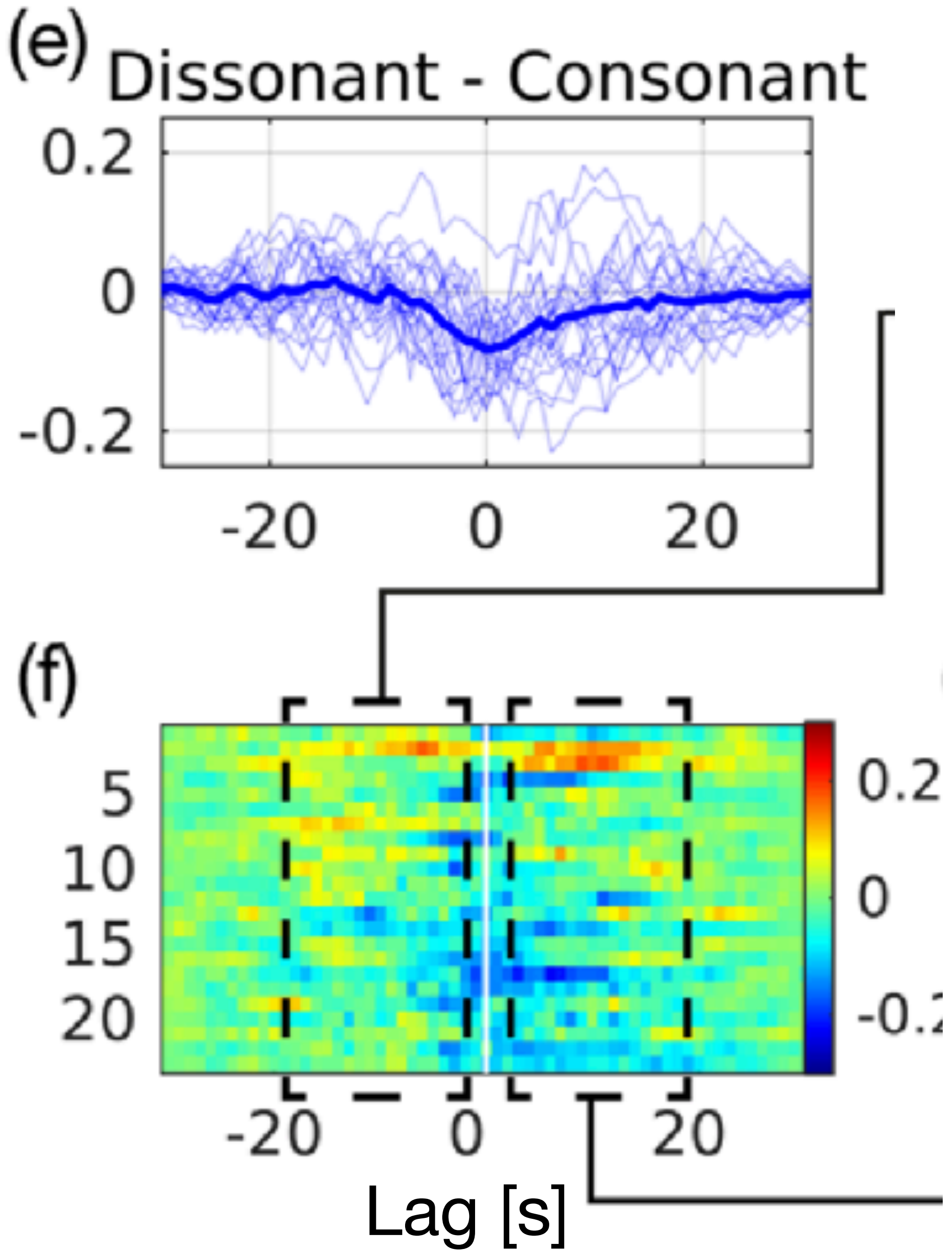


Cross-correlation



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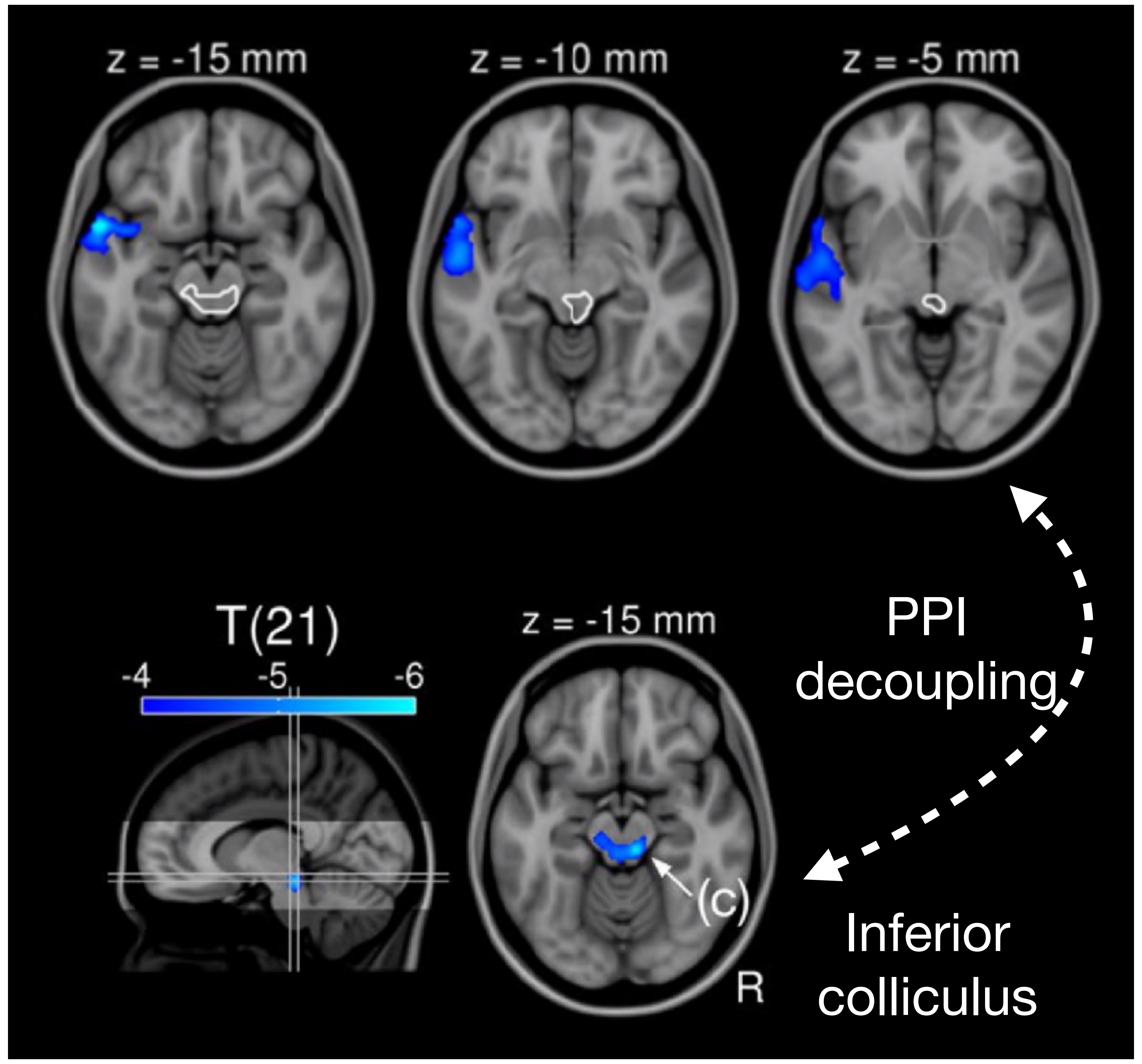

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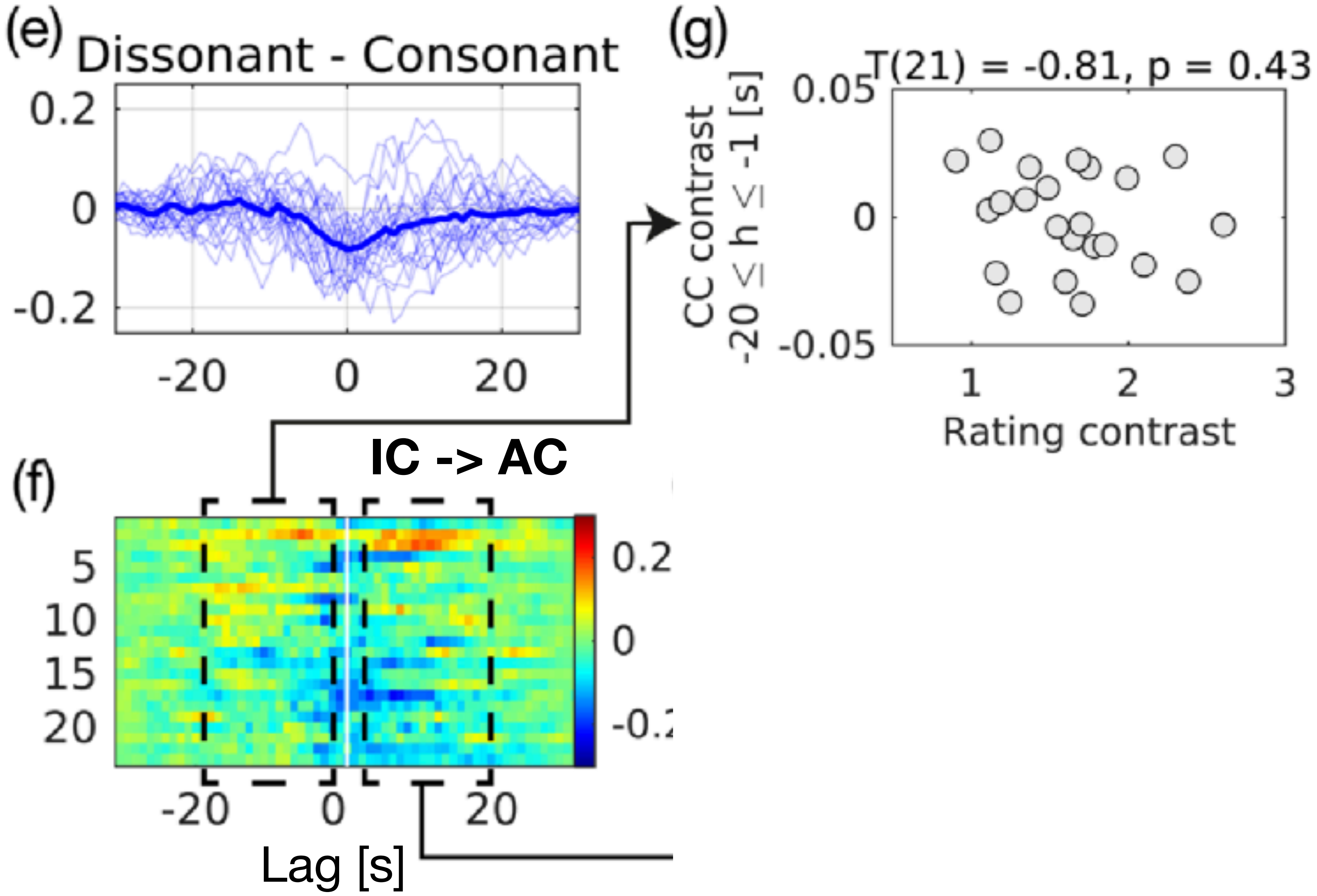

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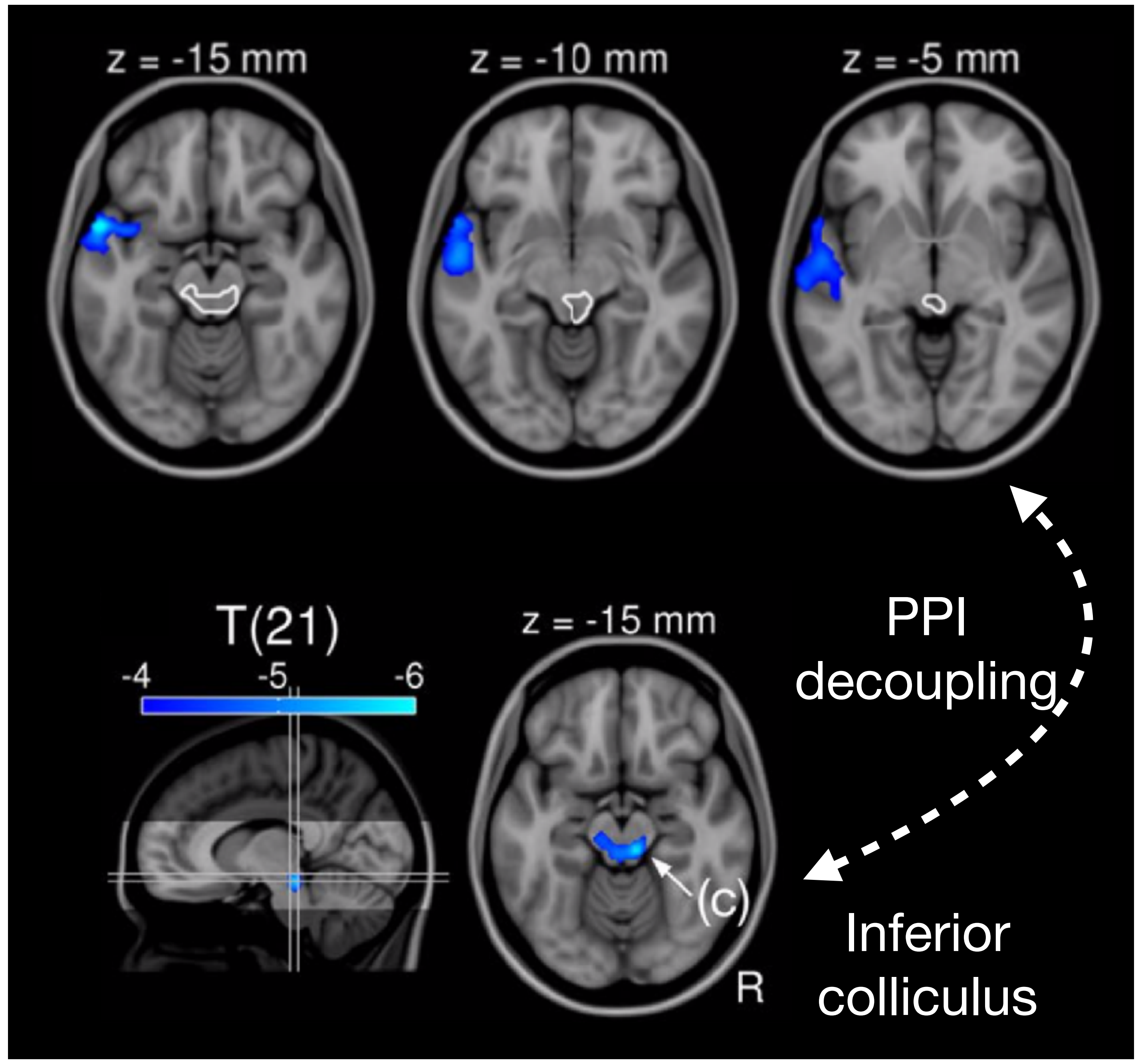

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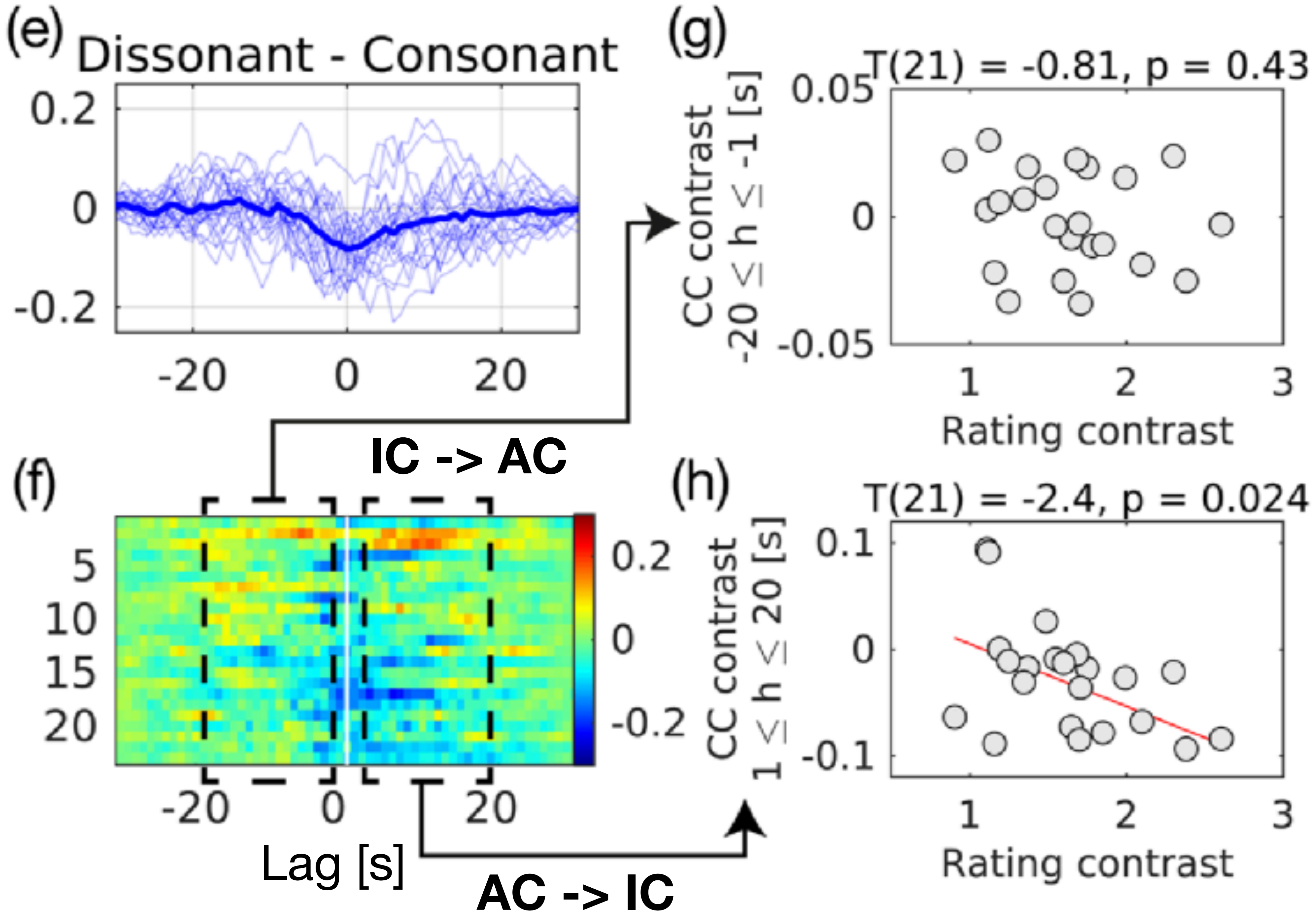

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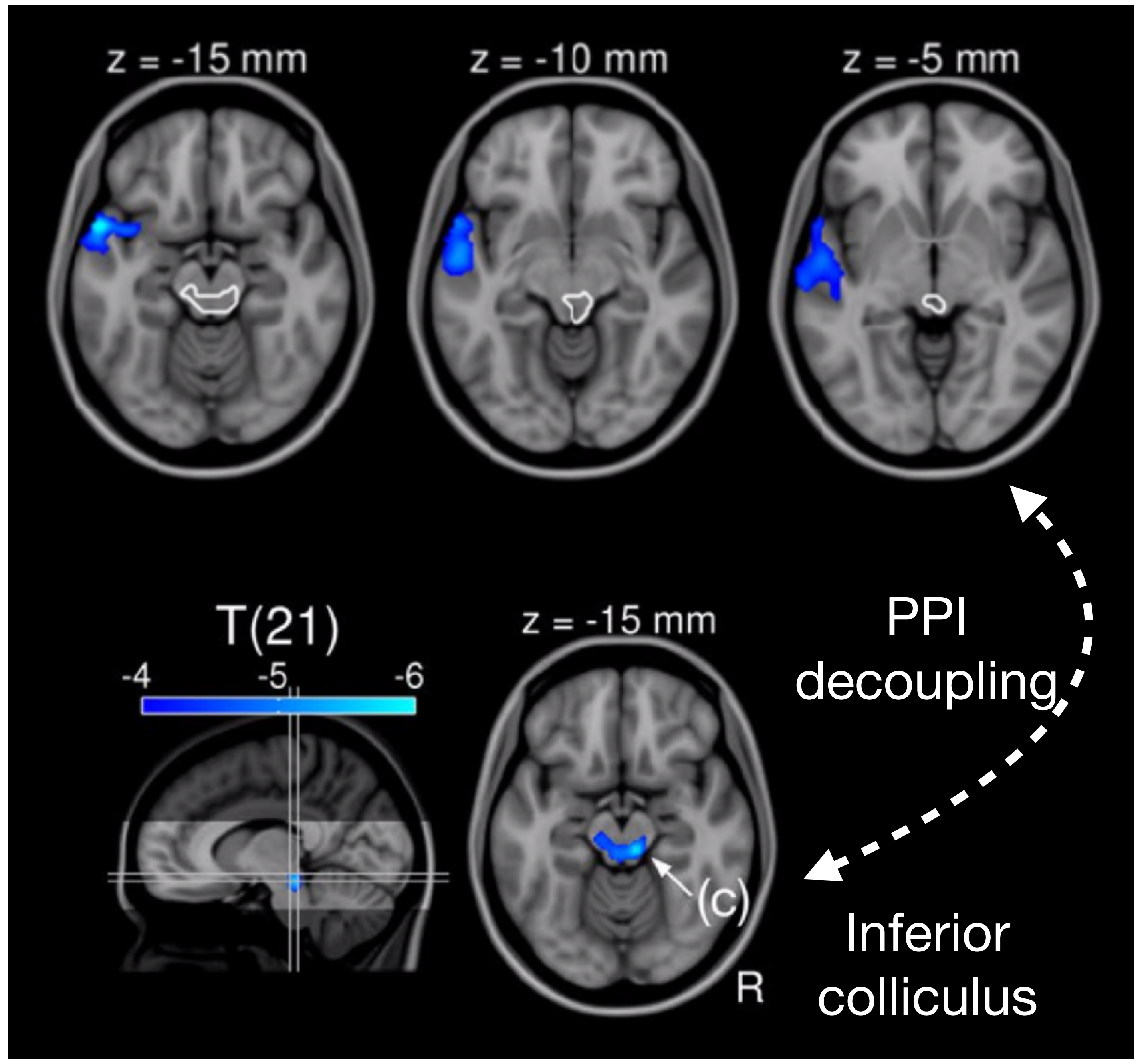

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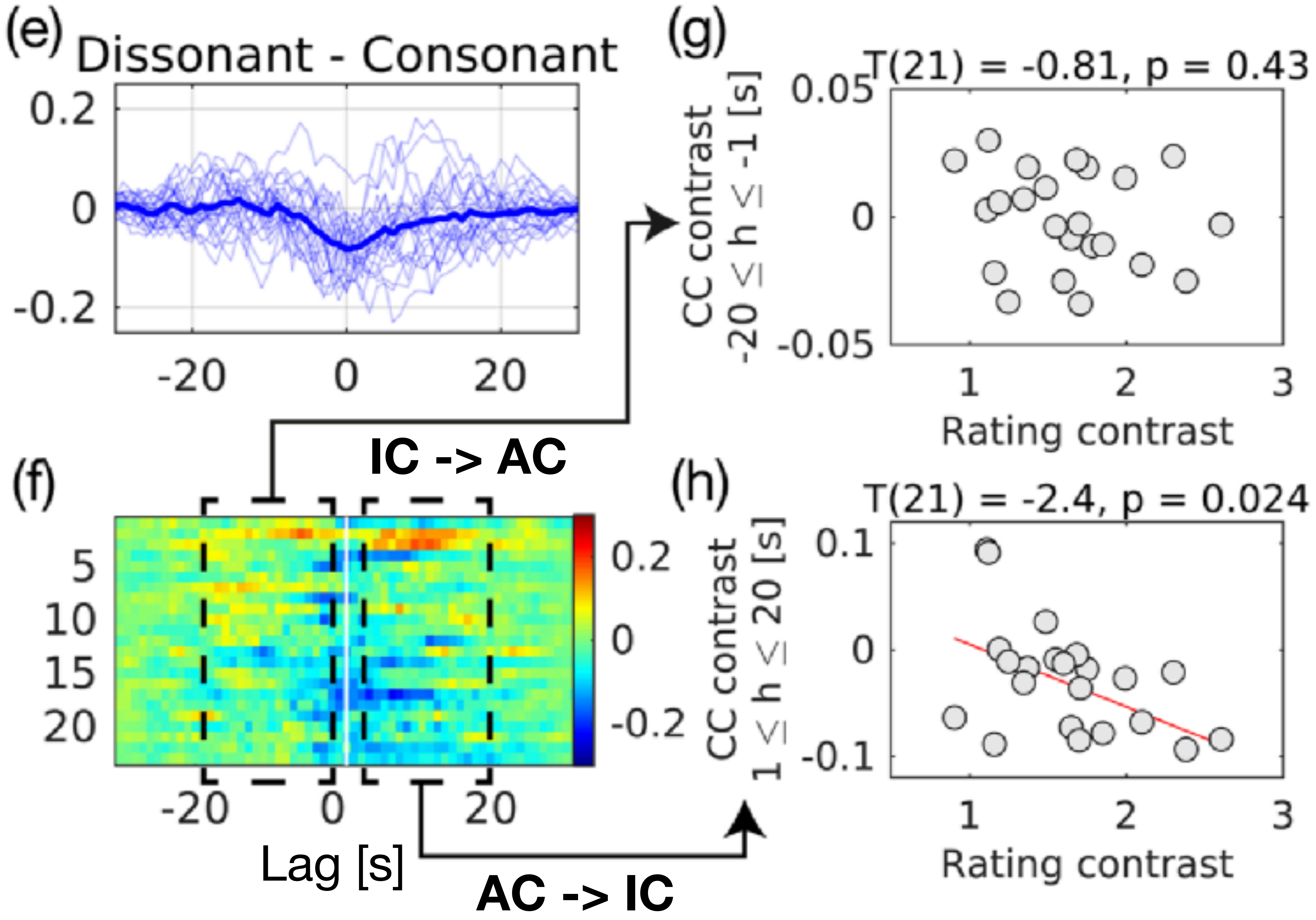
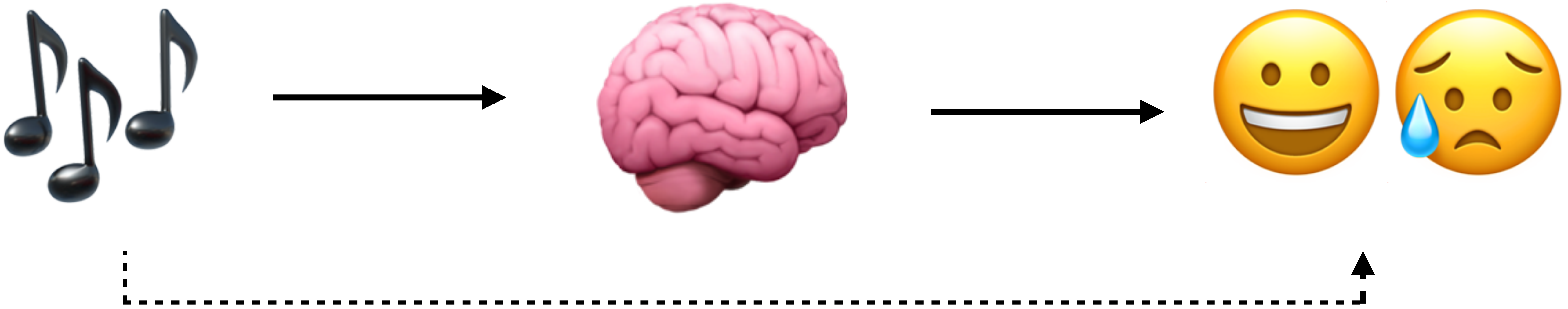


The IC decoupled more from the left auditory cortex (top-down) in individuals who rated dissonant versions worse.

Limitations of controlled stimuli

Ceteris paribus... and the subject is not listening.

Disruptive manipulations: validity, generalizability, & specificity?



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Limitations of controlled stimuli

Ceteris paribus... and the subject is not listening.

Disruptive manipulations: validity, generalizability, & specificity?

: But what else can we do?

Alternative approach: "naturalistic neuroimaging"

Embracing complexity for ecological validity

1980 *1990* *2000* *2010* *2020*

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Gibson, 1978, The Ecological Approach to the Visual Perception of Pictures, *Leonardo.*

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- **Hamilton & Huth**, 2020, The Revolution Will Not Be Controlled: Natural Stimuli in Speech Neuroscience, *Language, Cognition and Neuroscience*.

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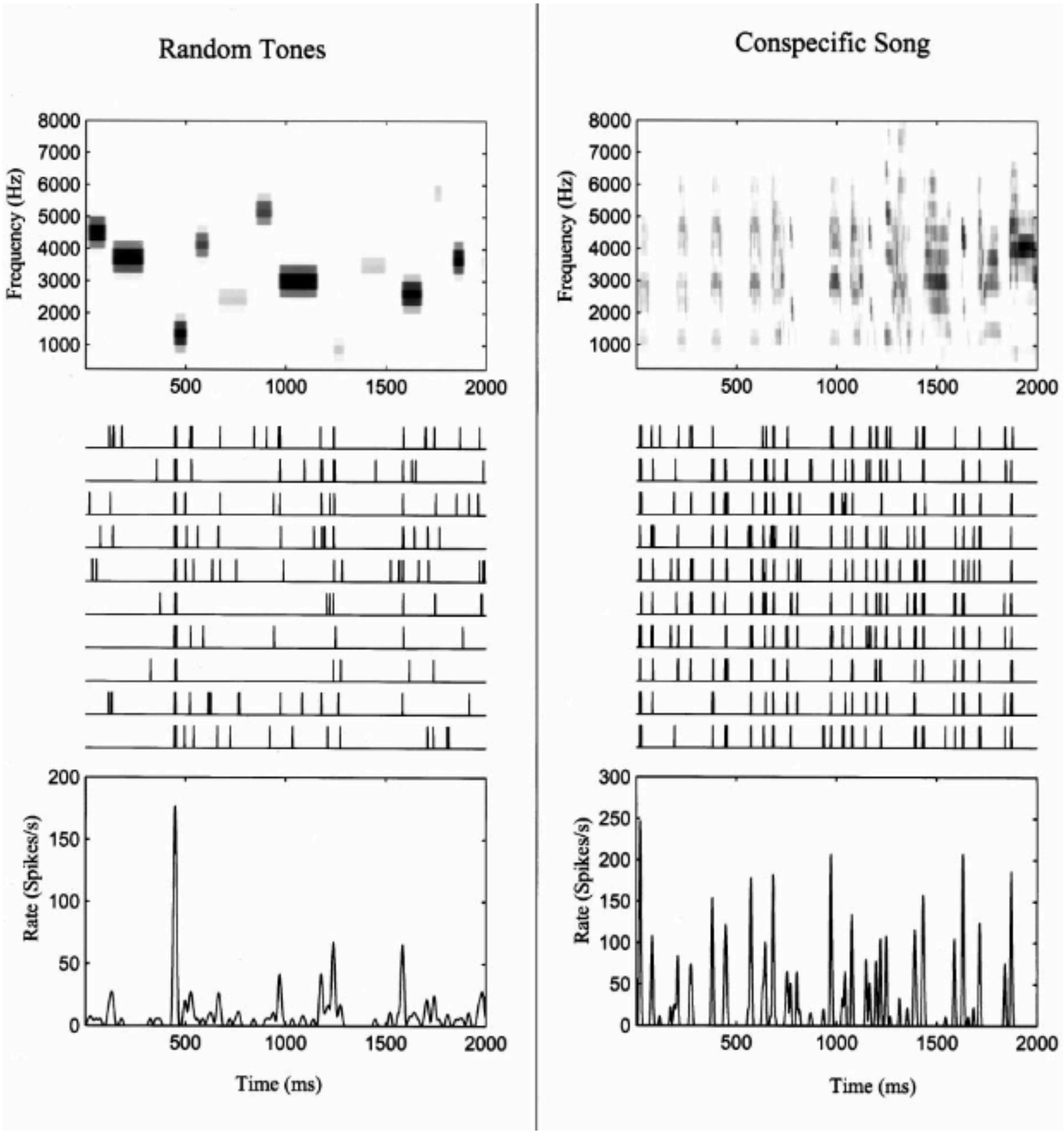
Receptive field mapping of a conspecific calls

Invasive recording of local field potential of neurons



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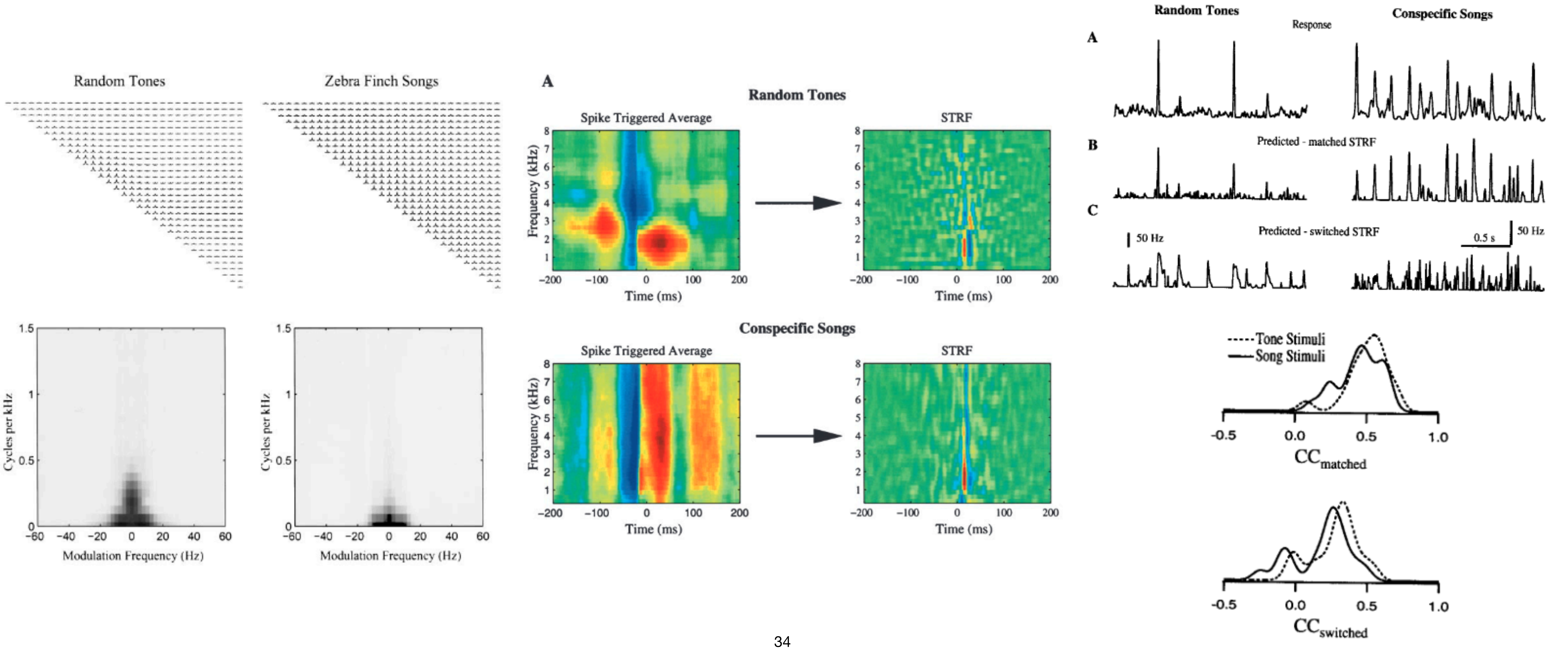
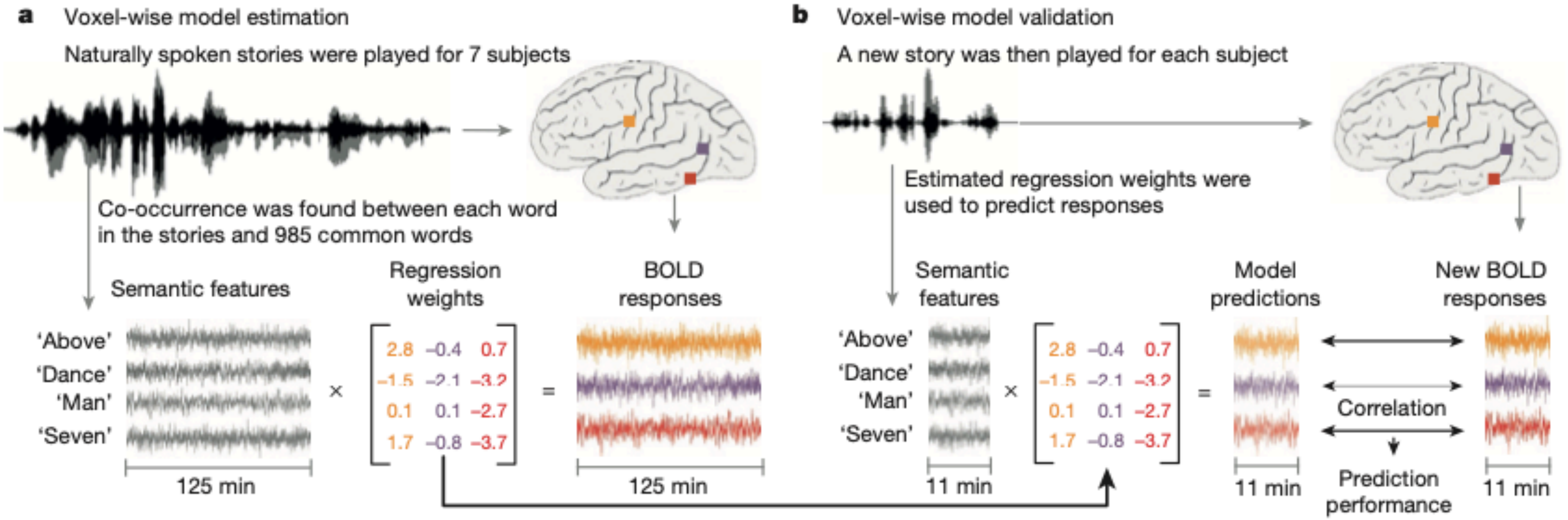


Semantic representation in the whole cortex

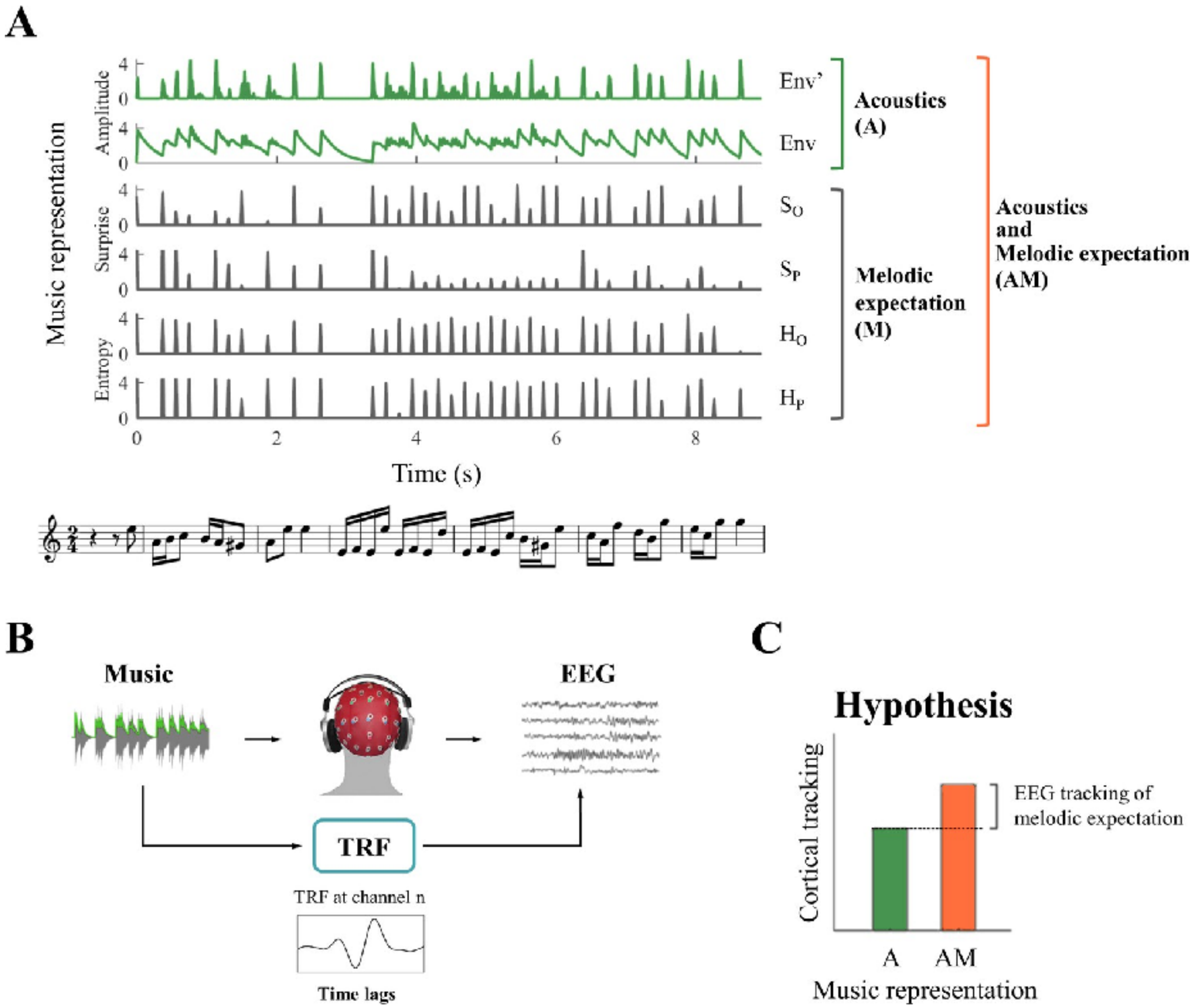
Non-invasive scanning of functional MRI (local paramagnetism)



Huth et al., 2016, https://doi.org/10.1038/nature17637

Temporal response function of melodic surprisal

Non-invasive recording of EEG (scalp potential)



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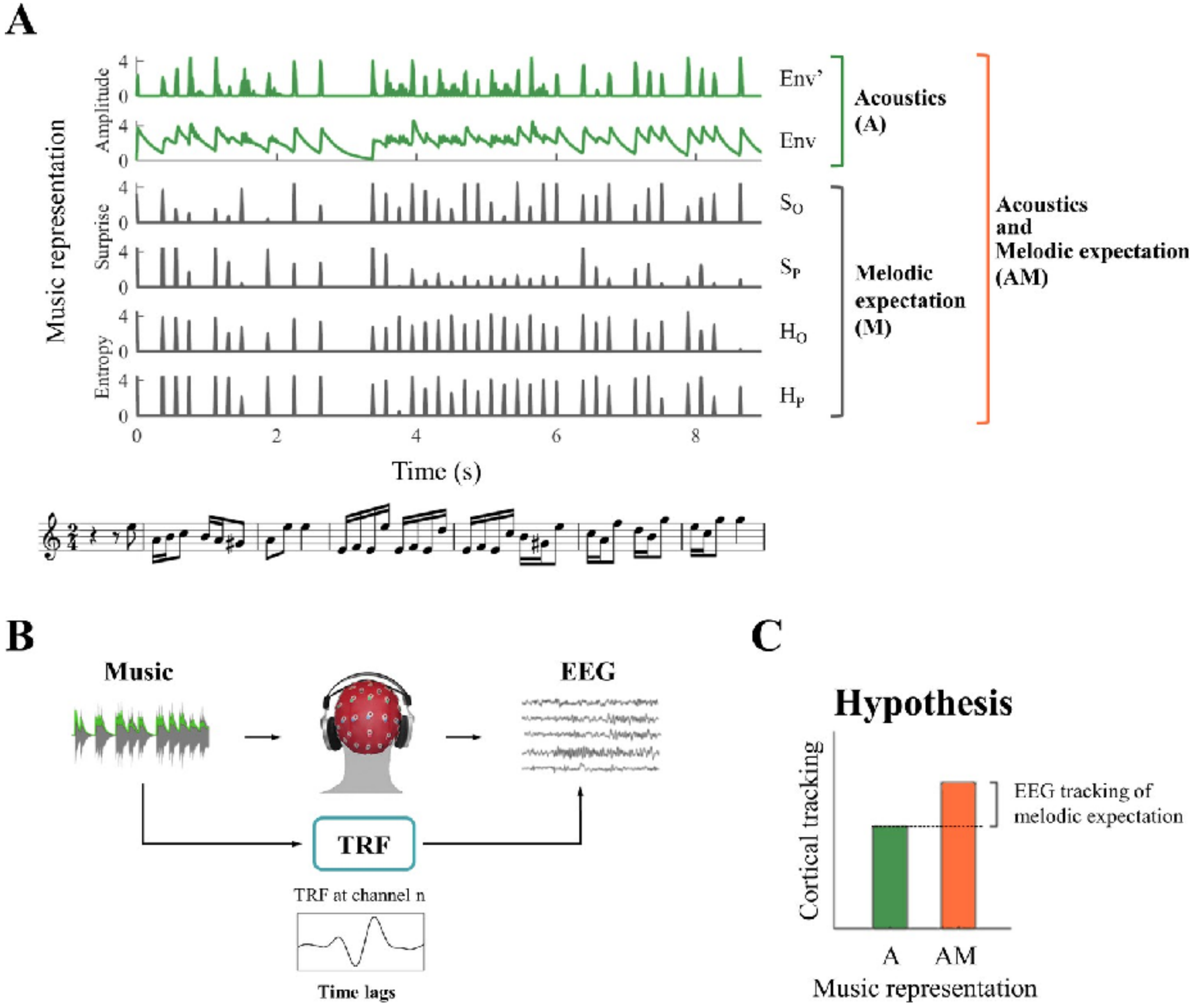

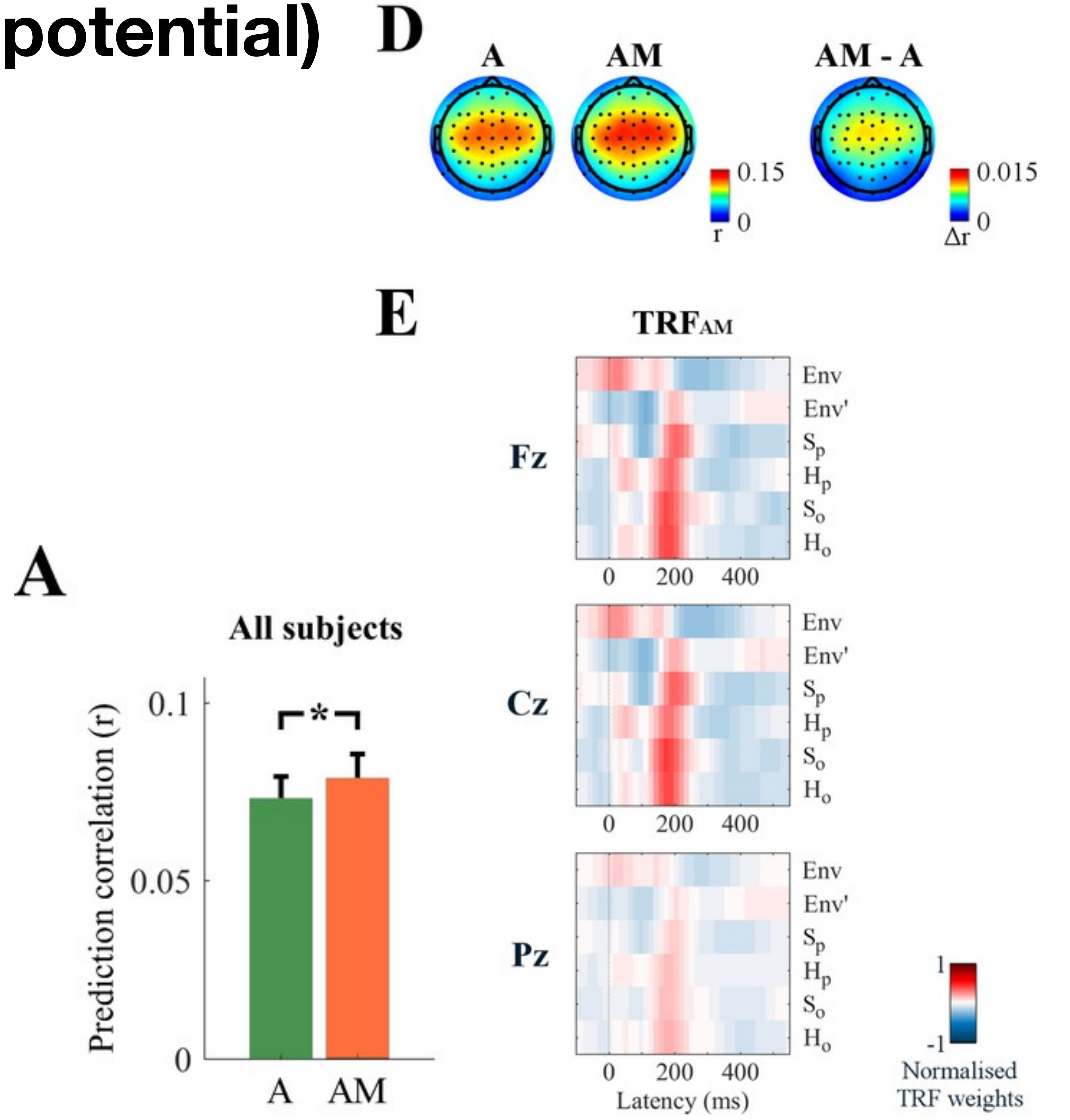

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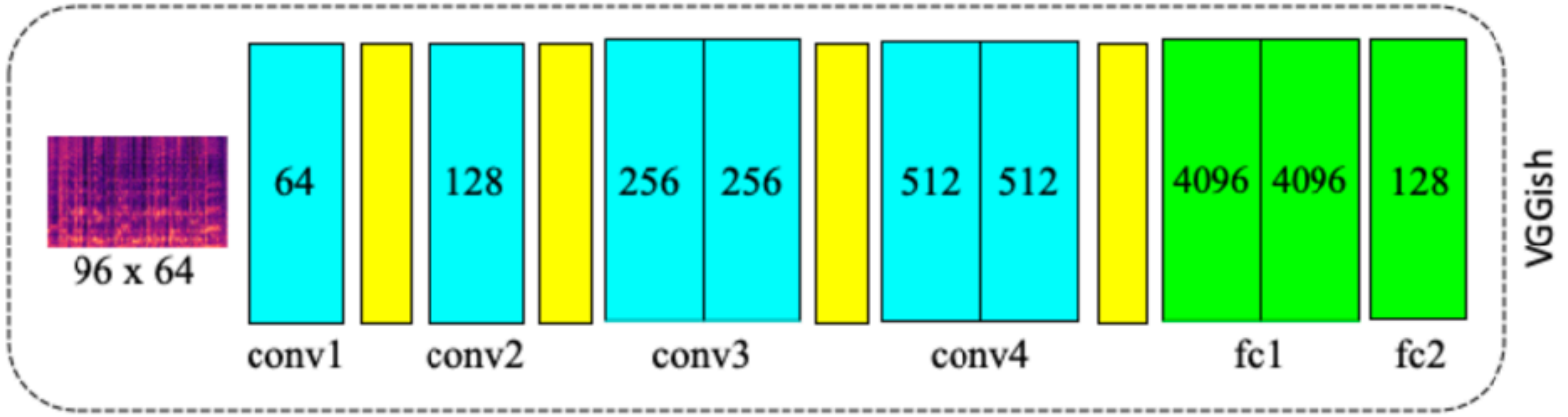
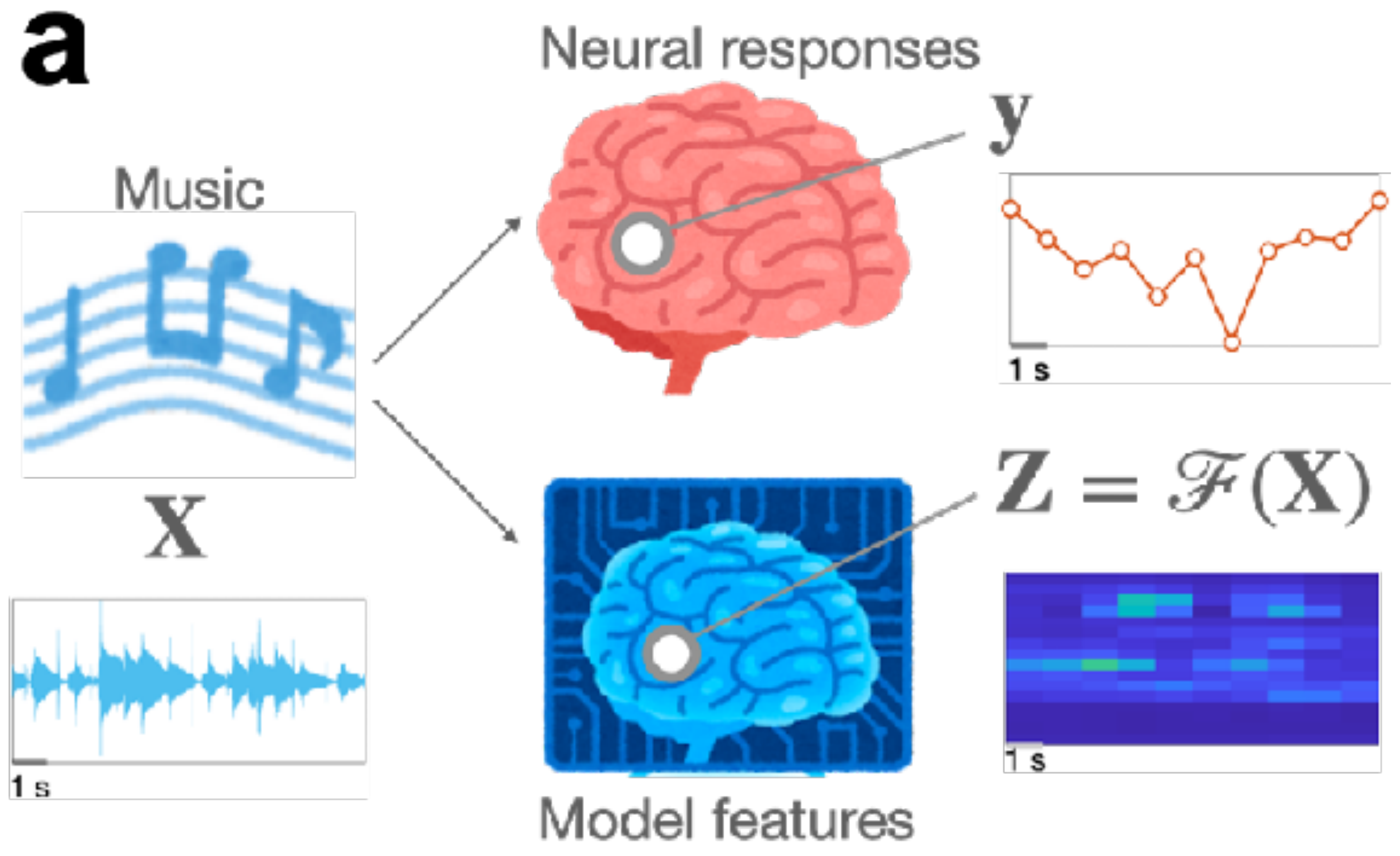
Representational gradient of musical emotions in fMRI

Non-invasive scanning of functional MRI (local paramagnetism)





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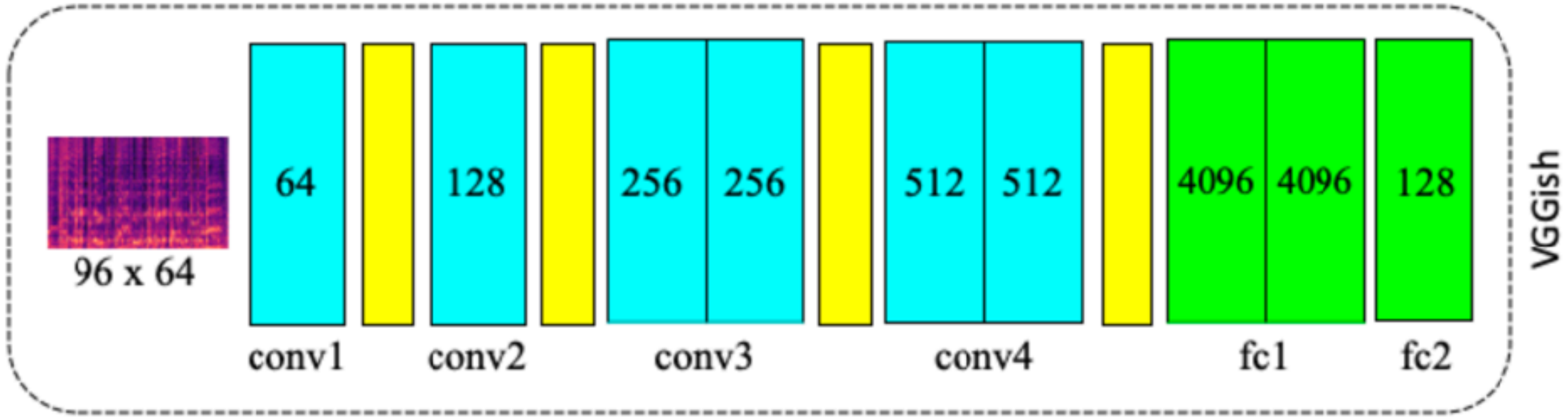
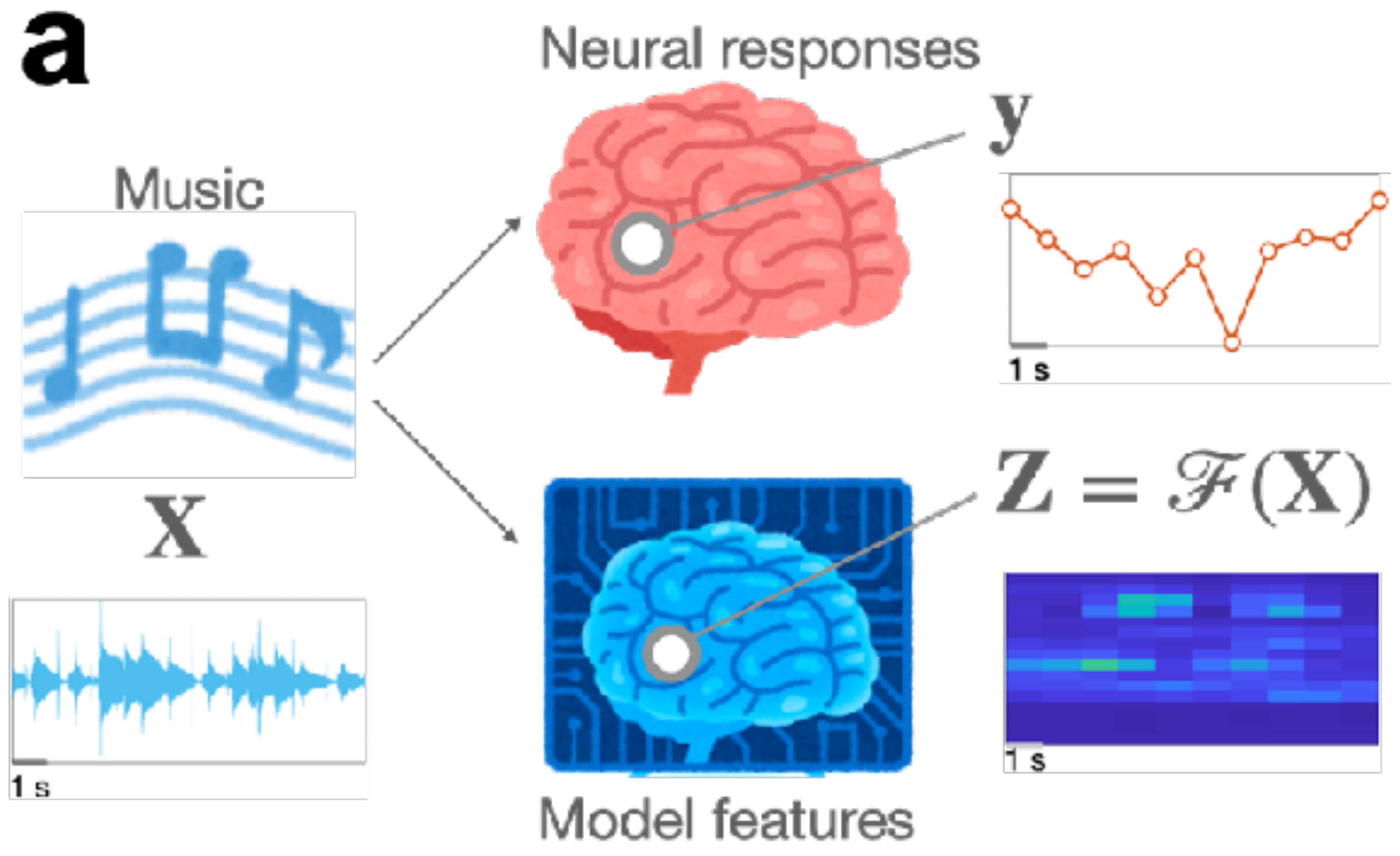
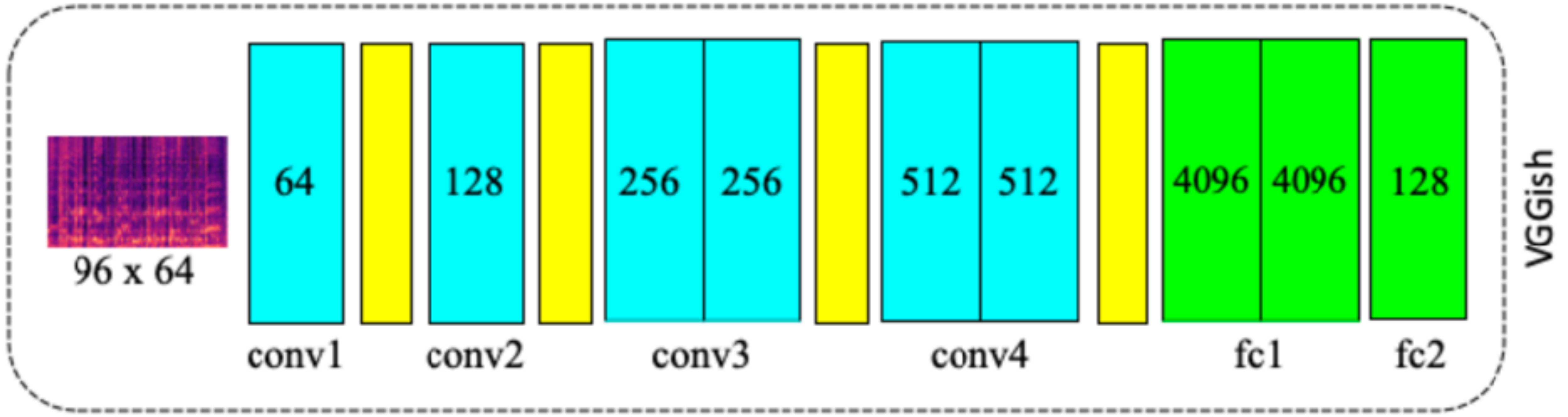


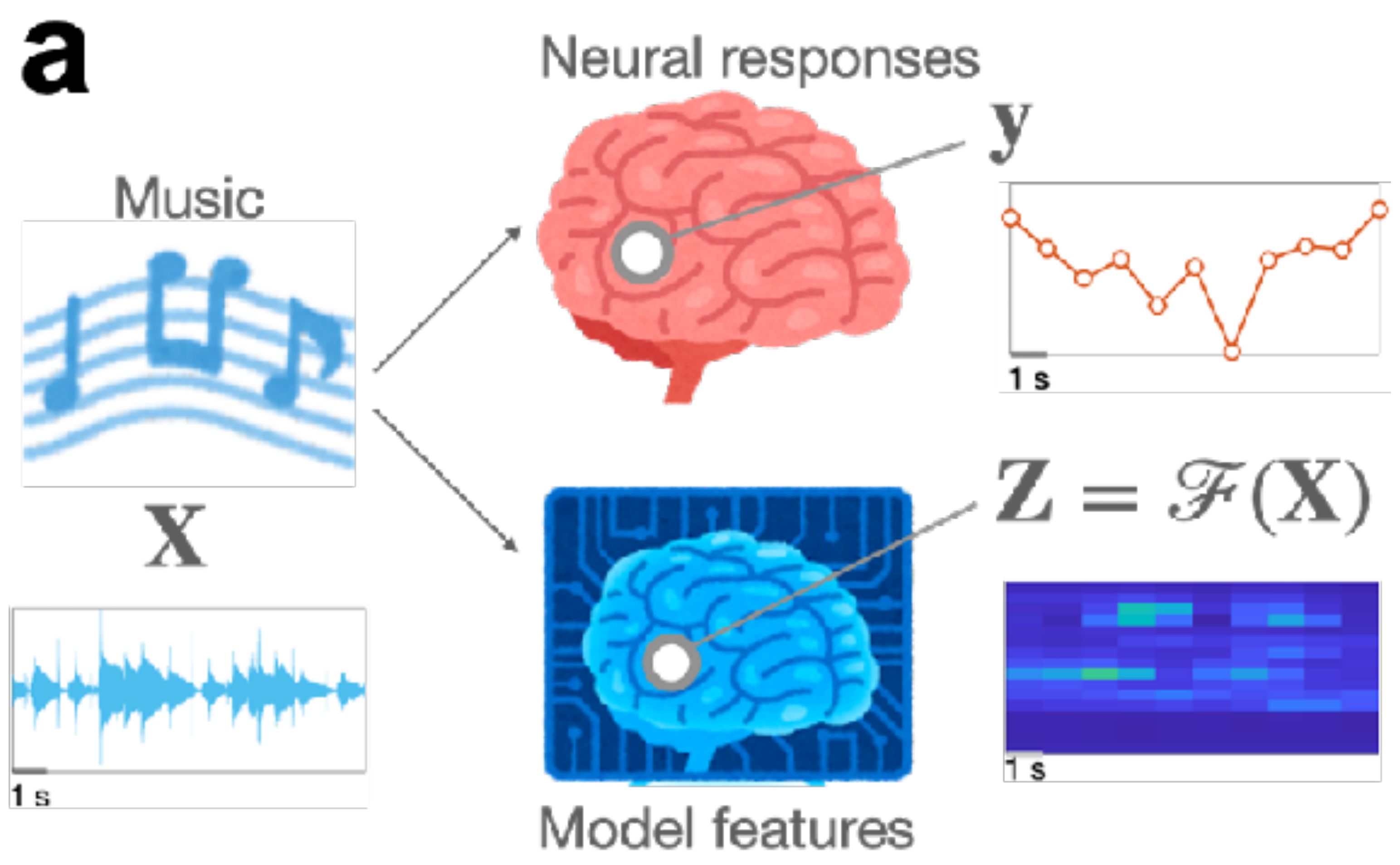


How good the "Layer X" is for
this brain area?

Representational gradient of musical emotions in fMRI

Non-invasive scanning of functional MRI (local paramagnetism)





b How good the "Layer X" is for this brain area?

$$y^{(1)} = \mathcal{F}_1(\mathbf{X}^{(1)})\mathbf{b}_1 + \varepsilon \rightarrow r_1 = \mathrm{corr}(\hat{y}_1^{(2)}, y^{(2)})$$

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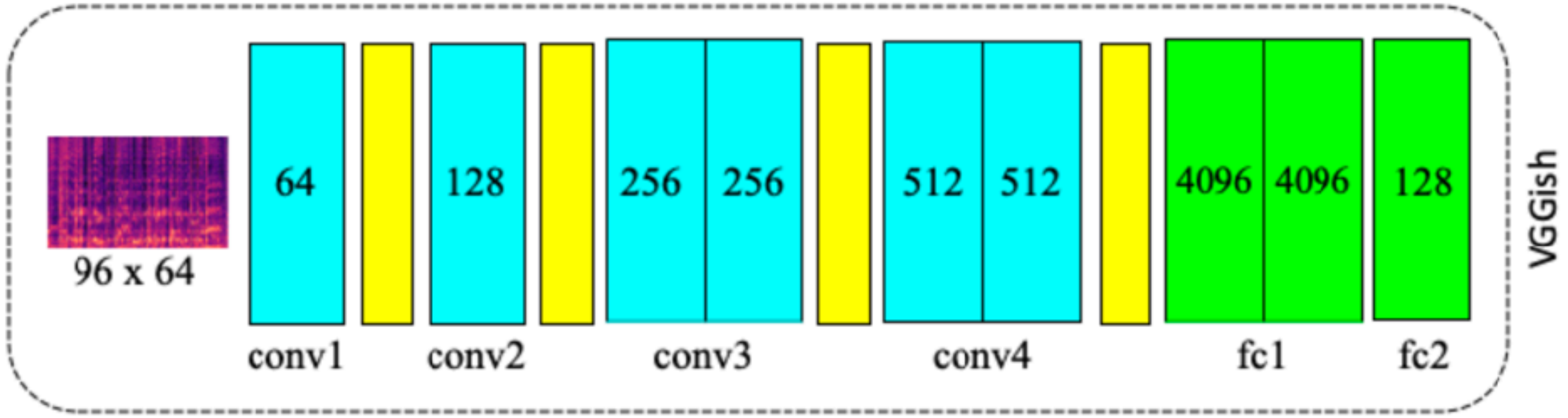

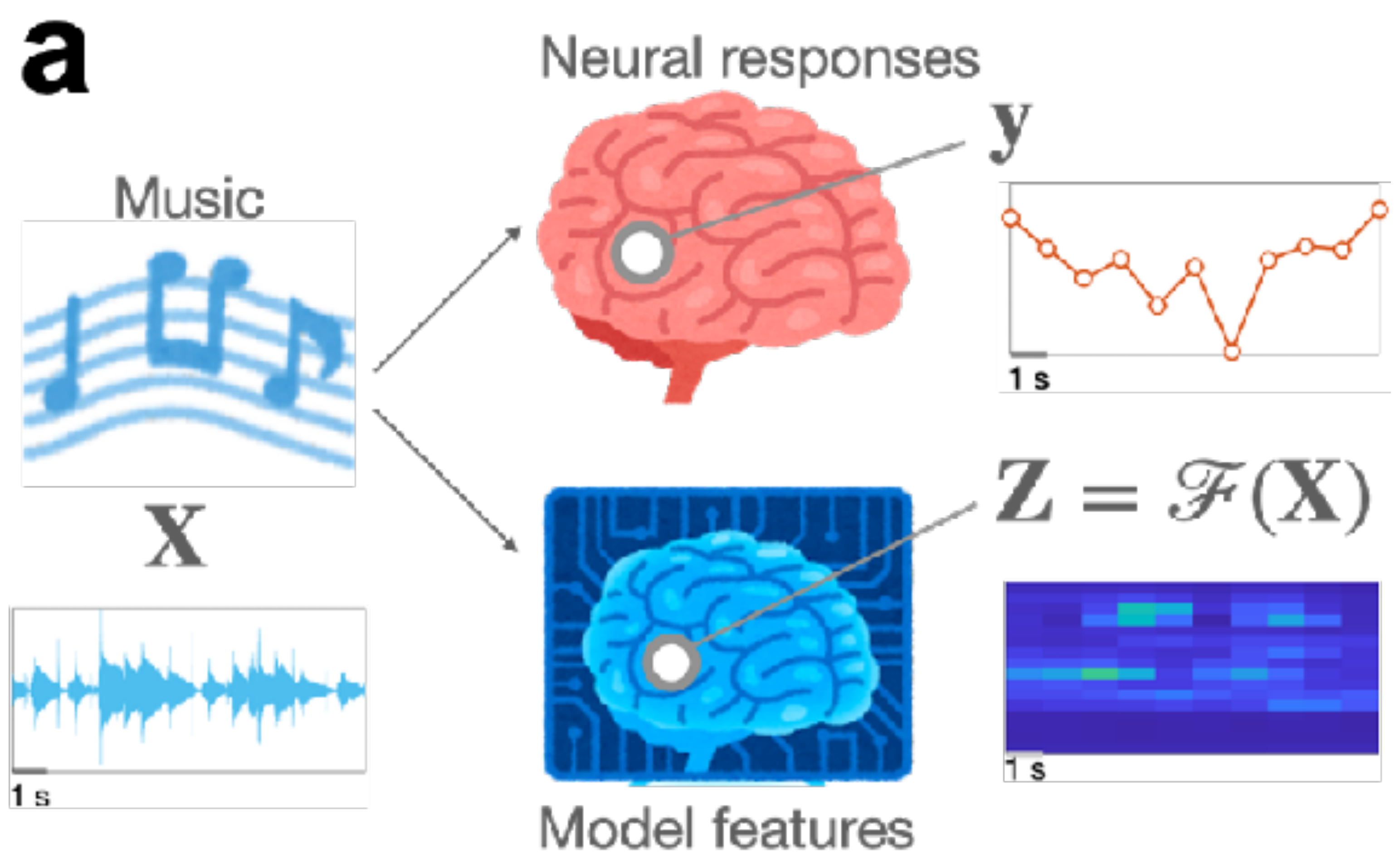

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A "profile" of layer-specific prediction accuracies

Representational gradient of musical emotions in fMRI

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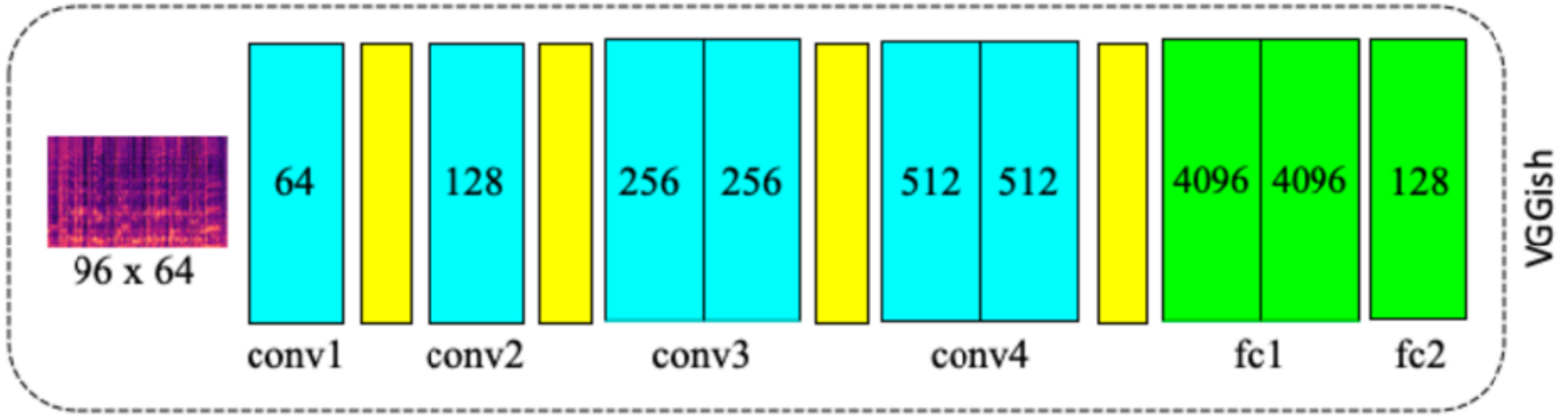

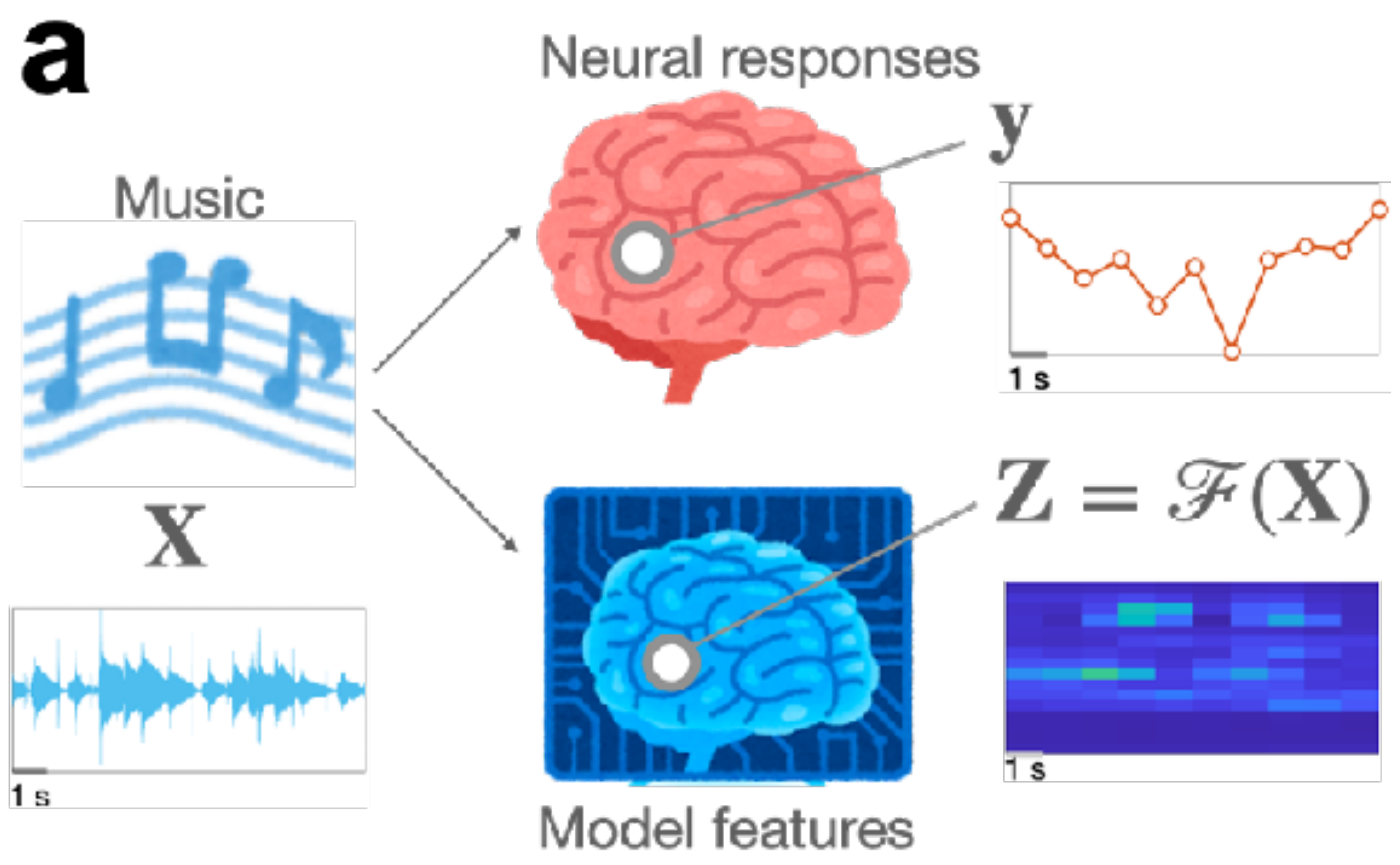

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c

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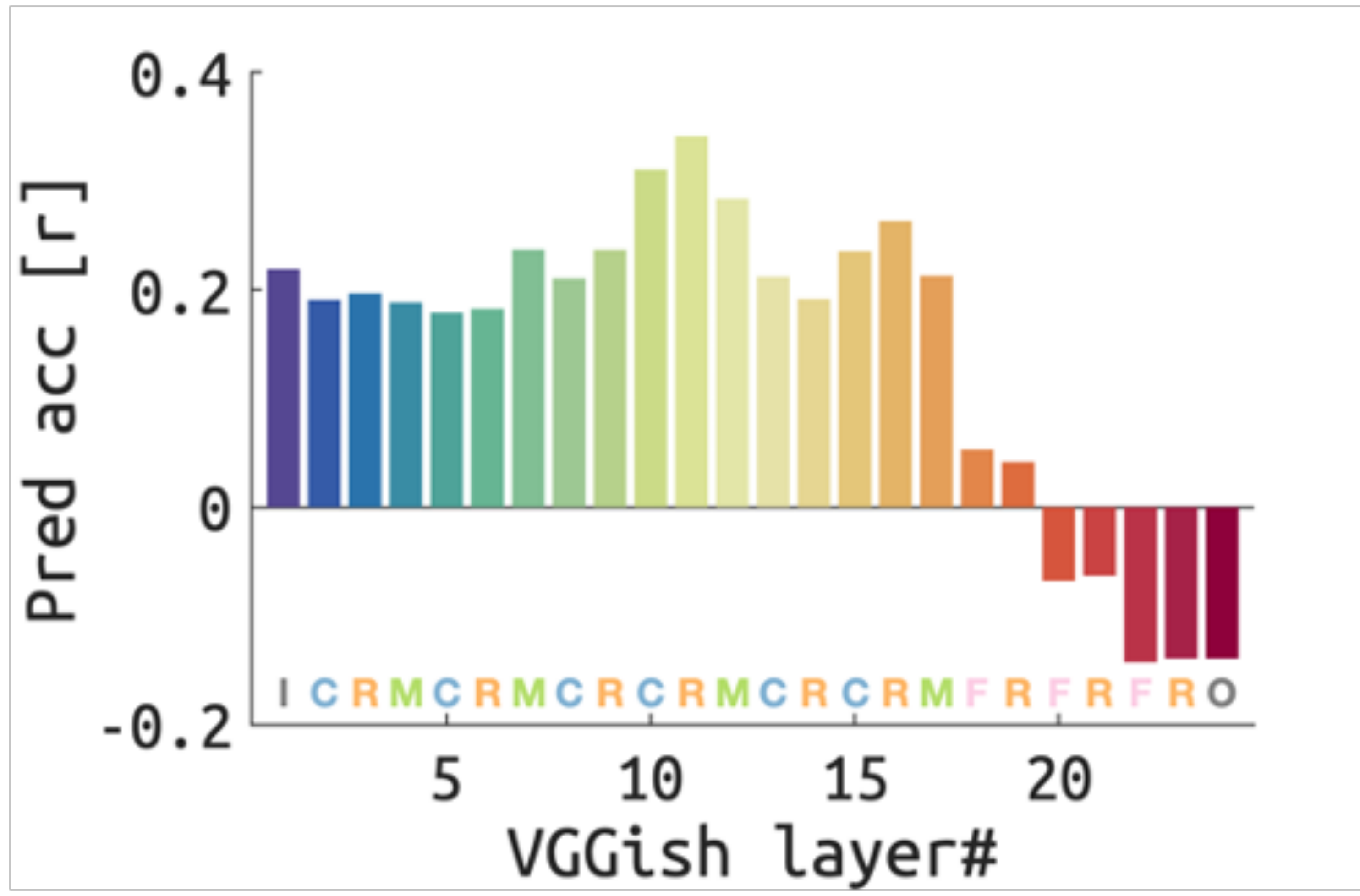

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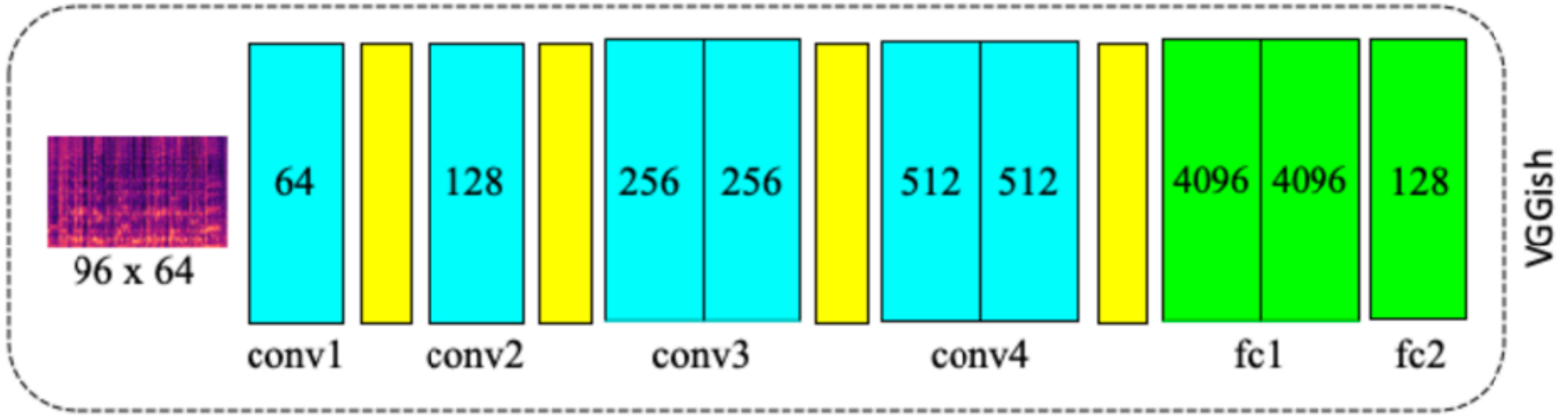

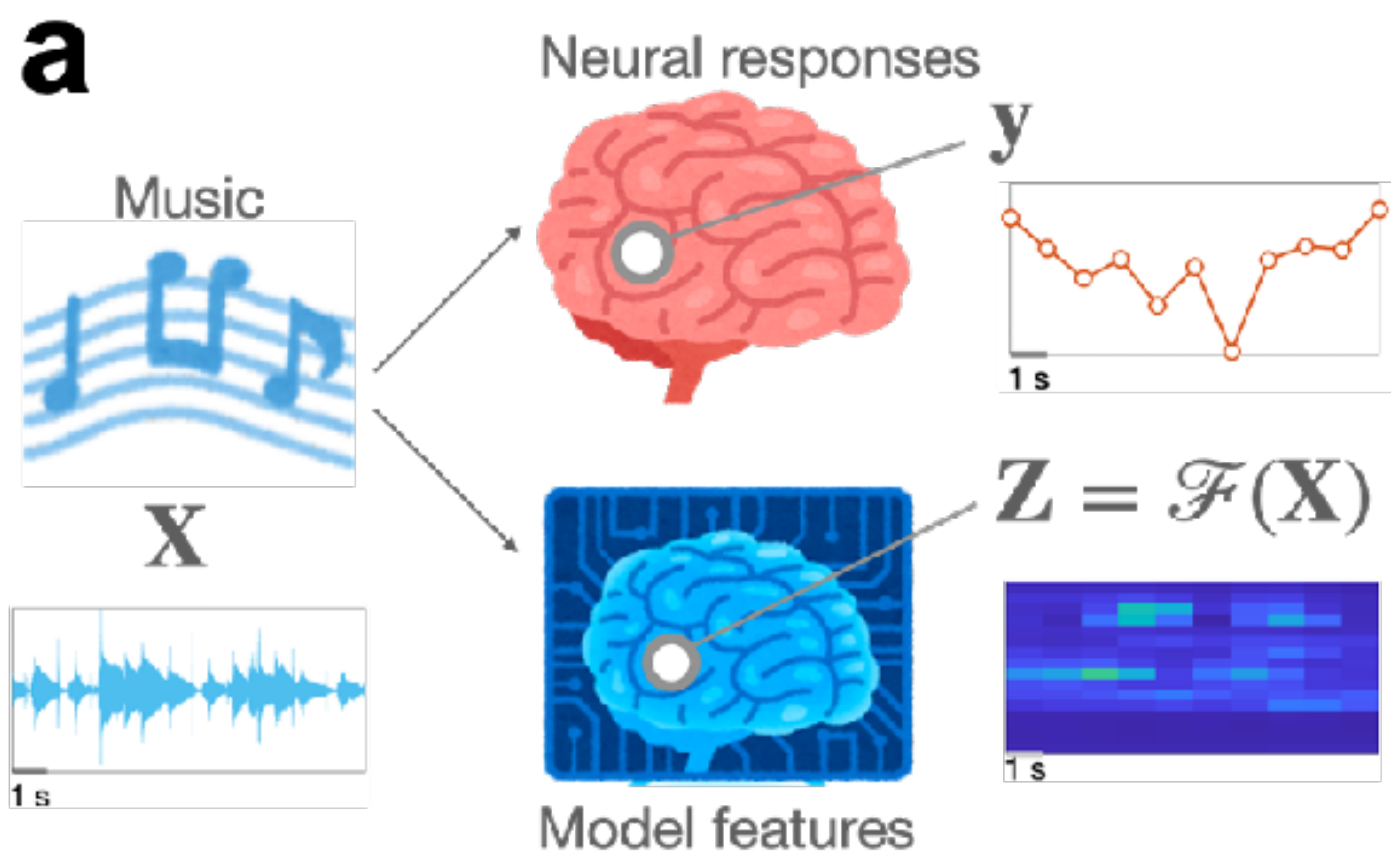

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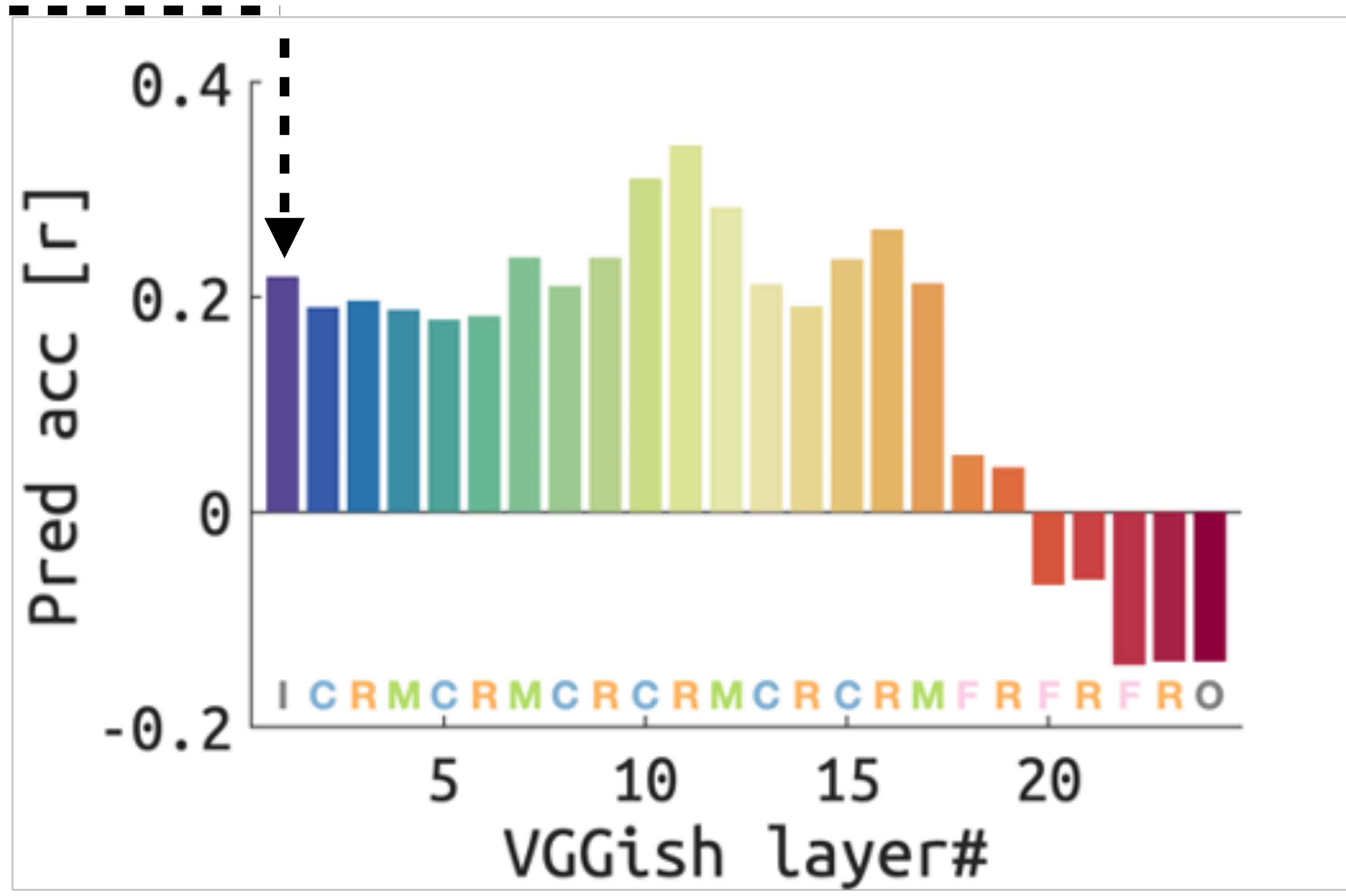

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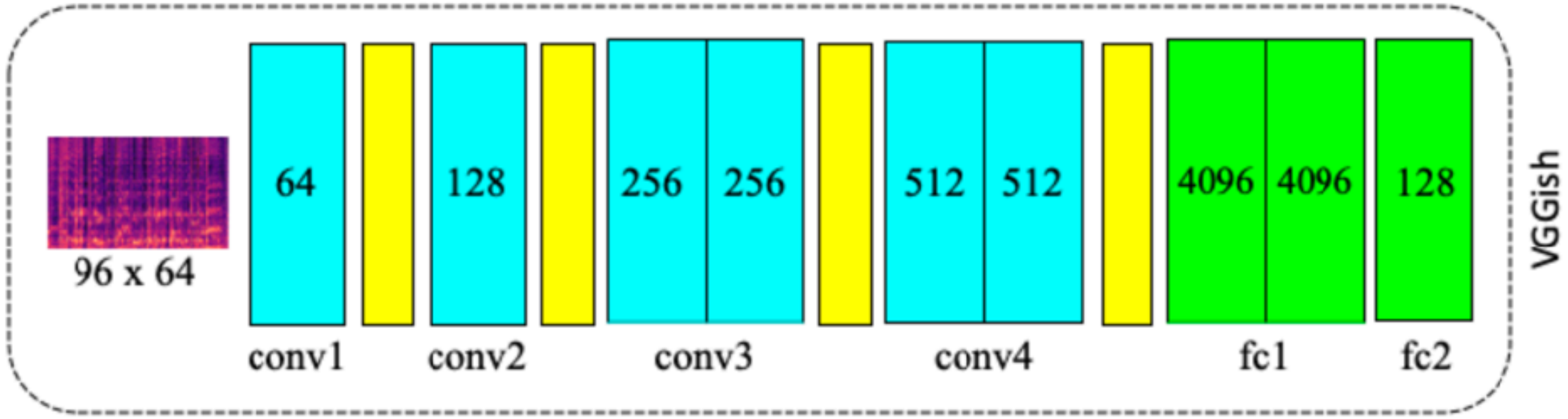

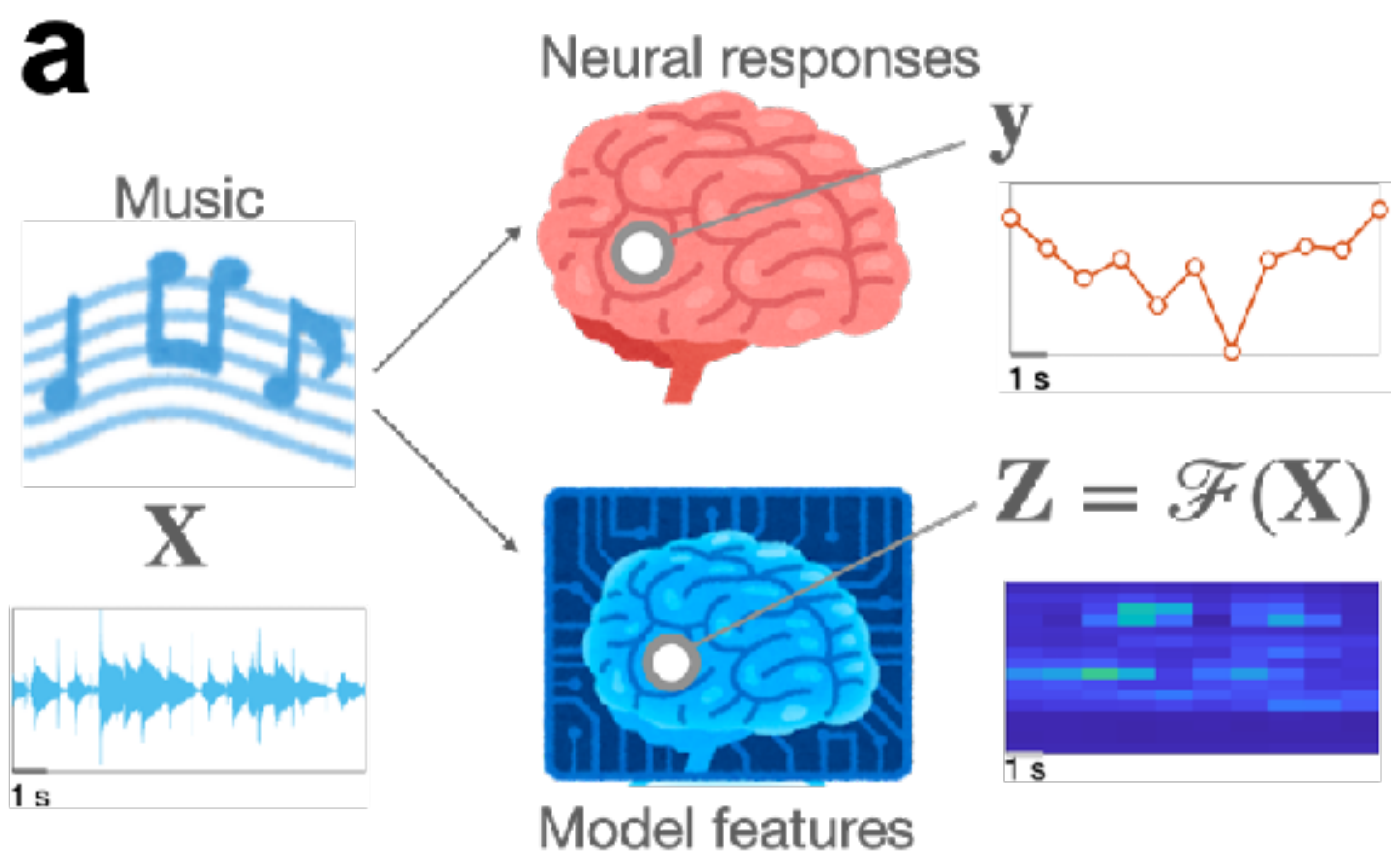

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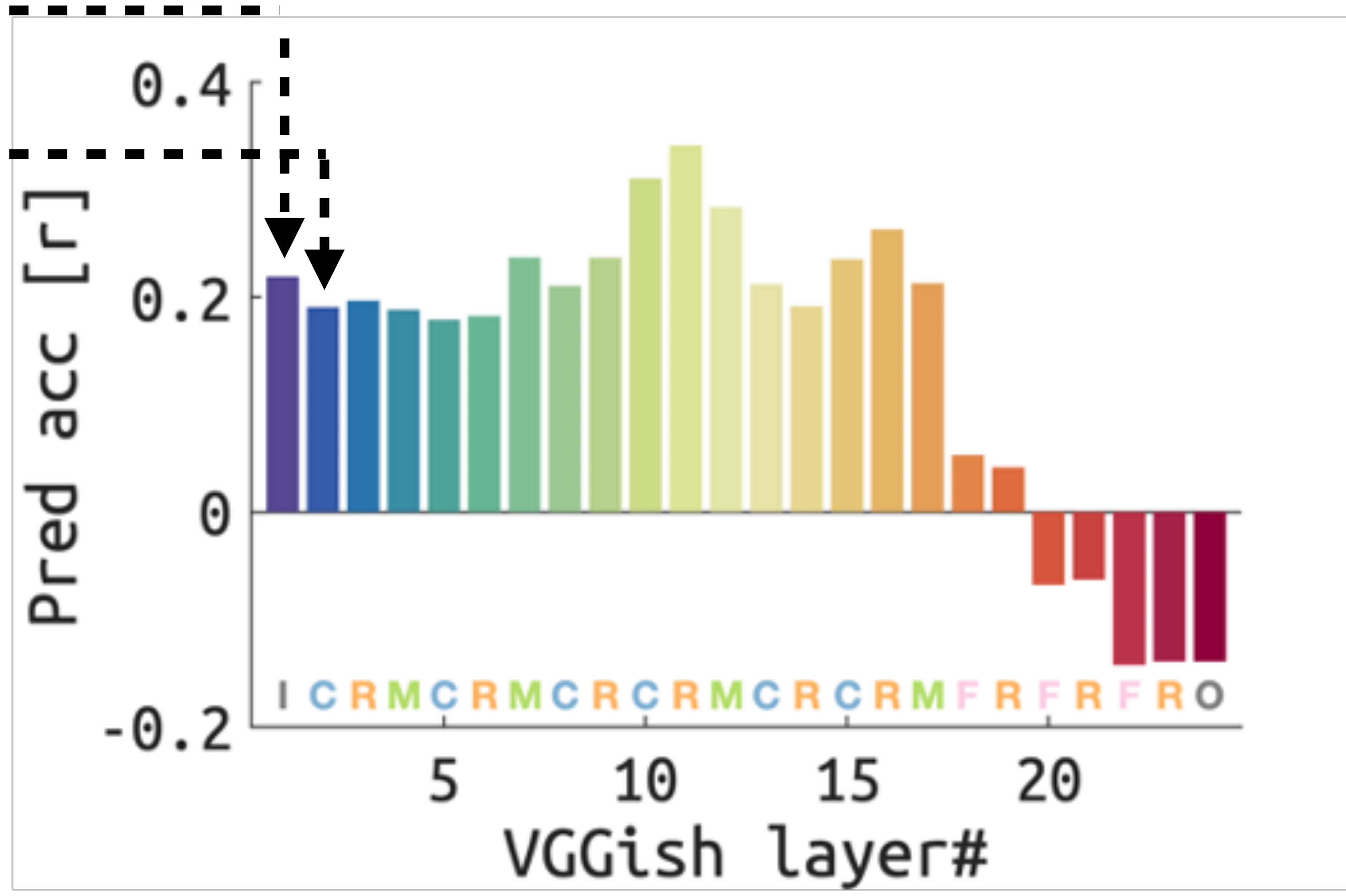

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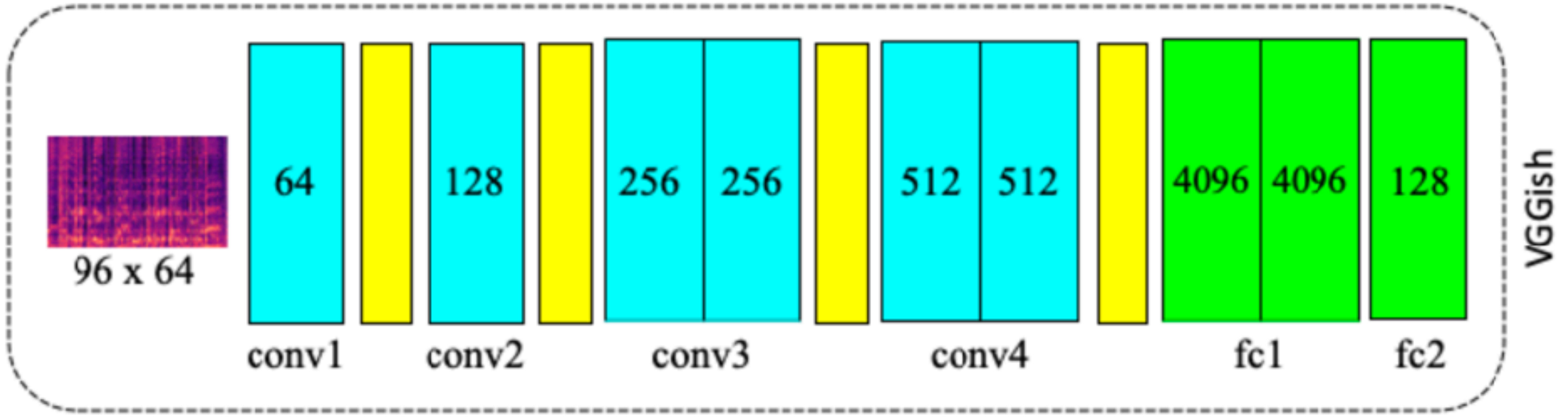

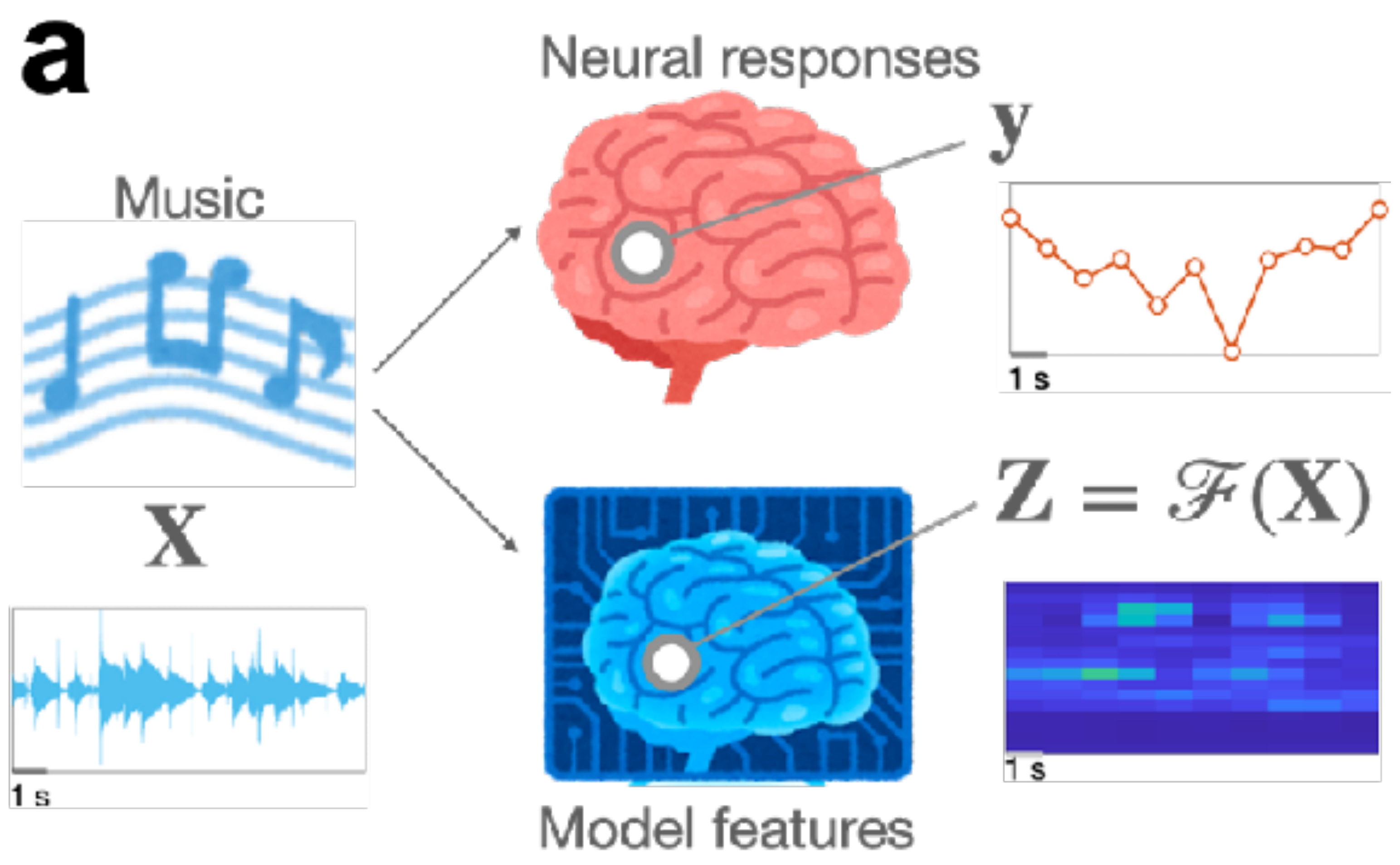

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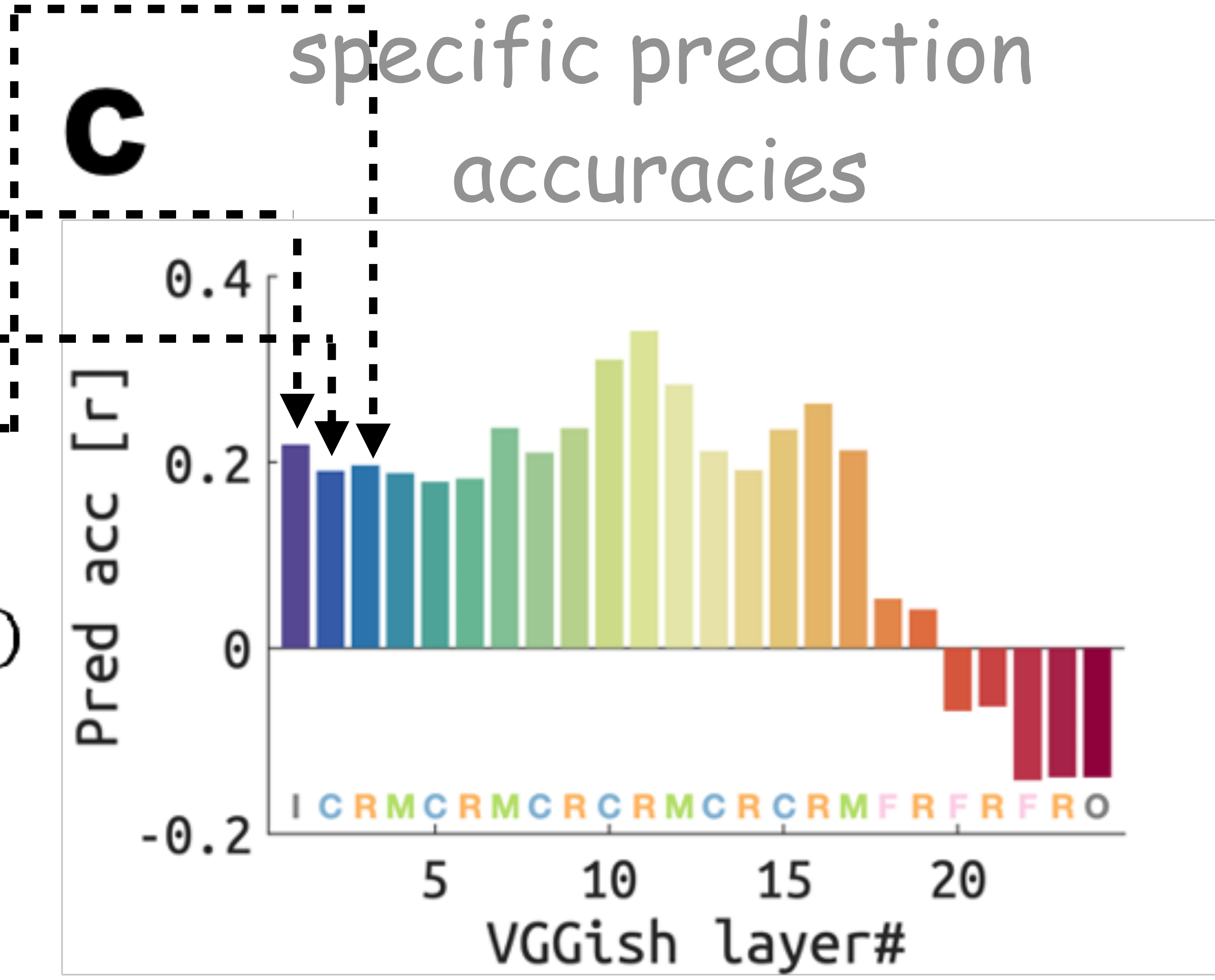

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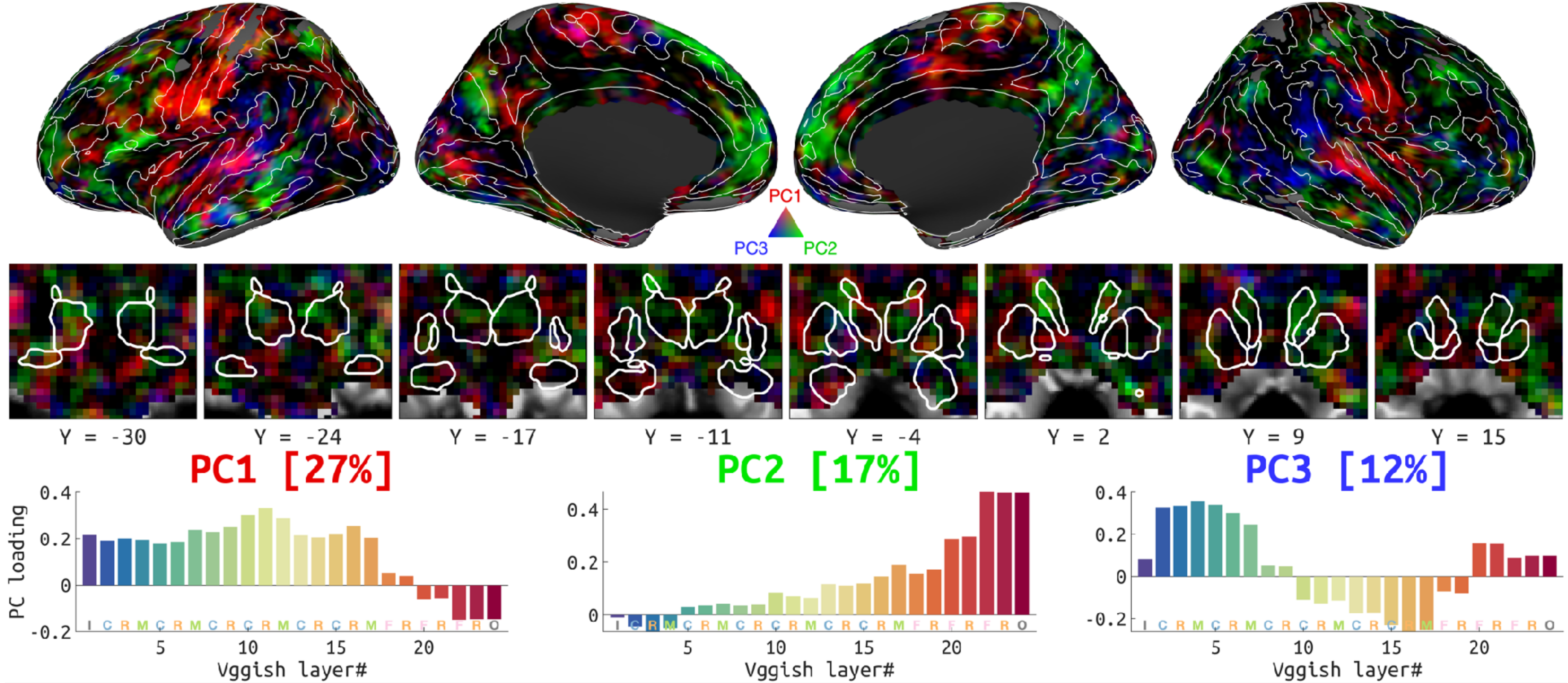

Any questions so far?

(Or I'll ask one 😈)

Go back to SESSION PLAN

Motivations (WHYs):
Linearized Encoding Analysis

How can we understand a nonlinear system?

Let's say we magically know what the brain does:

$$\mathbf{X}$$
$$(t \times p)$$

Stimulus

How can we understand a nonlinear system?

Let's say we magically know what the brain does:

$$\mathbf{X} \qquad \mathscr{F} : \mathbb{R}^p \mapsto \mathbb{R}^v$$

$$(t \times p)$$

Stimulus

System

How can we understand a nonlinear system?

Let's say we magically know what the brain does:

$$\mathbf{X} \qquad \mathscr{F} : \mathbb{R}^p \mapsto \mathbb{R}^v \qquad \mathbf{Y}$$

$$(t{\times}p) \qquad\qquad\qquad (t{\times}v)$$

Stimulus $\longrightarrow$ System $\longrightarrow$ Response

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Stimulus

$\longrightarrow$

System

$\longrightarrow$

Response

$$\underset{(t\times v)}{\mathbf{Y}} = \underset{(t\times v)}{\mathscr{F}(\mathbf{X})} + \underset{(t\times v)}{\mathbf{E}}$$

How can we understand a nonlinear system?

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$$\mathbf{X}$$
$$(t \times p)$$

Stimulus

How can we understand a nonlinear system?

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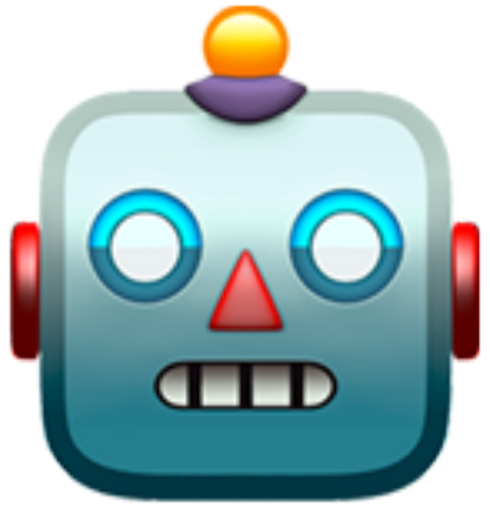
$$\mathbf{X} \quad (t \times p)$$

$$\mathscr{G} : \mathbb{R}^p \mapsto \mathbb{R}^f$$

Stimulus

$\longrightarrow$



Model

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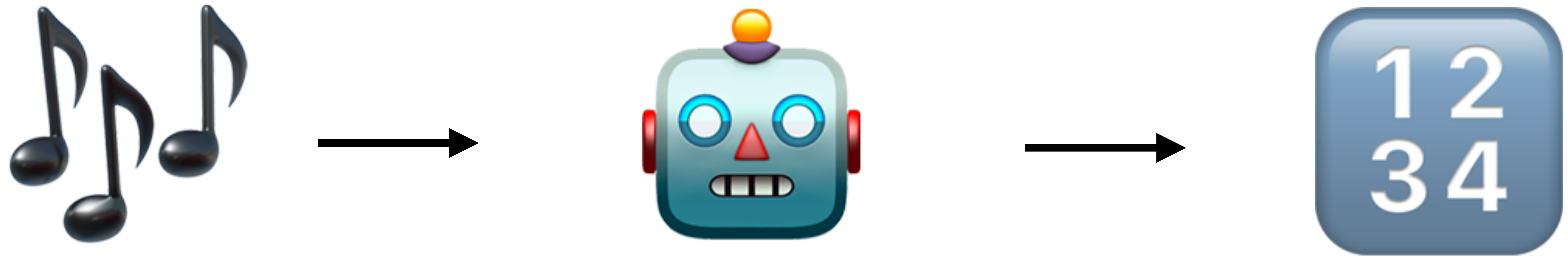
$$\mathbf{X} \qquad \mathscr{G} : \mathbb{R}^p \mapsto \mathbb{R}^f \qquad \mathbf{Z}$$

$(t{\times}p)$ $\qquad$ $(t{\times}f)$



Stimulus — Model — Features

How can we understand a nonlinear system?

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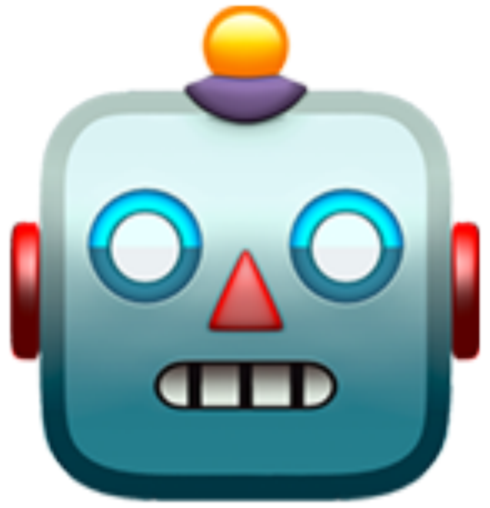
$\mathbf{X}$ $(t \times p)$

$\mathcal{G} : \mathbb{R}^p \mapsto \mathbb{R}^f$

$\mathbf{Z}$ $(t \times f)$

$\mathbf{Y}$ $(t \times v)$

Stimulus →



Model →

Features →

Response

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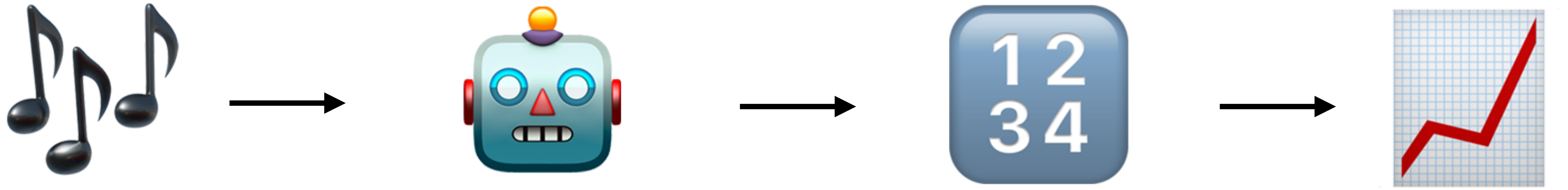

Stimulus — Model — Features — Response

$$\underset{(t\times v)}{\mathbf{Y}} = \underset{(t\times f)}{\mathscr{G}(\mathbf{X})}\ \underset{(f\times v)}{\mathbf{W}} + \underset{(t\times v)}{\mathbf{E}}$$

Linearized encoding analysis

A linear time-invariant system identification

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$$\mathbf{Y} = \mathscr{F}(\mathbf{X}) + \varepsilon$$

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A linear time-invariant system identification

- The method is widely known as "system identification": we separate a nonlinear transform (stim→resp) into a simpler nonlinear transform (stim→feat) and a linear transform (feat→resp).

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🎶→🧠→📈

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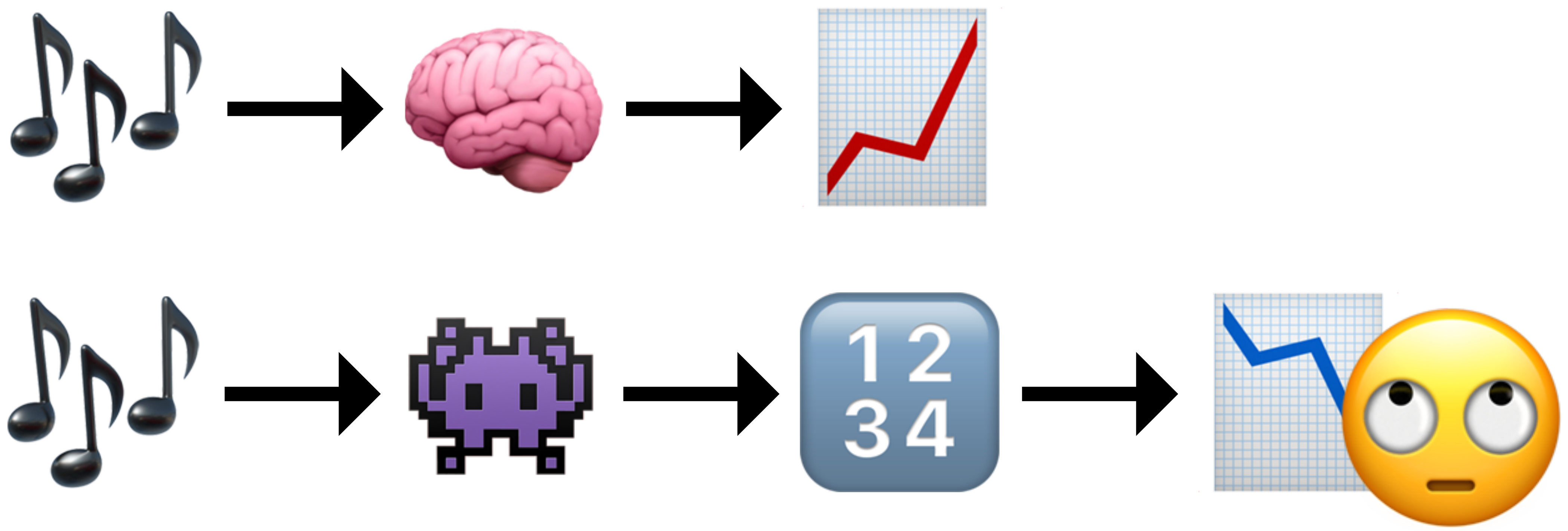

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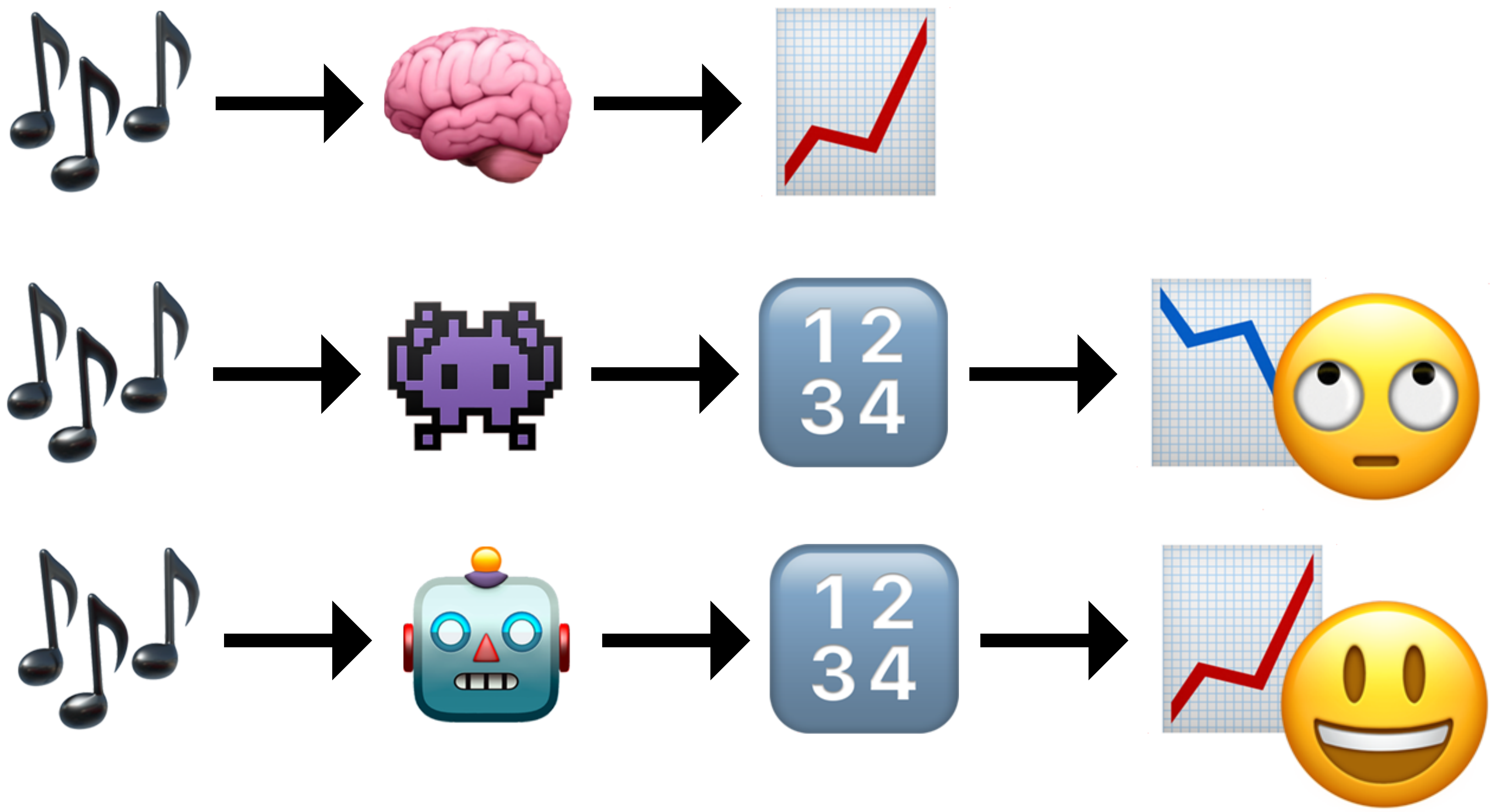

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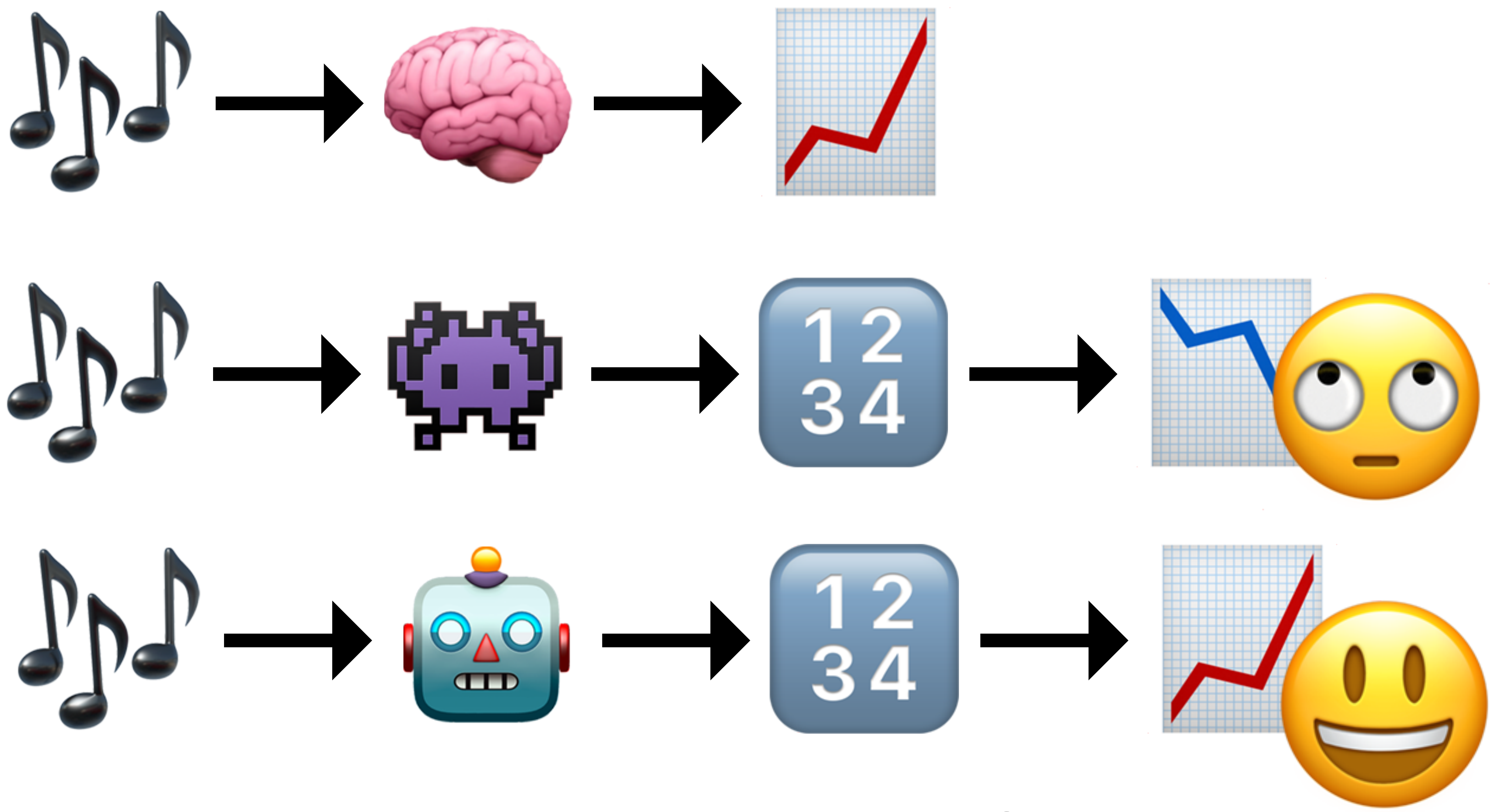

This means the hypothesis is ***FALSIFIABLE!***

👾: ❌ but 🤖: ✅

Linearized encoding analysis

A linear time-invariant system identification

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- How the stimulus is *linearized* (by which function) is <u>your hypothesis.</u>
- Then, the rest is to recover a linear filter ("convolution kernel") that transforms features $\mathscr{F}^*(\mathbf{X})$ to response $\mathbf{Y}$.

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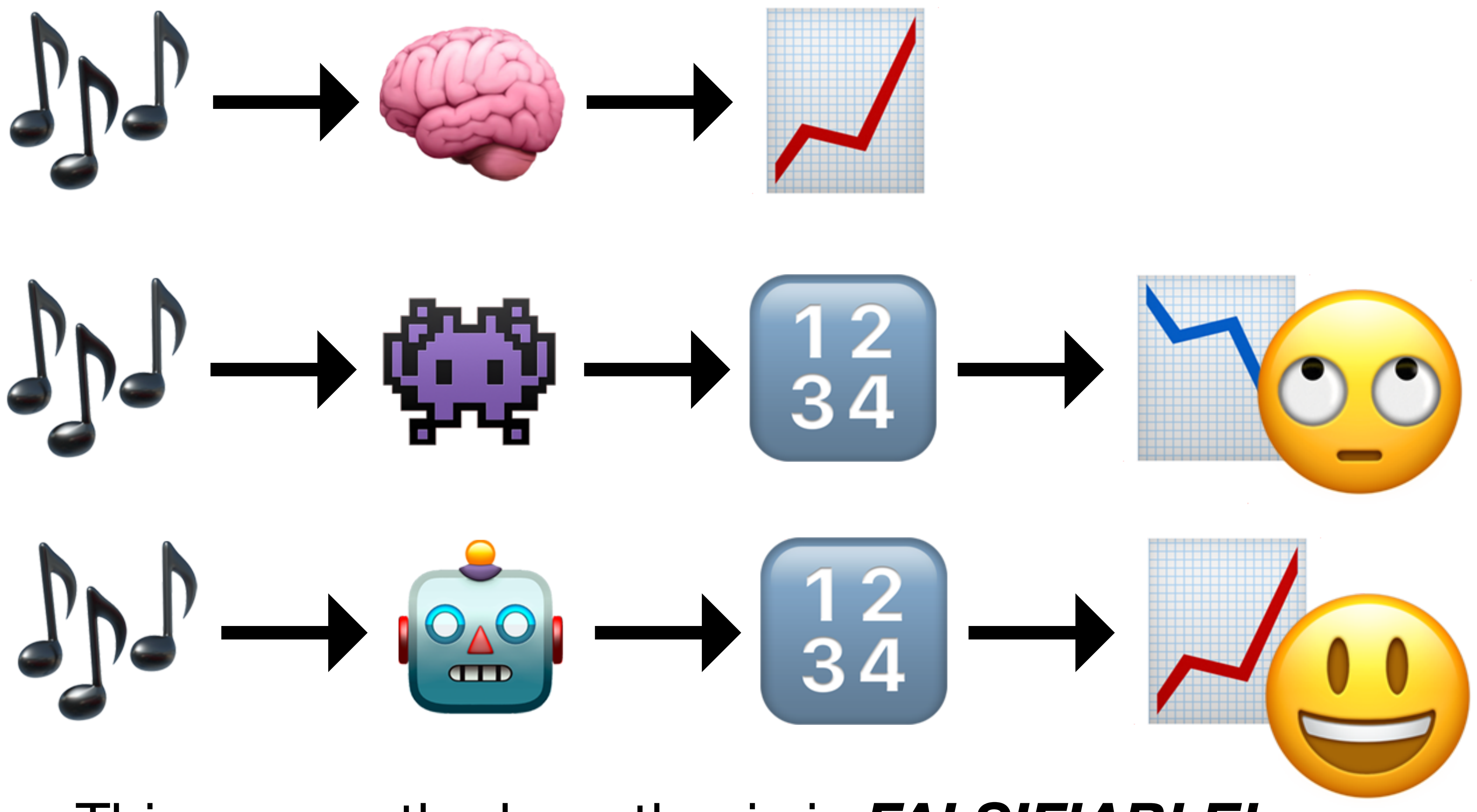

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🤔: But what if the internal process takes unknown time?

Topic 1: Finite impulse response modeling

Modeling (neural) system delays

$$y_t = b_0 + x_t b_1 + \epsilon$$

y(t) is only influenced by x(t)

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🤔: But does it work for the other case?

Topic 2 & 3: Predictive modeling

Training set

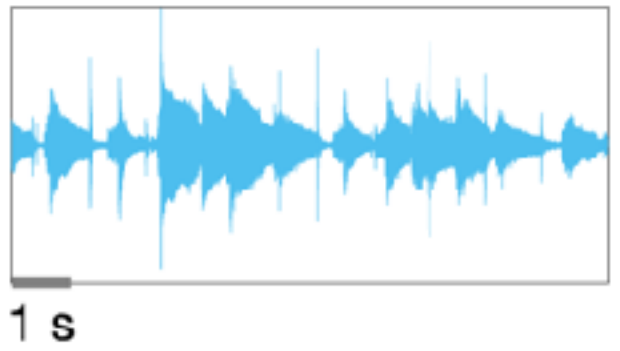
Kim, 2022, https://doi.org/10.3389/fnins.2022.928841

Topic 2 & 3: Predictive modeling

Training set

Music #1

$\mathbf{X}_1$



Topic 2 & 3: Predictive modeling

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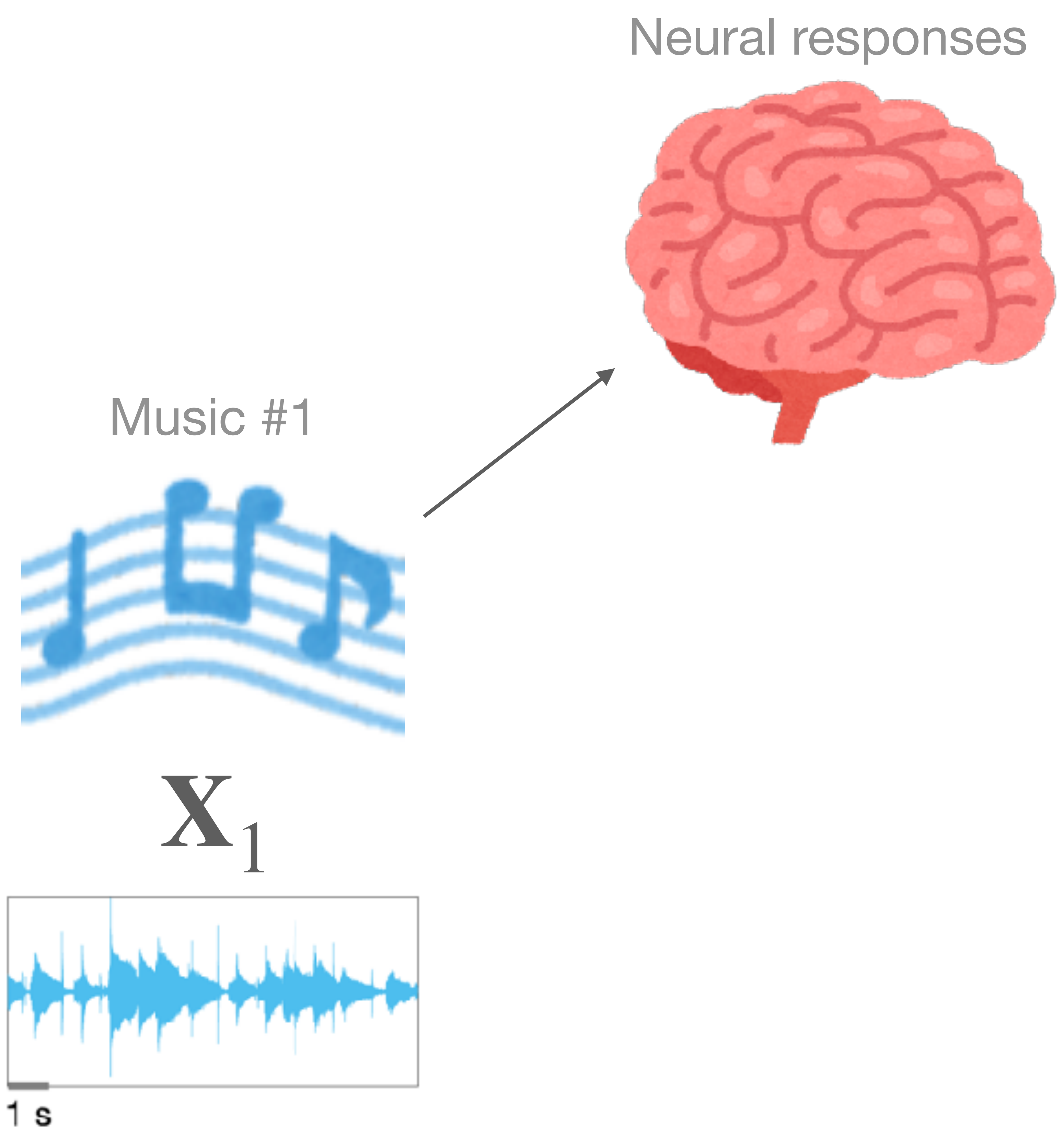

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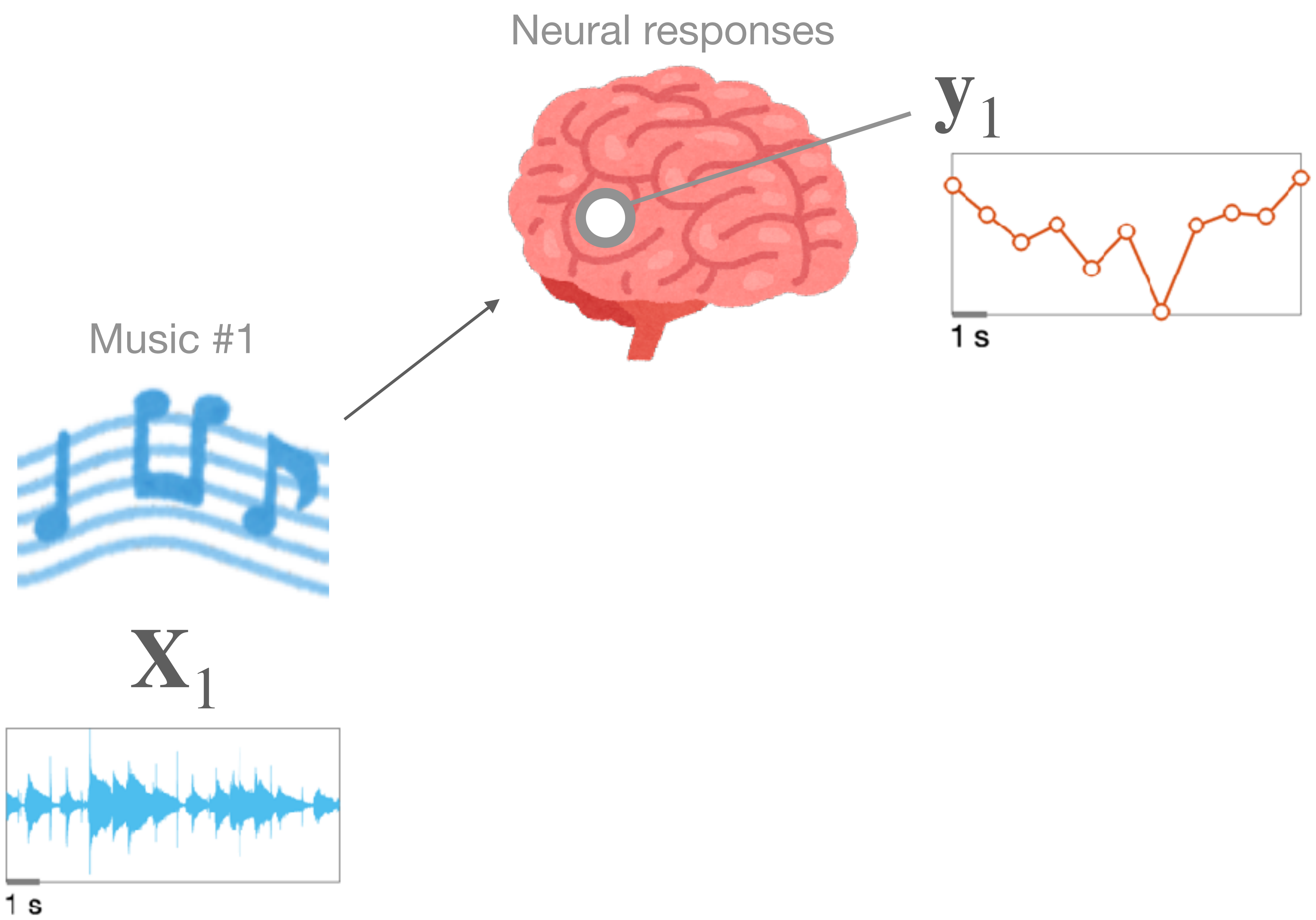

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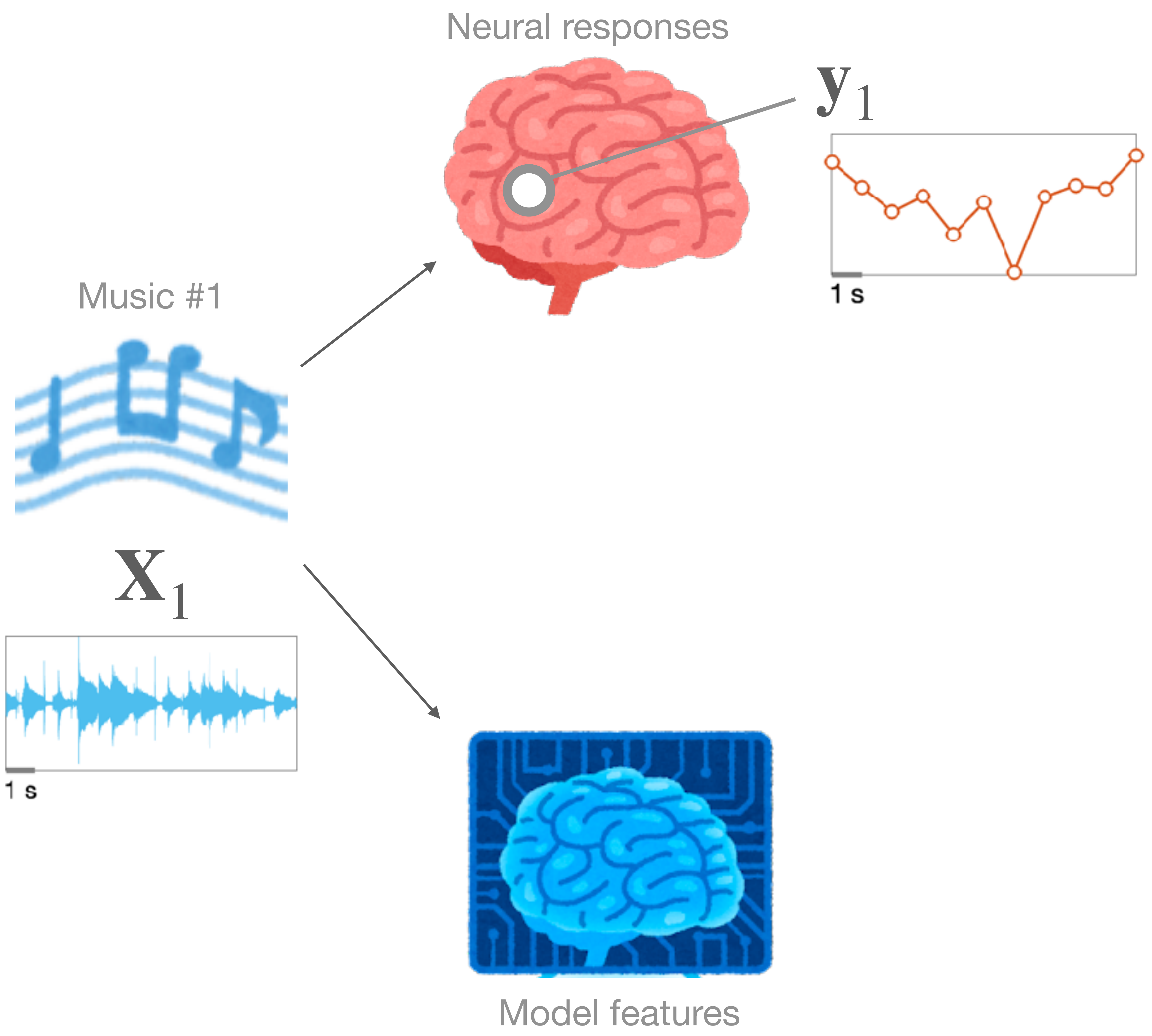
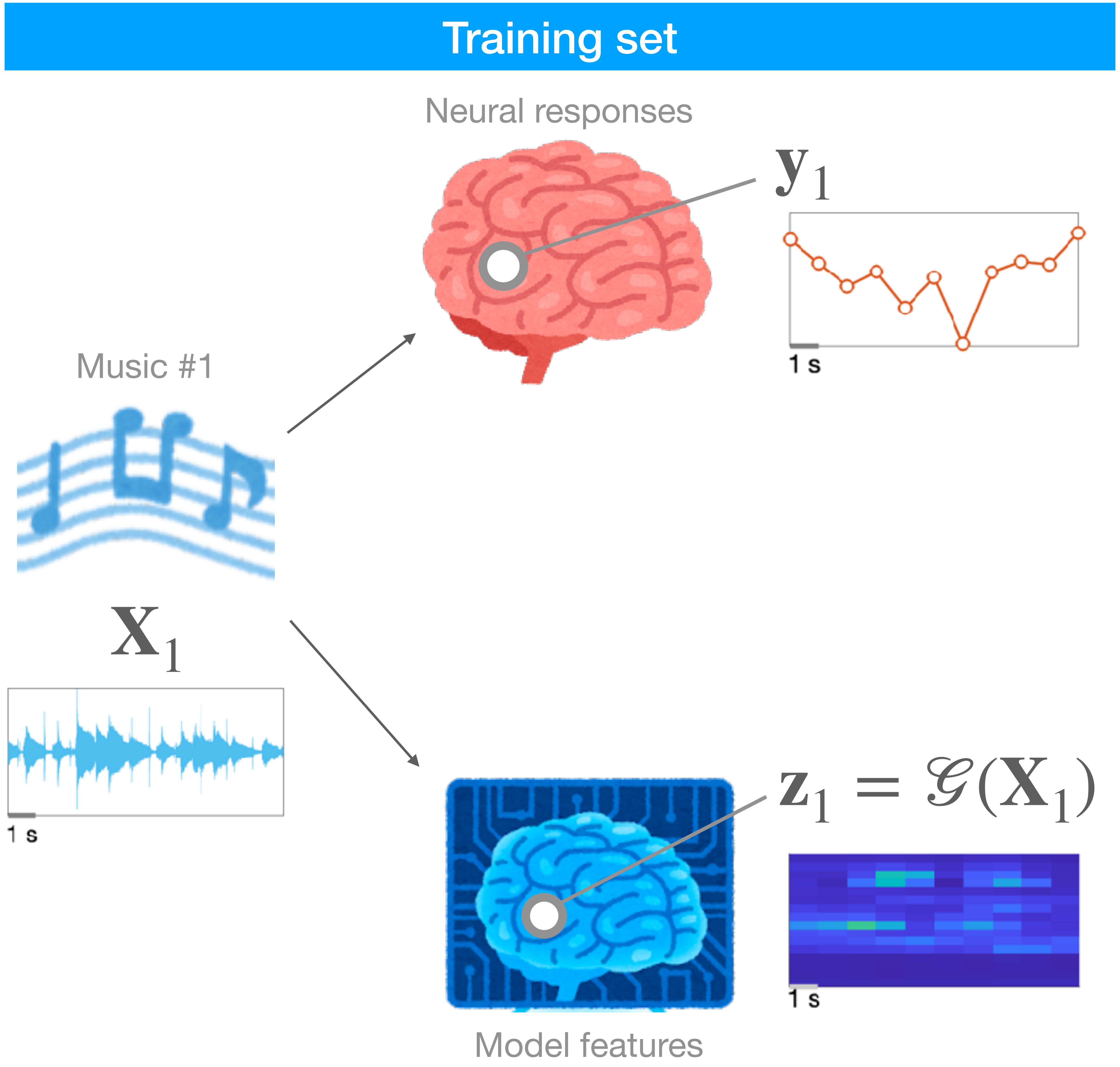
Topic 2 & 3: Predictive modeling

Training set



Topic 2 & 3: Predictive modeling



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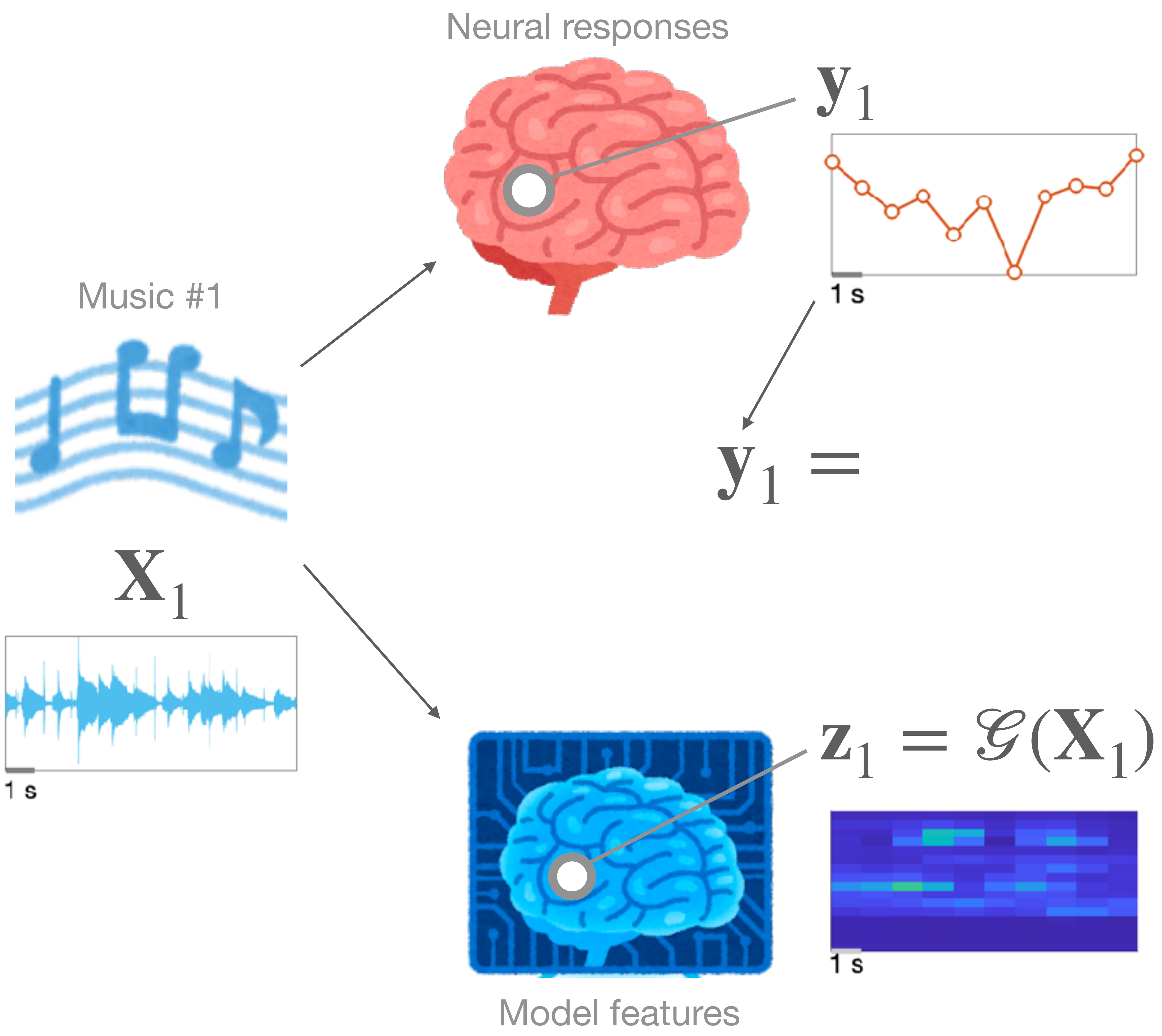

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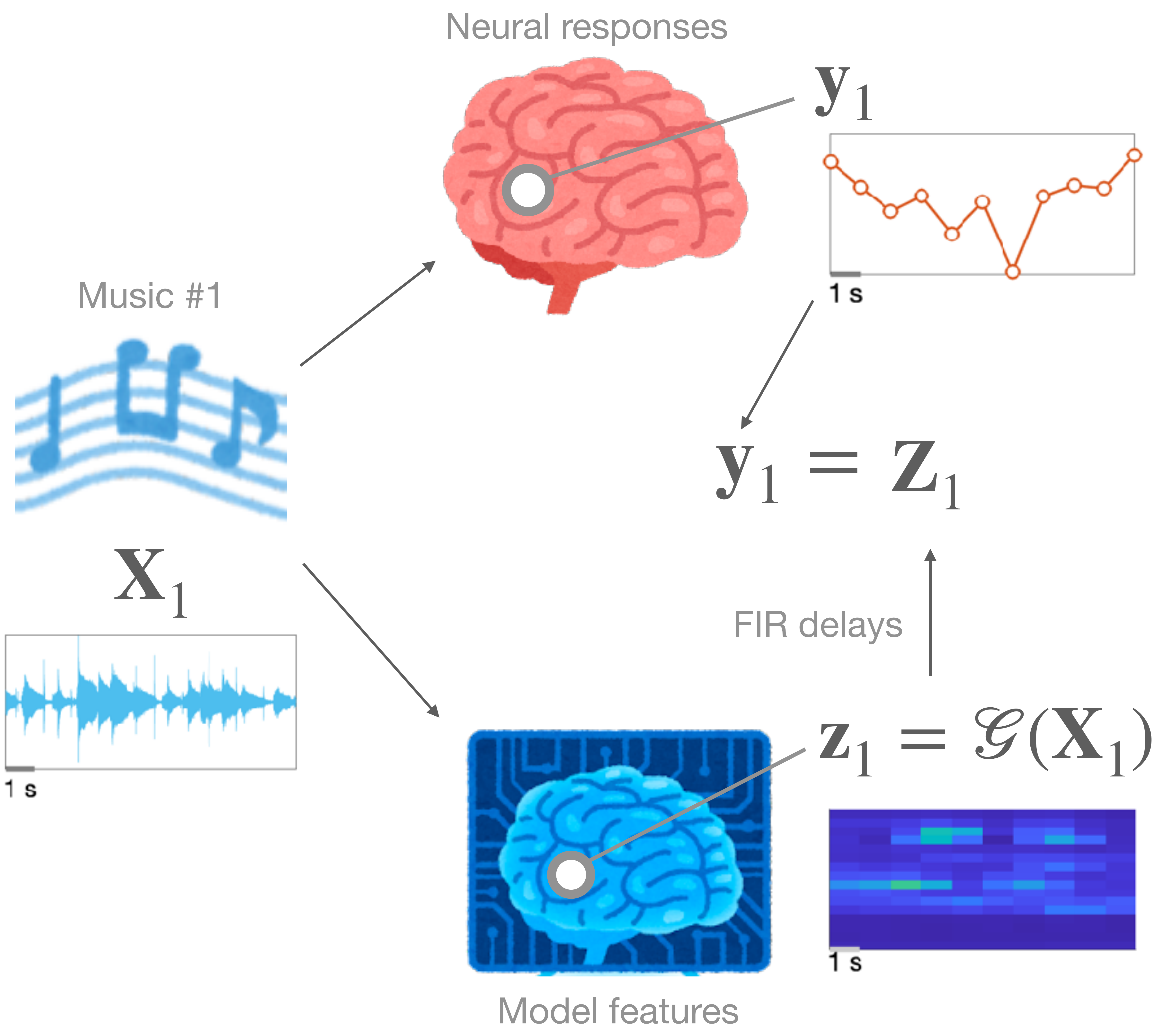

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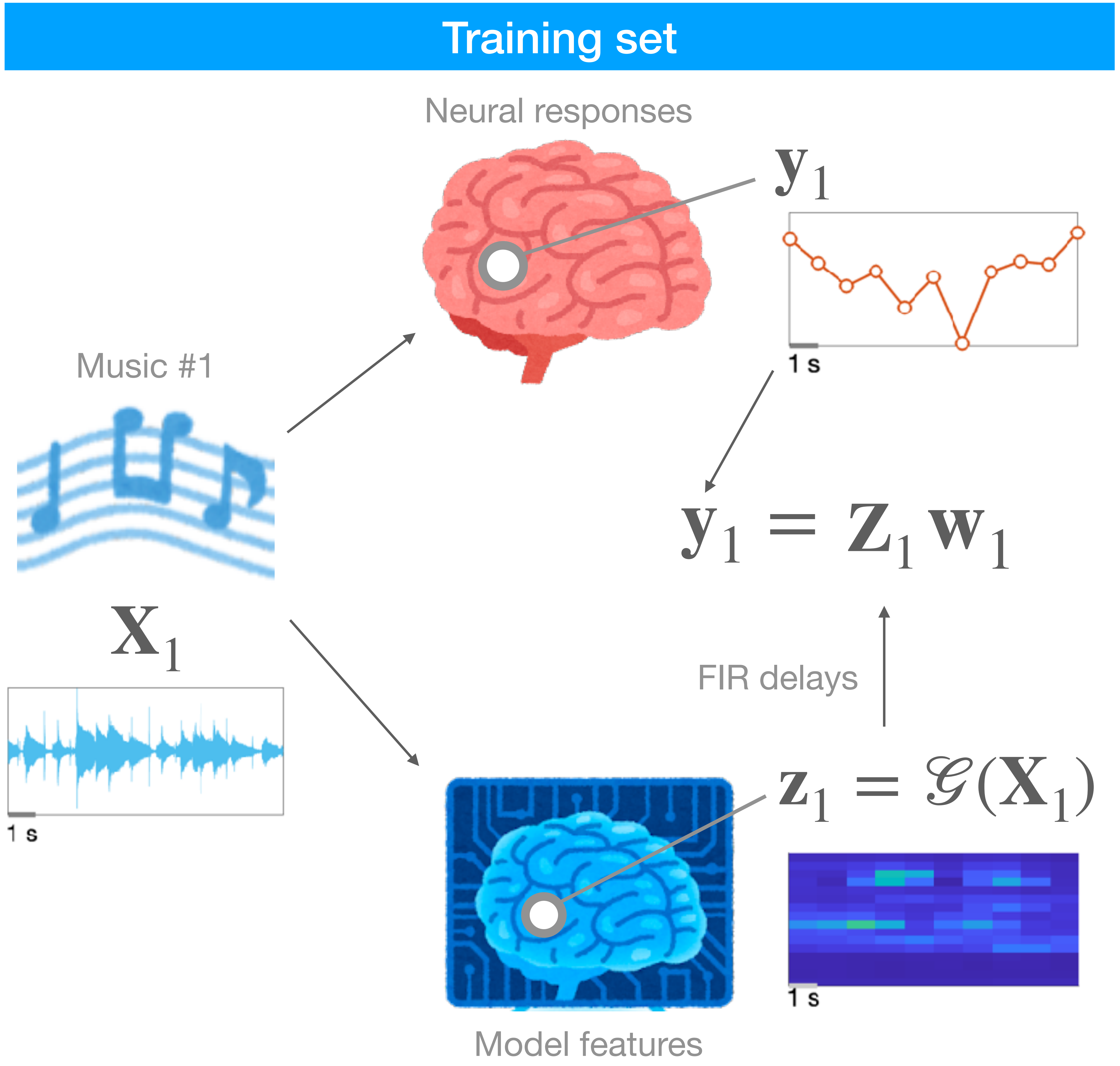

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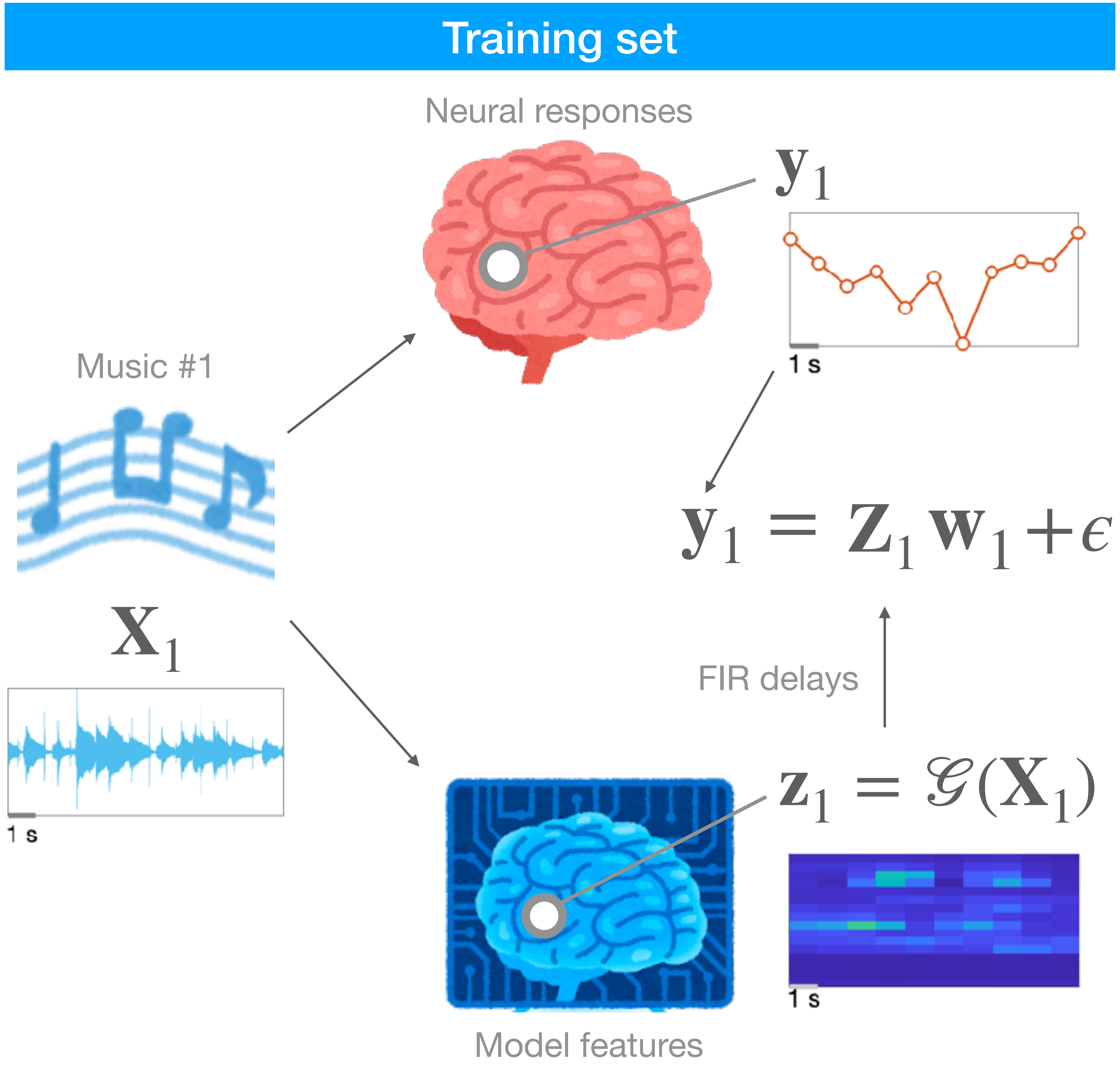

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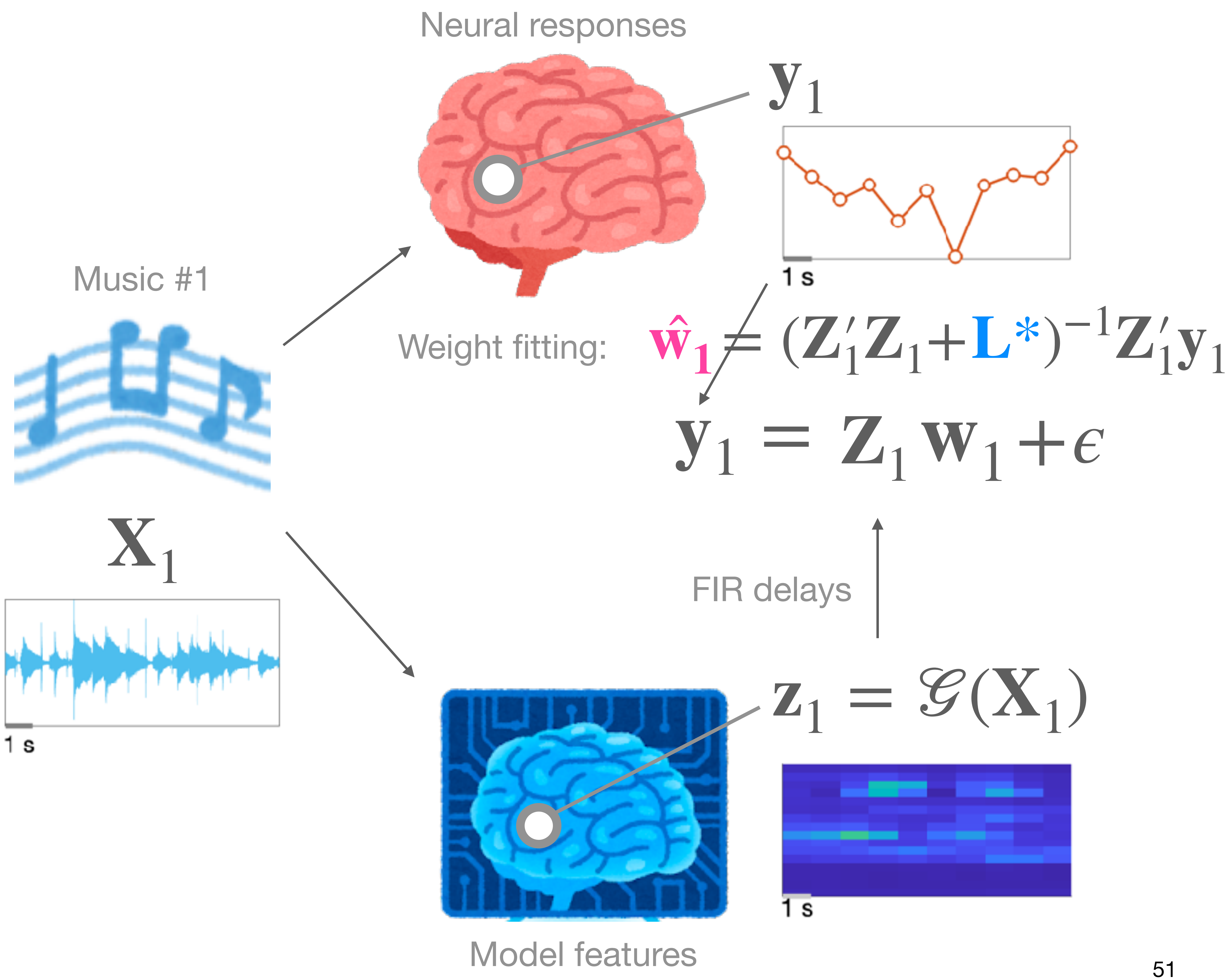

Topic 2 & 3: Predictive modeling

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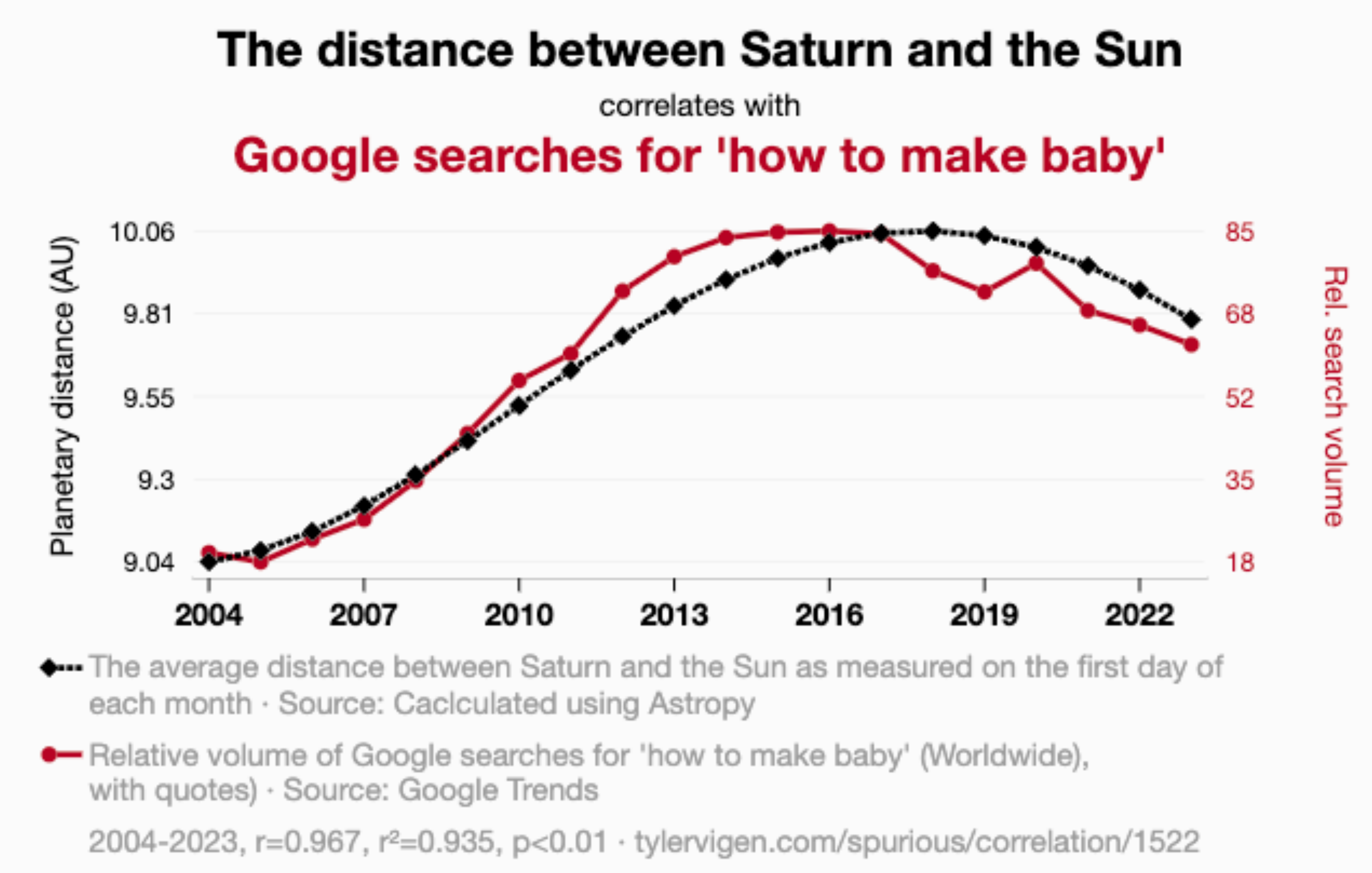
🤔: Still, how do we know if this is not due to the random noise in the data?


The distance between Saturn and the Sun
correlates with
Google searches for 'how to make baby'
Planetary distance (AU)
10.06
9.81
9.55
9.3
9.04
85
68
52
35
18
Rel. search volume
2004
2007
2010
2013
2016
2019
2022
The average distance between Saturn and the Sun as measured on the first day of each month · Source: Caclculated using Astropy
Relative volume of Google searches for 'how to make baby' (Worldwide), with quotes) · Source: Google Trends
2004-2023, r=0.967, r²=0.935, p<0.01 · tylervigen.com/spurious/correlation/1522

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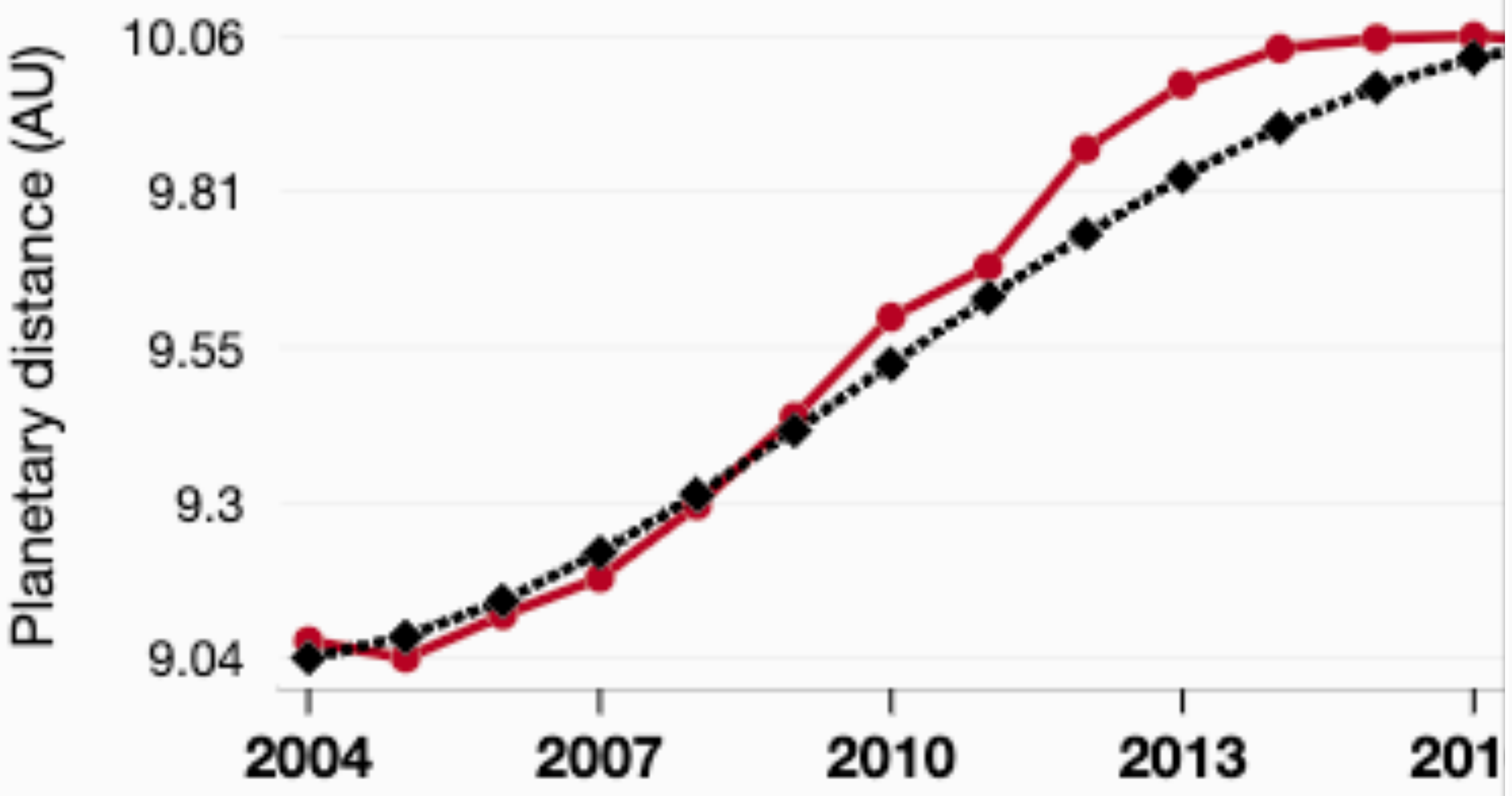

The average distance between Saturn and the Sun as r
each month · Source: Caclculated using Astropy

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2004-2023, r=0.967, r²=0.935, p<0.01 · tylervigen.com/spurious/correlation/1522

Ringed Planet's Orbit and Desire to Procreate: A Statistical Analysis

Show GenAI's made-up explanation

Fewer distractions from Saturn's bling led to some out-of-this-world romance. Looks like love isn't the only thing that's been cosmic lately!

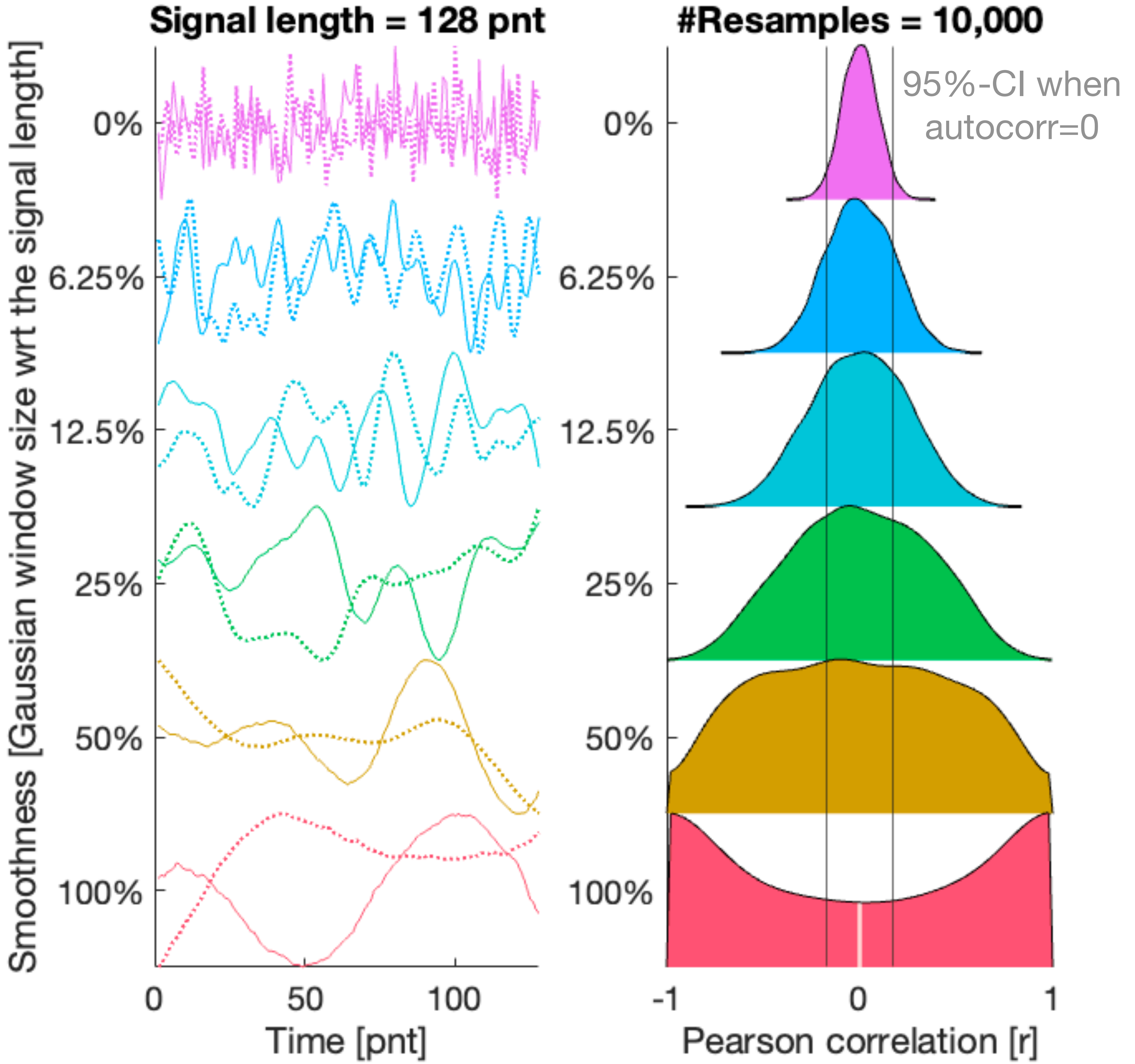
Show GenAI image

https://www.tylervigen.com/spurious-correlations

Topic 4: Statistical inference

Tests for time series

- Many **time series** look alike (i.e., spurious correlation) due to auto/serial-correlation.



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Topic 4: Statistical inference

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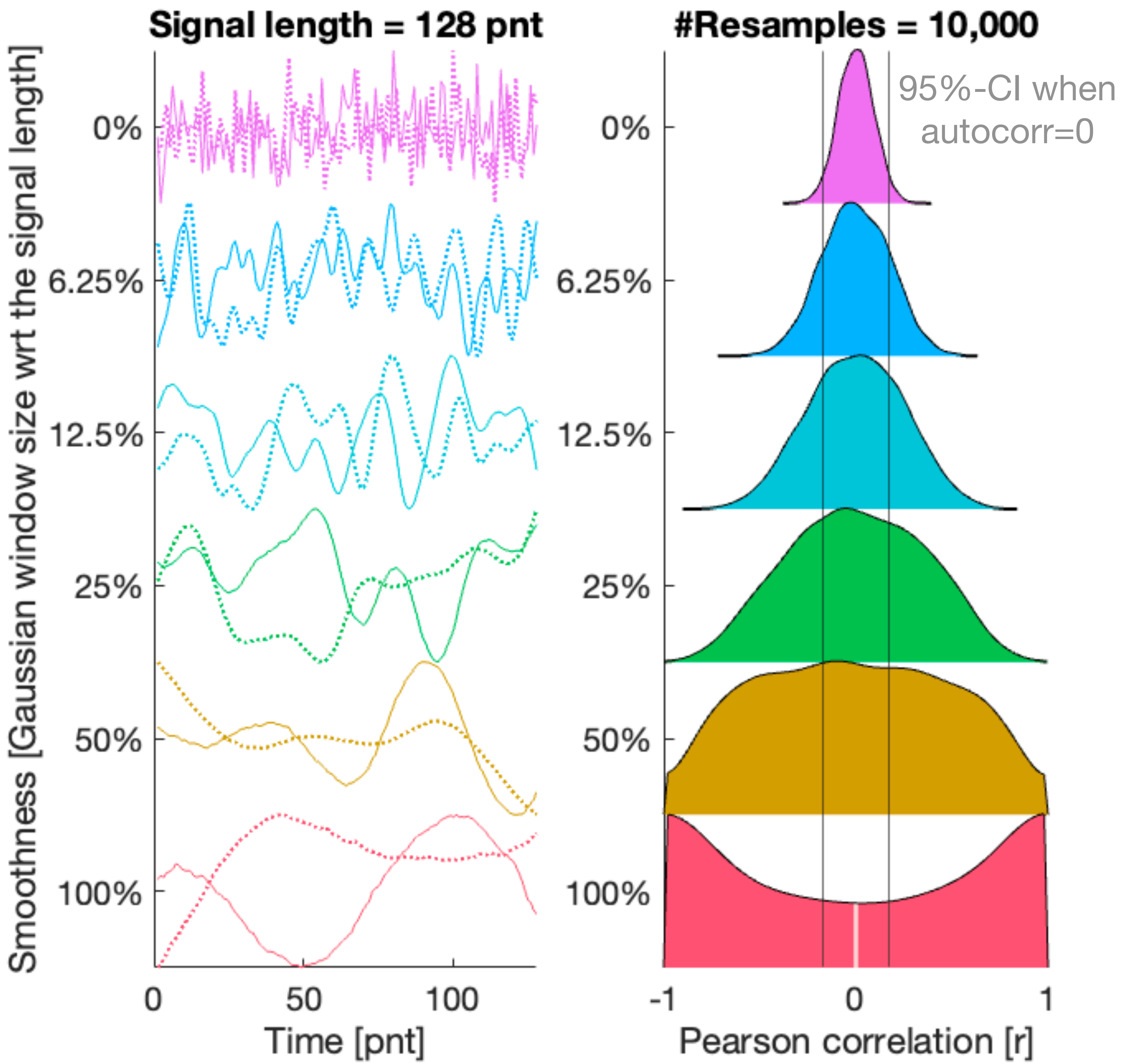
- Many **time series** look alike (i.e., spurious correlation) due to auto/ serial-correlation.

- **Non-parametric statistical tests are feasible for any arbitrary noise distribution** with "proper" null (surrogate) data.



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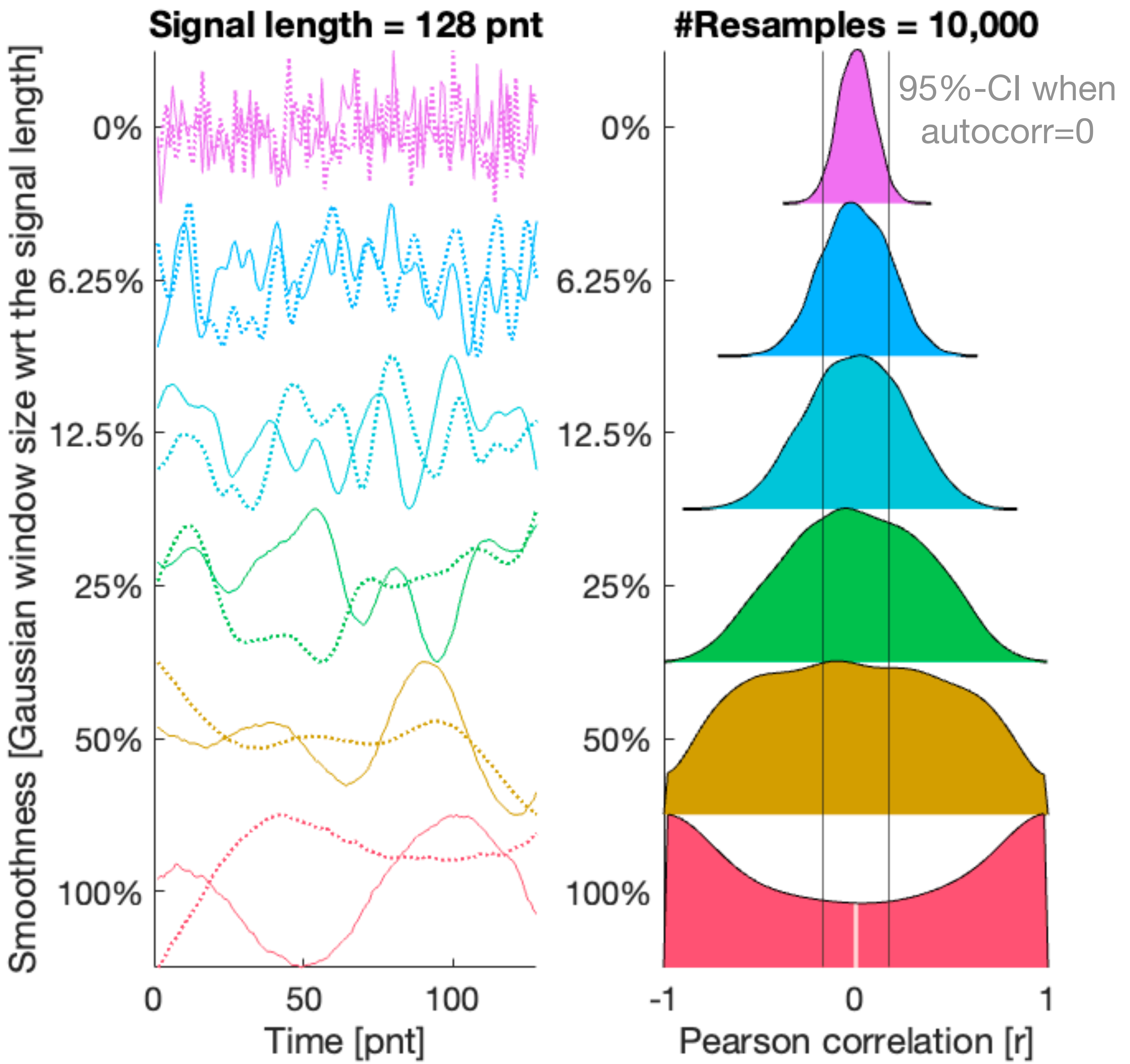

Topic 4: Statistical inference

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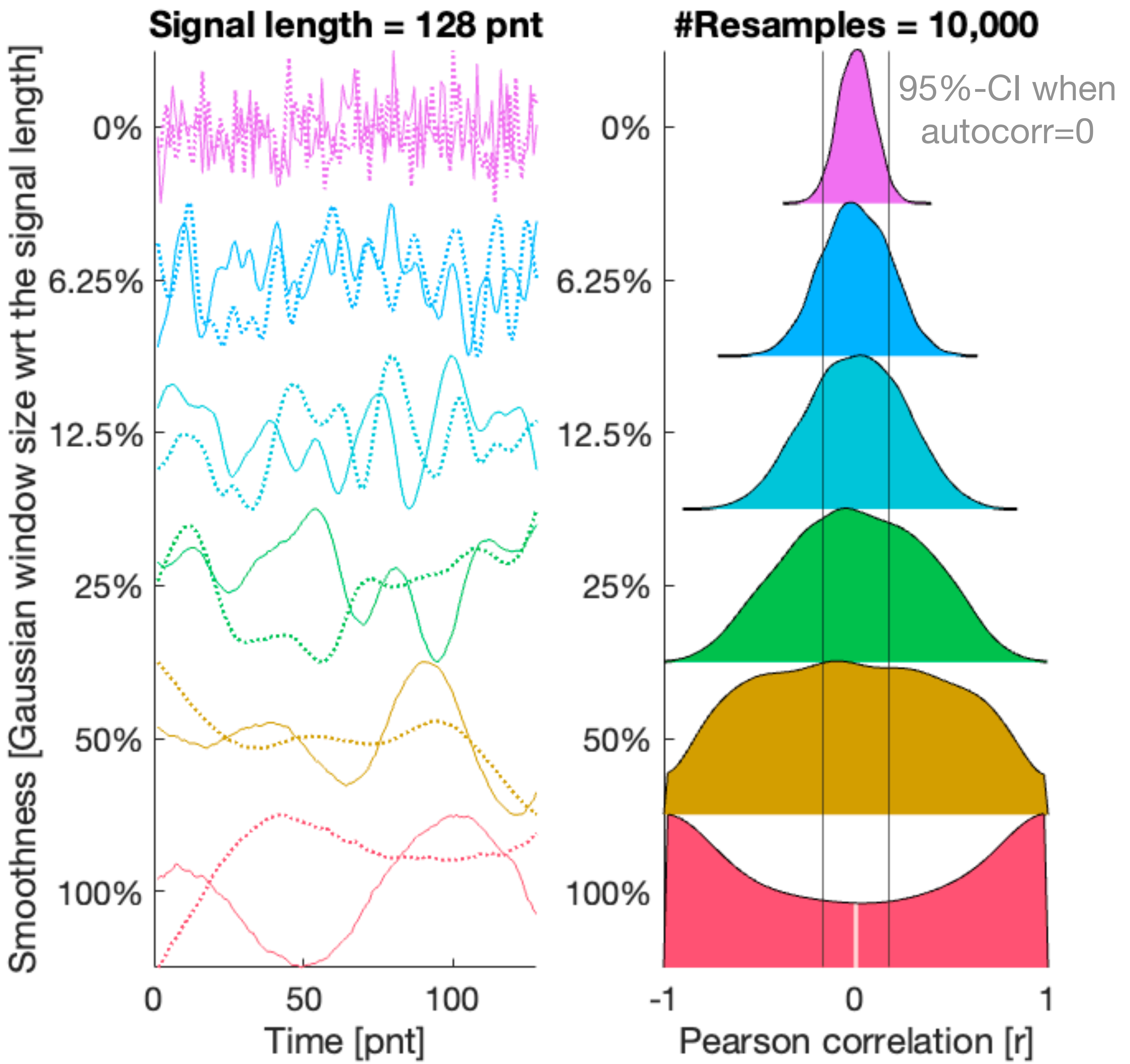
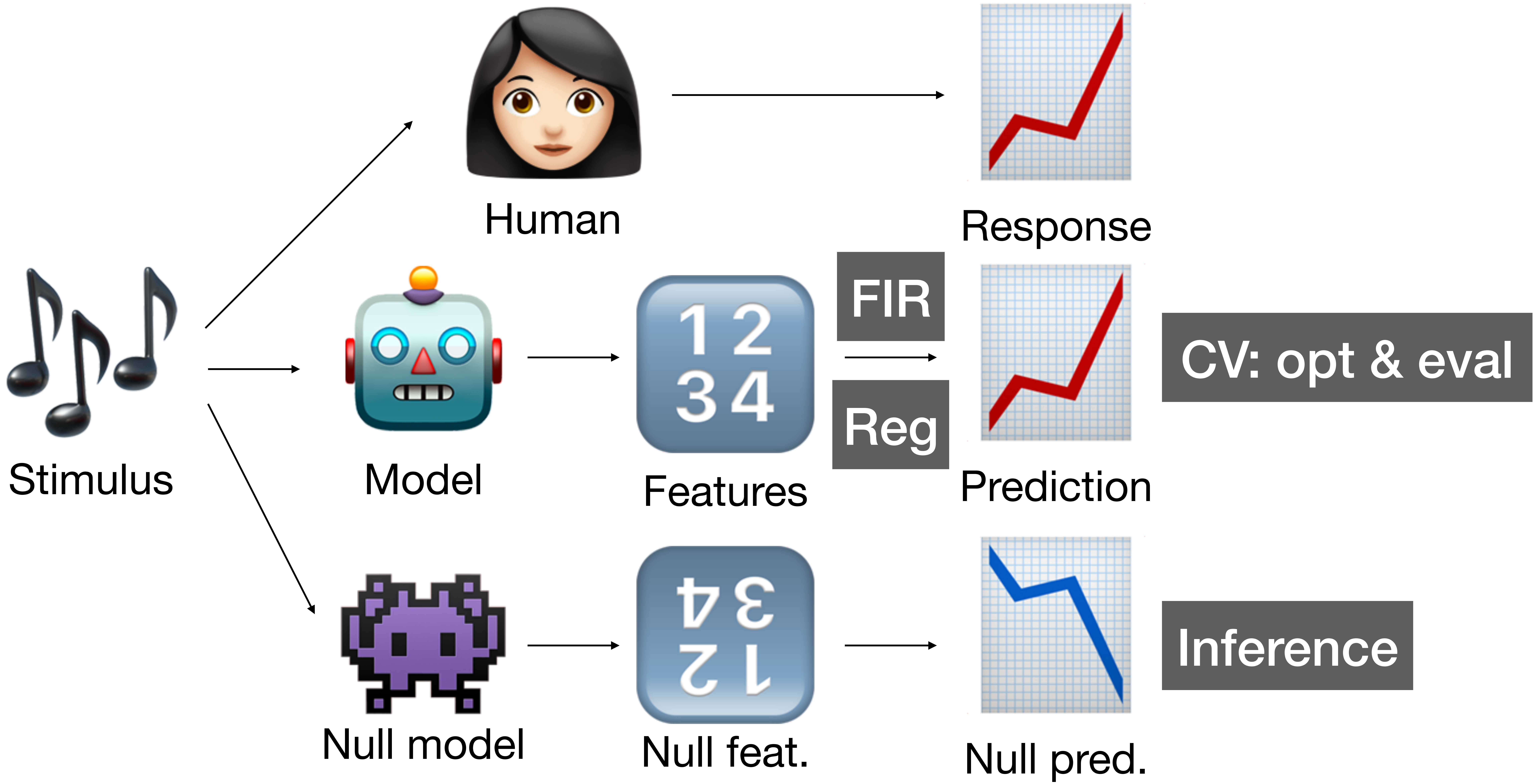
- **Non-parametric statistical tests are feasible for any arbitrary noise distribution** with "proper" null (surrogate) data.
- Explicitly estimation autocorrelation from finite (non-infinite) data is hard.
- Preserving the dependency structure (e.g., serial/spatial, ...) is rather easy.



Summary: linearized encoding analysis



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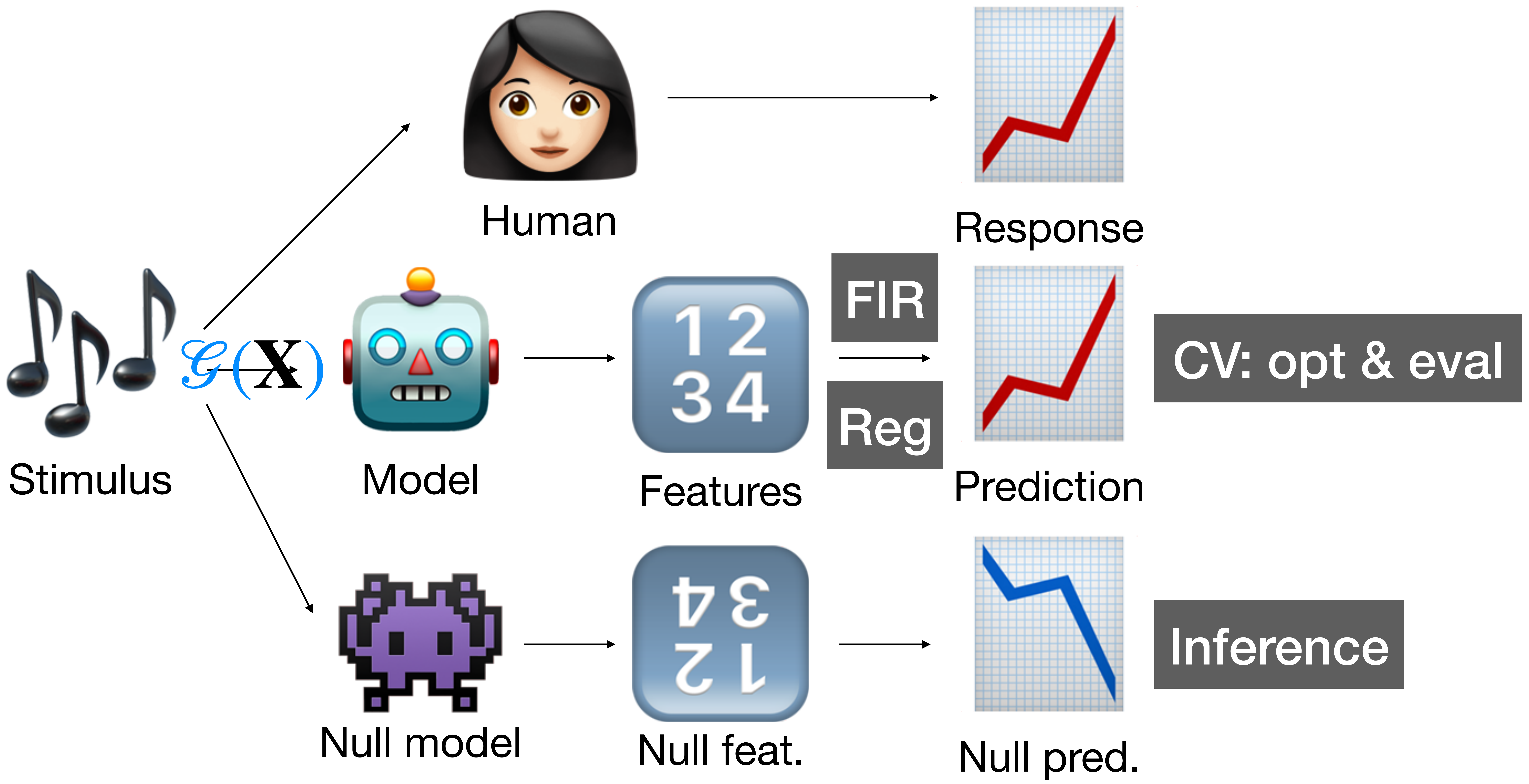

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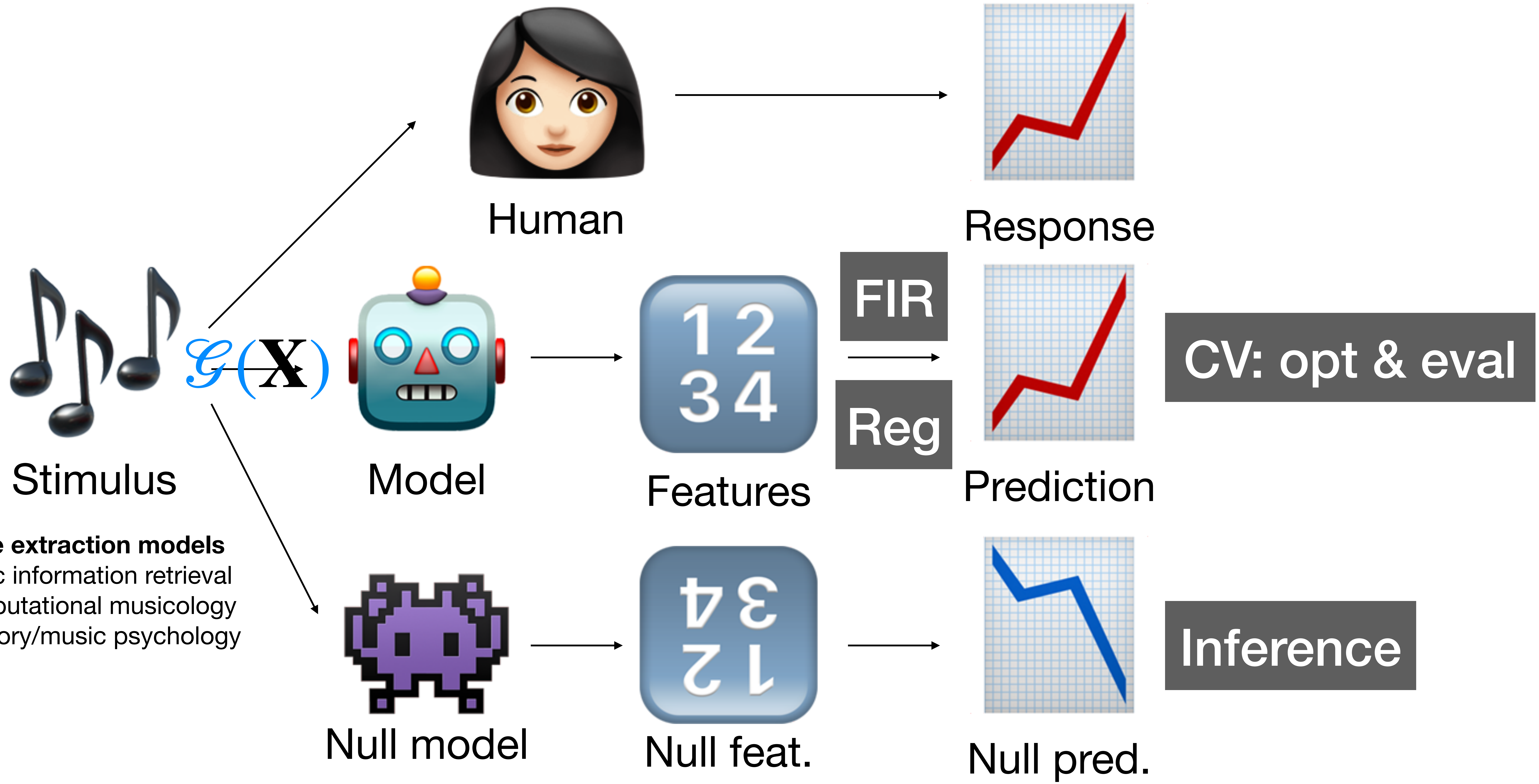


Feature extraction models
- Music information retrieval
- Computational musicology
- Auditory/music psychology
- ...

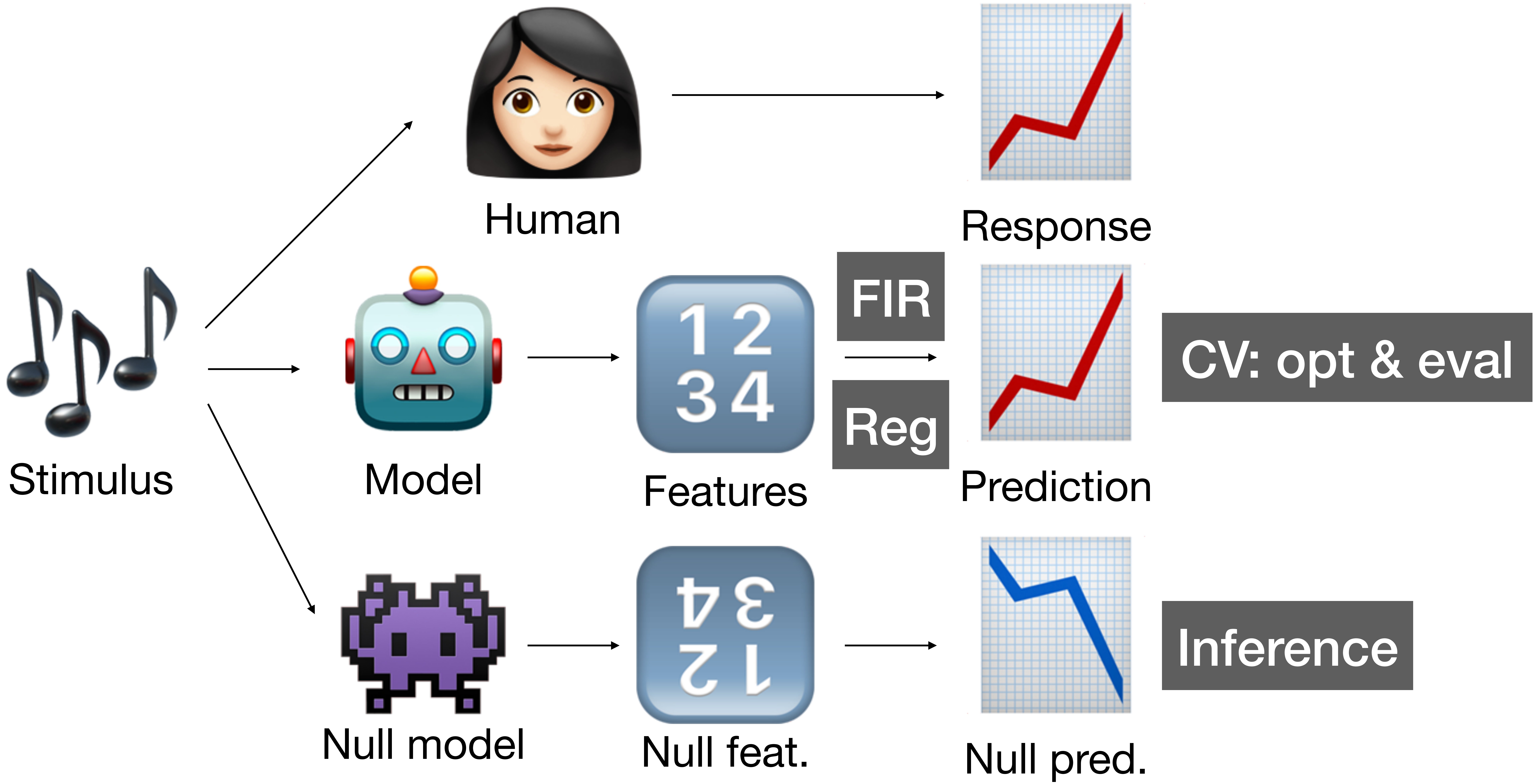
Any questions so far?

(Or I'll ask one 😈)

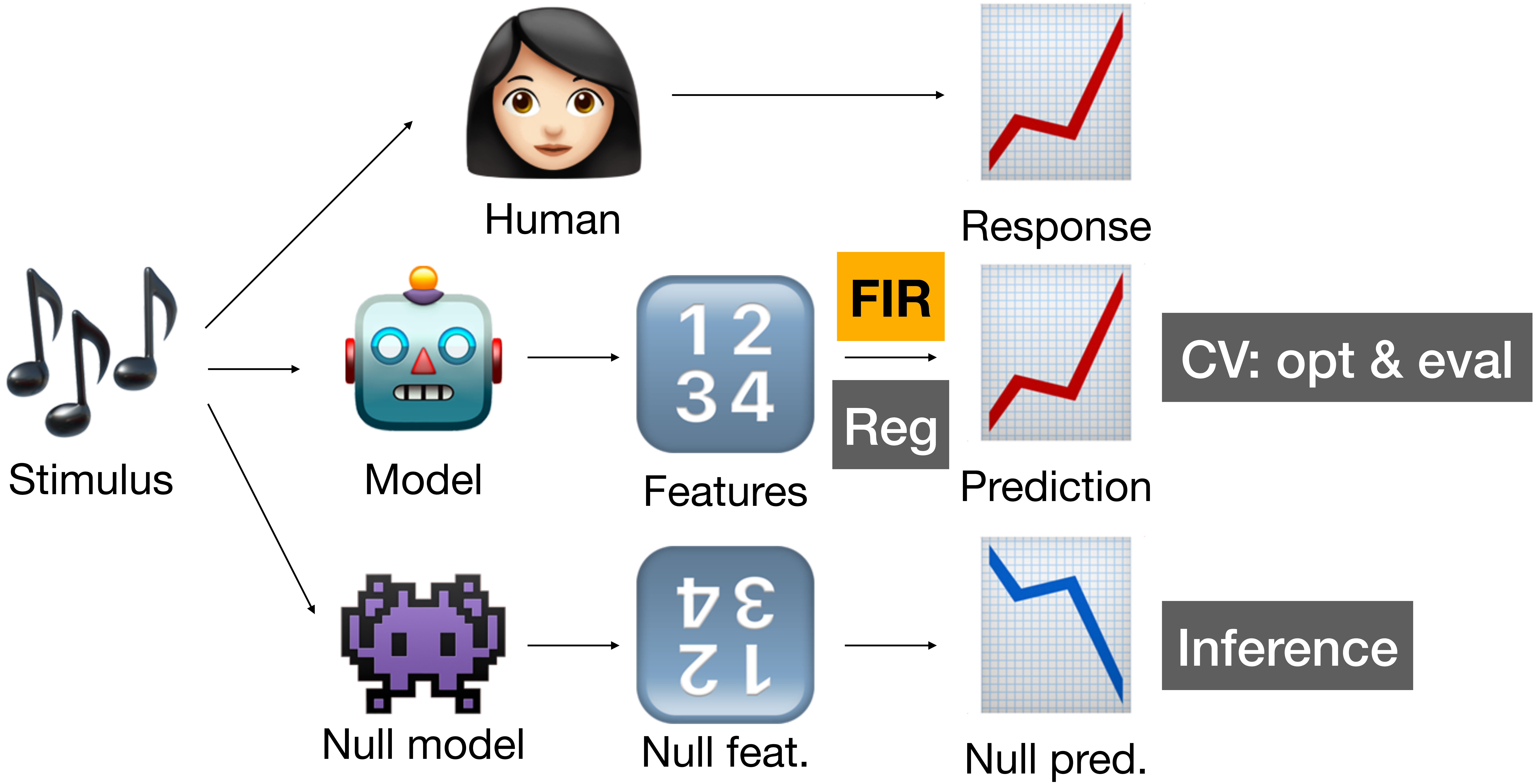
Go back to SESSION PLAN

Methods (HOWs):
Linearized Encoding Analysis

Linearized encoding analysis overview (HOWs)

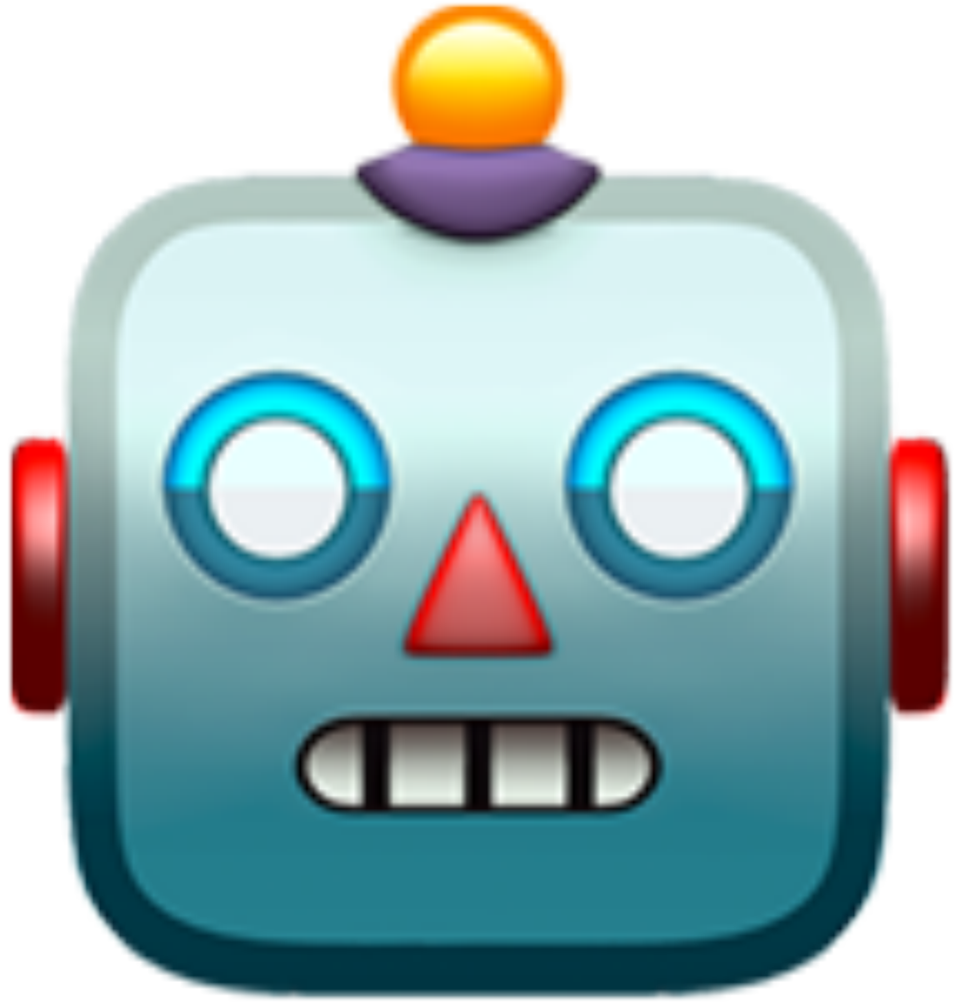


Linearized encoding analysis overview (HOWs)



Finite impulse response modeling in time

A single-pixel time series



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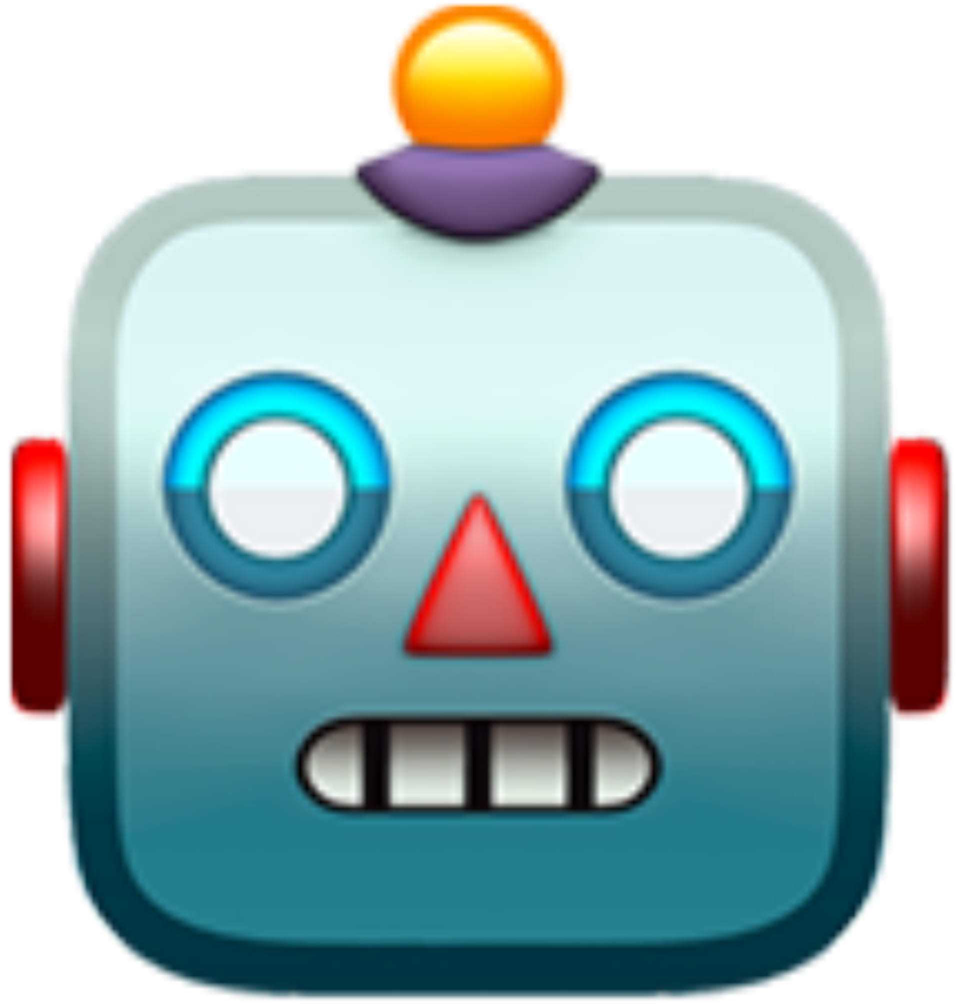

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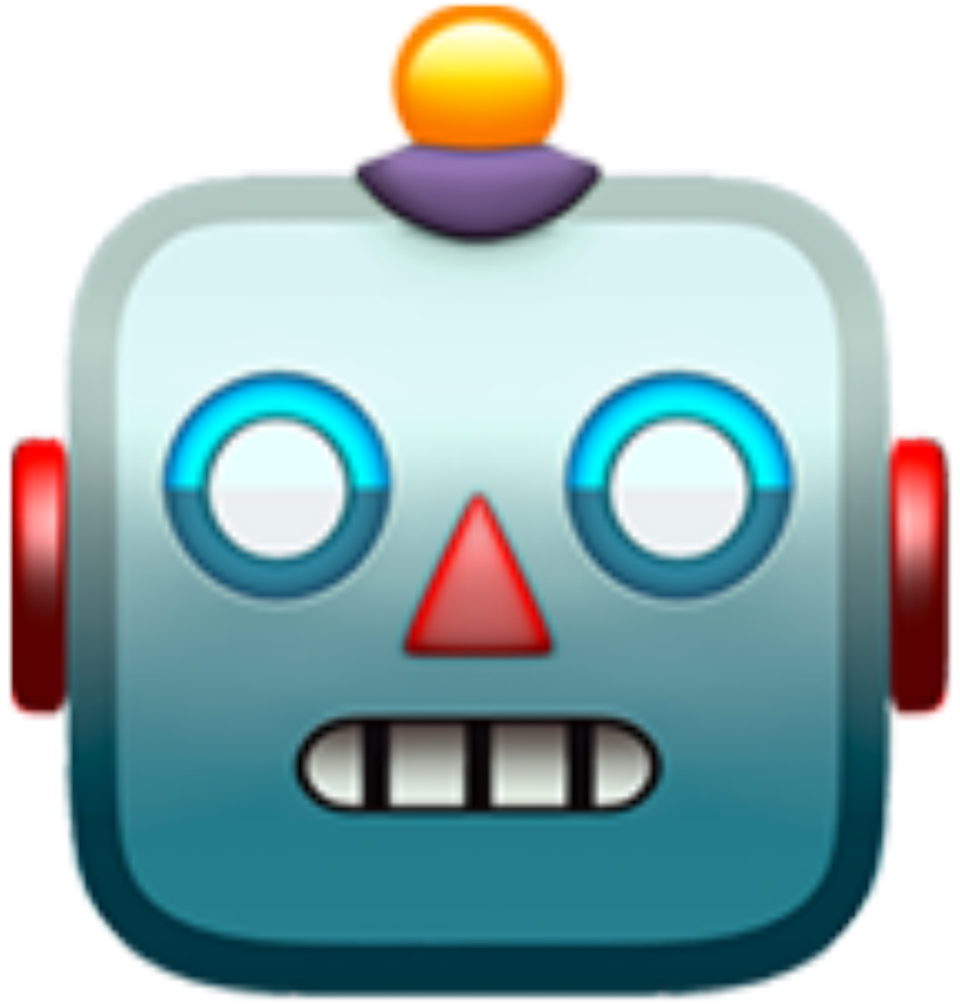

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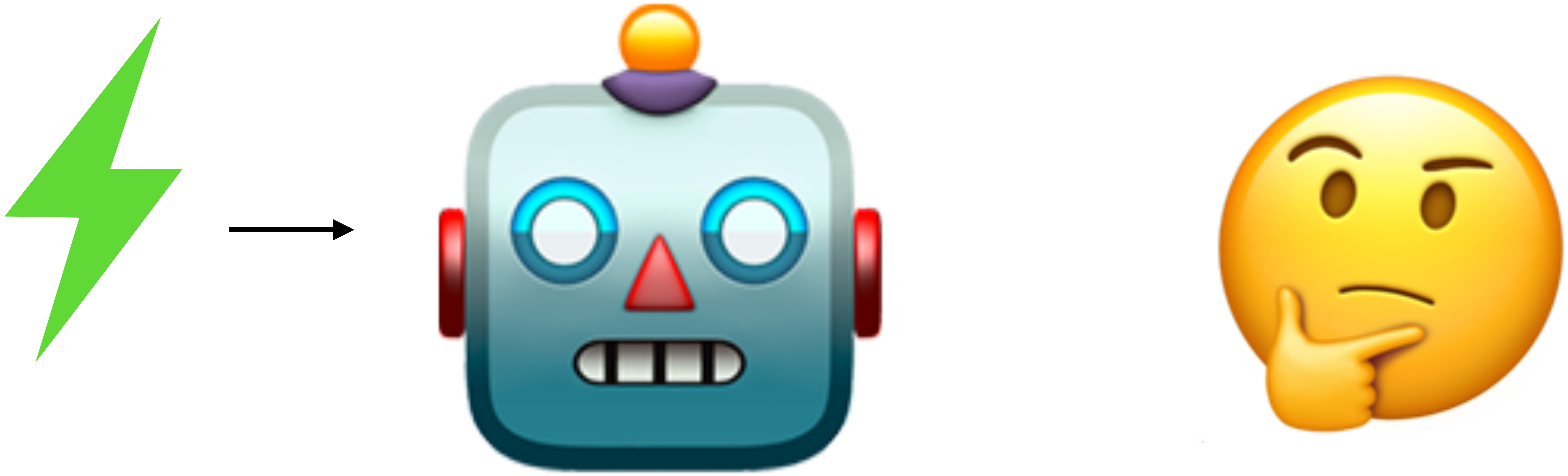

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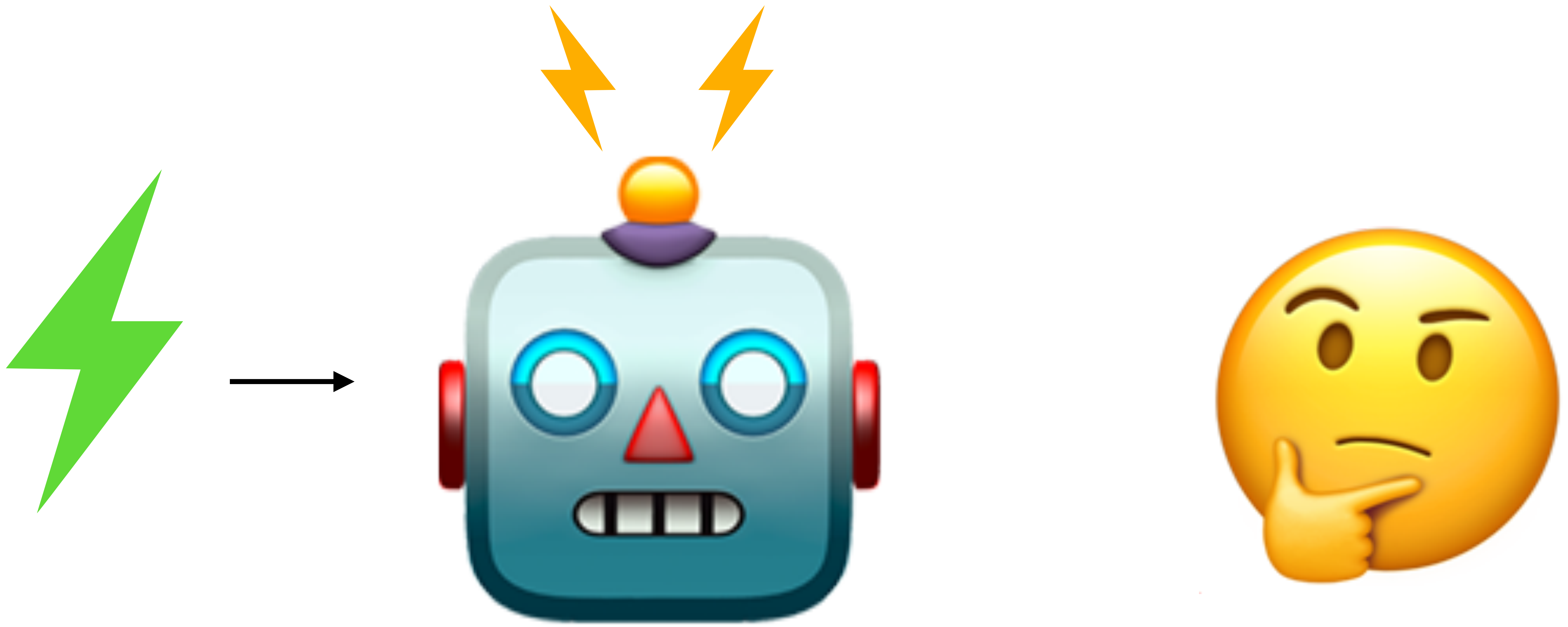

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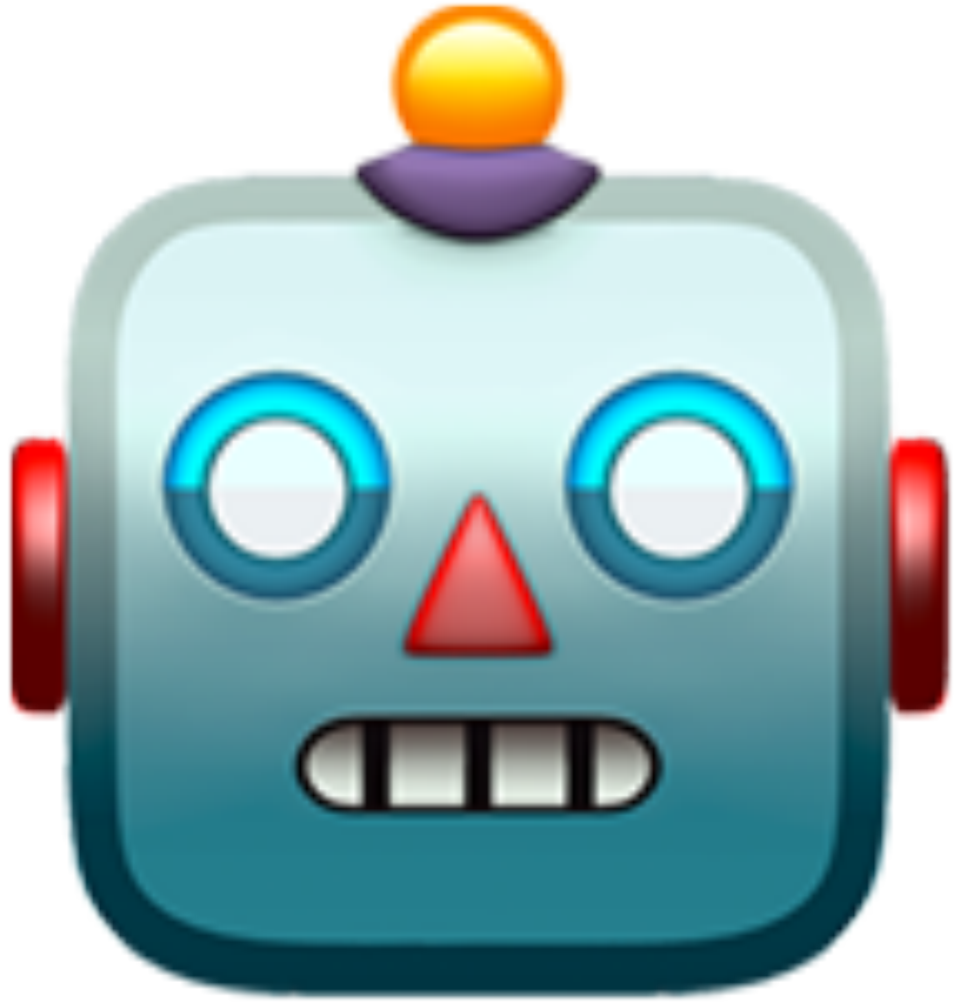

Finite impulse response modeling in time

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$\emptyset \longrightarrow$ 🤖 🤔

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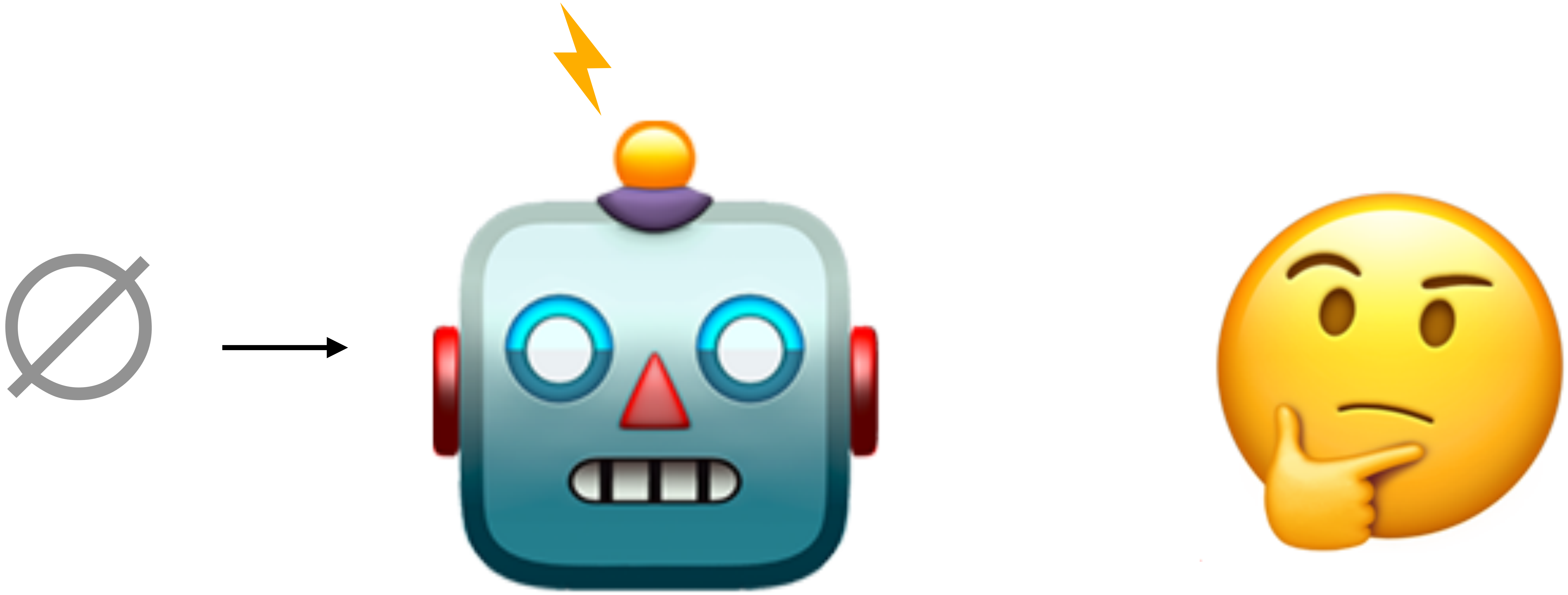

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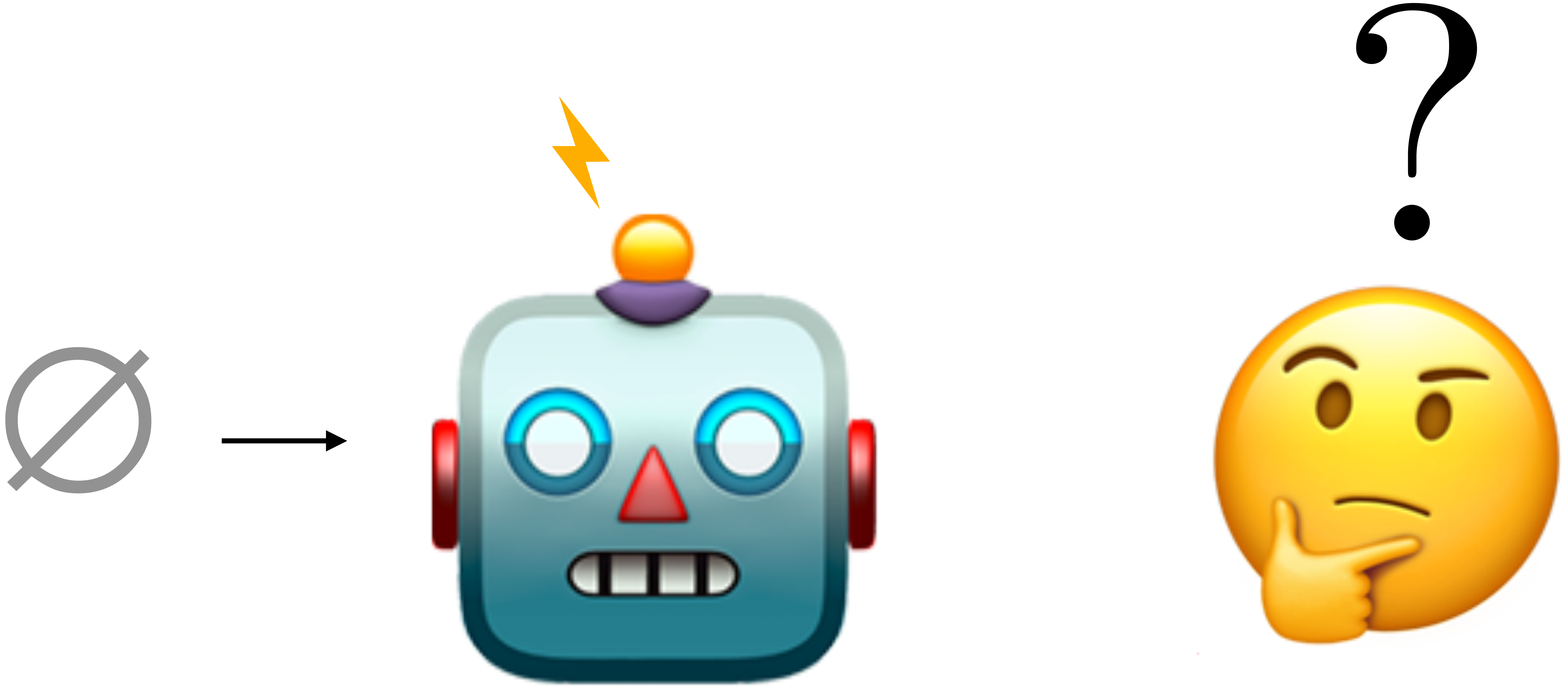

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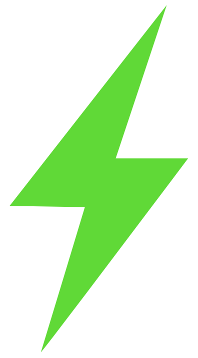
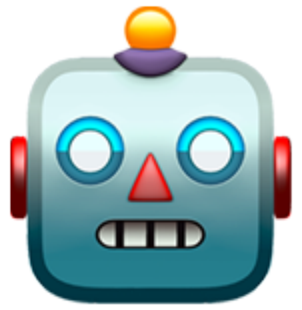
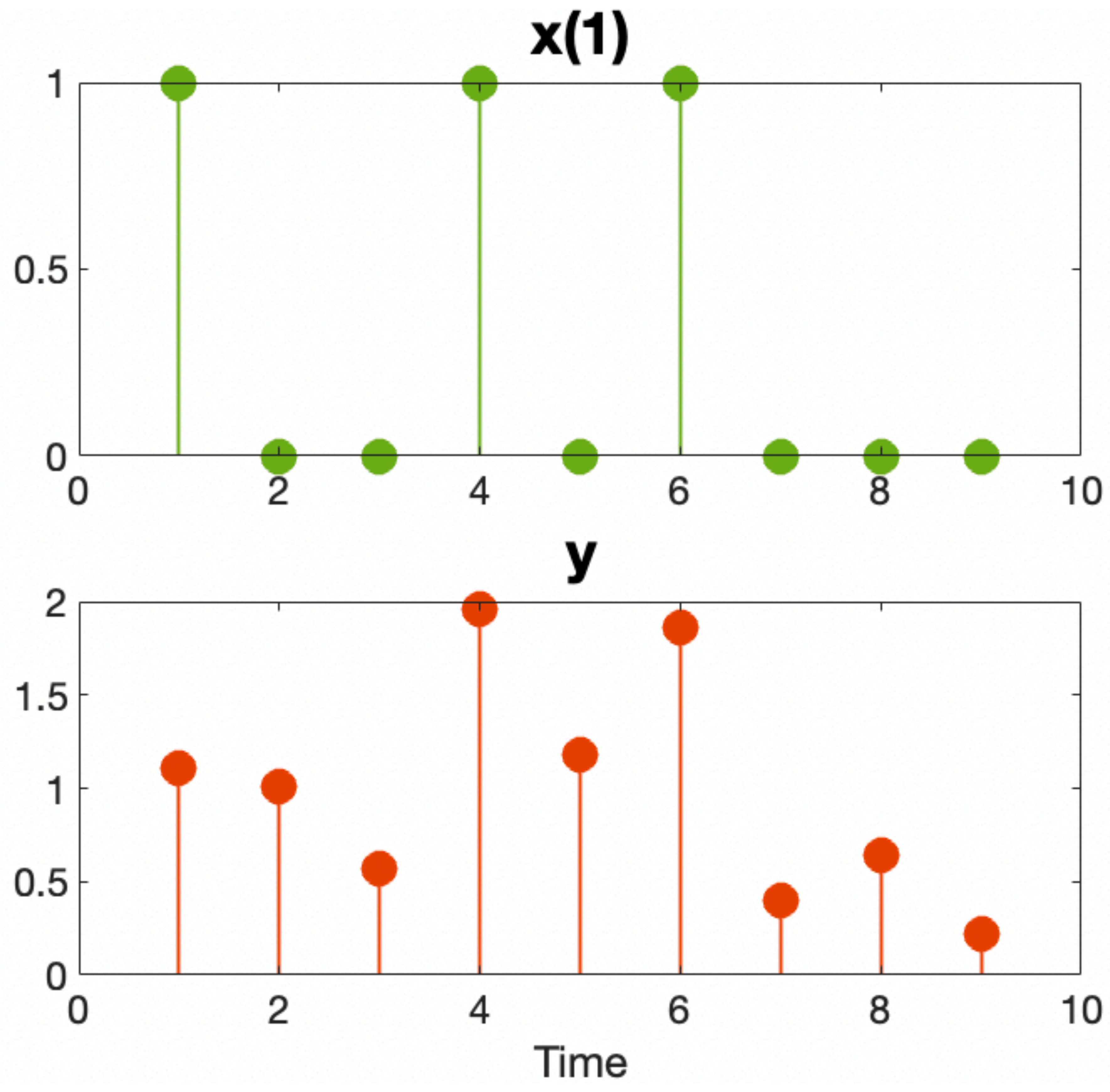
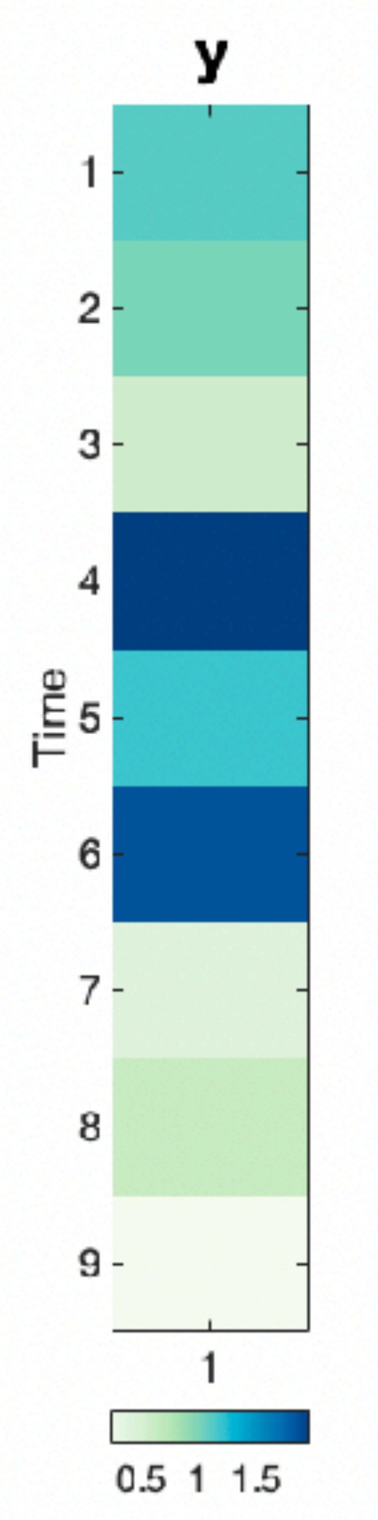


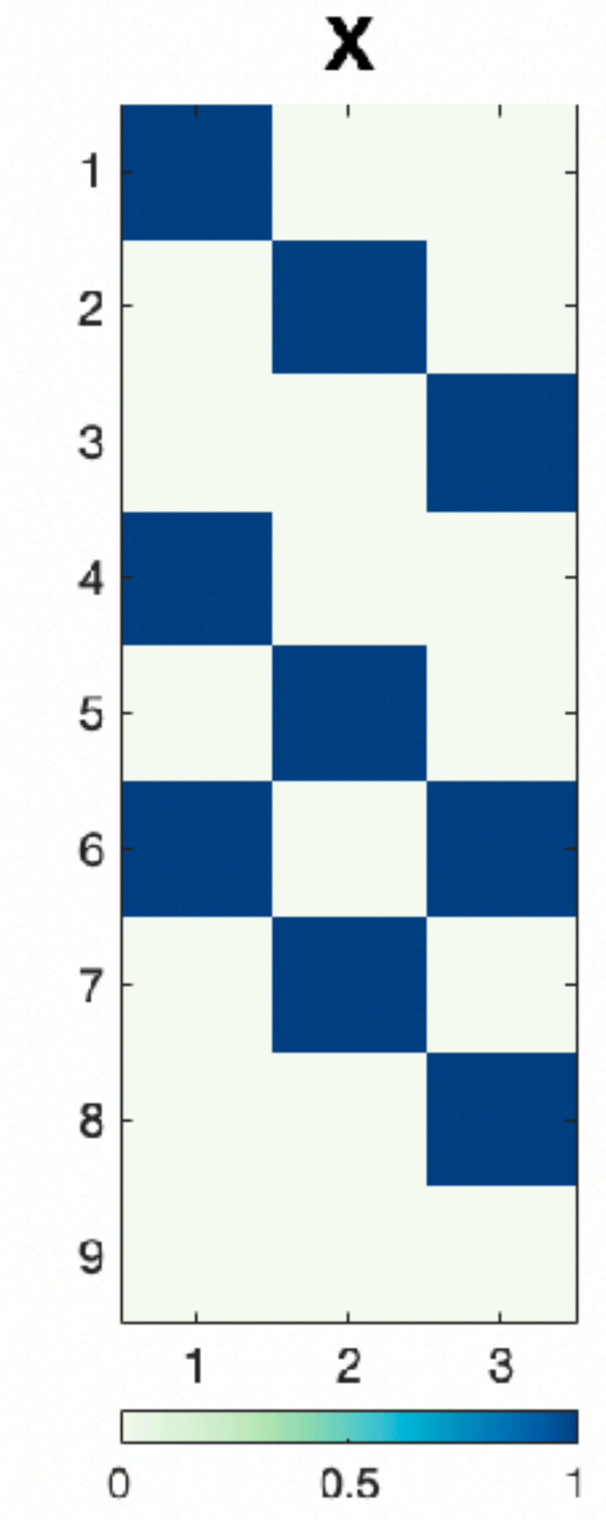




FIR as a linear regression

$$\underset{(t\times 1)}{\mathbf{y}} = \underset{(t\times d)}{\mathbf{X}} \; \underset{(d\times 1)}{\mathbf{b}} + \underset{(t\times 1)}{\mathbf{e}}$$





Ordinary least squares (OLS):

$$\hat{\mathbf{b}} = \mathbf{X}^{+}\mathbf{y}$$

$$= (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$$

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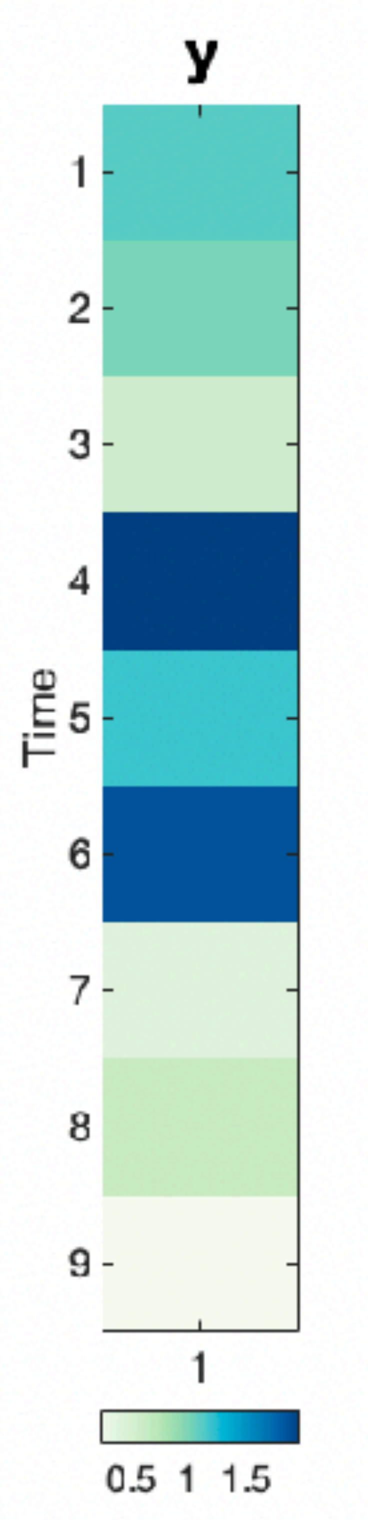
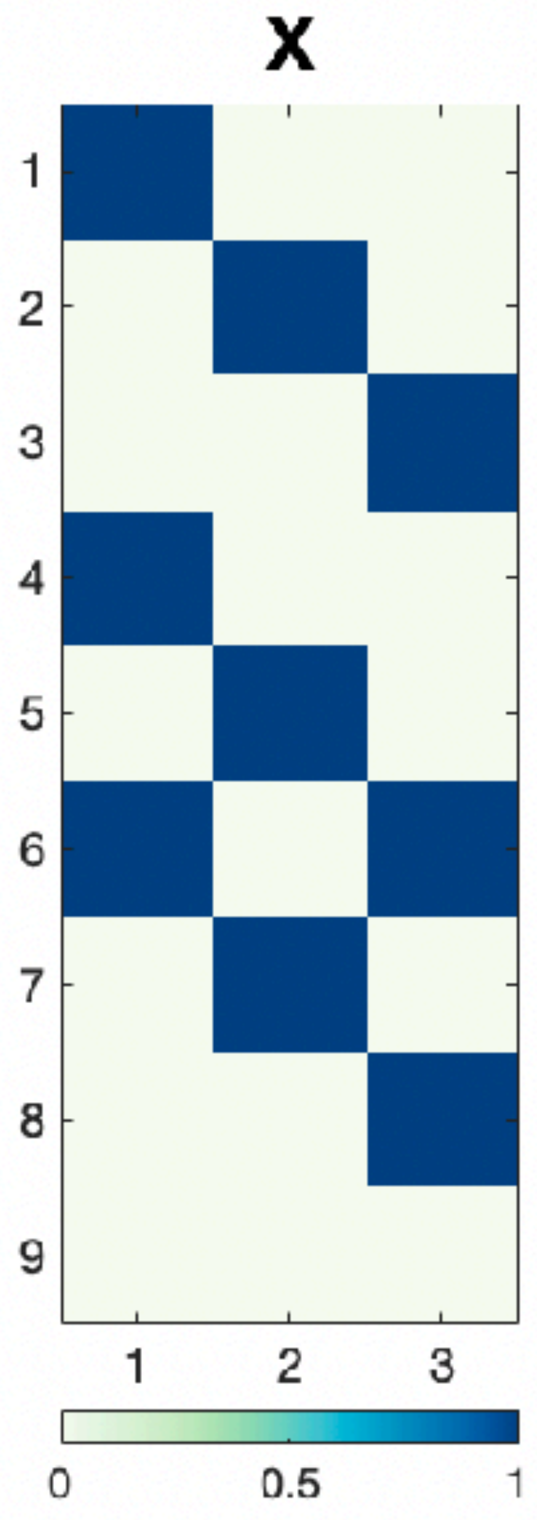
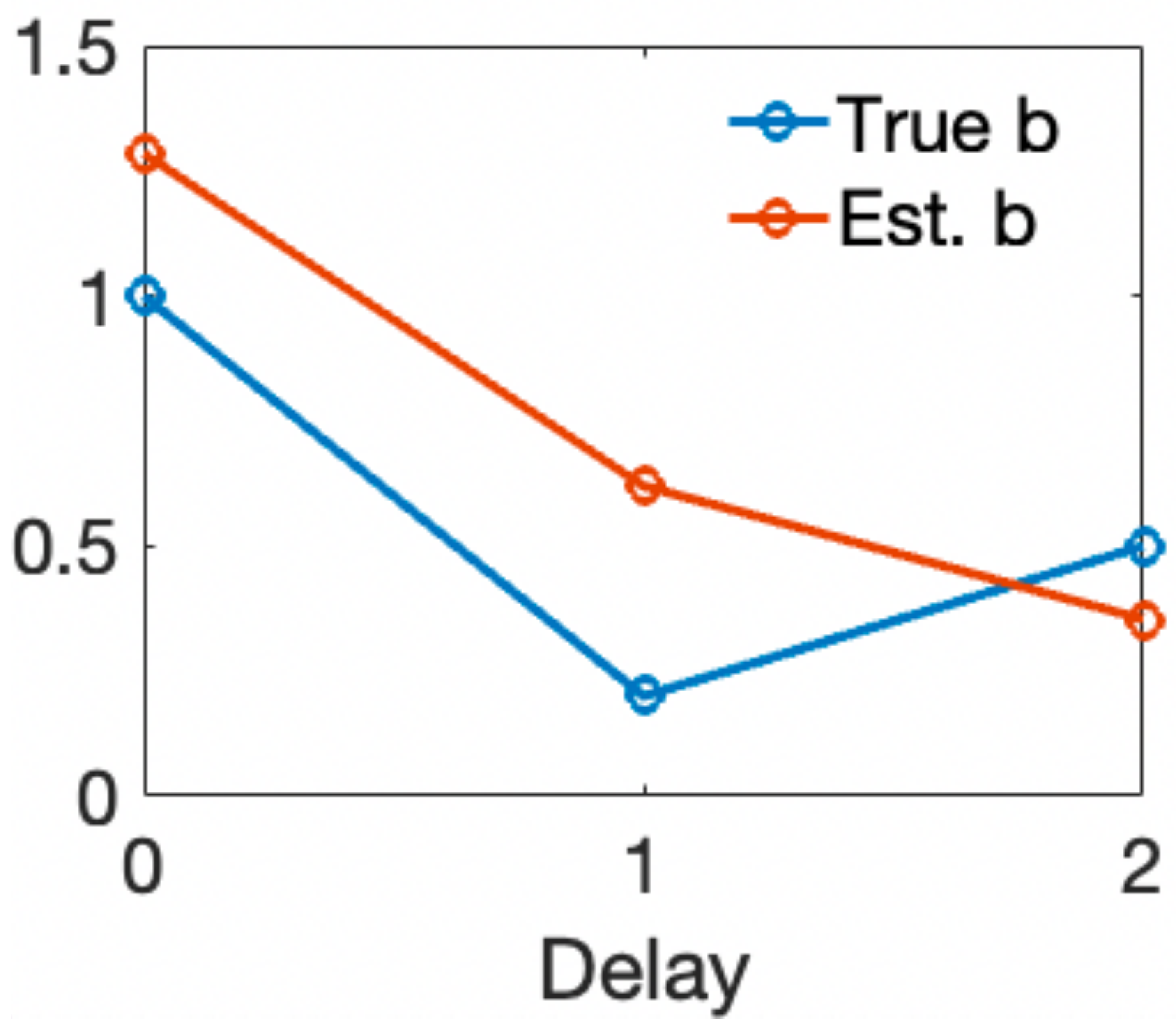
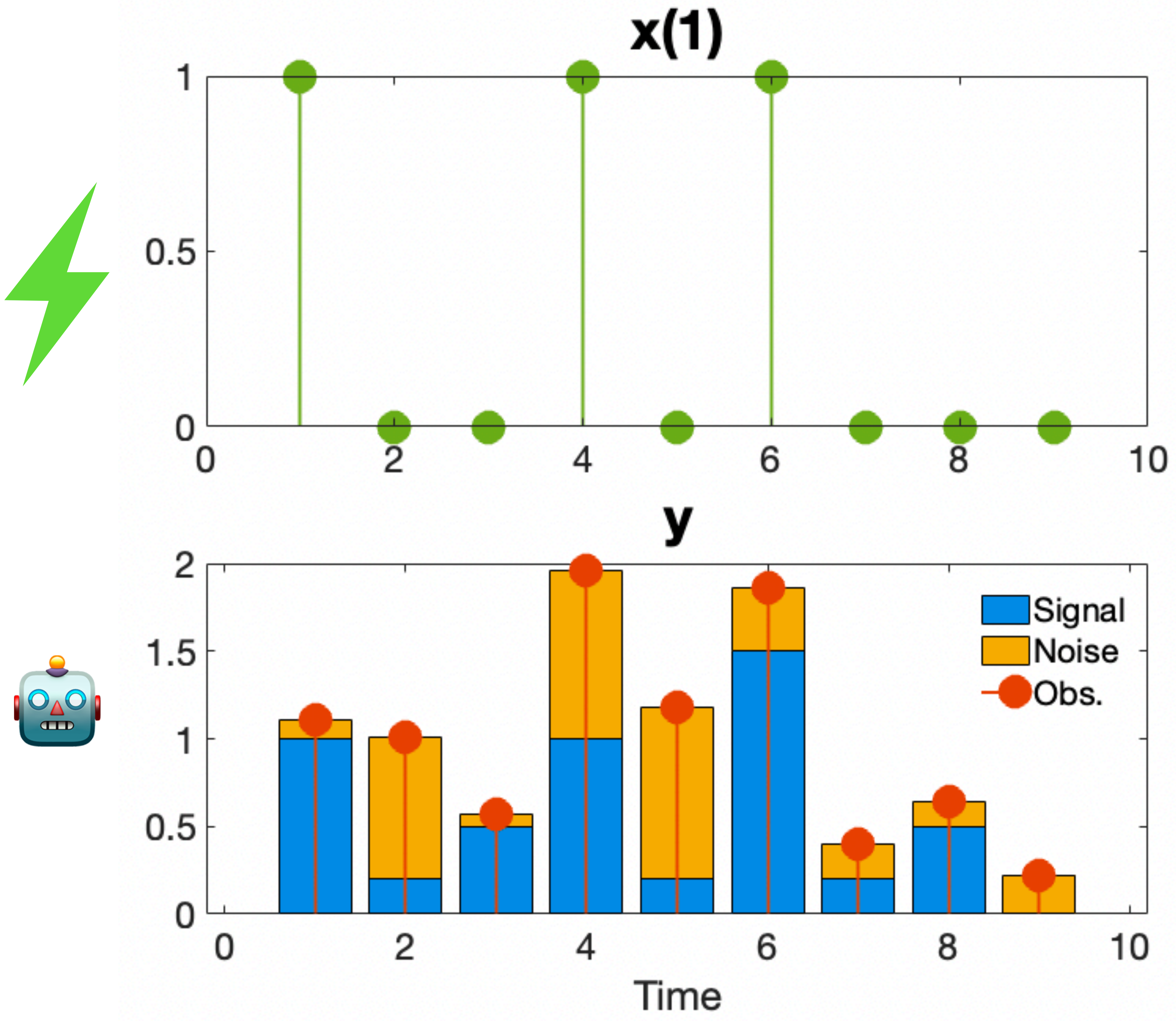


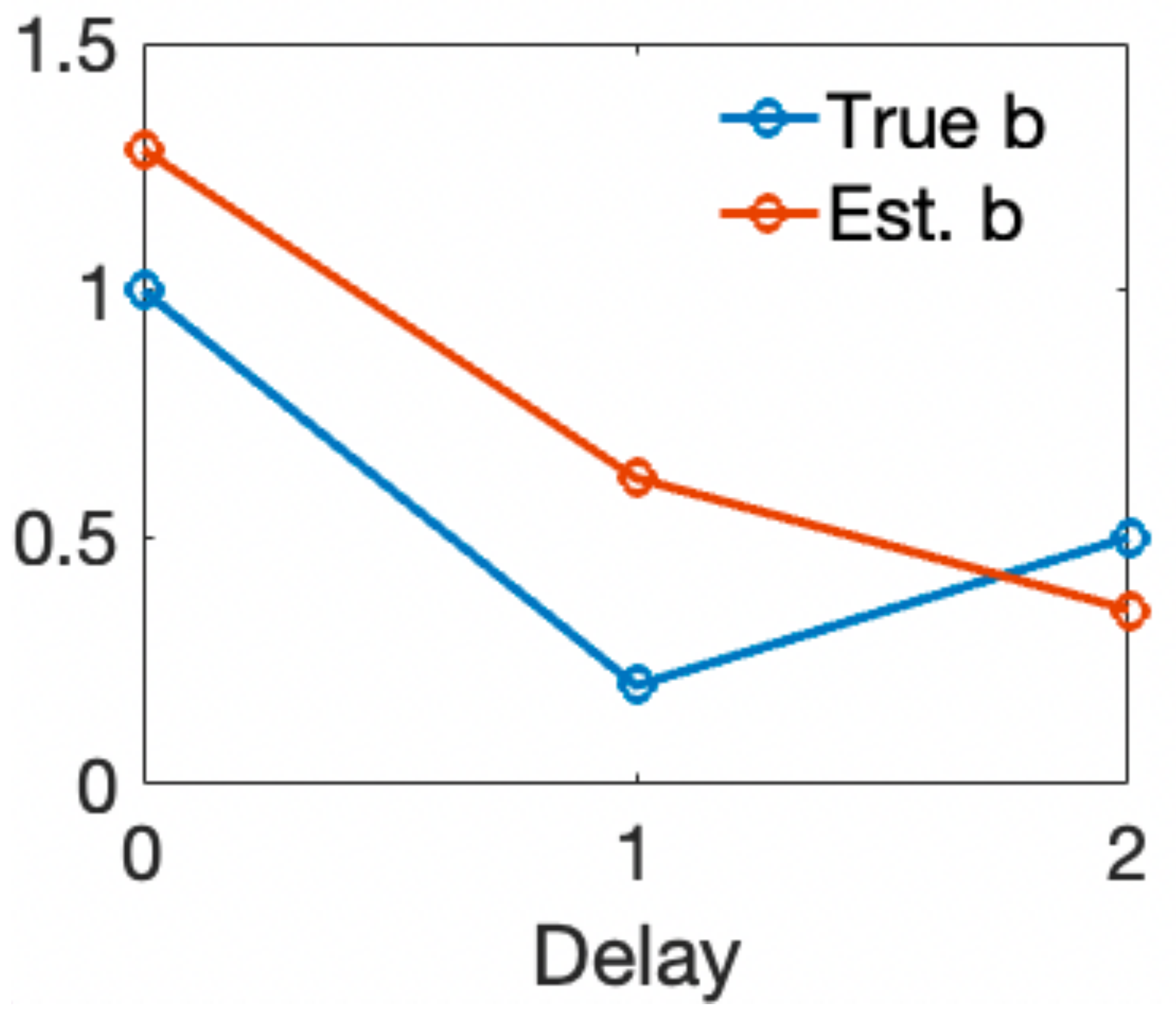




🤔: But why not identical?

Because there is no sample without noise!





Estimation is overfitting to **noise**🙄

Interactive demo

Summary [1/4]: Finite impulse response

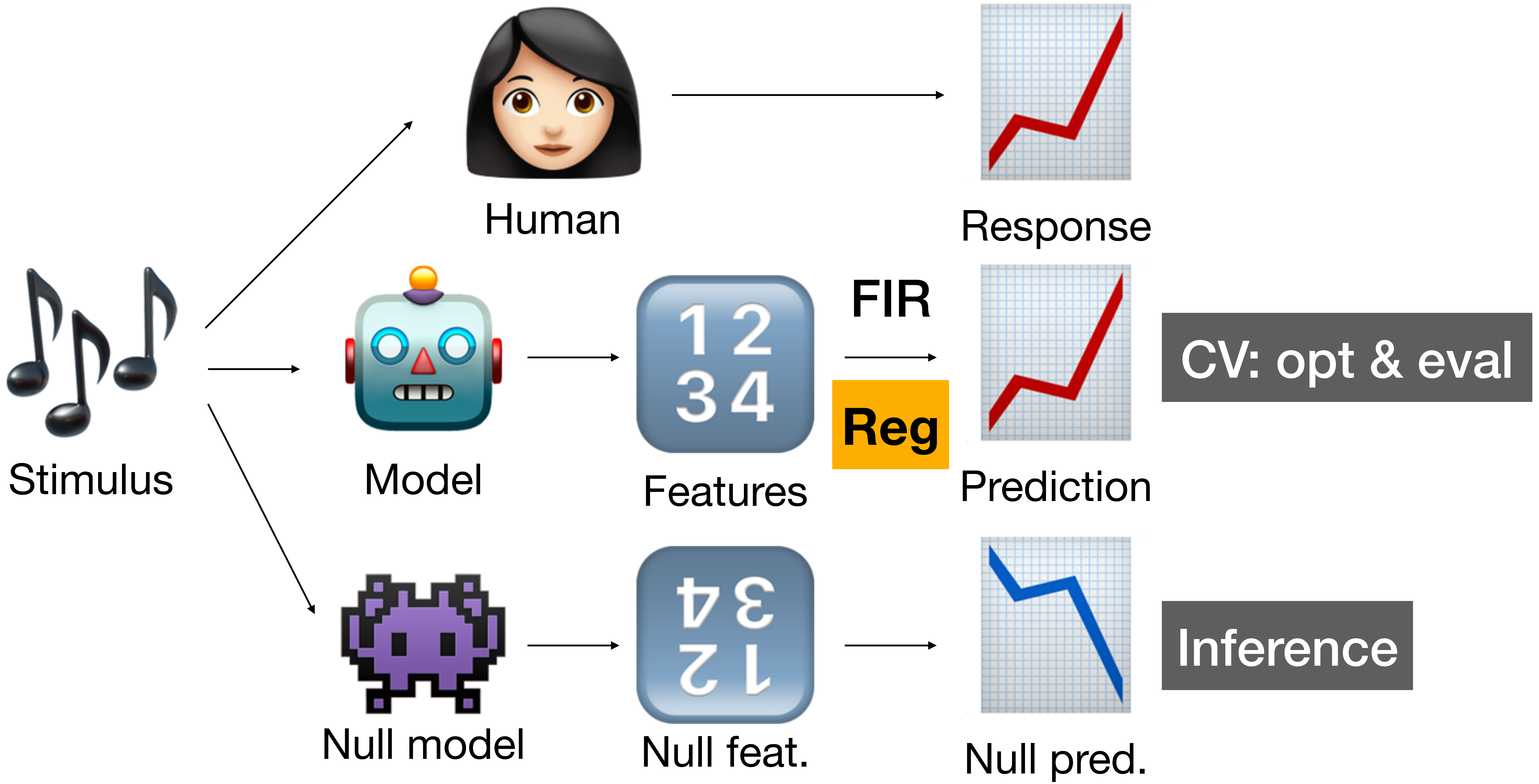
FIR modeling in the time domain

Summary [1/4]: Finite impulse response

FIR modeling in the time domain

- A linear filter ("***temporal response function***") can be recovered by fitting a linear model with a set of delayed predictors.
- The recovery can be difficult with noisy data (**overfitting to noise**).
- 🤔: Then how can we make this better (less sensitive to noise)?

Linearized encoding analysis overview (HOWs)



Regularization

Regularize what?

- What it does:
  - It **regularizes** the estimates (increasing stability) by **penalizing** the loss function (adding additional terms to the loss function)
  - It trades off accuracy (offset) and stability (spread) of estimates.
- 🤔: But what is it?

Ridge regression

Regularized linear regression

- LSE: $b^* = \arg\min_{\mathbf{b}} \|\mathbf{y} - \mathbf{X}\mathbf{b}\|_2^2 = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y} = \mathbf{X}^+\mathbf{y}$
- Ridge: $\mathbf{b}^* = \arg\min_{\mathbf{b}} \|\mathbf{y} - \mathbf{X}\mathbf{b}\|_2^2 + \lambda\|\mathbf{b}\|_2^2 = (\mathbf{X}'\mathbf{X} + \lambda^2\mathbf{I})^{-1}\mathbf{X}'\mathbf{y}$
    - $\lambda = 0$: LSE
    - $\lambda \gg 0$: it makes $\mathbf{b}^* \approx \mathbf{0}$
- But how do we know the 'optimal' λ for this data?
    - Grid-search: compute errors for all 'reasonable' λ values then find one that gives you the least error (on the independent 'optimization set')

Interactive demo

Other types of regularization for regression

- LSE:
  $$\mathbf{b}_{\text{LSE}} = \arg\min_{\mathbf{b}} \|\mathbf{y} - \mathbf{X}\mathbf{b}\|_2^2 = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y} = \mathbf{X}^{+}\mathbf{y}$$

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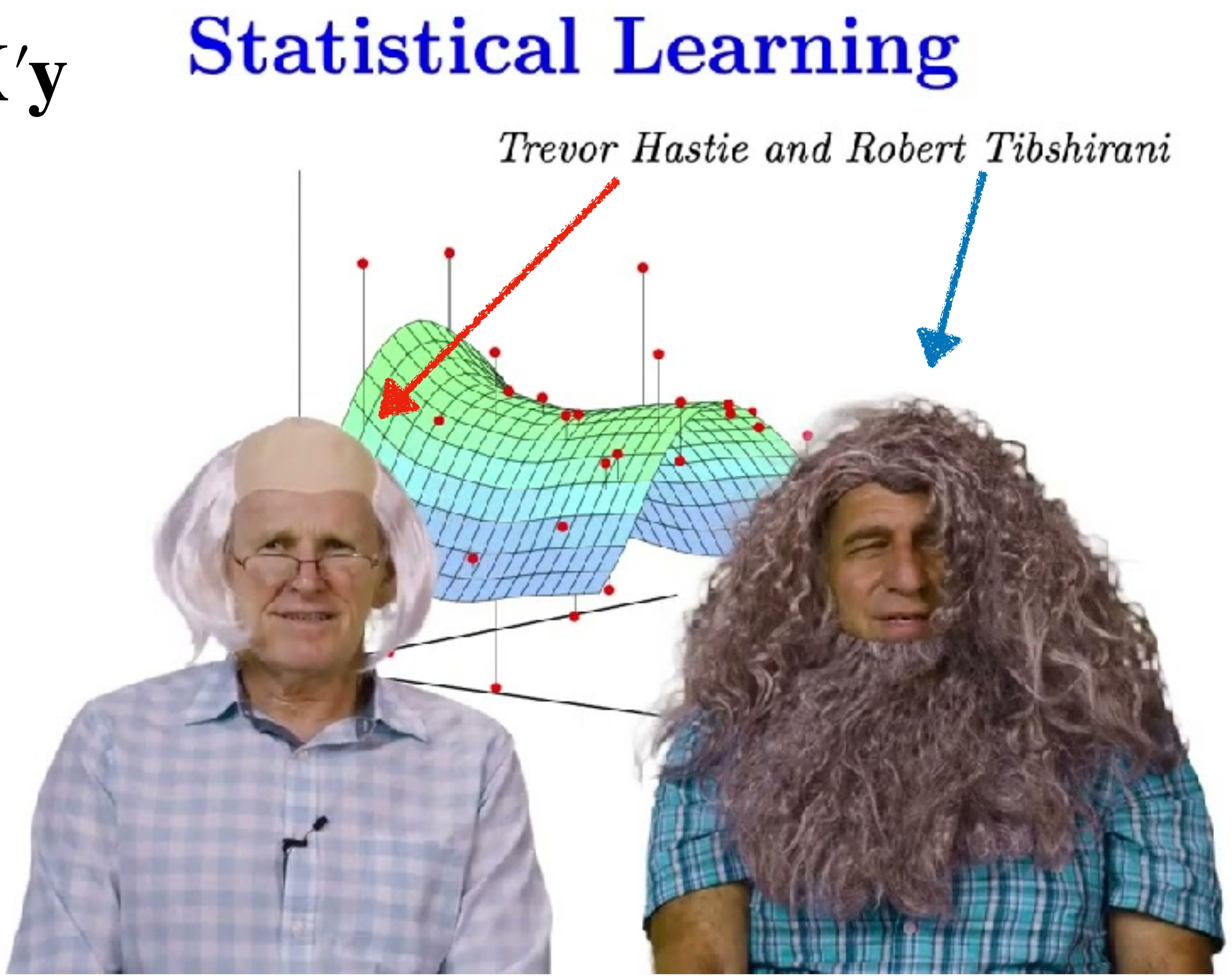

https://www.youtube.com/watch?v=9vIDVxG4uIA

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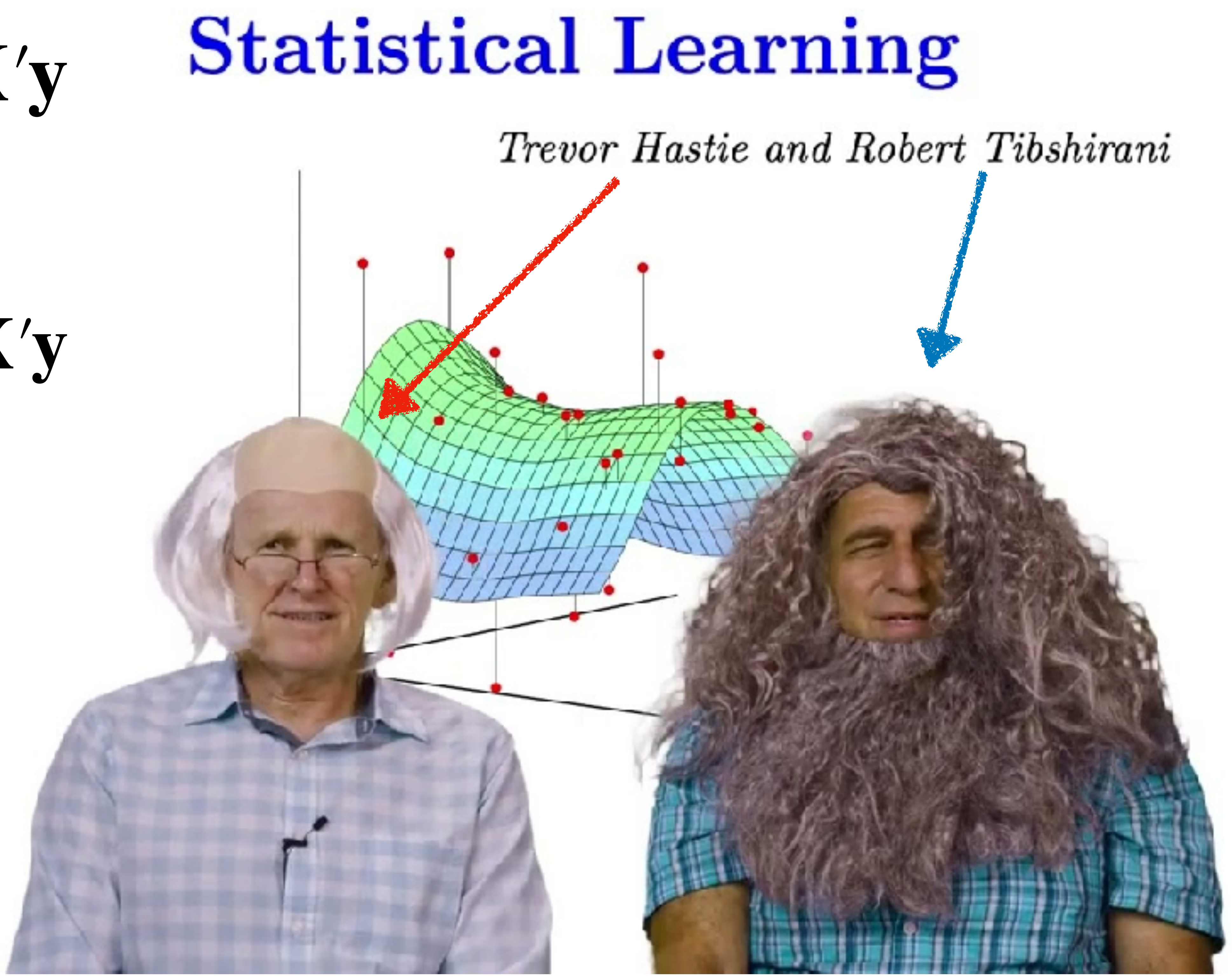

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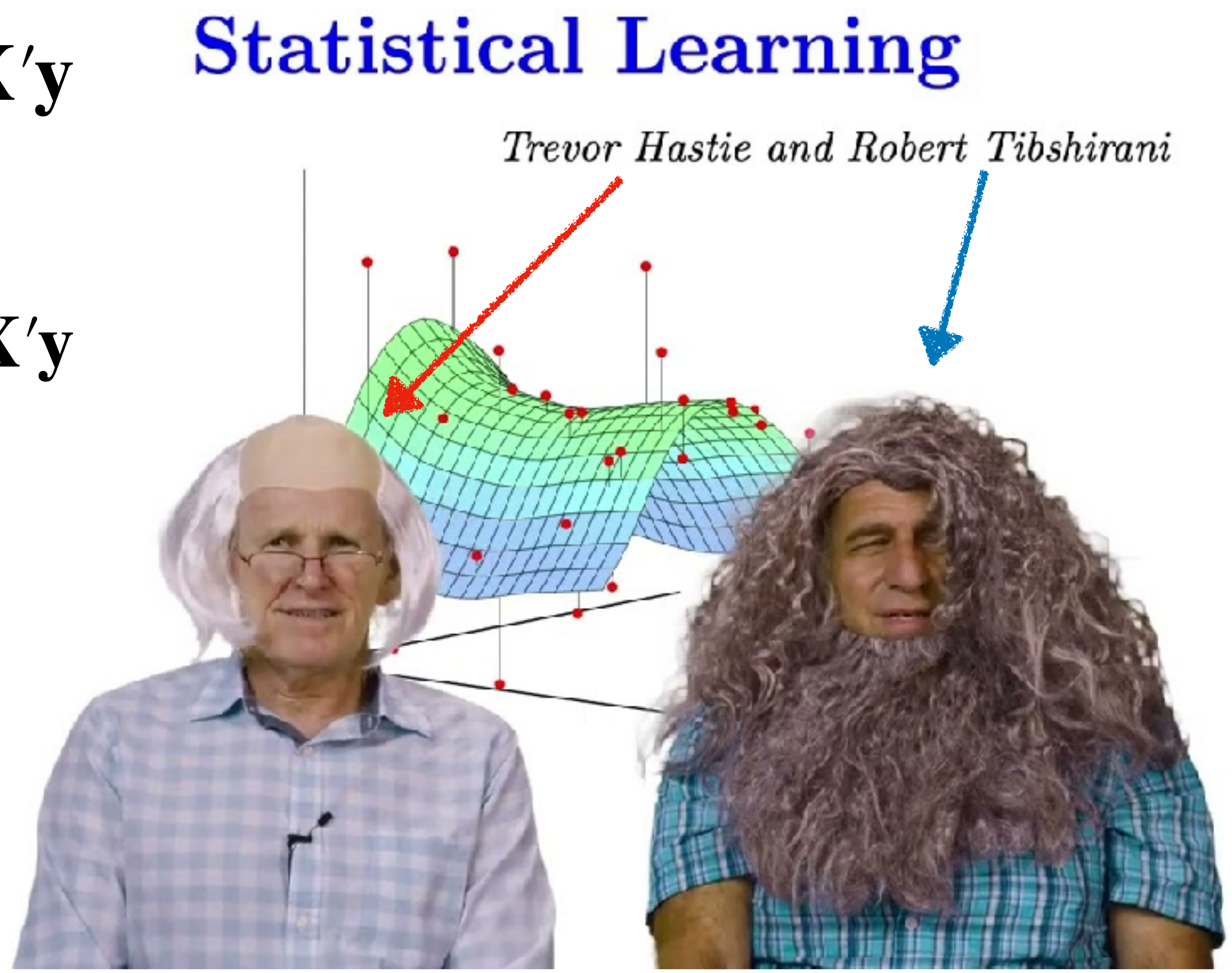
- Lasso (L1-norm; Santosa et al., 1986; **Tibshirani**, 1996): $\mathbf{b}_{\text{lasso}} = \arg\min_{\mathbf{b}} \|\mathbf{y} - \mathbf{X}\mathbf{b}\|_2^2 + \|\lambda\mathbf{b}\|_1$



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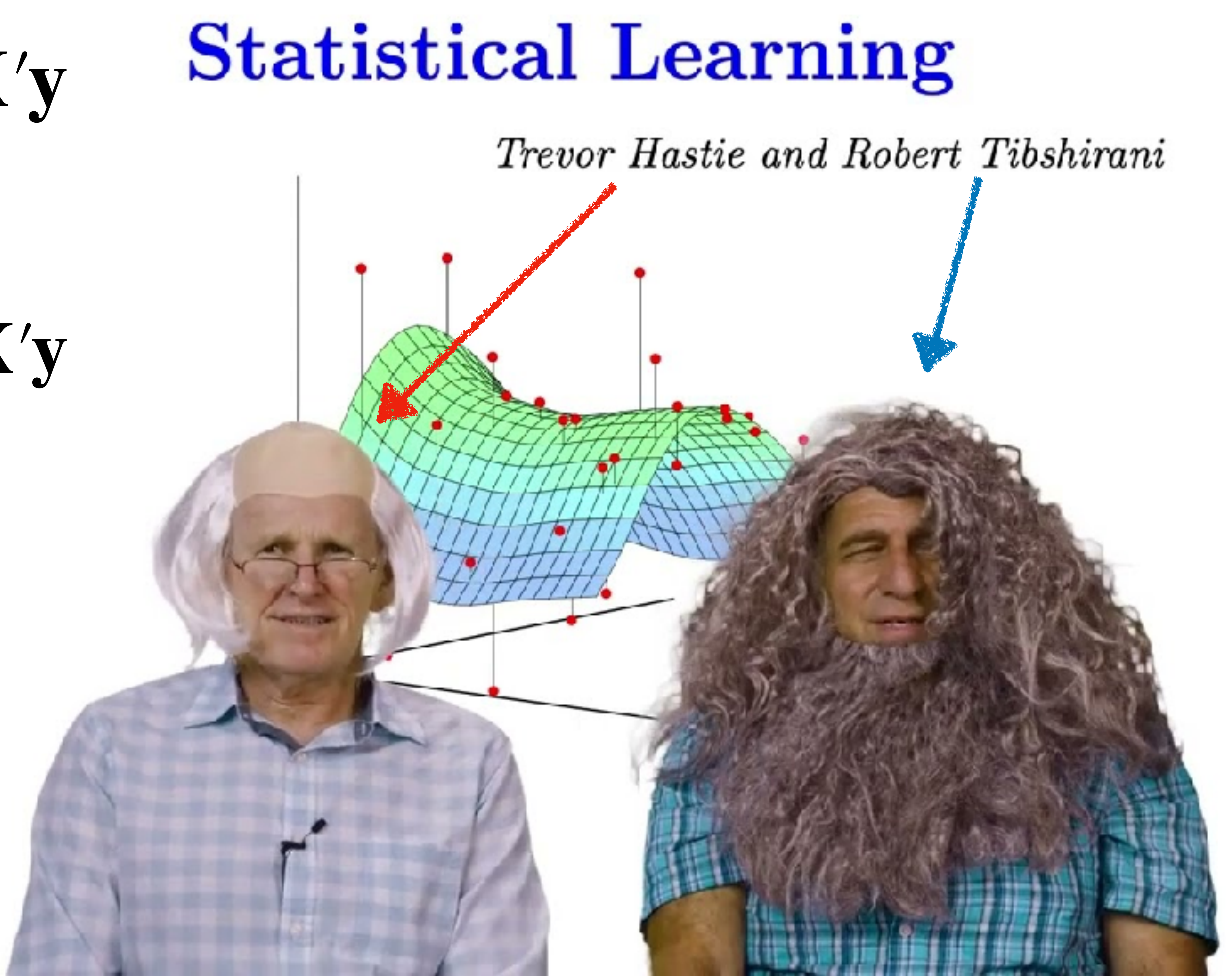
- Elastic net (L1-norm + L2-norm; Zou & **Hastie**, 2005):
  $\mathbf{b}_{\text{elastic}} = \arg\min_{\mathbf{b}} \|\mathbf{y} - \mathbf{X}\mathbf{b}\|_2^2 + \|\lambda\mathbf{b}\|_1 + \lambda\|\mathbf{b}\|_2^2$

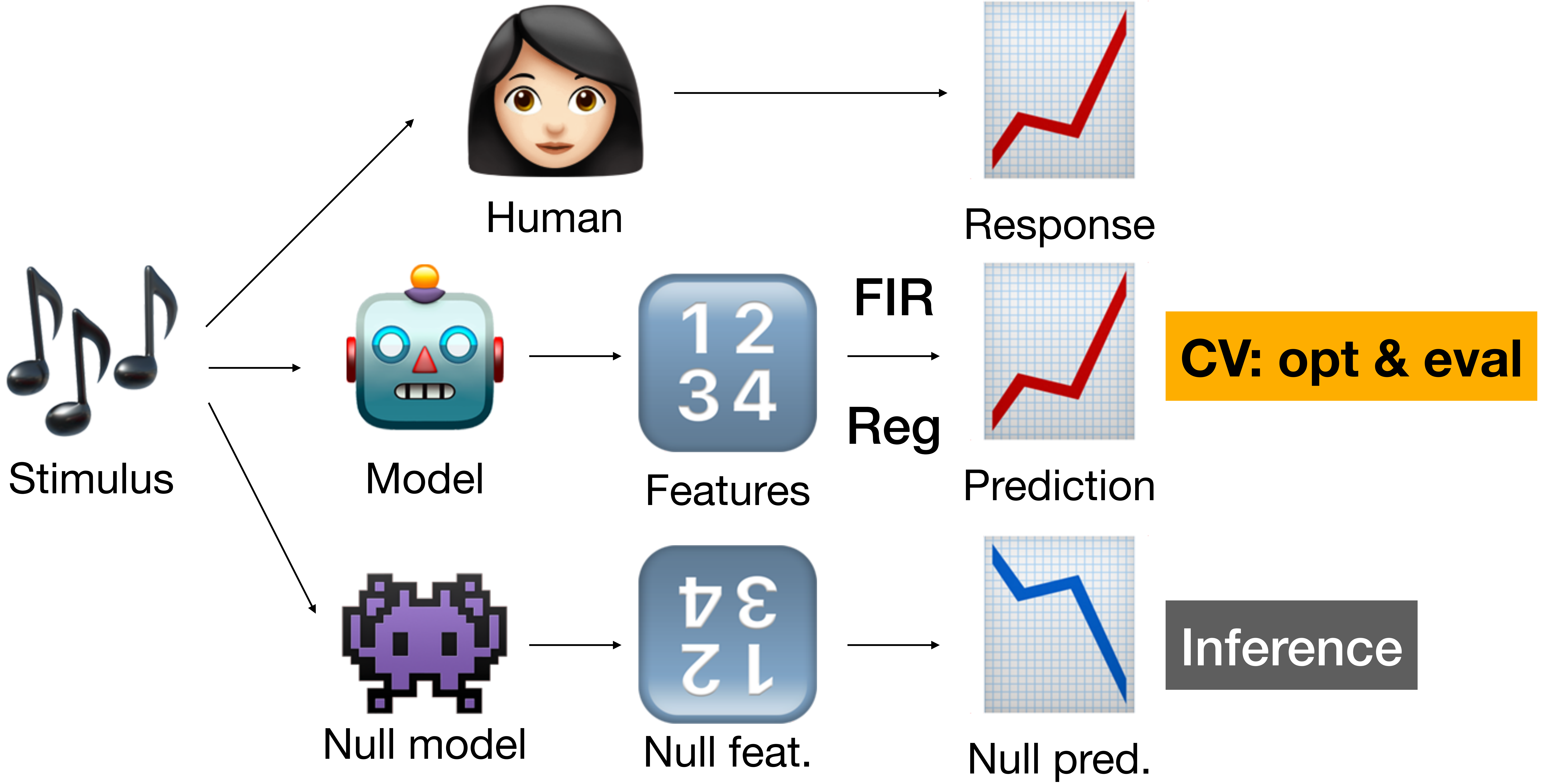


https://www.youtube.com/watch?v=9vIDVxG4ulA

Summary [2/4]: Regularization

- A regularization penalty term (e.g., λ in ridge regression; also called a "hyperparameter") governs **how sensitive** a linear model to be to a given (training) data.
- The **optimal sensitivity for out-sample prediction** can be lower than that of OLS (BLUE: the best linear unbiased estimator — but only for the training data).
- There can be other forms of regularization (LASSO, Elastic net, ...).
- 🤔: But how can we determine the optimal regularization?

Linearized encoding analysis overview (HOWs)



Validation (out-sample prediction)

Training set

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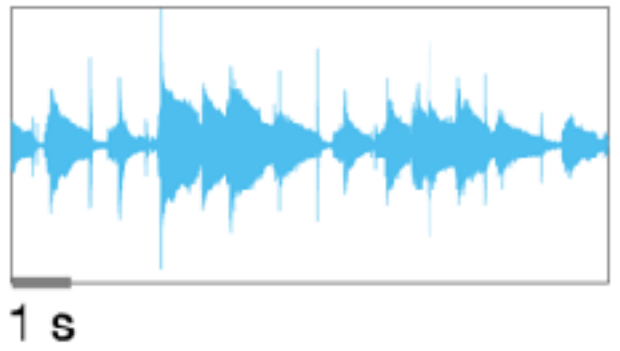
Validation (out-sample prediction)

Training set

Music #1

$\mathbf{X}_1$



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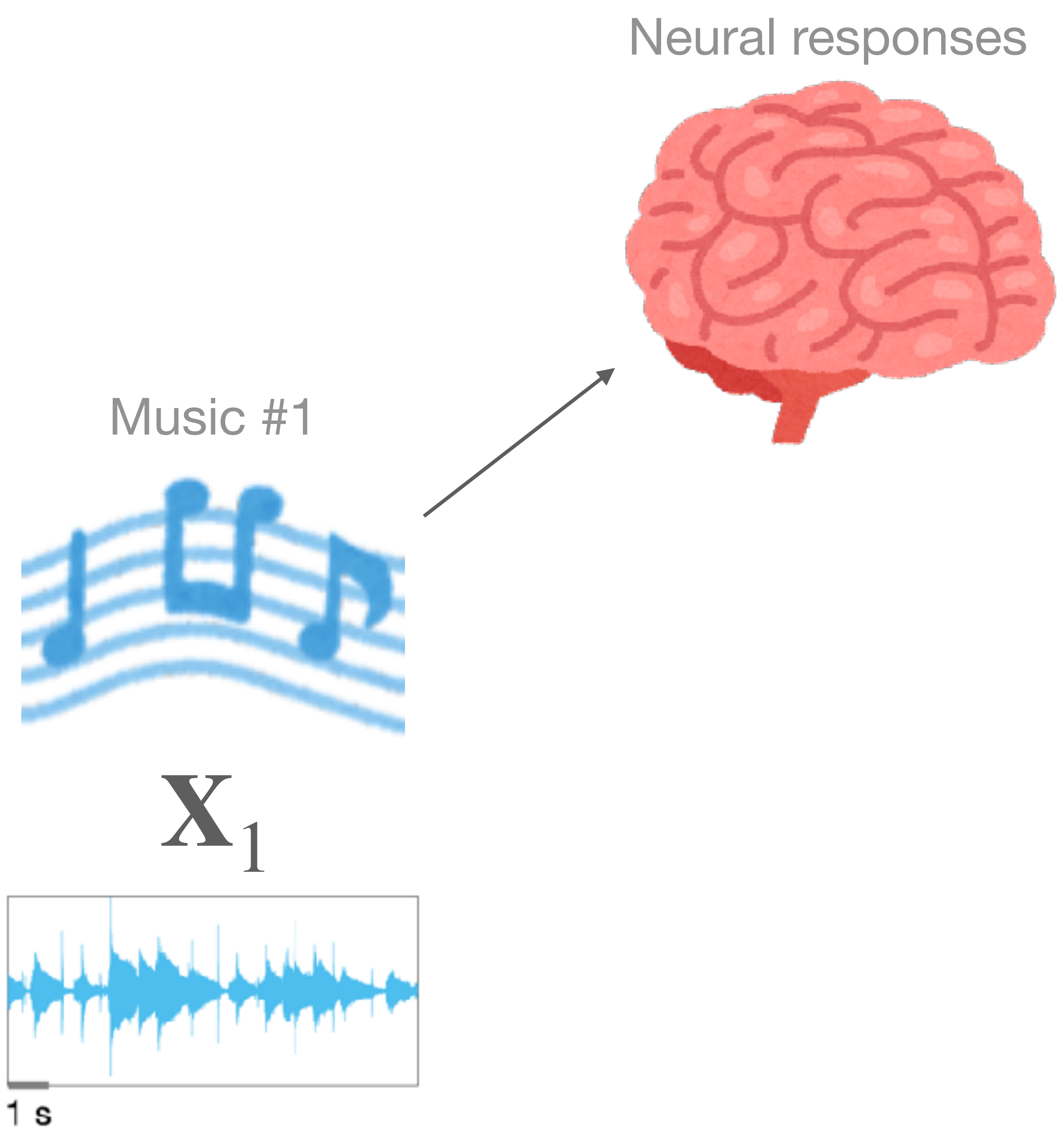

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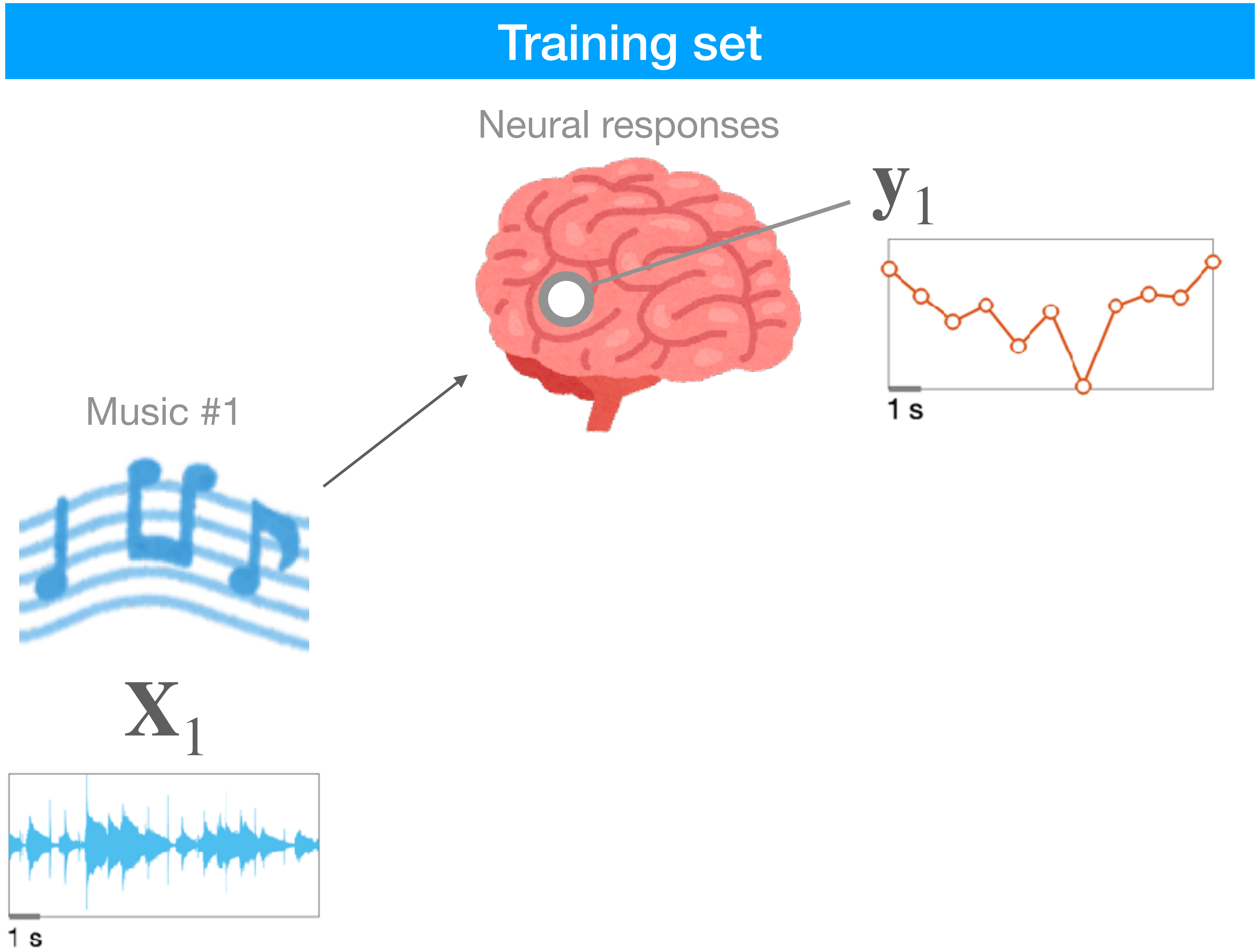

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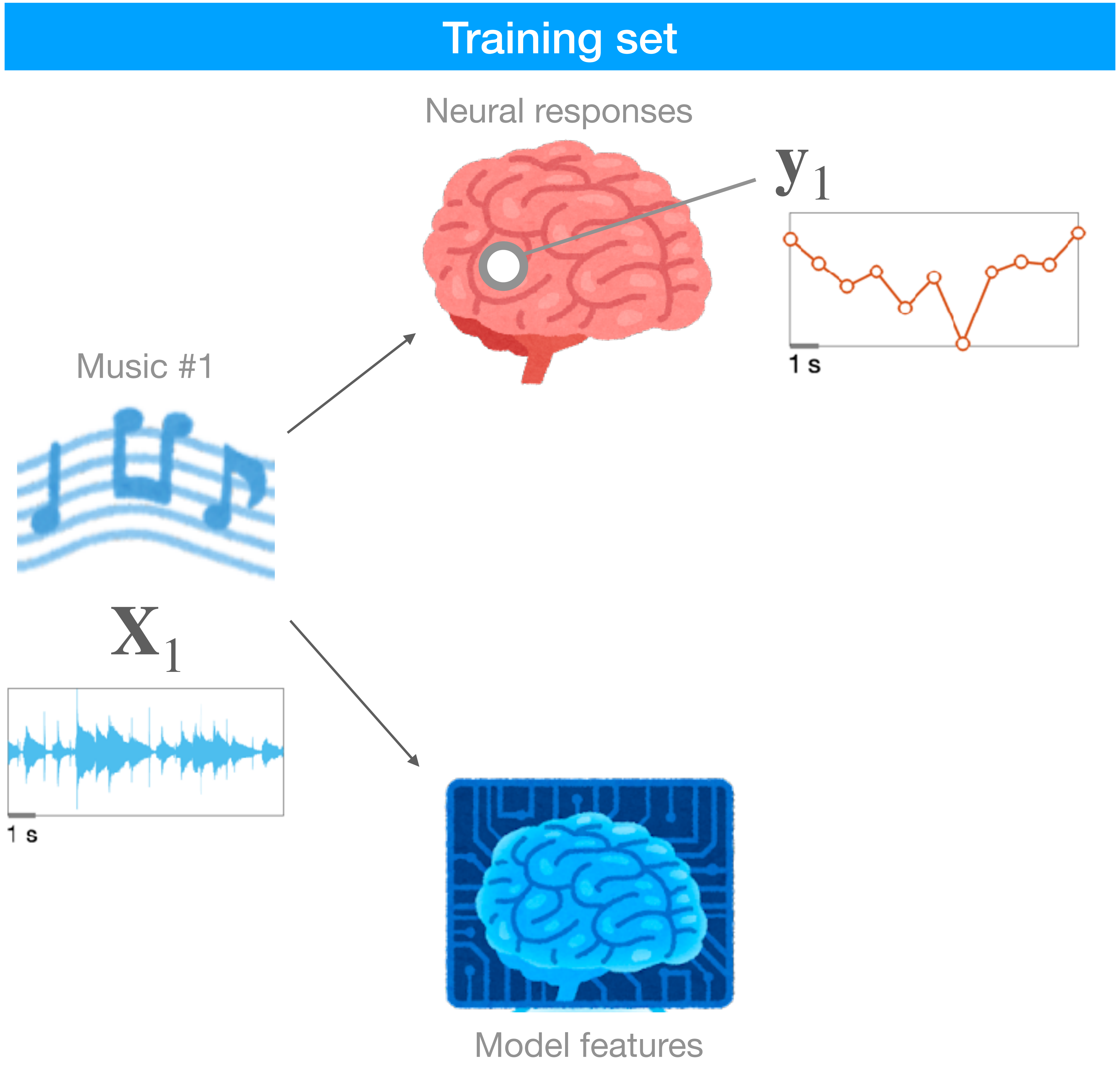

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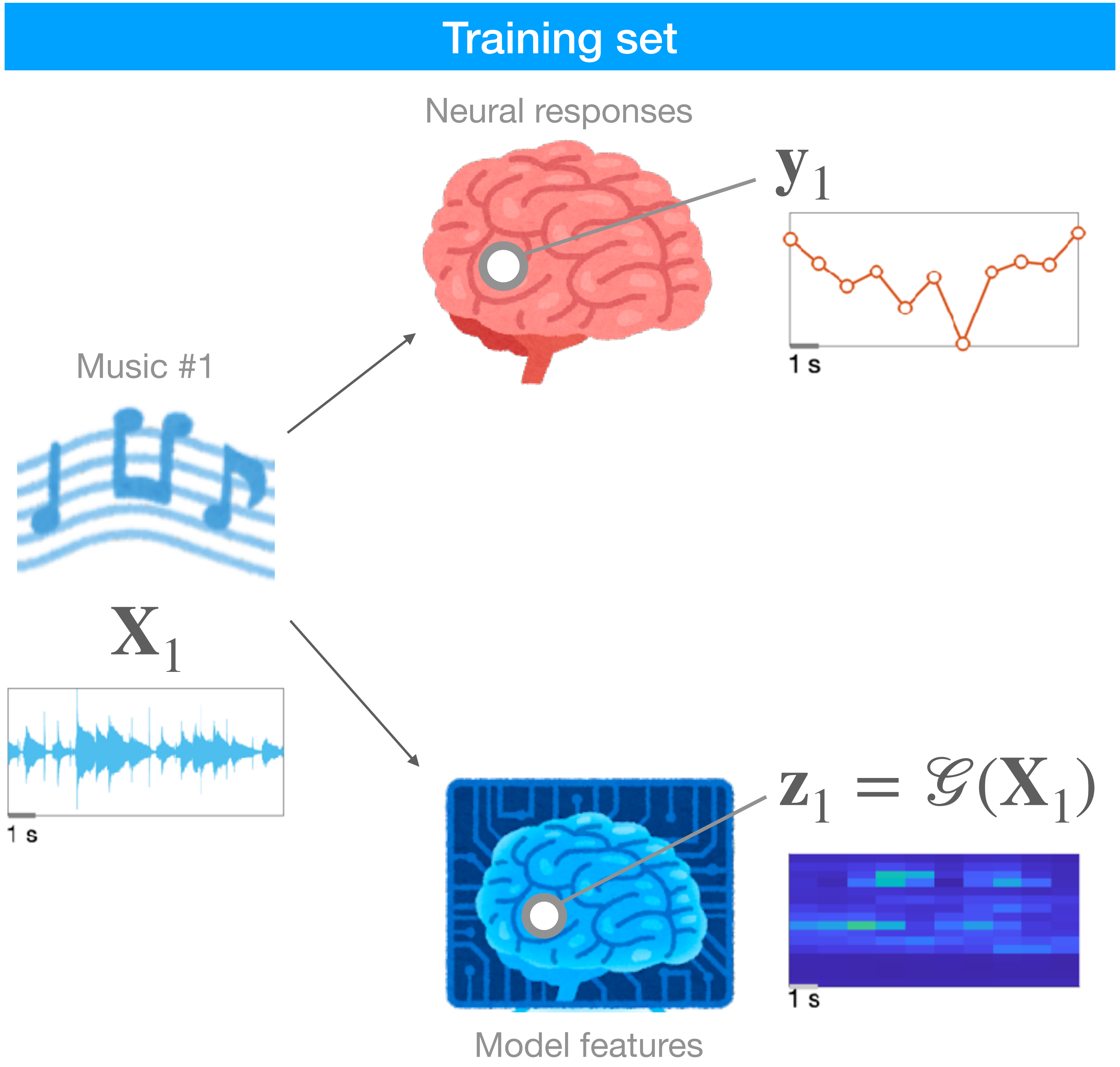

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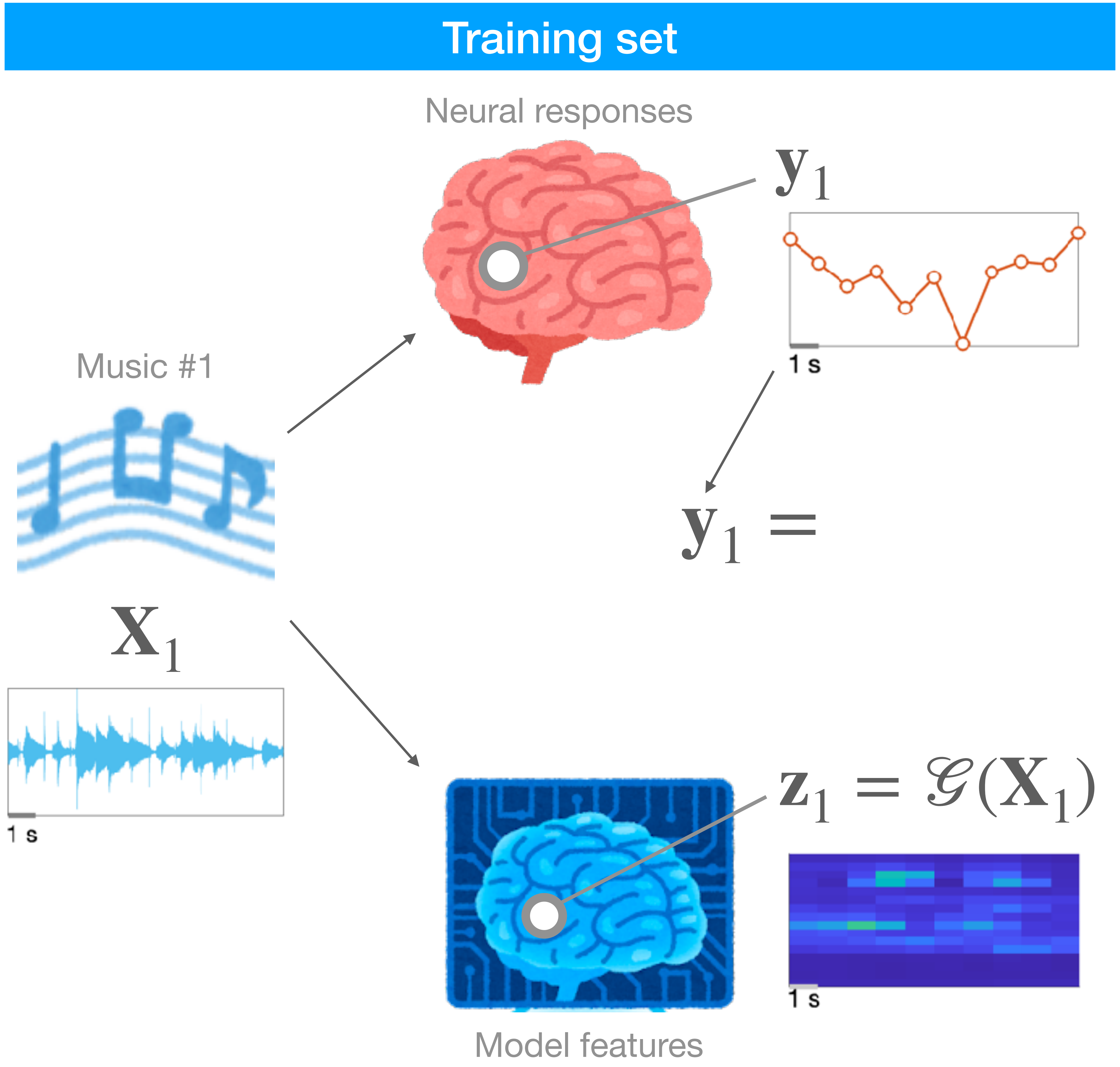

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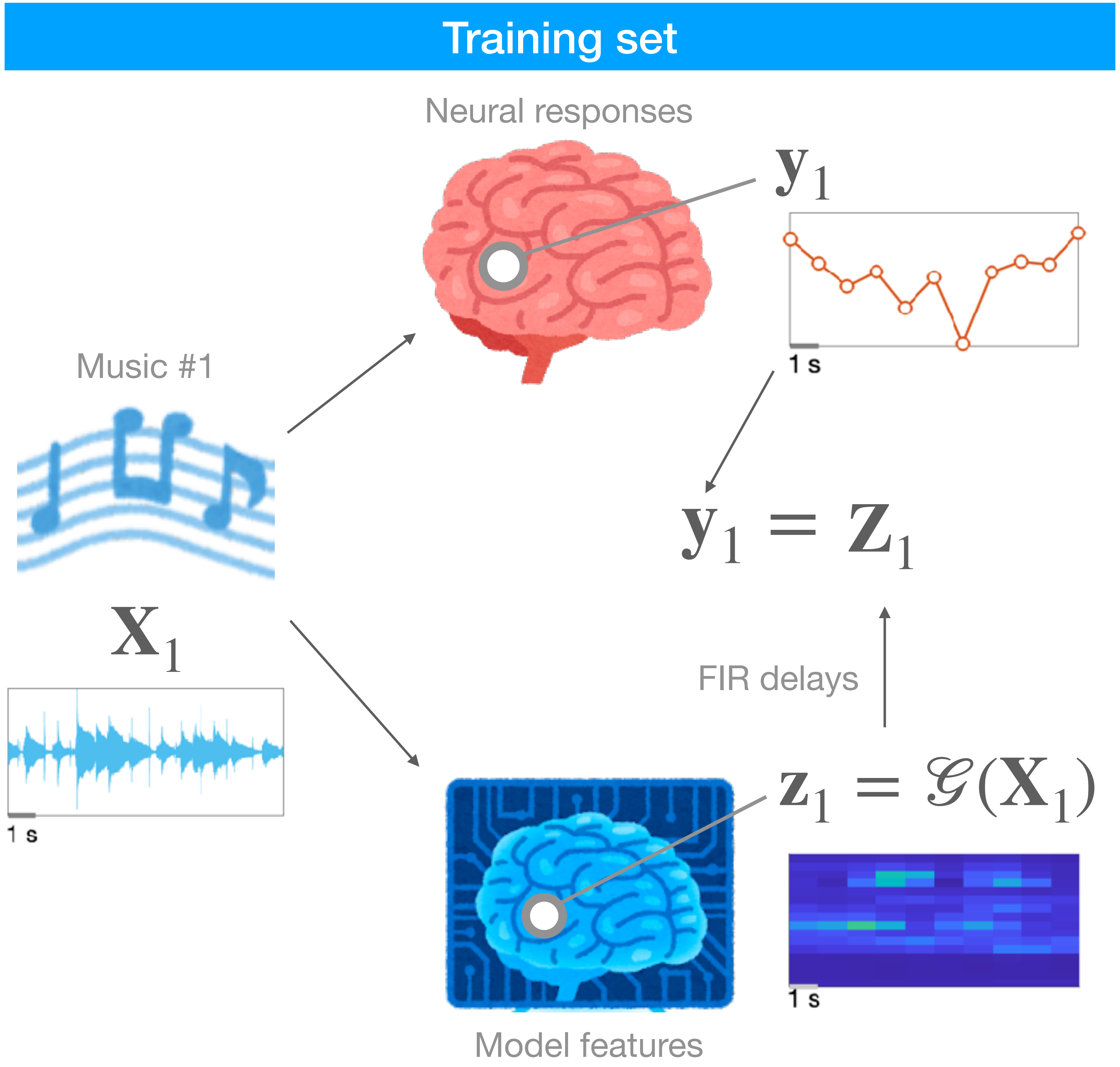

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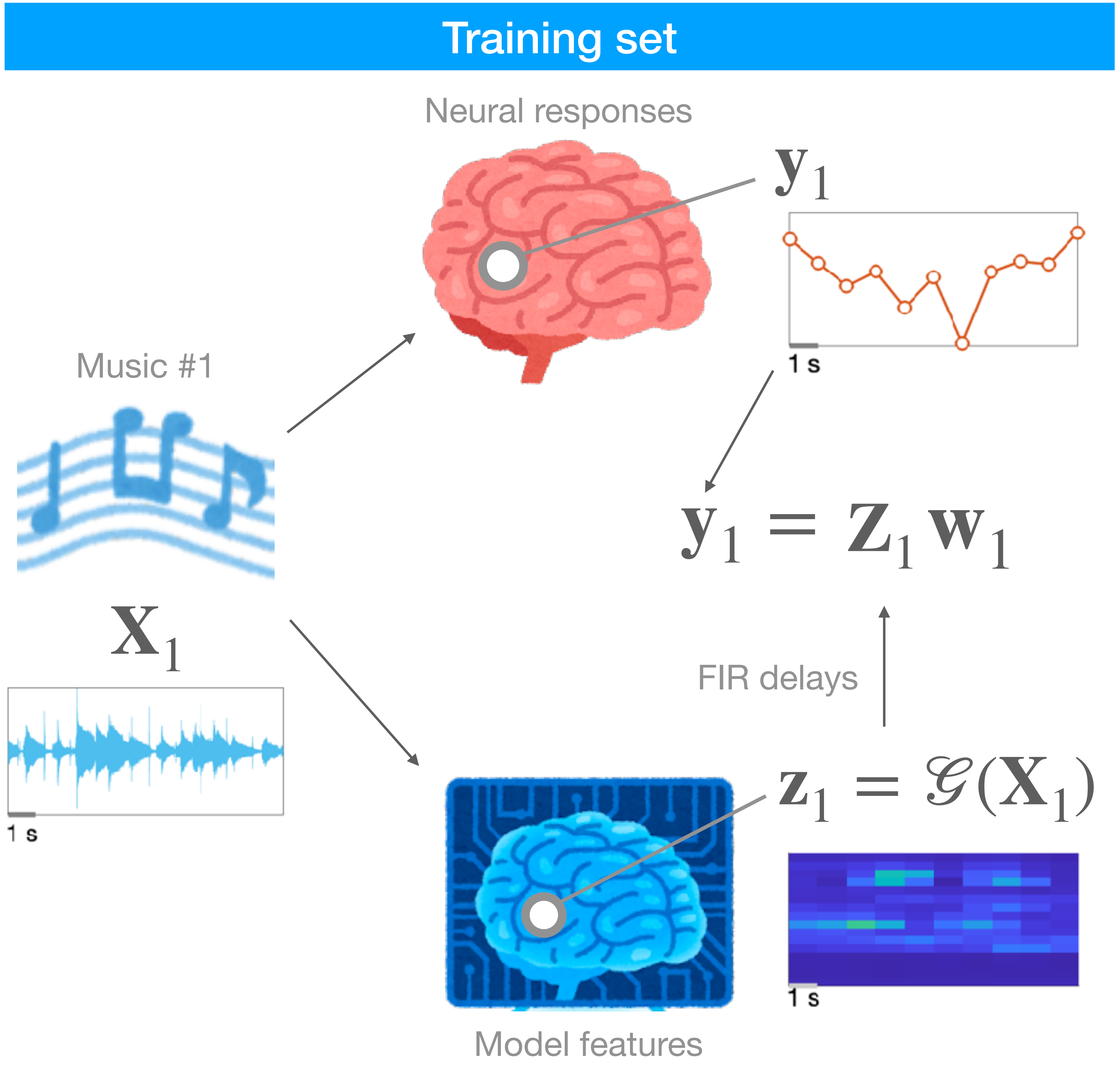

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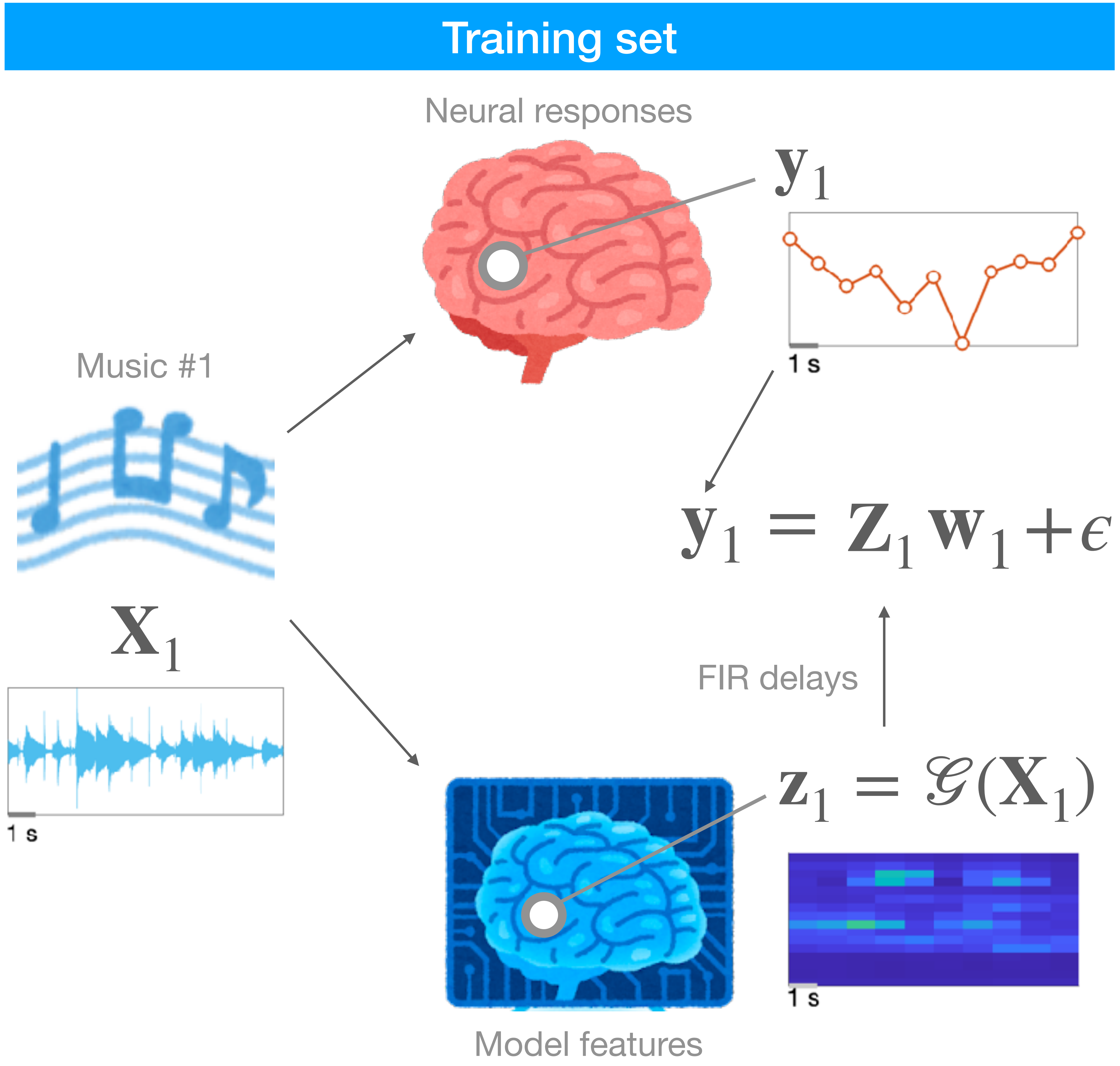
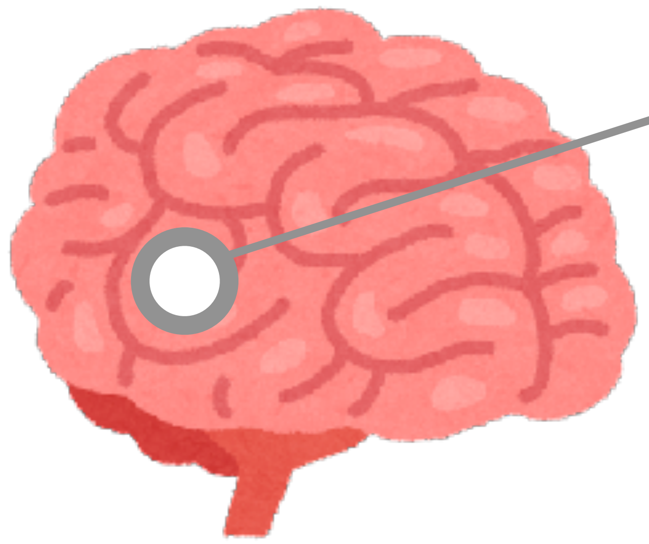


Validation (out-sample prediction)

Training set

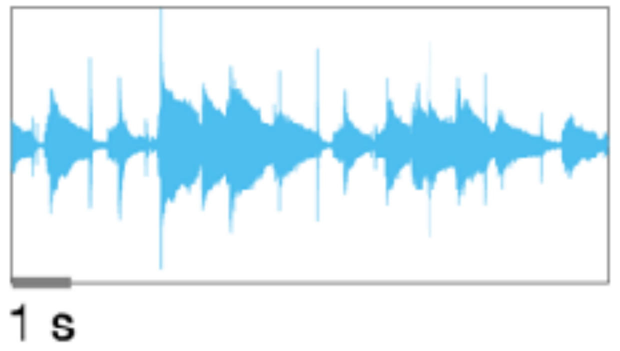
Neural responses



$\mathbf{y}_1$

Music #1

$\mathbf{X}_1$

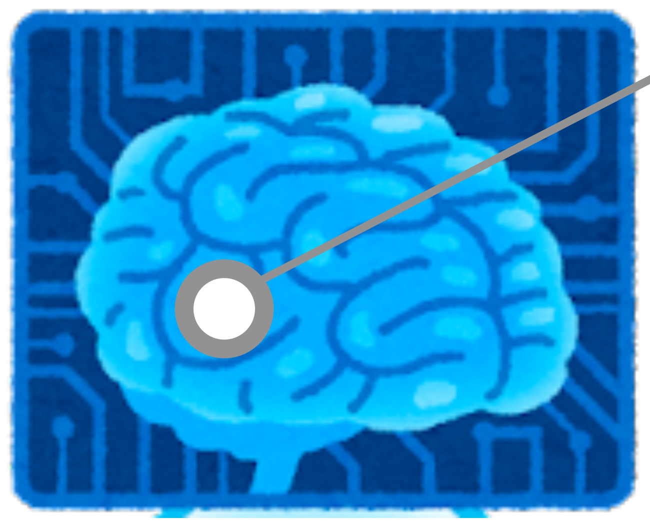


Weight fitting: $\hat{\mathbf{w}}_1 = \mathbf{Z}_1^{+}\mathbf{y}_1$

$$\mathbf{y}_1 = \mathbf{Z}_1 \mathbf{w}_1 + \epsilon$$

FIR delays

$$\mathbf{z}_1 = \mathcal{G}(\mathbf{X}_1)$$

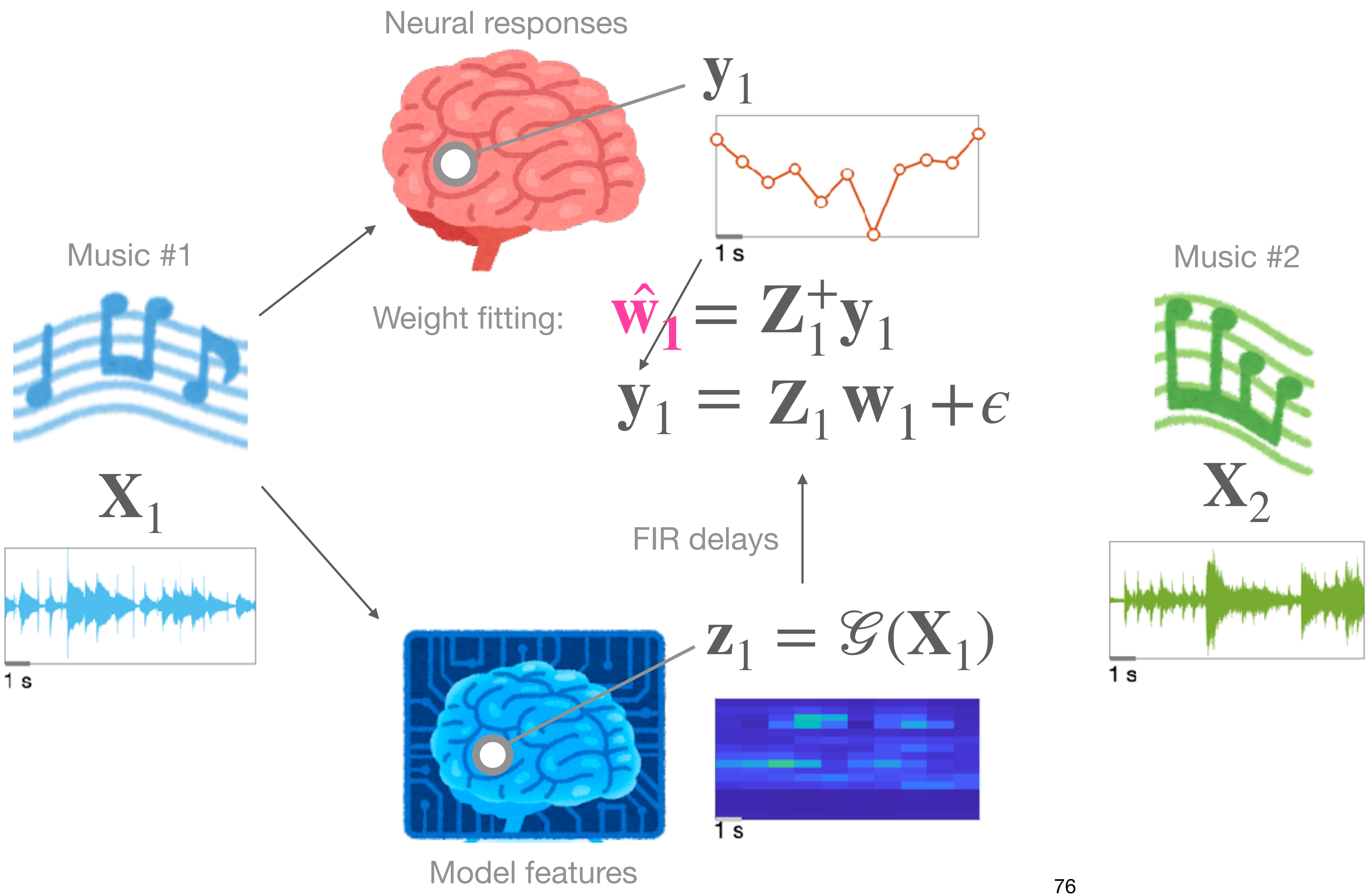


Model features

Validation (out-sample prediction)

Training set

Test set



Validation (out-sample prediction)

Training set | **Test set**

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Validation (out-sample prediction)

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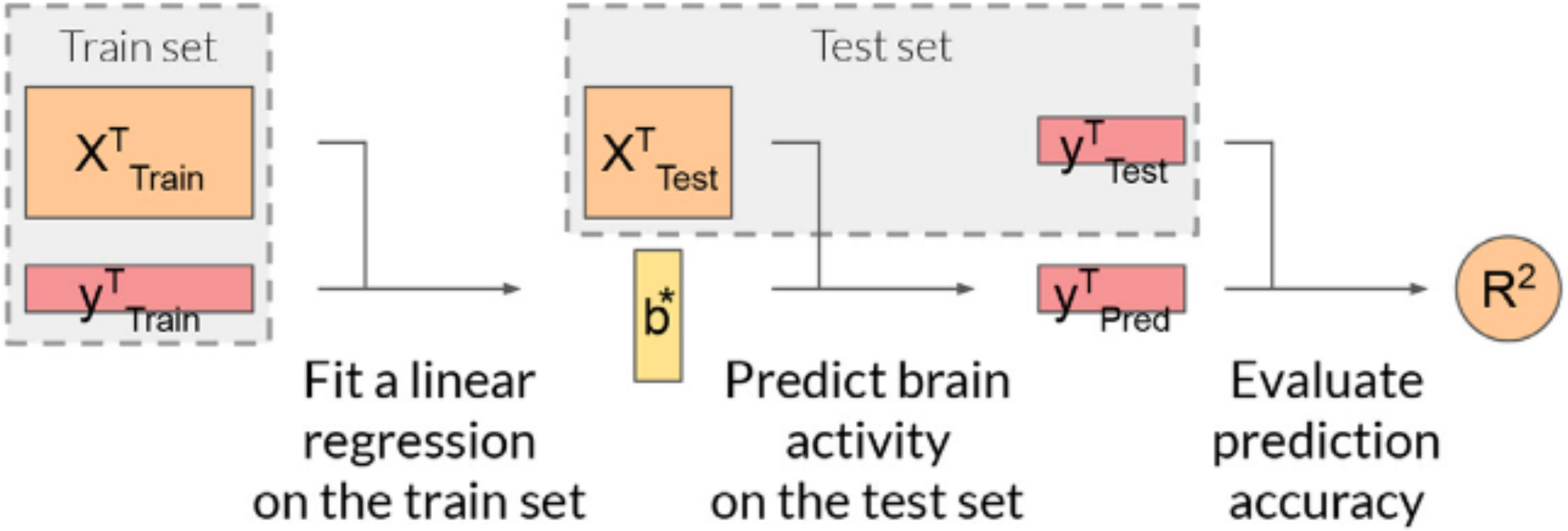
Validation (out-sample prediction)

Prediction accuracy measure

R^2 (or Pearson's r)

- Cross-validation R-squared:

$$R^2 = 1 - \frac{\|\mathbf{y} - \hat{\mathbf{y}}\|_2^2}{\|\mathbf{y} - \bar{\mathbf{y}}\|_2^2} = 1 - \frac{\|\mathbf{y}_2 - \mathbf{X}_2\hat{\mathbf{b}}(\mathbf{X}_1, \mathbf{y}_1, \lambda)\|_2^2}{\|\mathbf{y}_2 - \bar{\mathbf{y}}_2\|_2^2}$$



Dupré la Tour et al., 2020, *NeuroImage*.

How do we find the optimal lambda?

Optimization methods

- **Ridge trace**: find a lambda where the shrinkage of weights is stable per given training set
- **Hold-out**: if you have lots of data (so that sampling variance due to random splitting is negligible; rarely the case in neuroimaging studies), split only once and optimize lambda only once.
- **Cross-validation**: find a lambda that minimizes prediction error on an "optimization set"
  - CV can be (repeated) split-half, k-fold, leave-one-out, ...

Over-optimization

“Cross-validation failure”

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- If you find a lambda that minimizes prediction error in a "TEST SET", can you use THAT minimized error as the model's performance?

Over-optimization

“Cross-validation failure”

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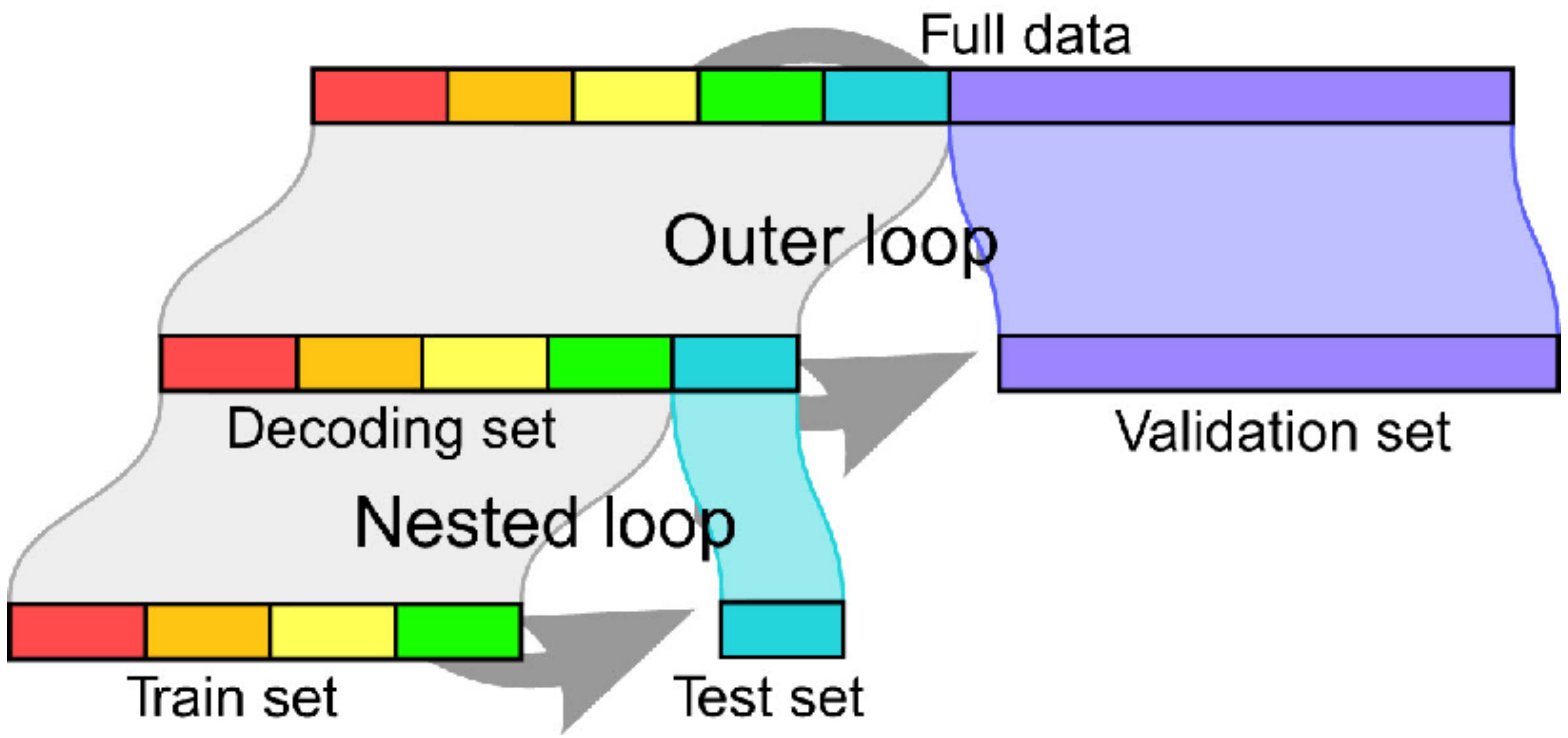
- NO. Because optimization itself introduces a bias towards the noise in the data for optimization (e.g., Varoquaux et al., 2017, *NeuroImage*).



Varoquaux et al., 2017, *NeuroImage*.

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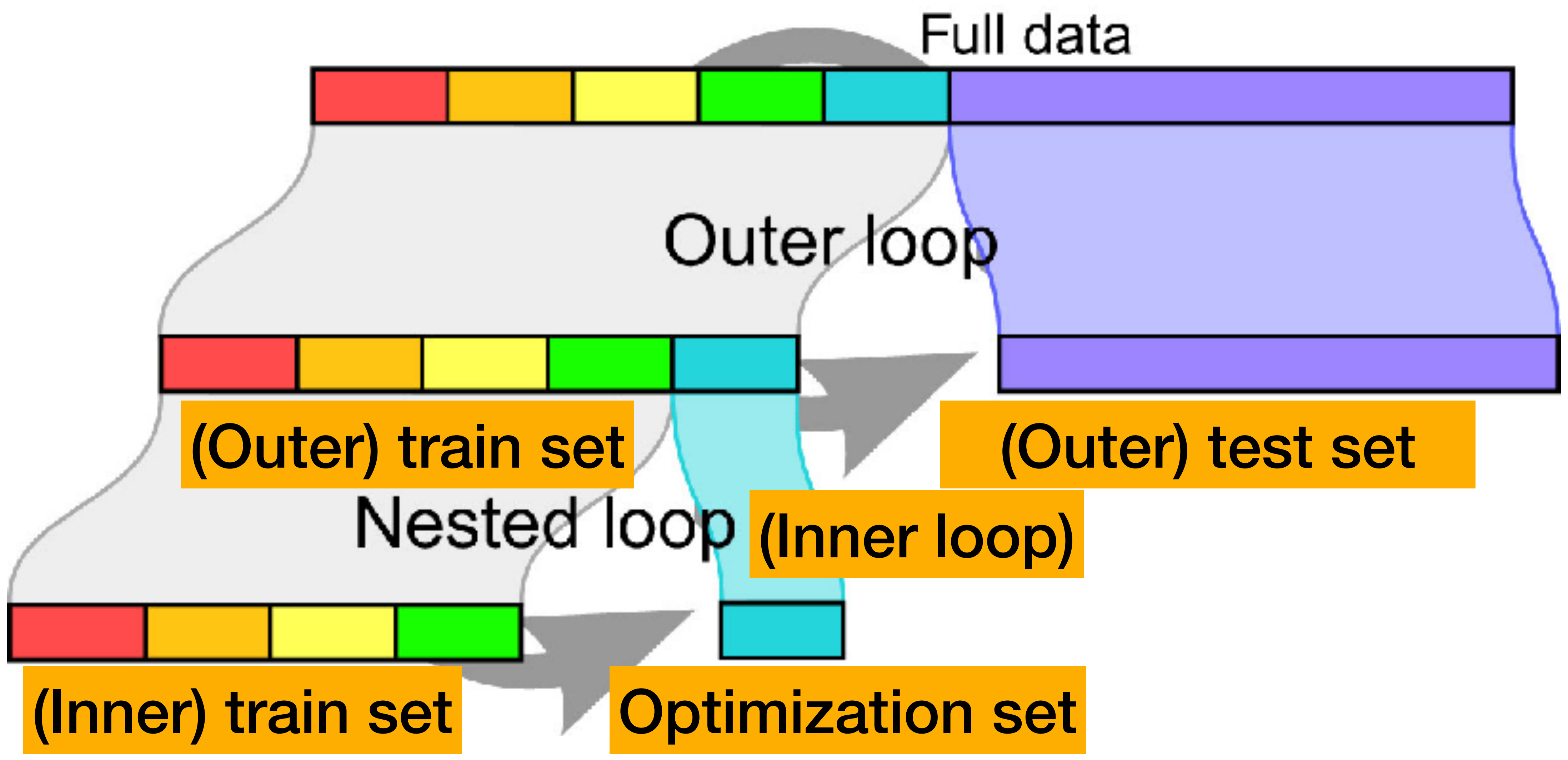
- NO. Because optimization itself introduces a bias towards the noise in the data for optimization (e.g., Varoquaux et al., 2017, *NeuroImage*).
- Hastie: "You need **THREE** partitions: **Training** / **Validation** (Optimization) / **Test** sets"
    - Hold-out: 50%, 25%, 25% (**Hastie** et al., 2009)
    - Nested CV: [50%, 25%], [25%]



Varoquaux et al., 2017, *NeuroImage*.

Information leakage

Kaufman et al., 2012, *ACM Trans KDD*

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Information leakage

Kaufman et al., 2012, *ACM Trans KDD*

- Leakage: In cross-validation, training and testing sets are not kept separate.

Information leakage

Kaufman et al., 2012, *ACM Trans KDD*

- Leakage: In cross-validation, training and testing sets are not kept separate.
- Result: "🤪: My model predicts everything at 100%!"

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Information leakage

Kaufman et al., 2012, *ACM Trans KDD*

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Kaufman et al., 2012, https://doi.org/10.1145/2382577.2382579

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- **Leakage in training examples** (e.g., one of identical twins in the training and the other in the testing set)

Double-dipping

Kriegeskorte et al., 2009, *Nat Neuro*

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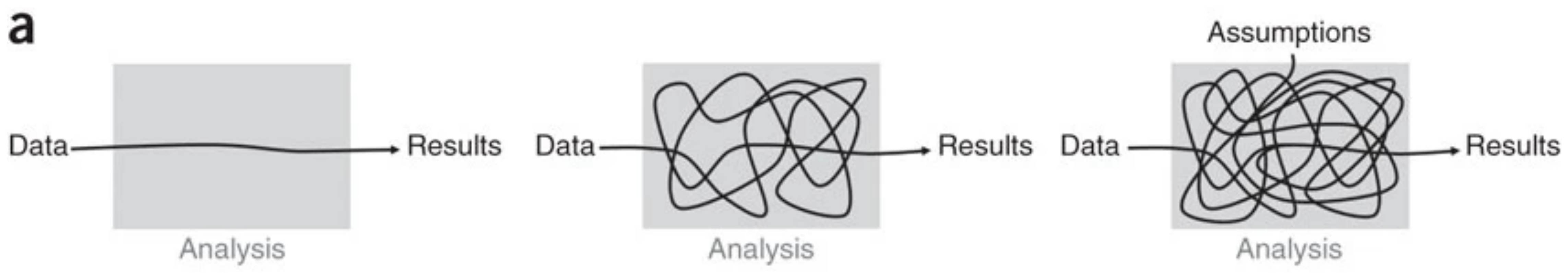

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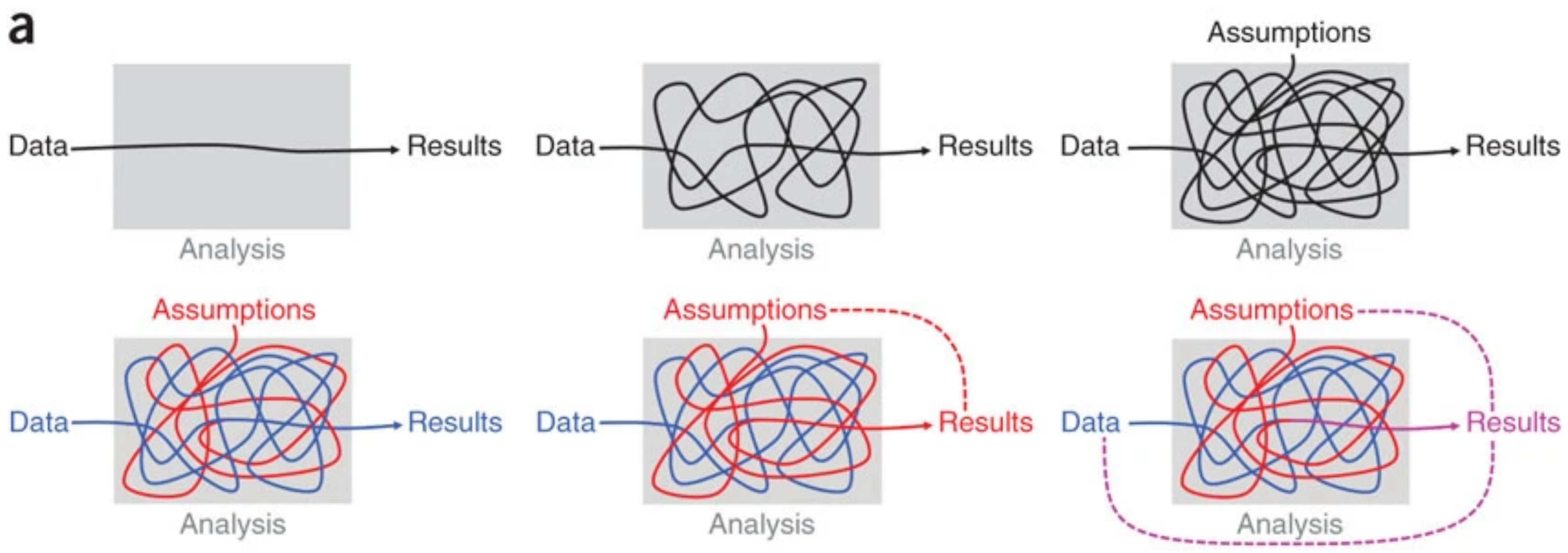

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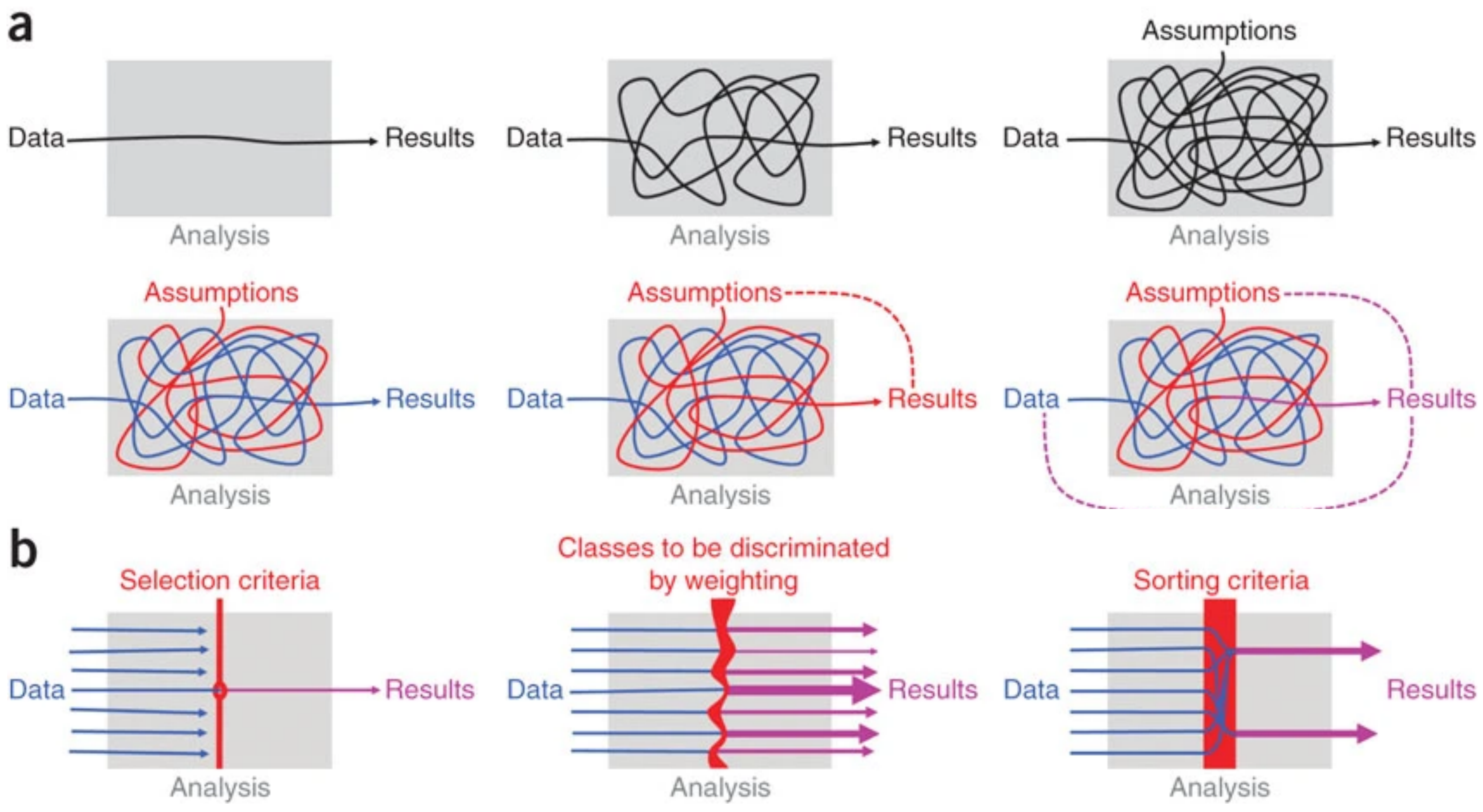

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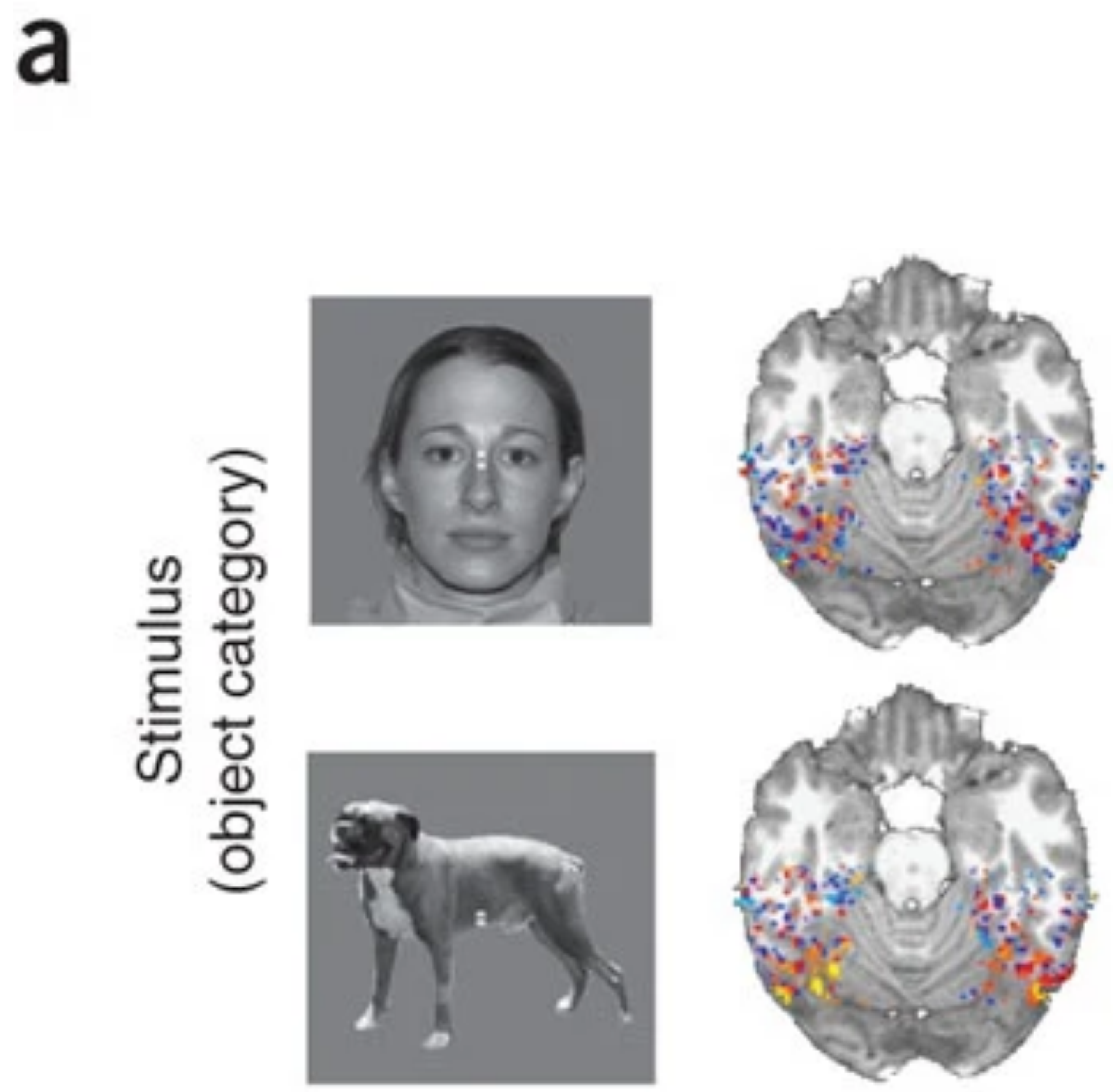

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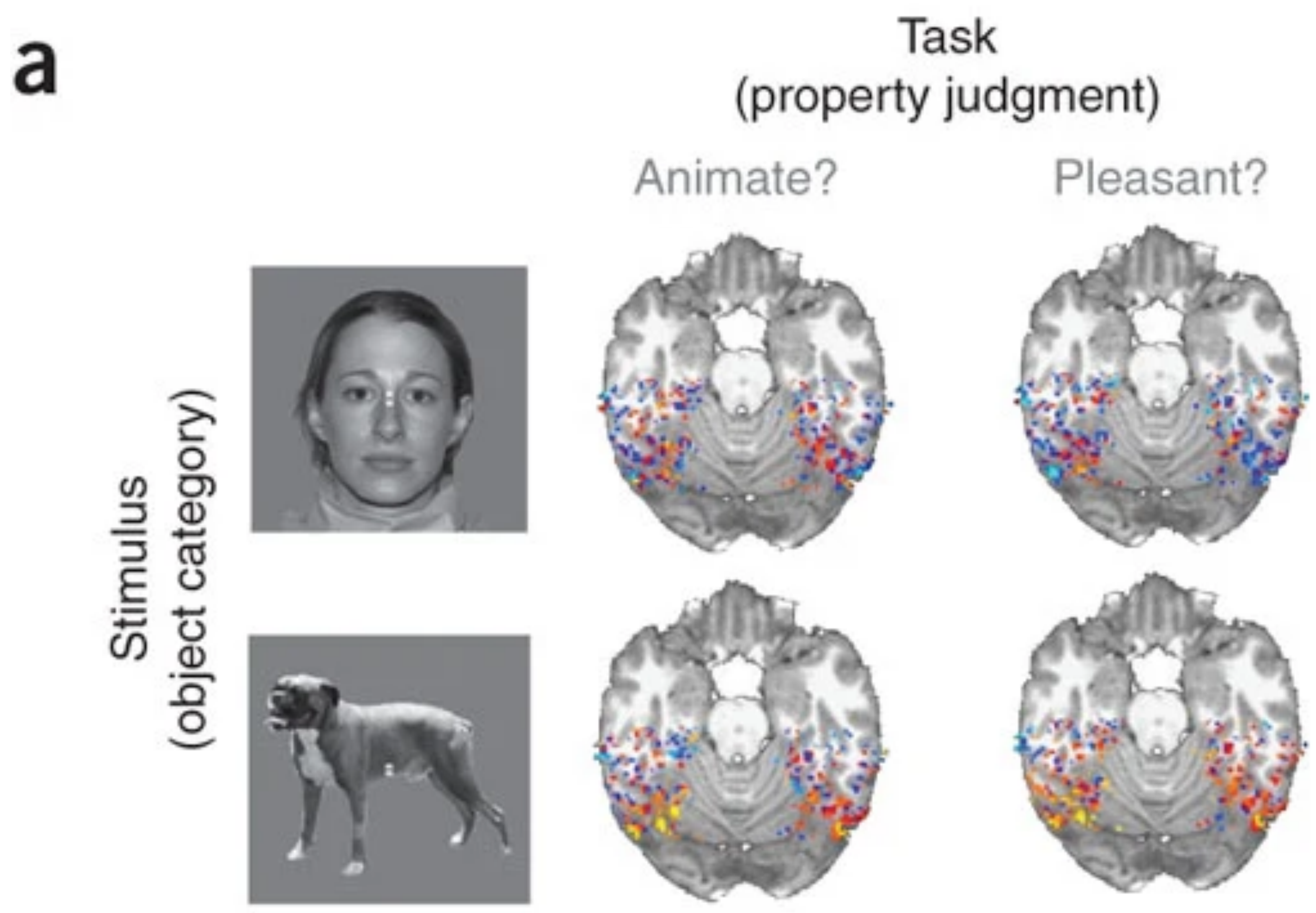

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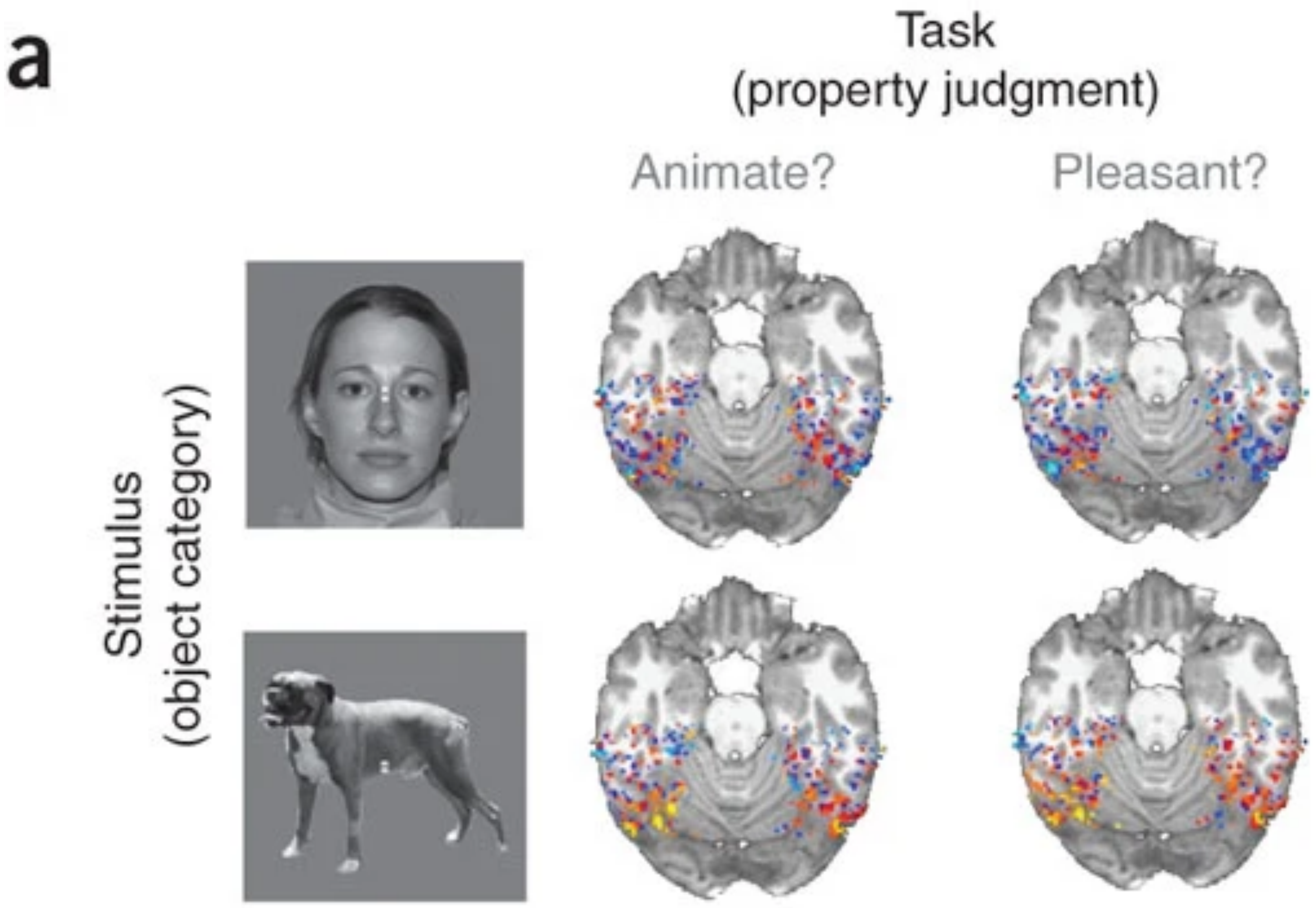

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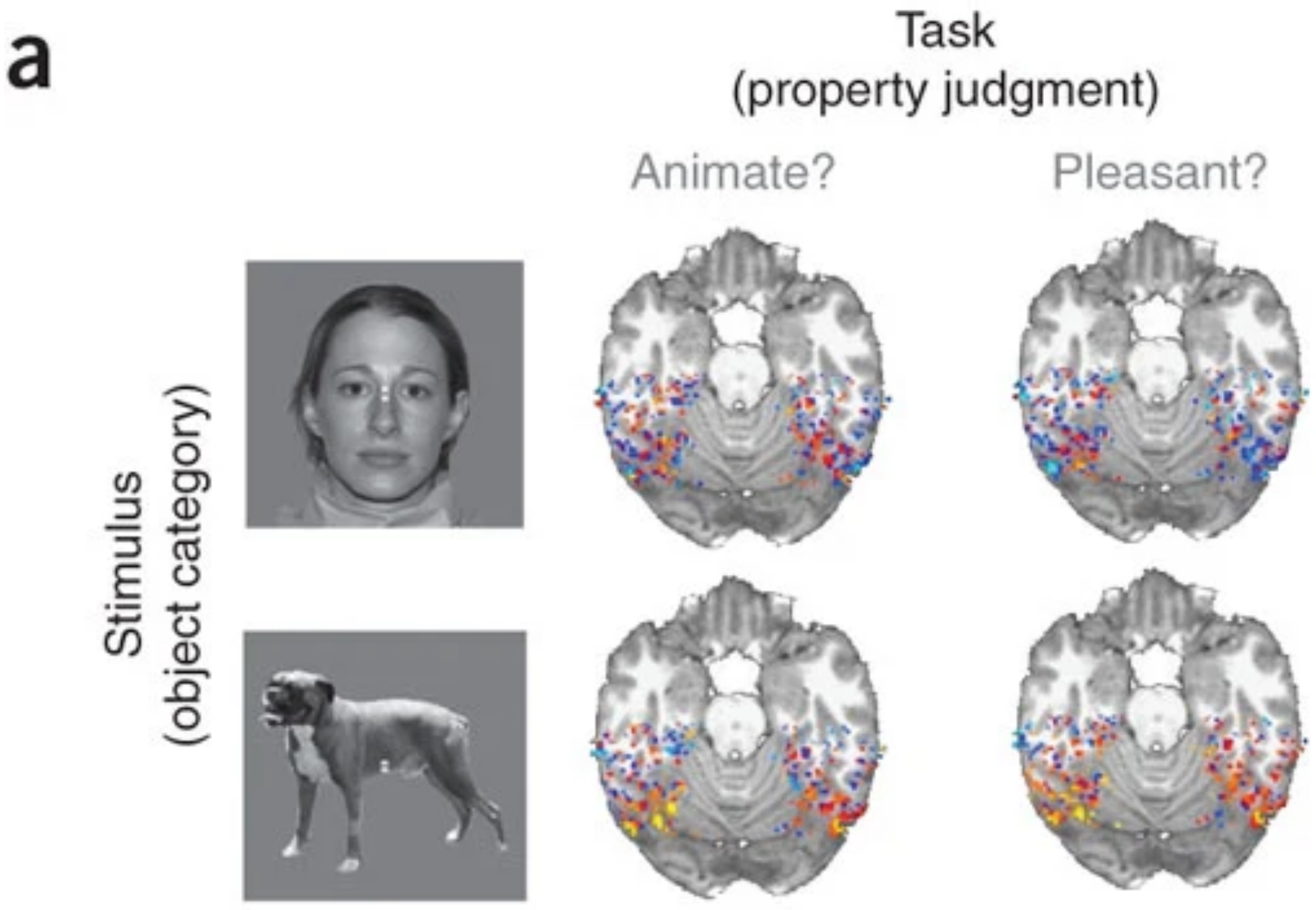
Training data (Run 1, 3, 5)	**Testing data** (Run 2, 4, 6)

Double-dipping

Example



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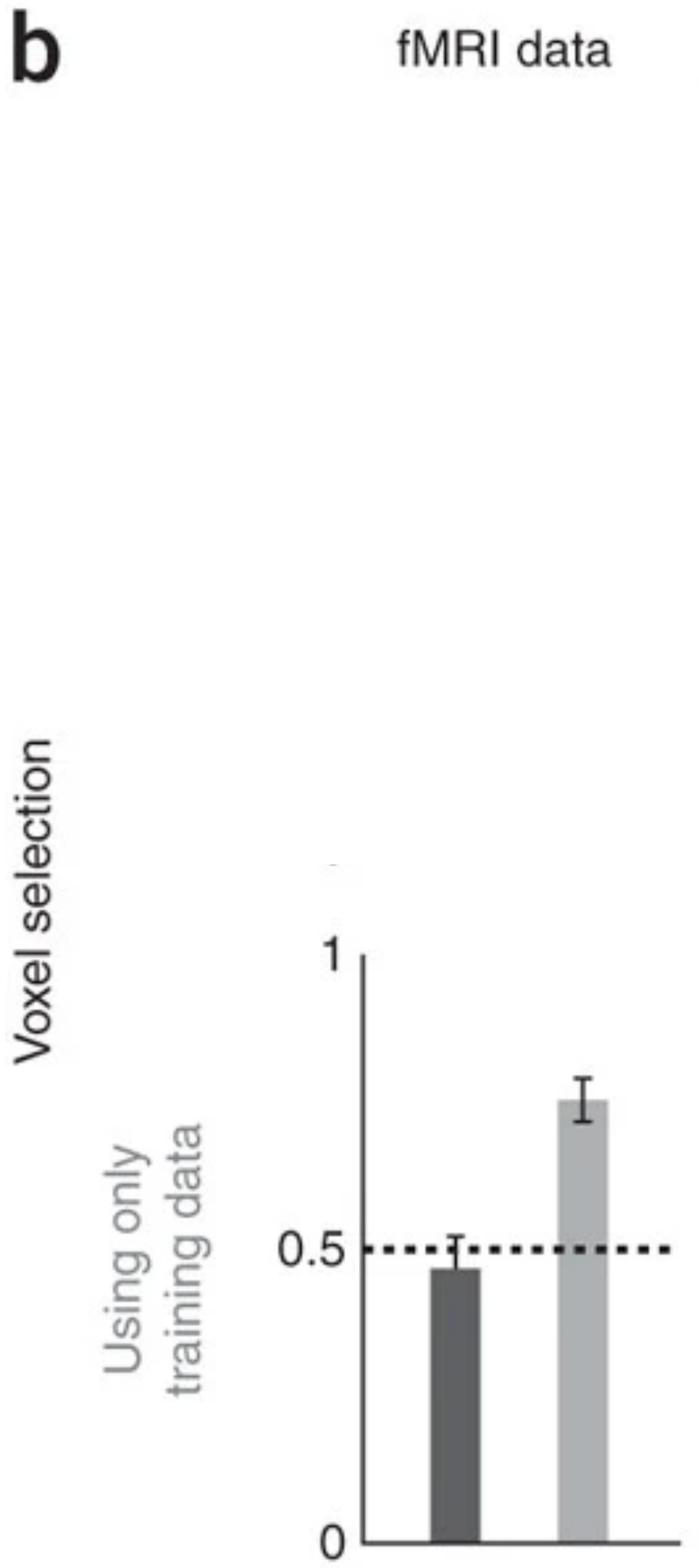

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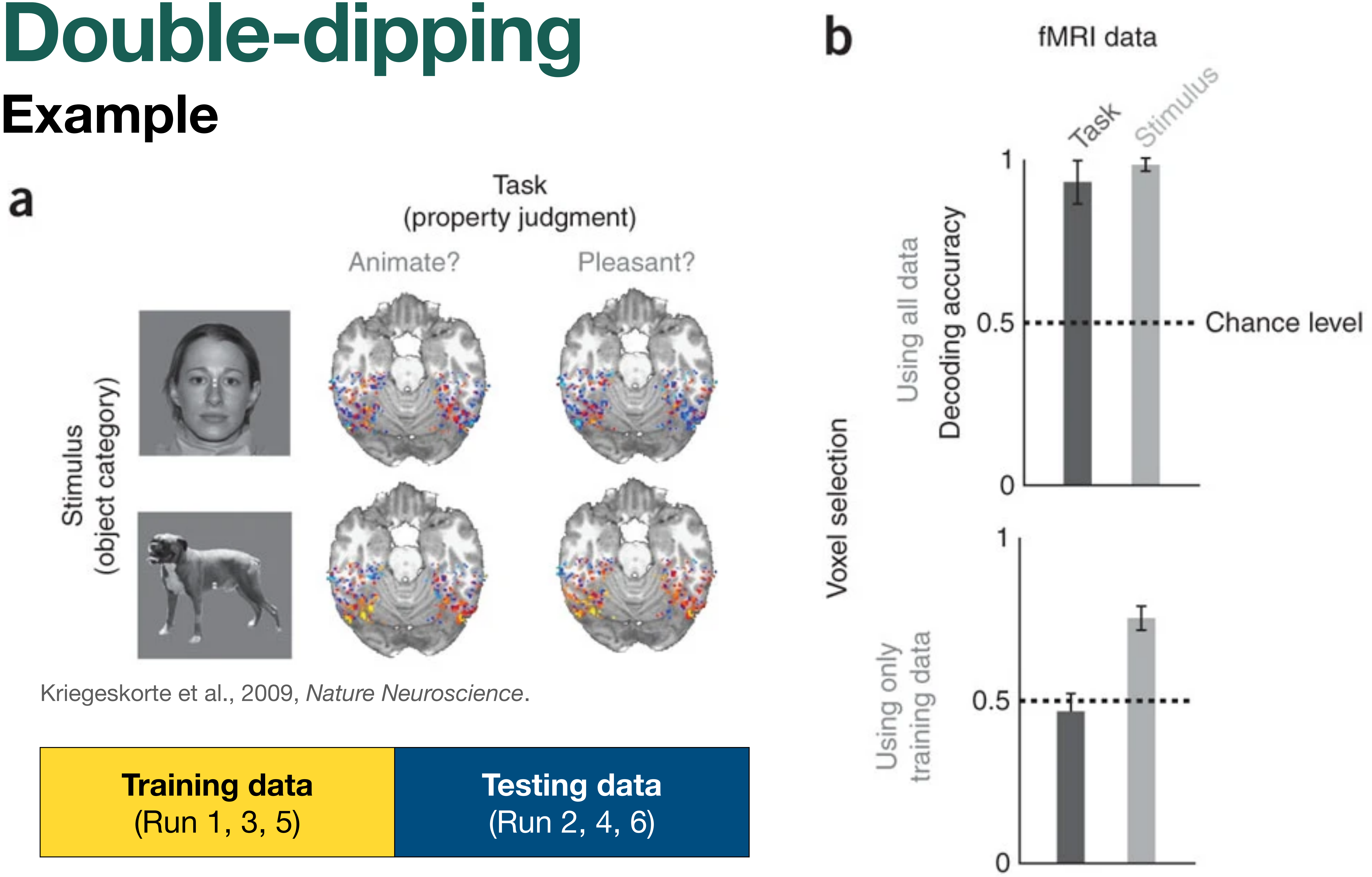

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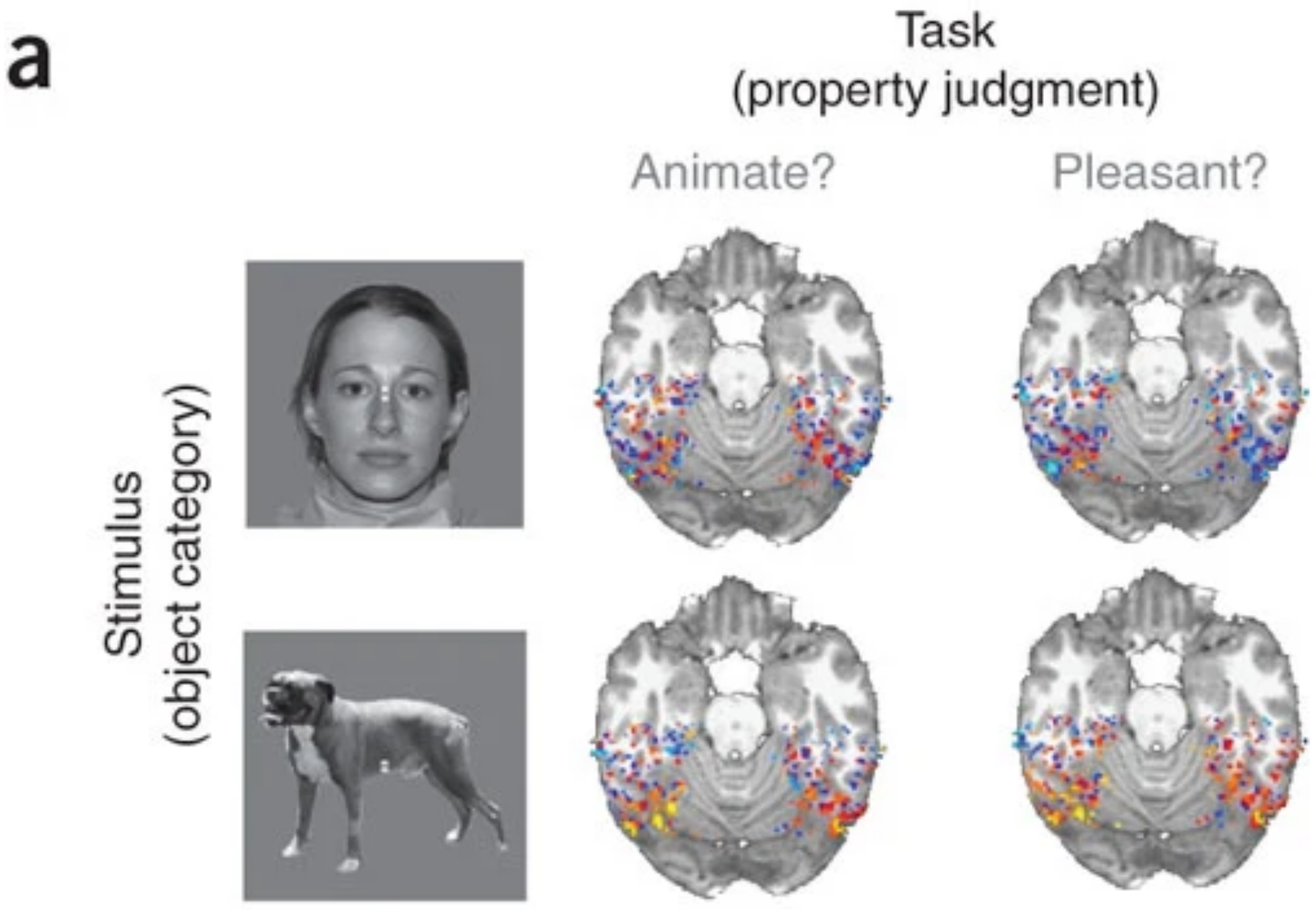
Example



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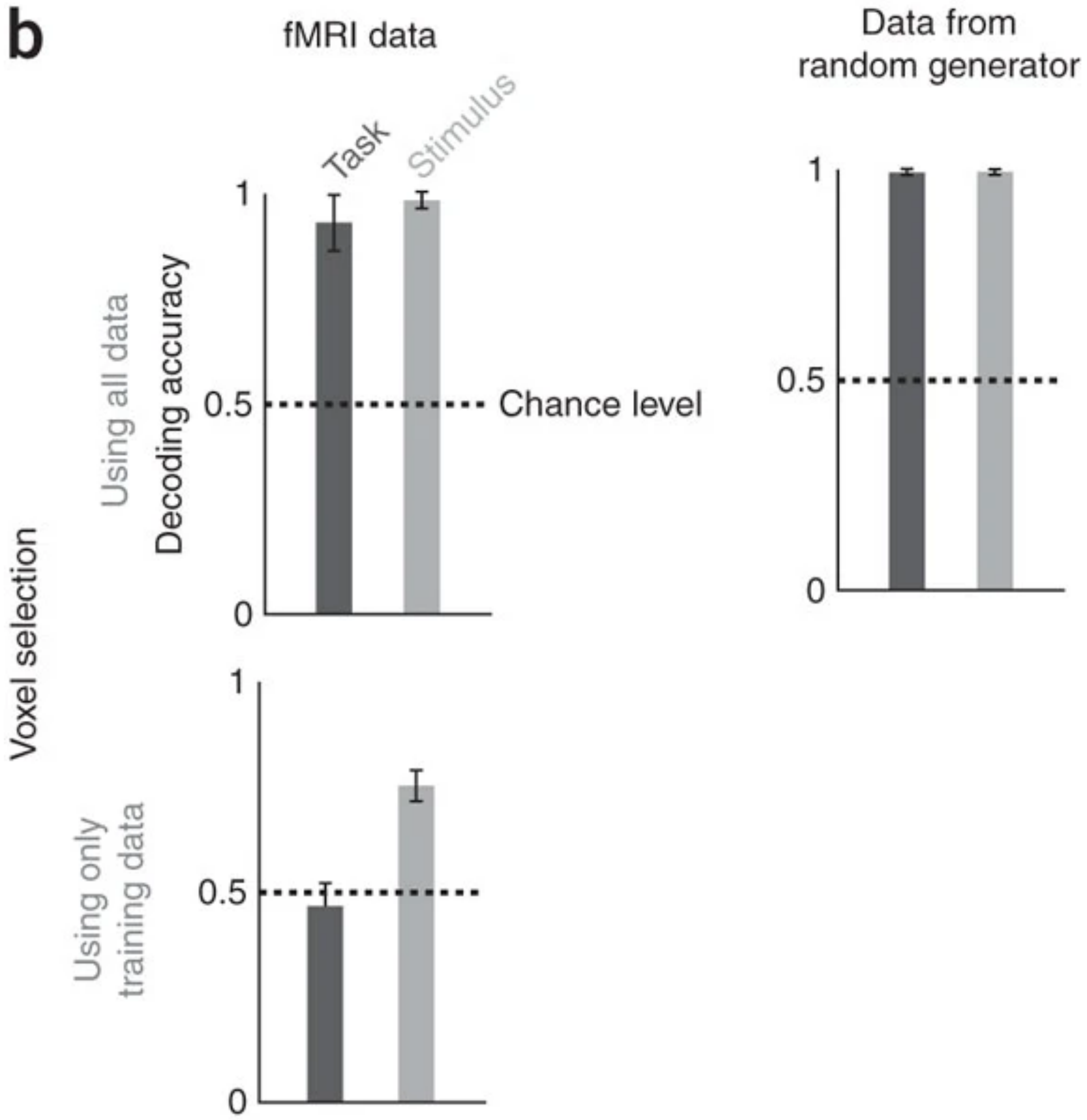

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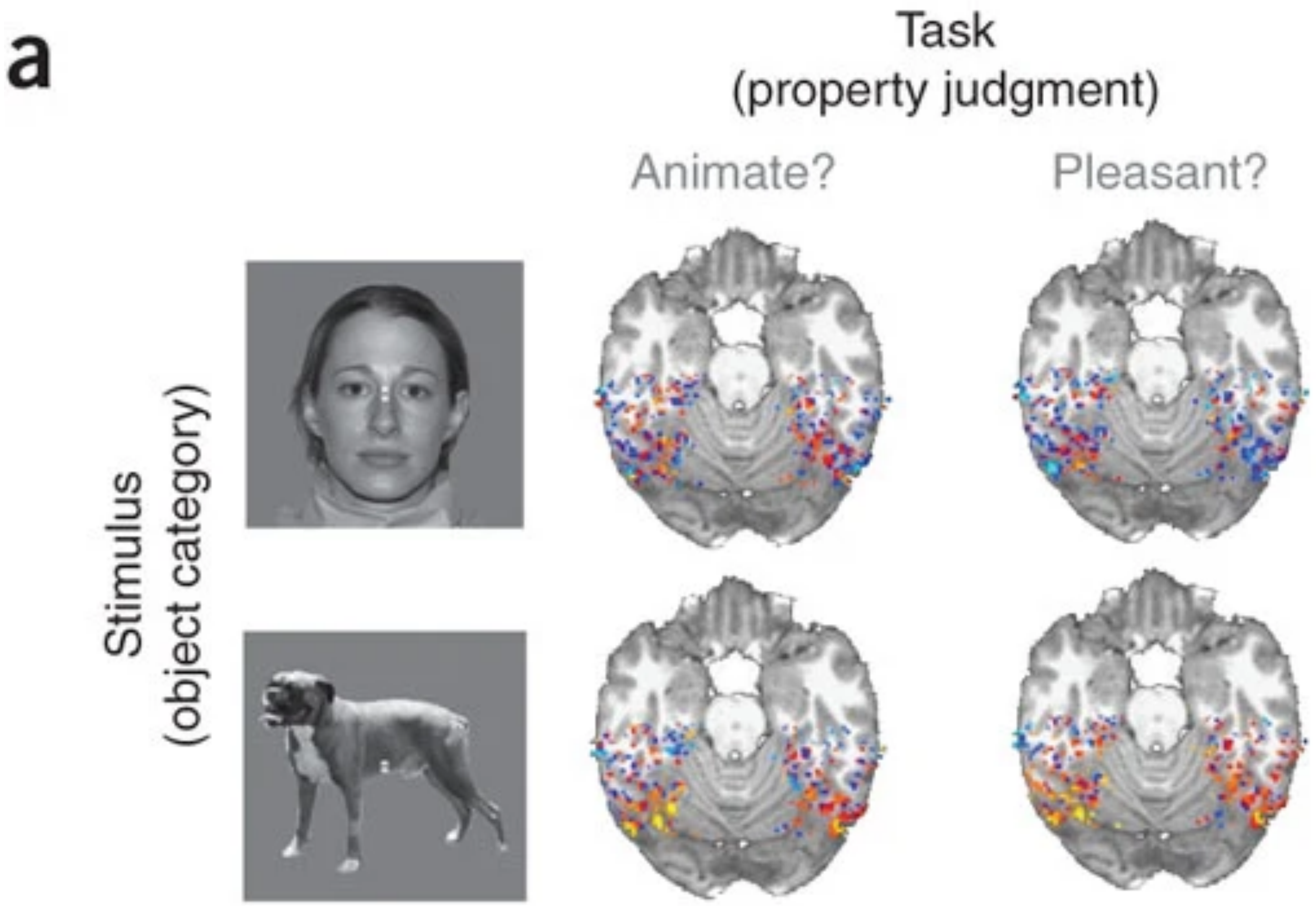

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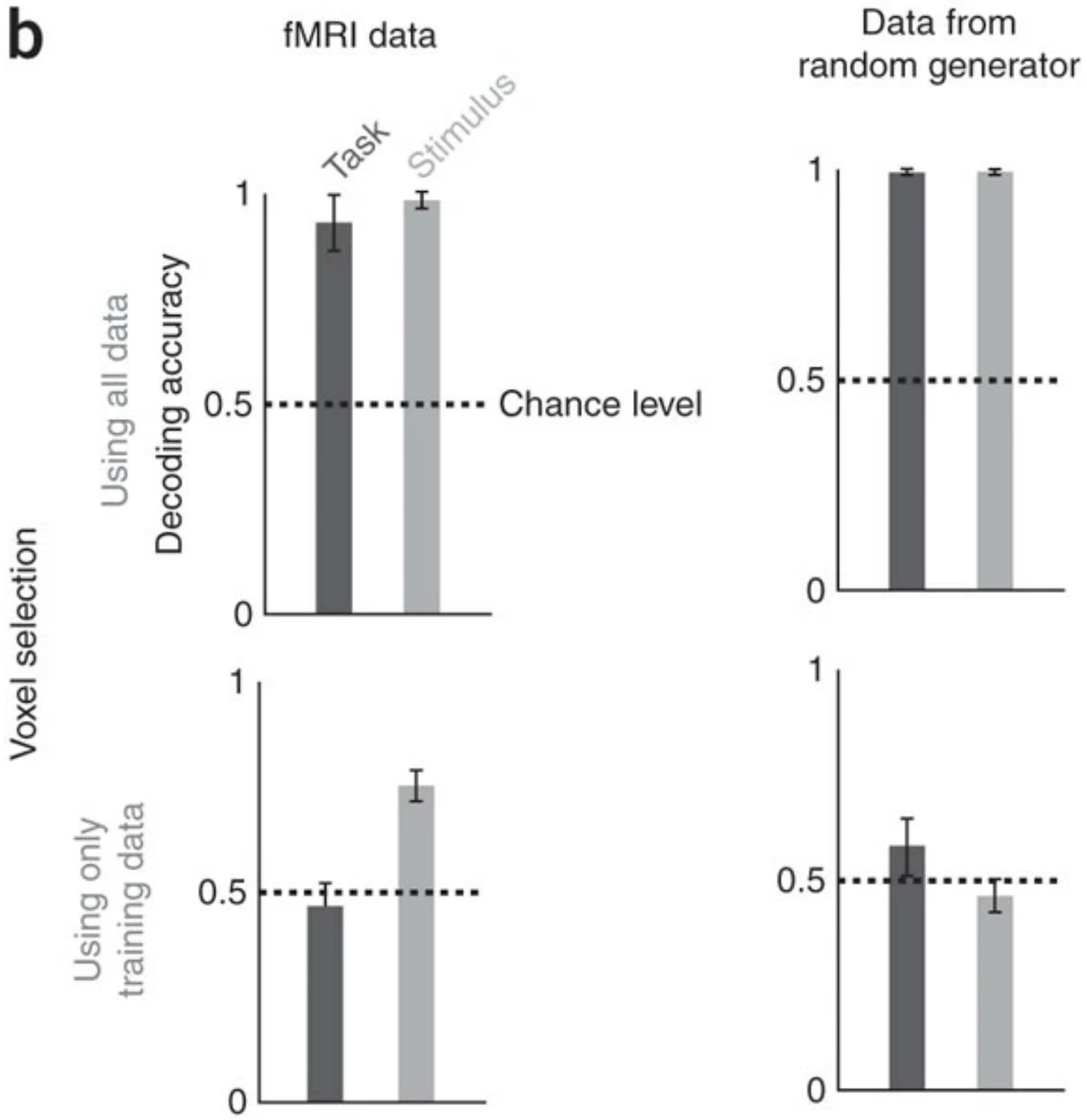
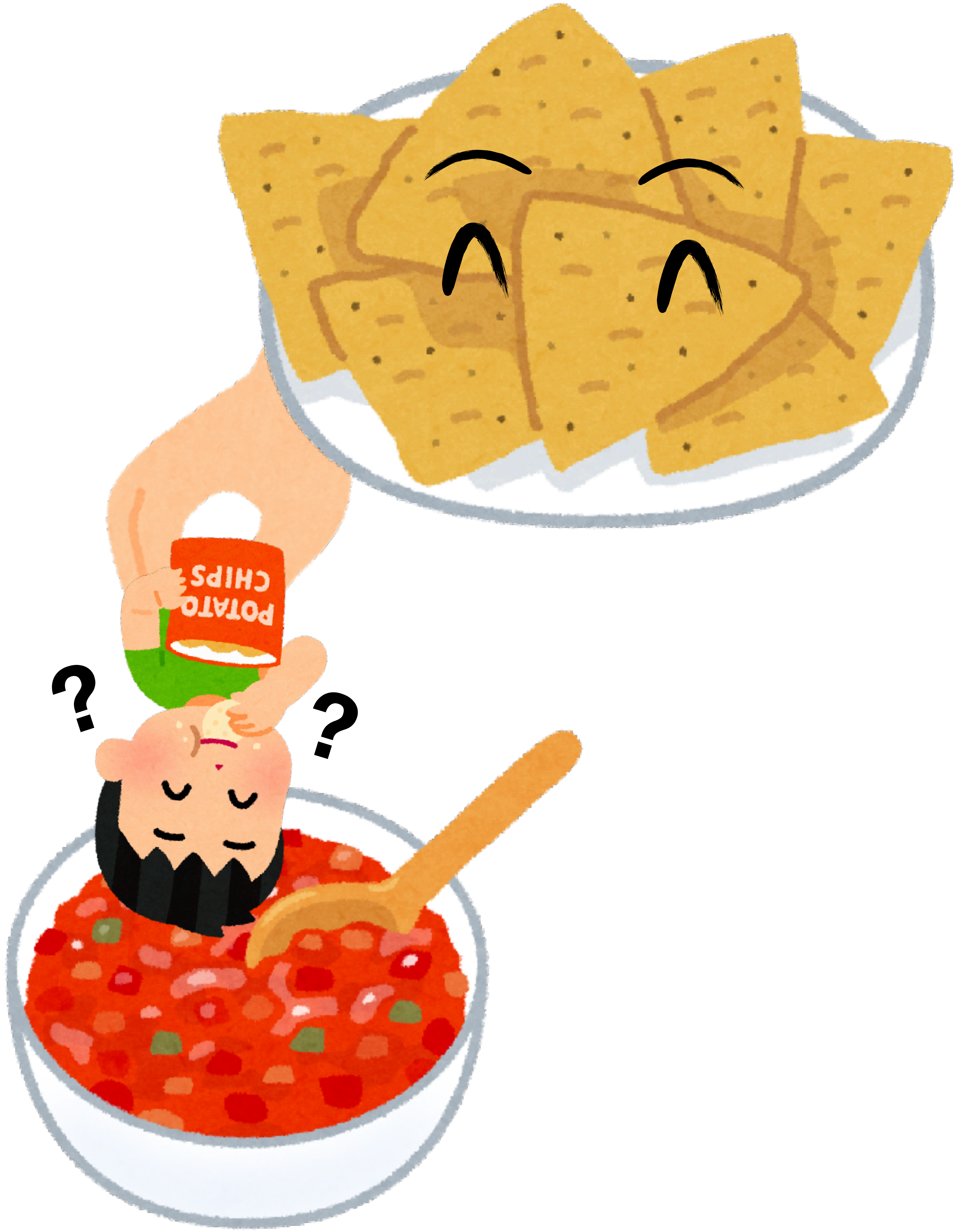


Reverse double-dipping

Kim, *in prep.*



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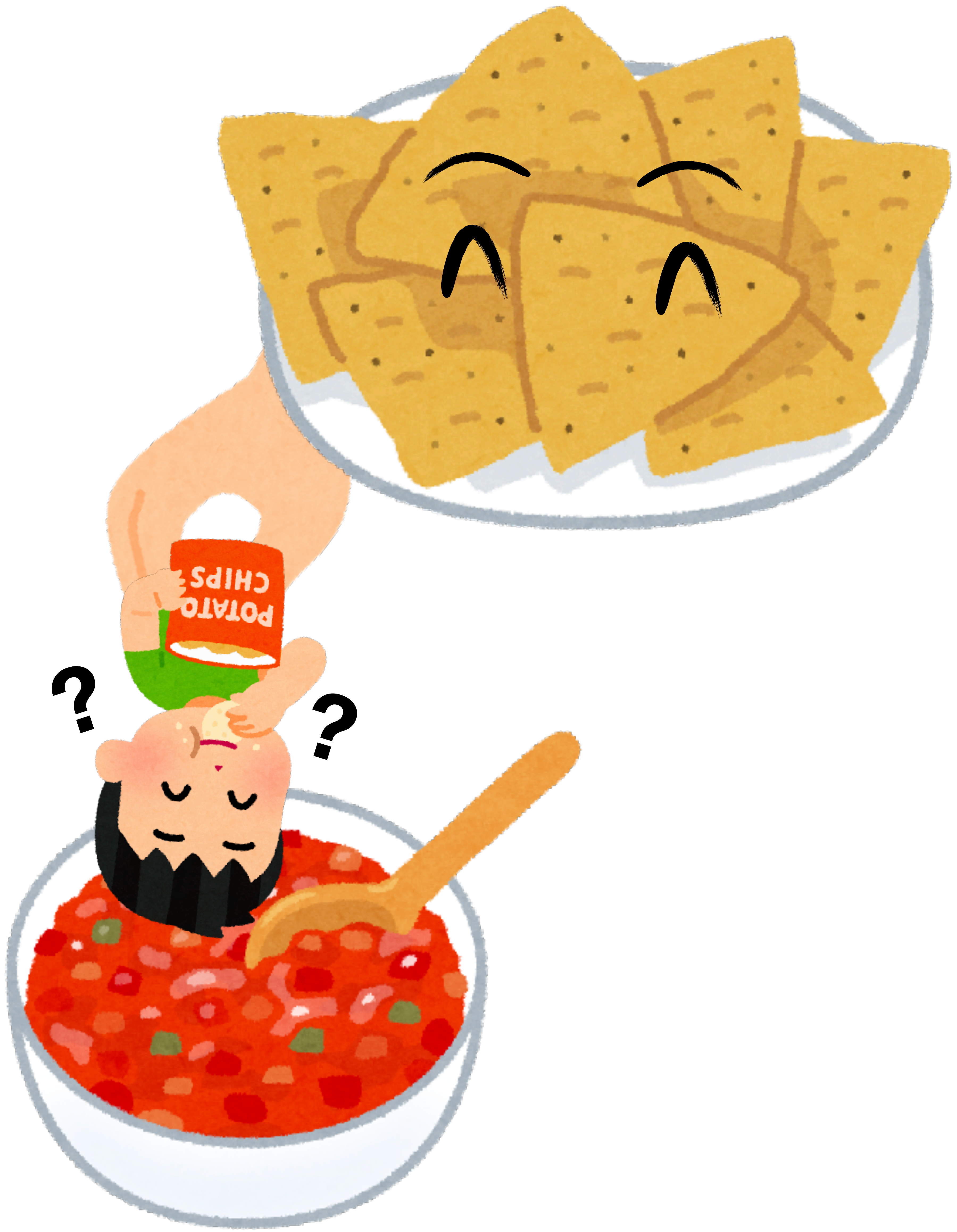

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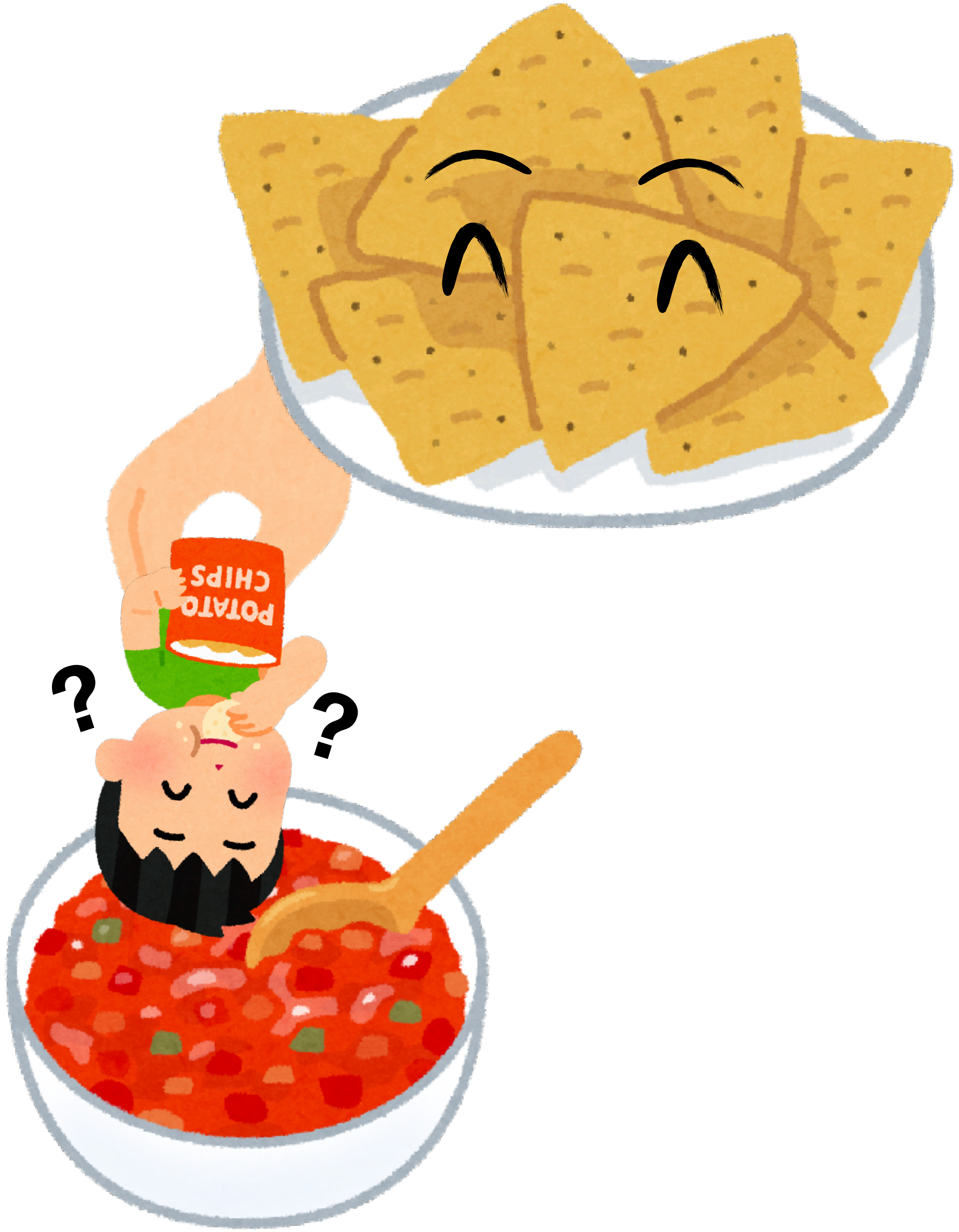
- You don't do particularly wrong.
- However, unbeknownst to the similarity between training and testing sets, you can fall victim to **Reverse Double-Dipping**!



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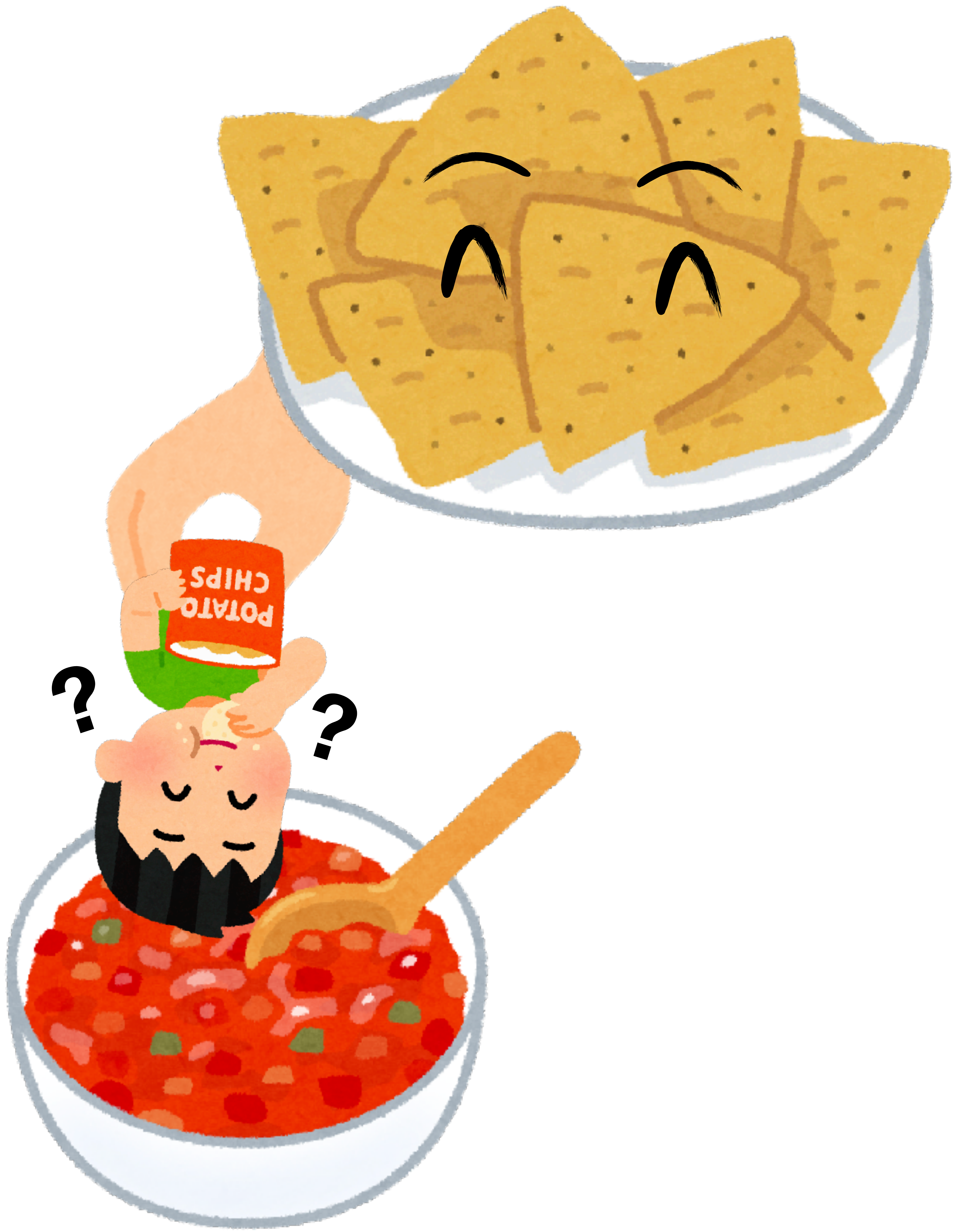

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- You don't do particularly wrong.
- However, unbeknownst to the similarity between training and testing sets, you can fall victim to **Reverse Double-Dipping**!
- The data dips you in the training set and testing set (twice).
- This happens due to the **common stimulus-evoked responses** across trials/subjects/...

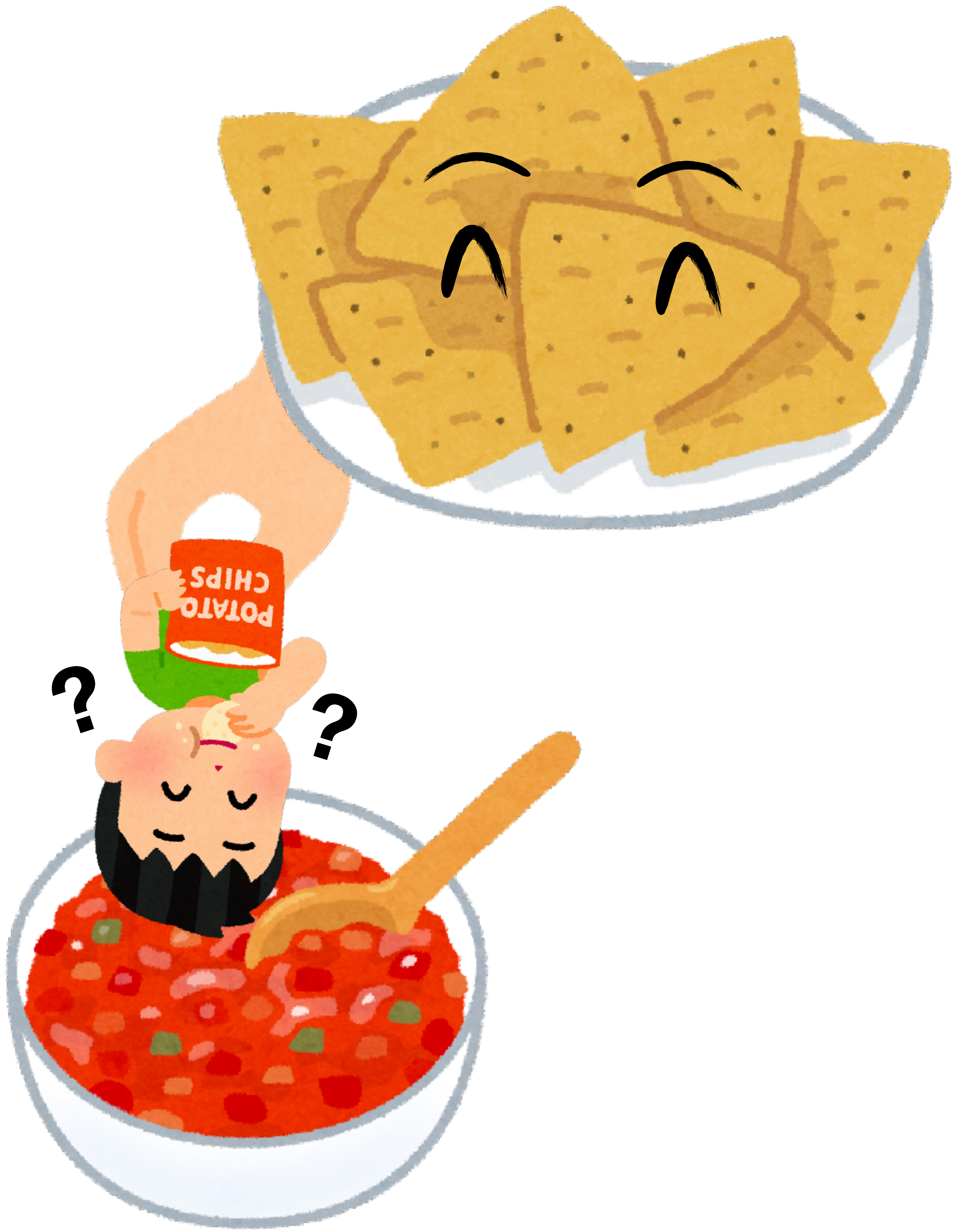
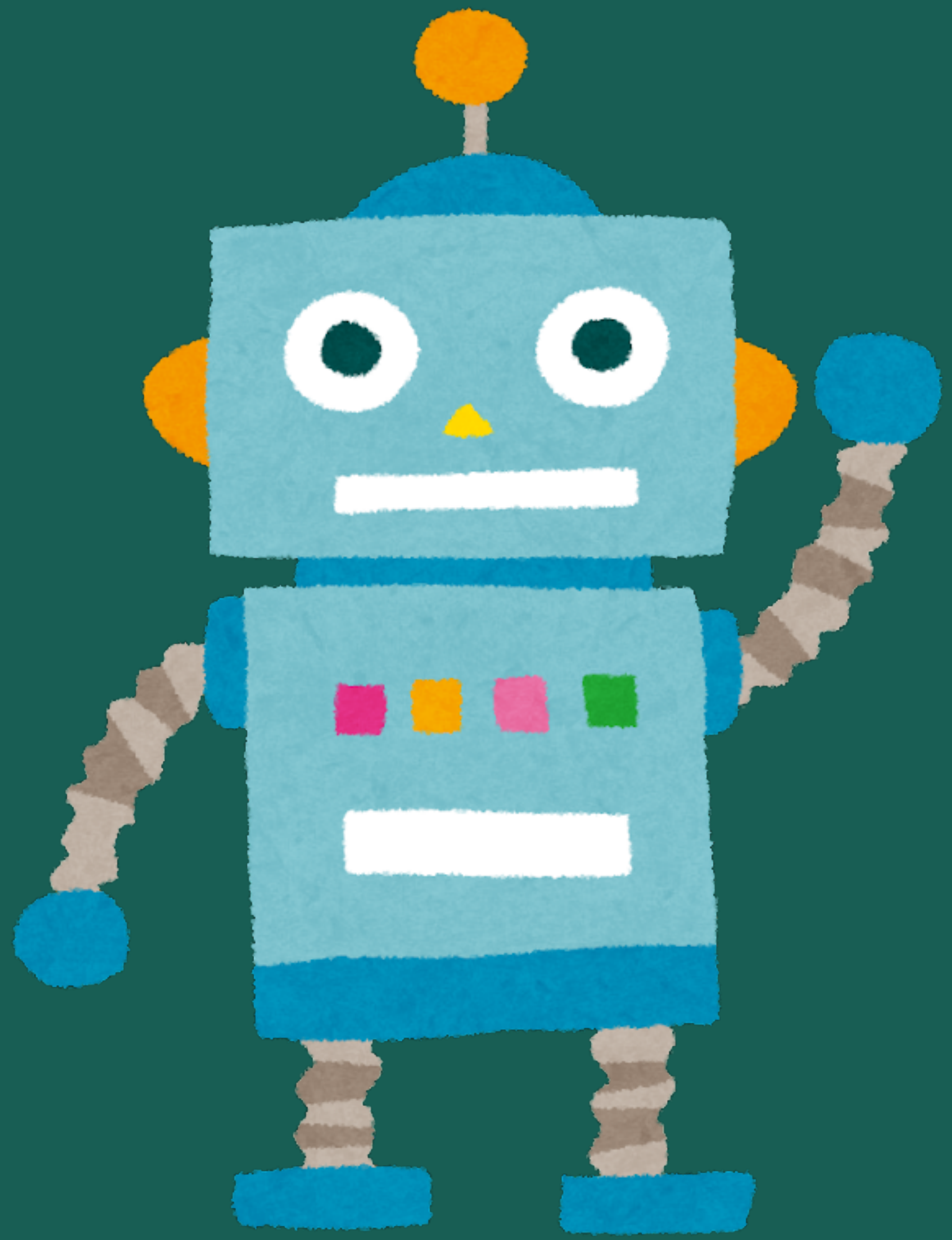


Image source: www.irasutoya.com

Toy example

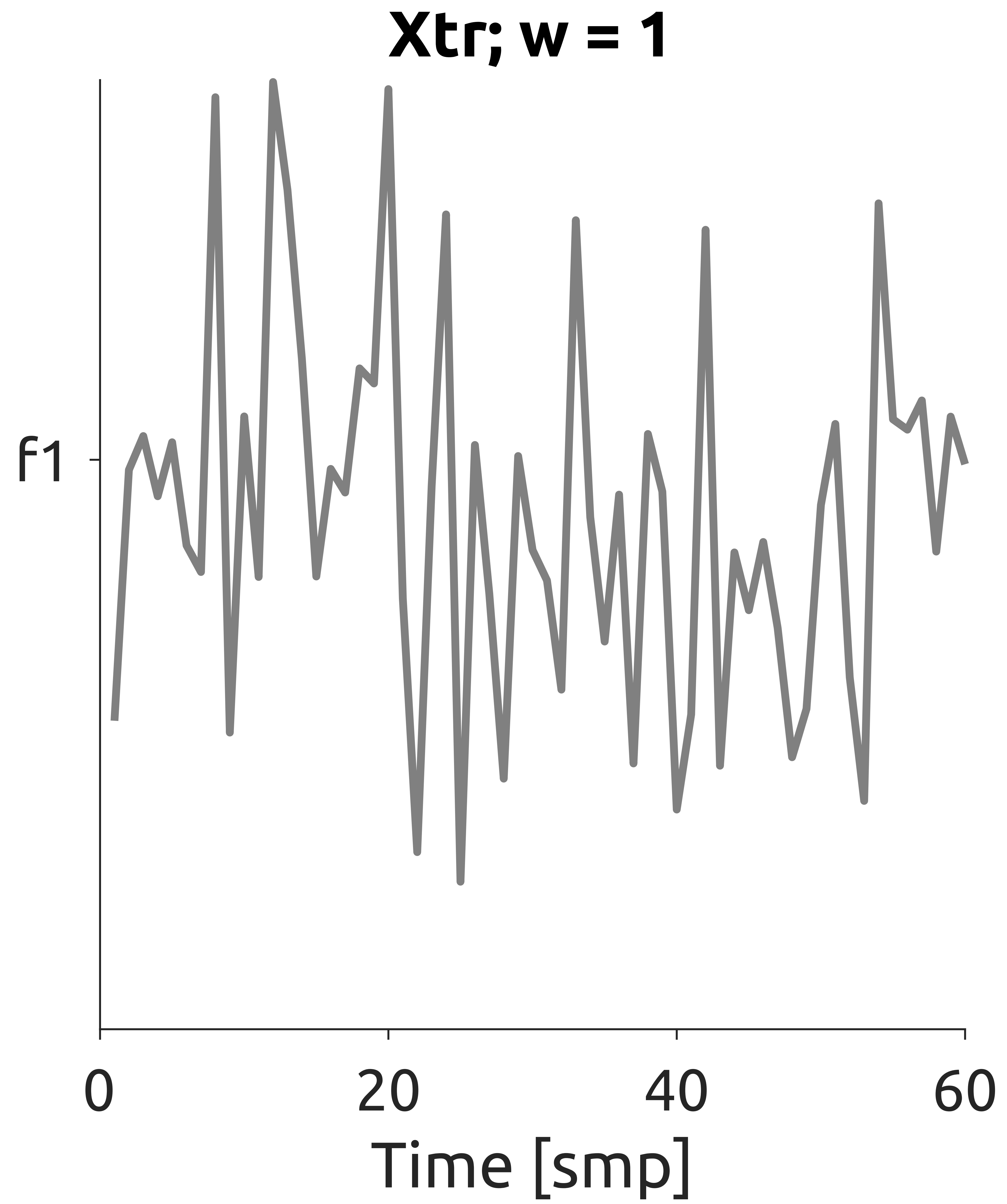


Toy specification

True features

$$\mathbf{Y} = \mathbf{X}\mathbf{B} + \mathbf{E}$$

- **X:** <#Timepoints x #Delays.#Features>
- #Timepoints = 60 samples
- #Delays = 1
- #Features = 1
- Feature smoothness = 1 (Gaussian kernel window size)

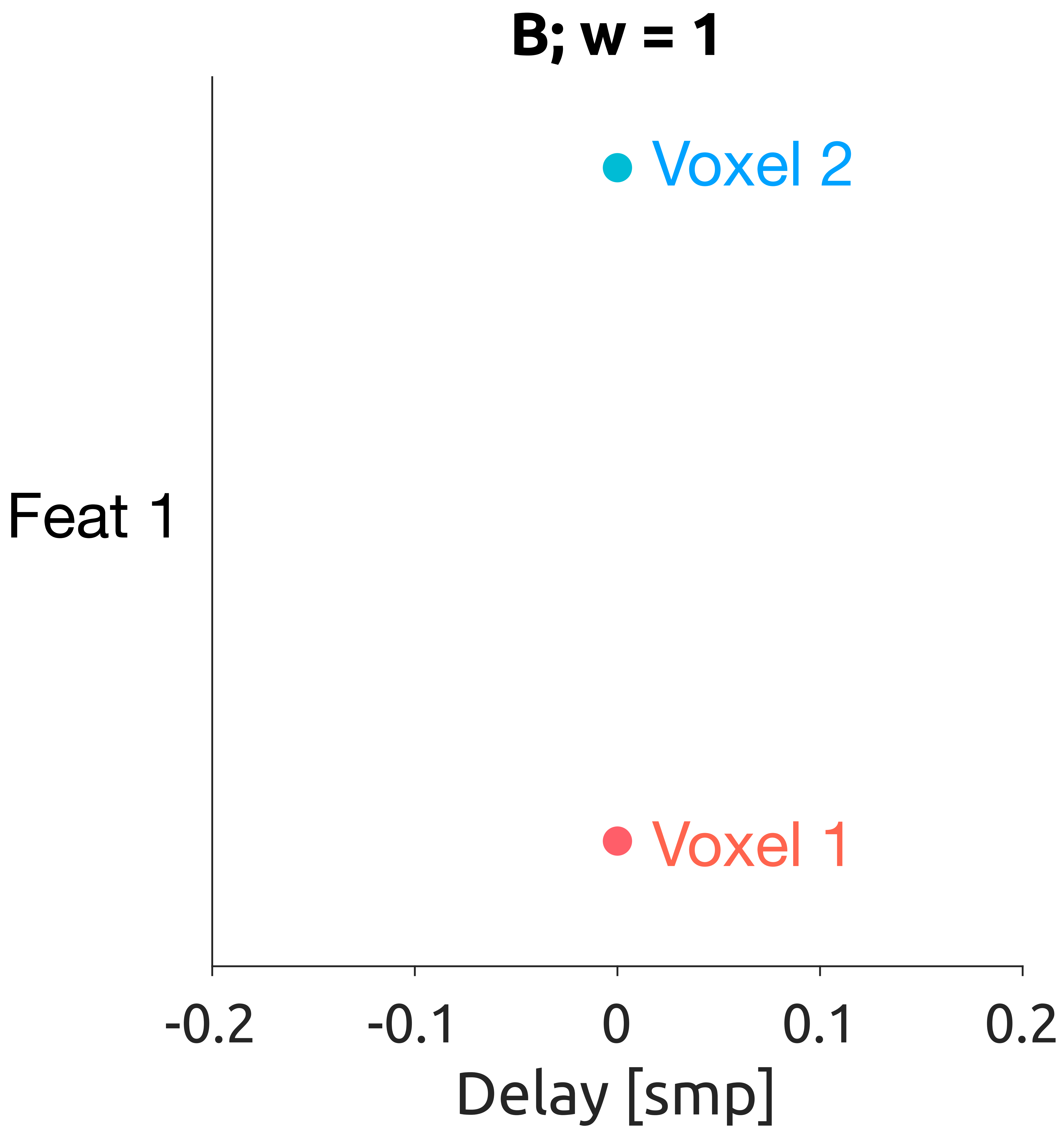


Toy specification

True weights

$$\mathbf{Y} = \mathbf{X}\mathbf{B} + \mathbf{E}$$

- **B:** <#Delays.#Features x #Voxels>
- #Delays = 1
- #Features = 1
- #Voxels = 2
- Weight smoothness window = 1

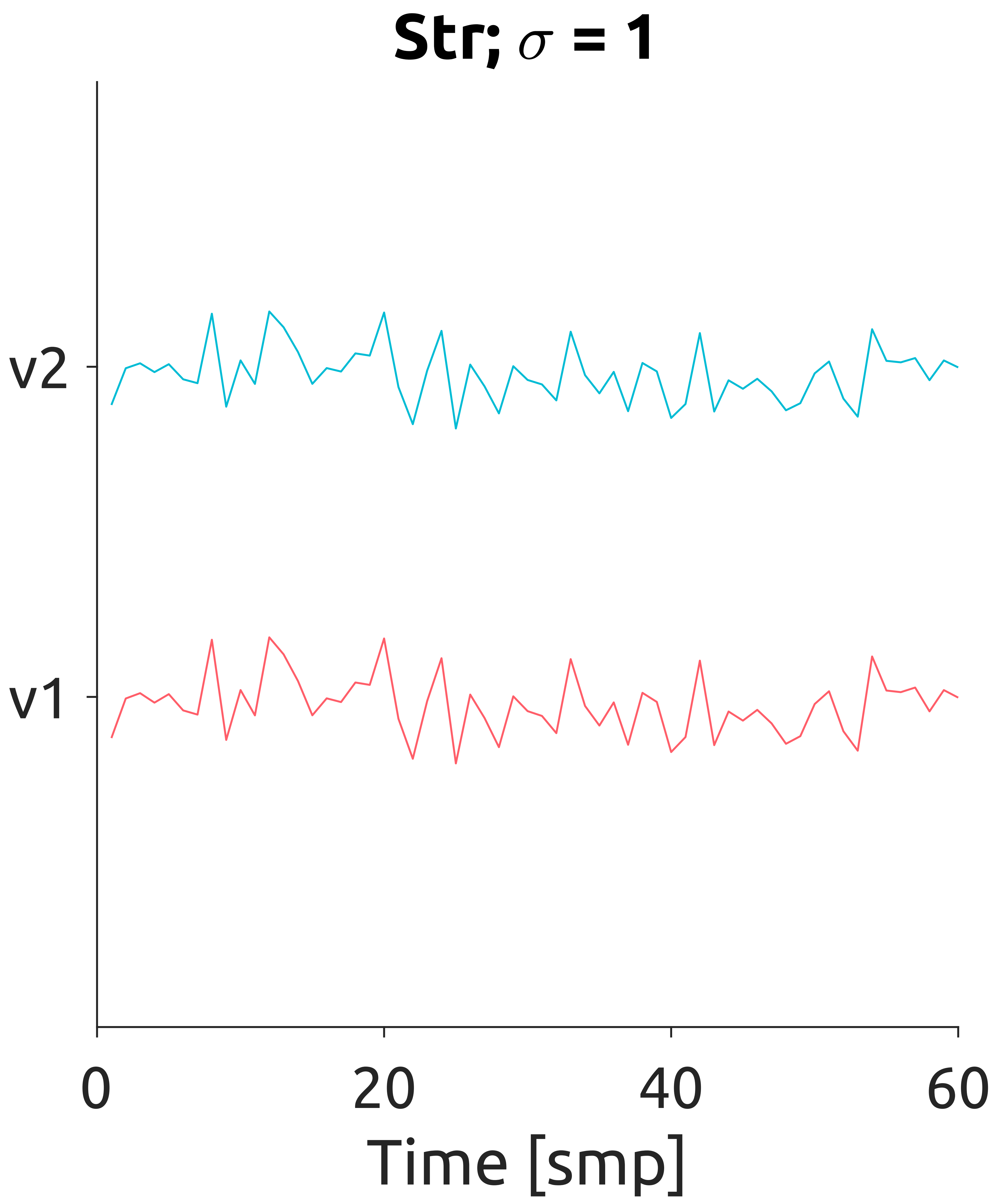


Toy specification

True signal (features x weights)

$$\mathbf{Y} = \mathbf{XB} + \mathbf{E}$$

- **XB:** <#Timepoints x #Voxels>
- #Timepoints = 60
- #Voxels = 2
- Signal amplitude (standard deviation, σ[signal]) = 1

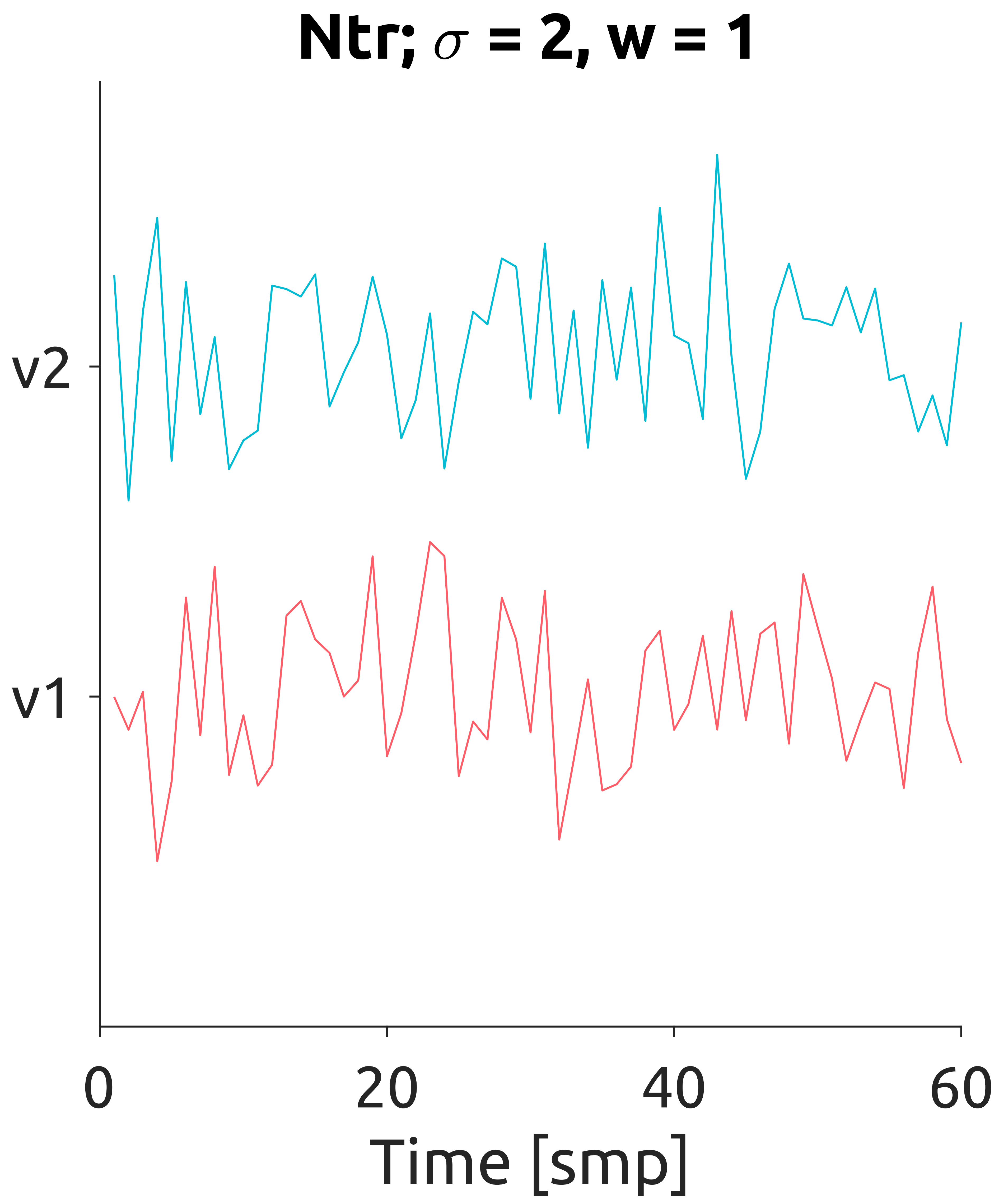


Toy specification

True noise

$$\mathbf{Y} = \mathbf{XB} + \mathbf{E}$$

- **E:** <#Timepoints x #Voxels>
- #Timepoints = 60
- #Voxels = 2
- Noise smoothness window = 1
- Noise amplitude (σ[noise]) = 2

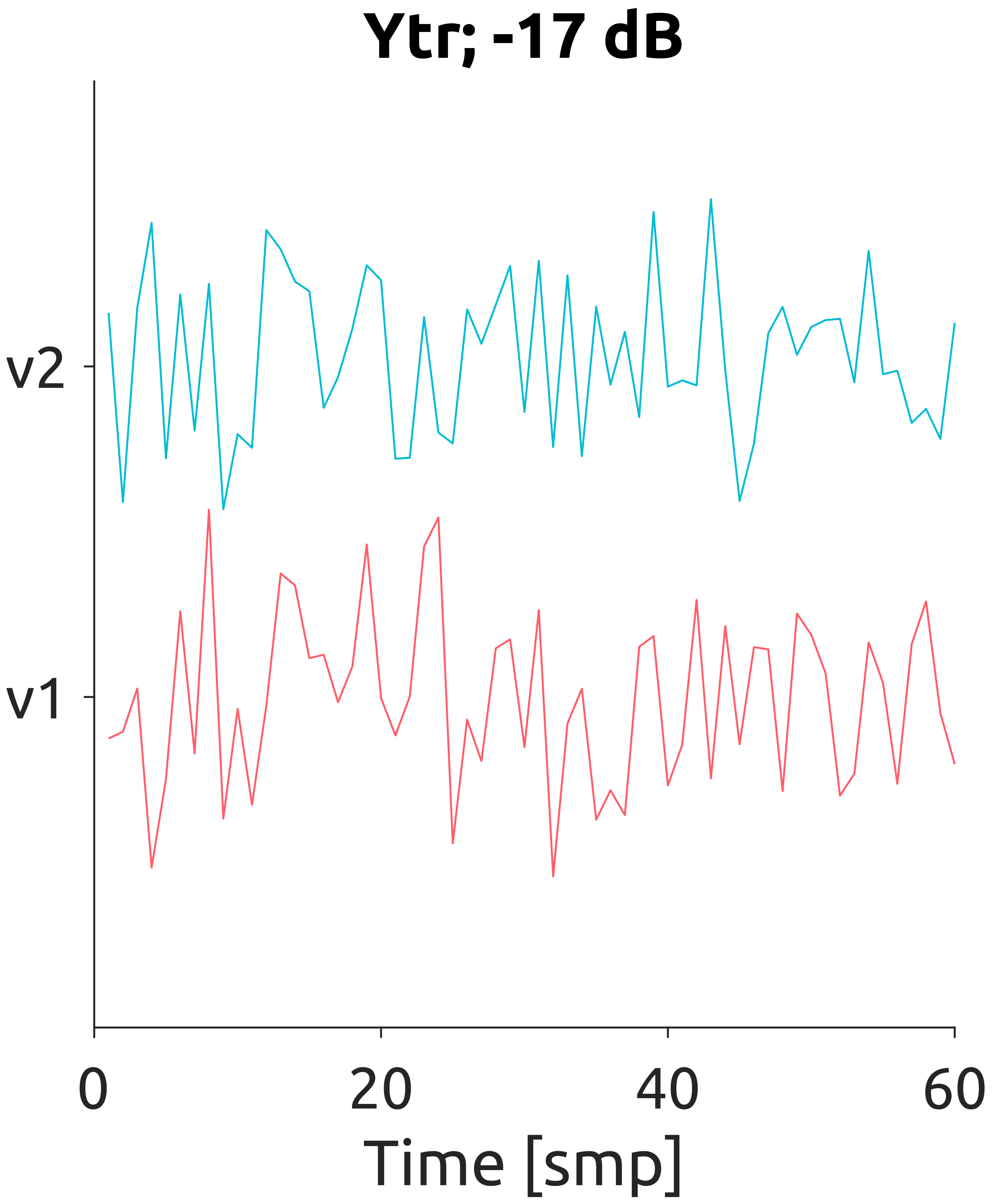


Toy specification

Training data = True signal + True noise

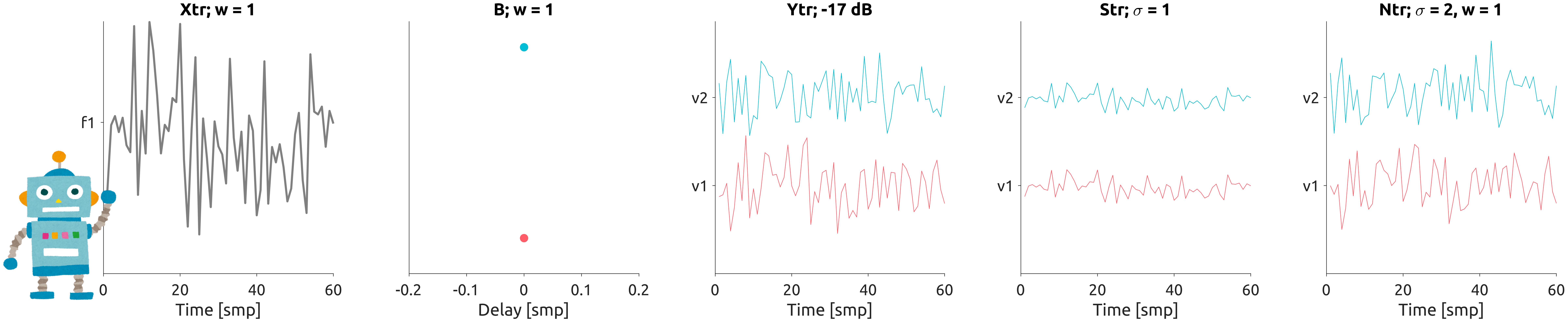
$$\mathbf{Y} = \mathbf{XB} + \mathbf{E}$$

- **Y:** <#Timepoints x #Voxels>
- #Timepoints = 60
- #Voxels = 2
- SNR = dB(σ^2[signal] / σ^2[noise])



Training & testing datasets

Training set



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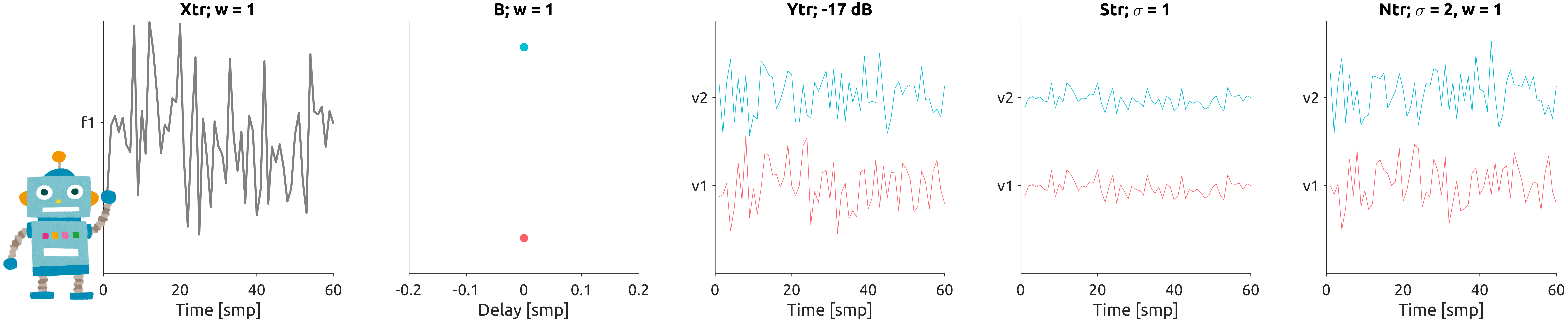
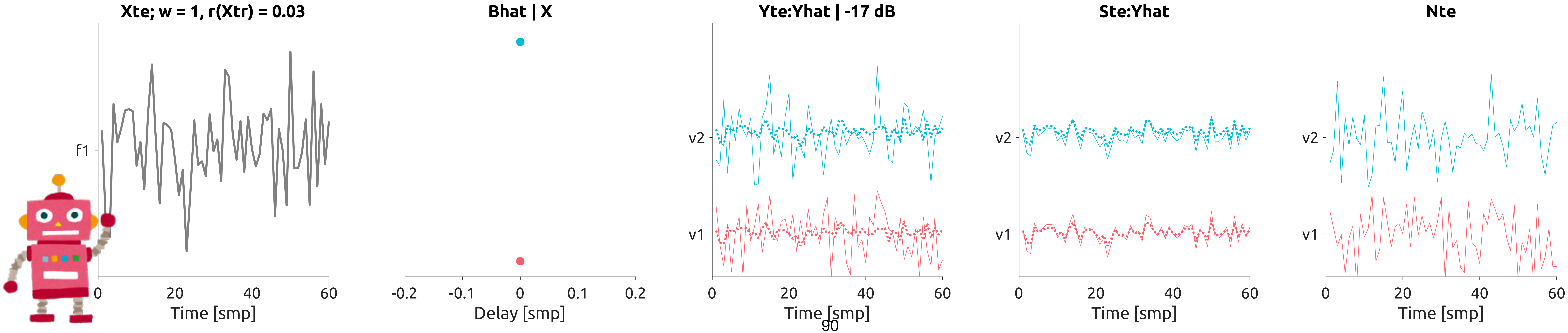


Testing set



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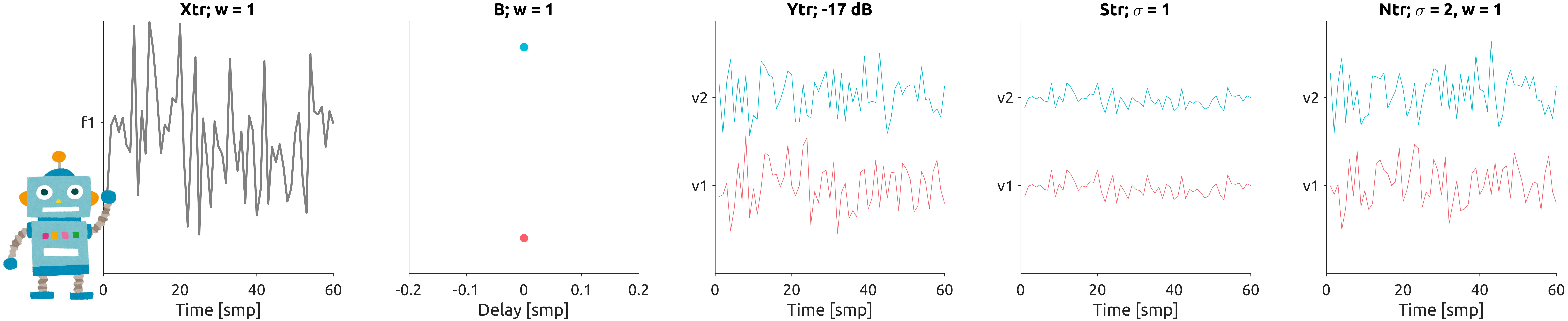

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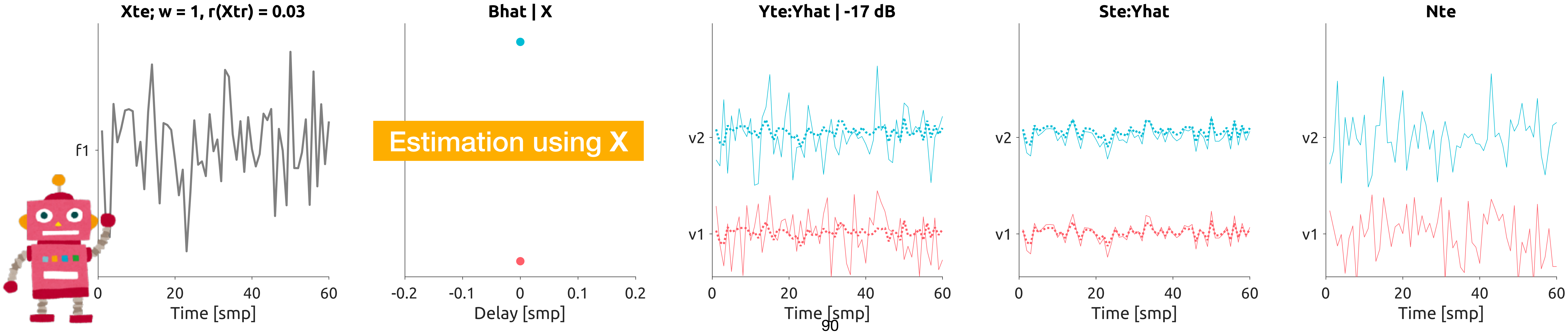

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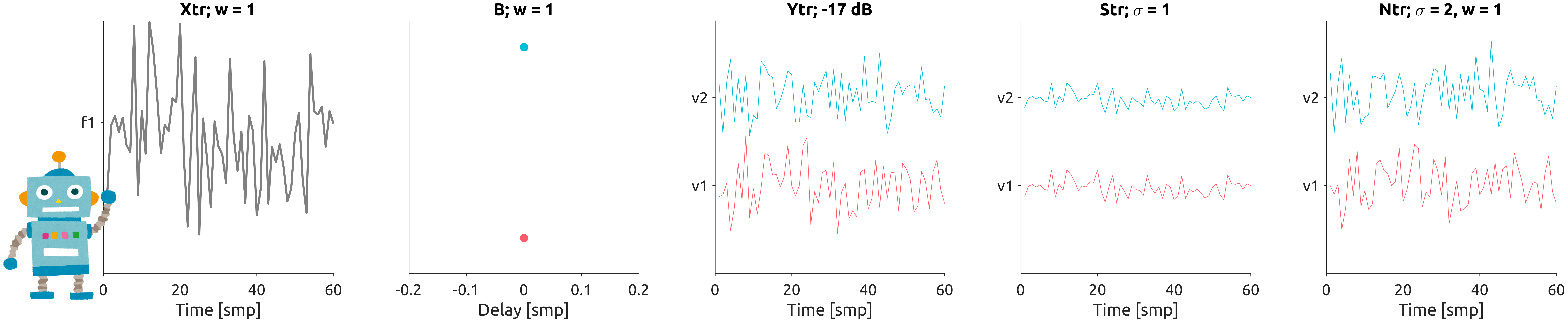

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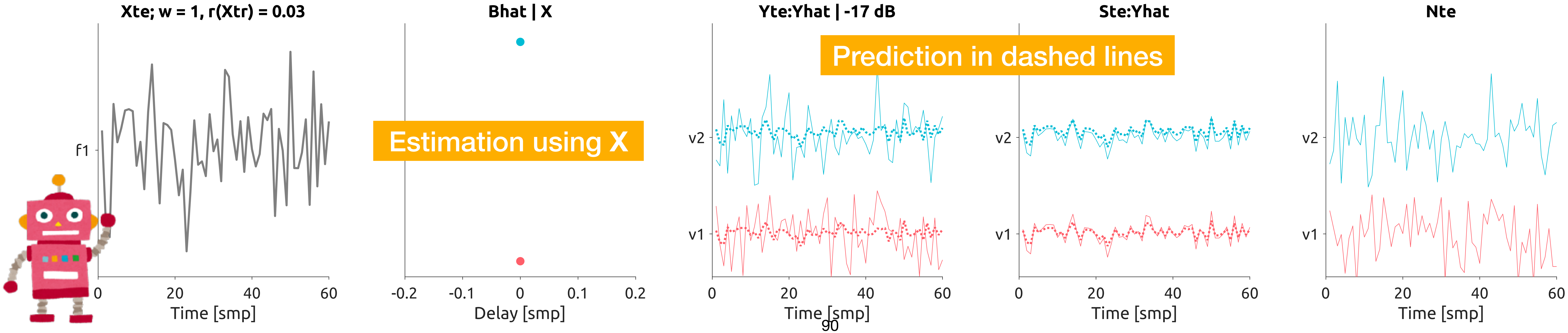
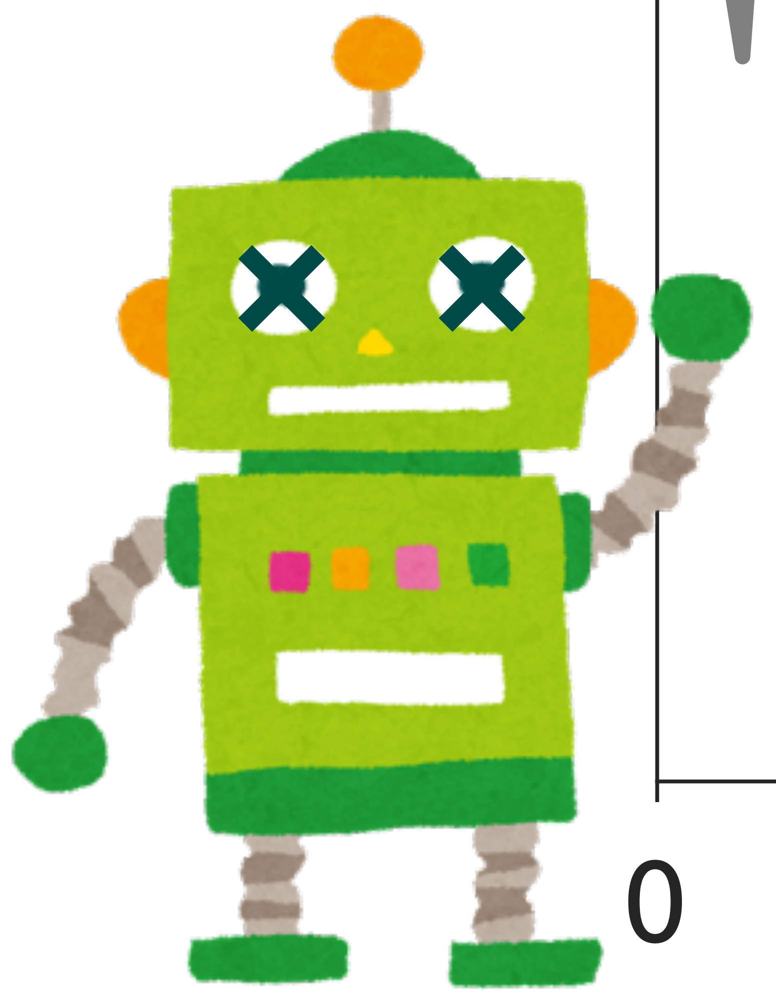


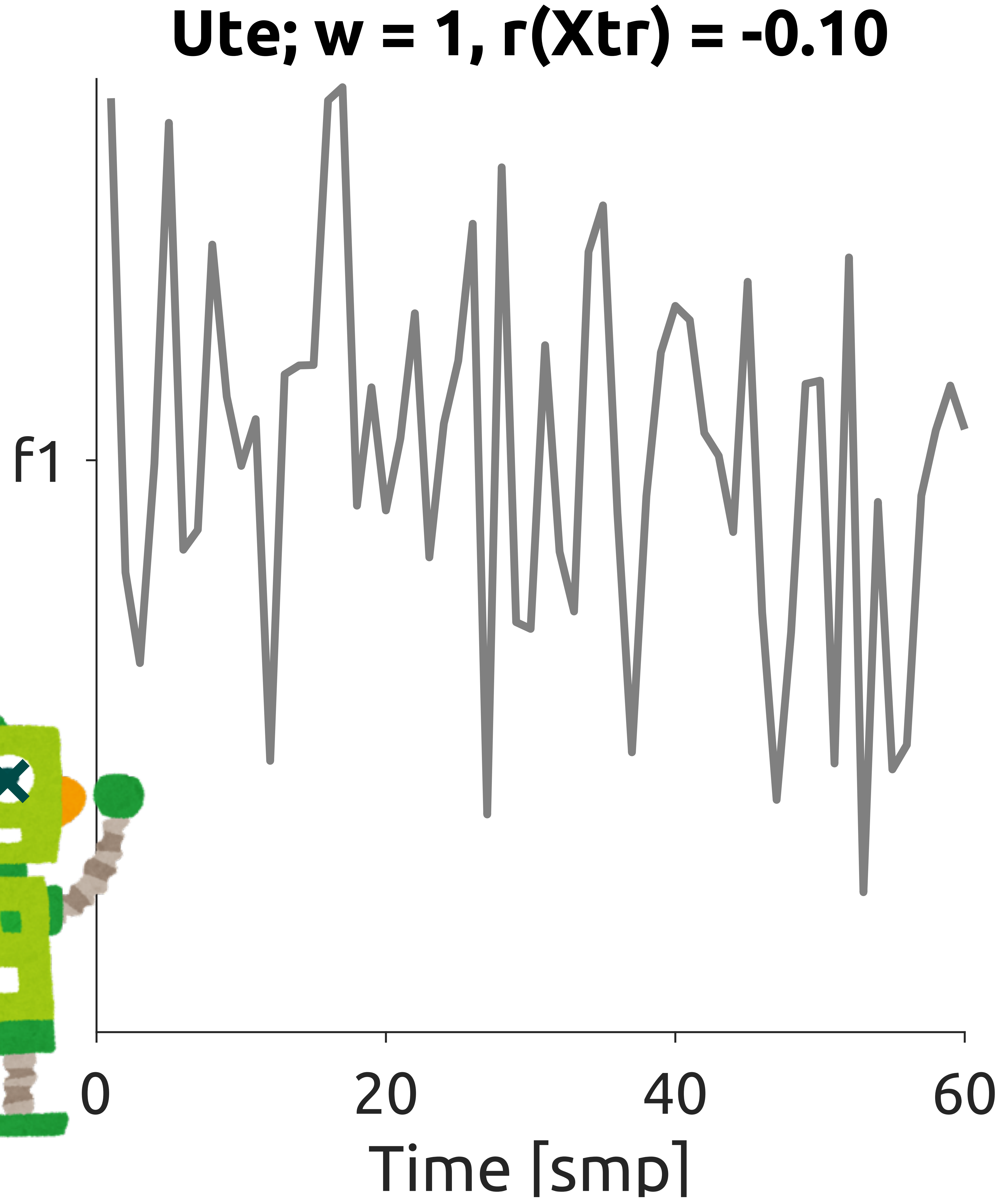
Toy specification

Null features

$$\hat{Y}_0 = \color{magenta}{U}\color{black}\hat{B}_0$$

- **U:** <#Timepoints x #Features>
- #Features = 1
- #Timepoints = 60 samples
- Null feature smoothness = 1
- Totally uncorrelated with the true feature (r = -0.10)





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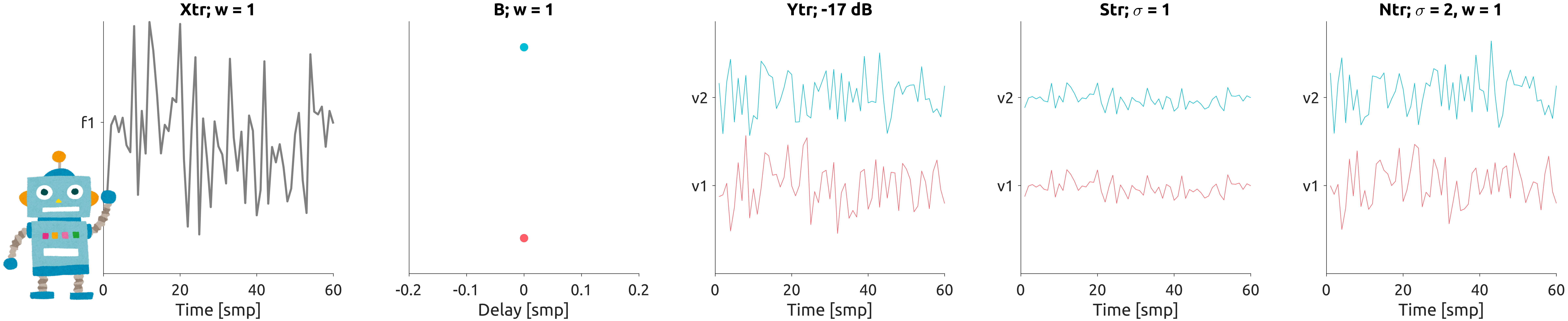
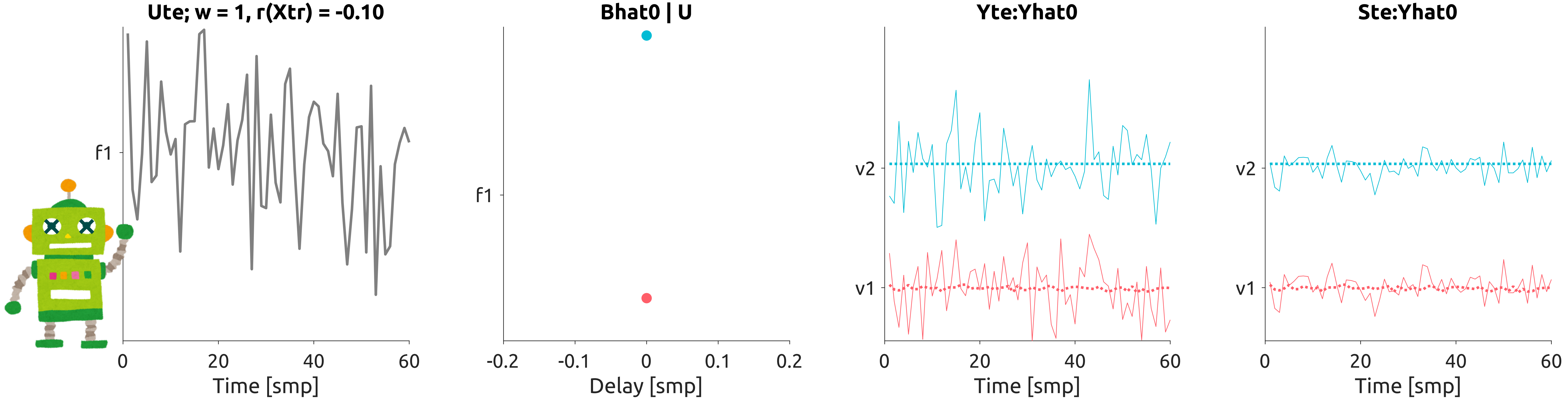
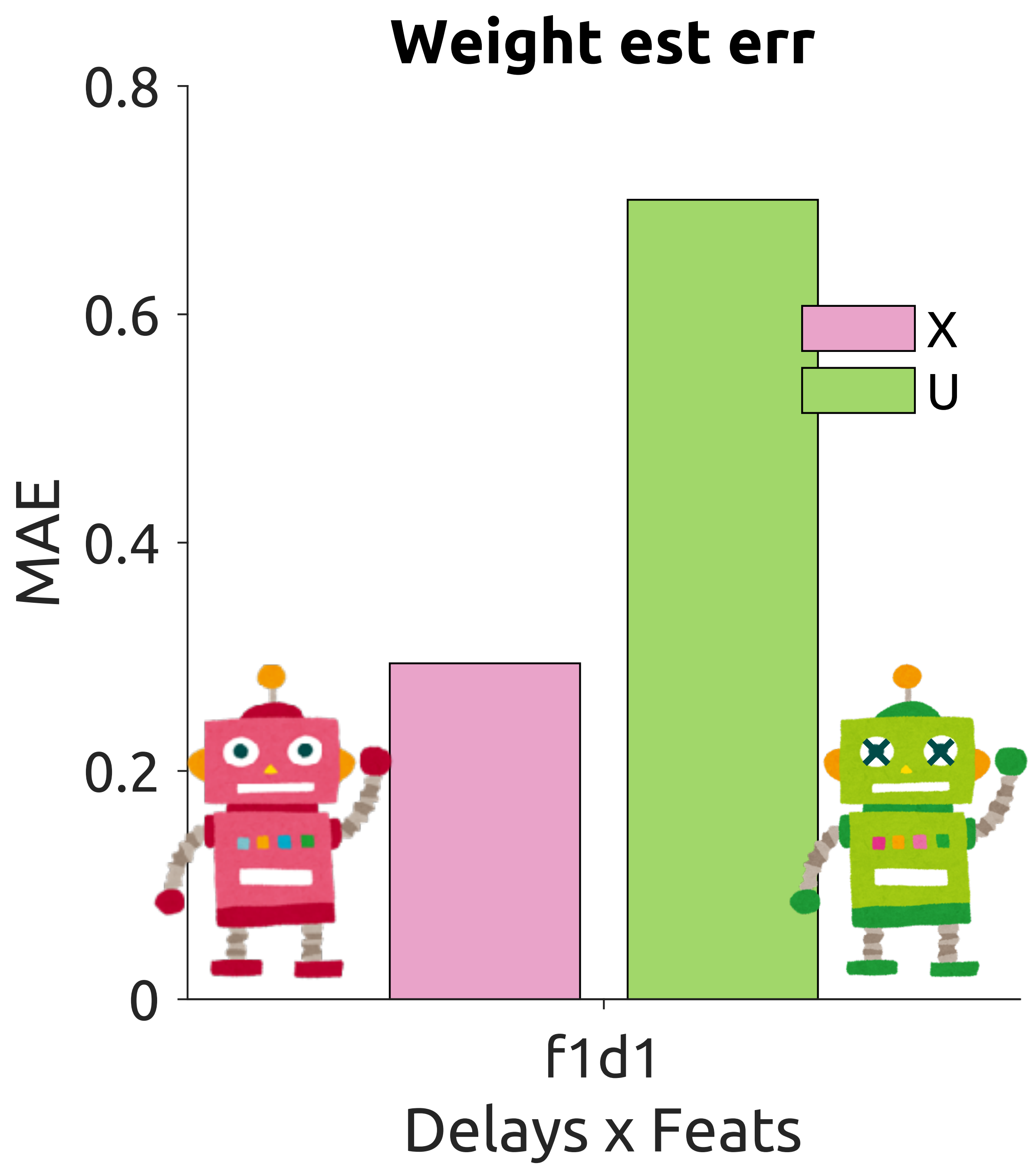


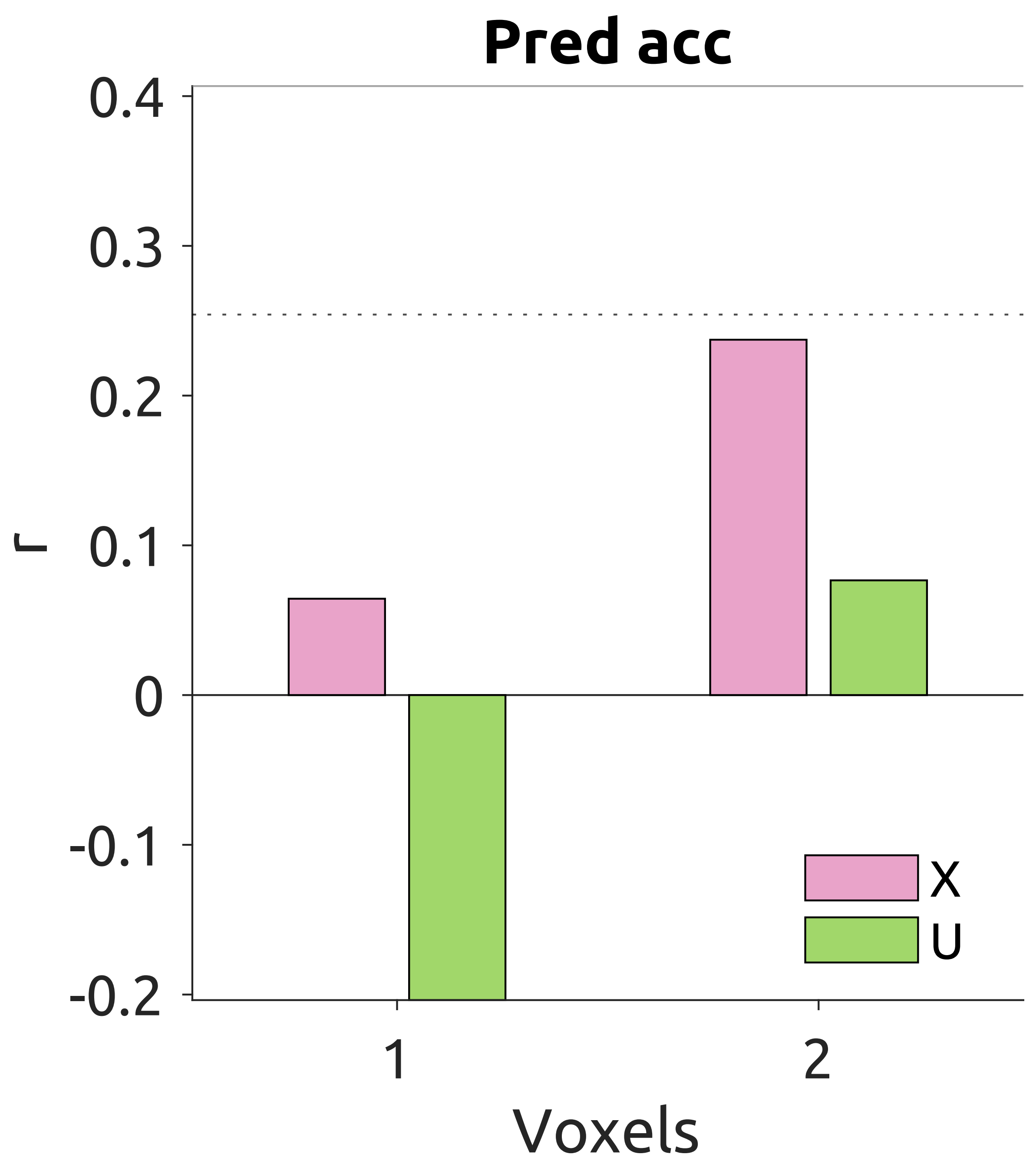
Null model



Prediction performances | #Sims = 100

MAE: mean absolute error; r: Pearson correlation





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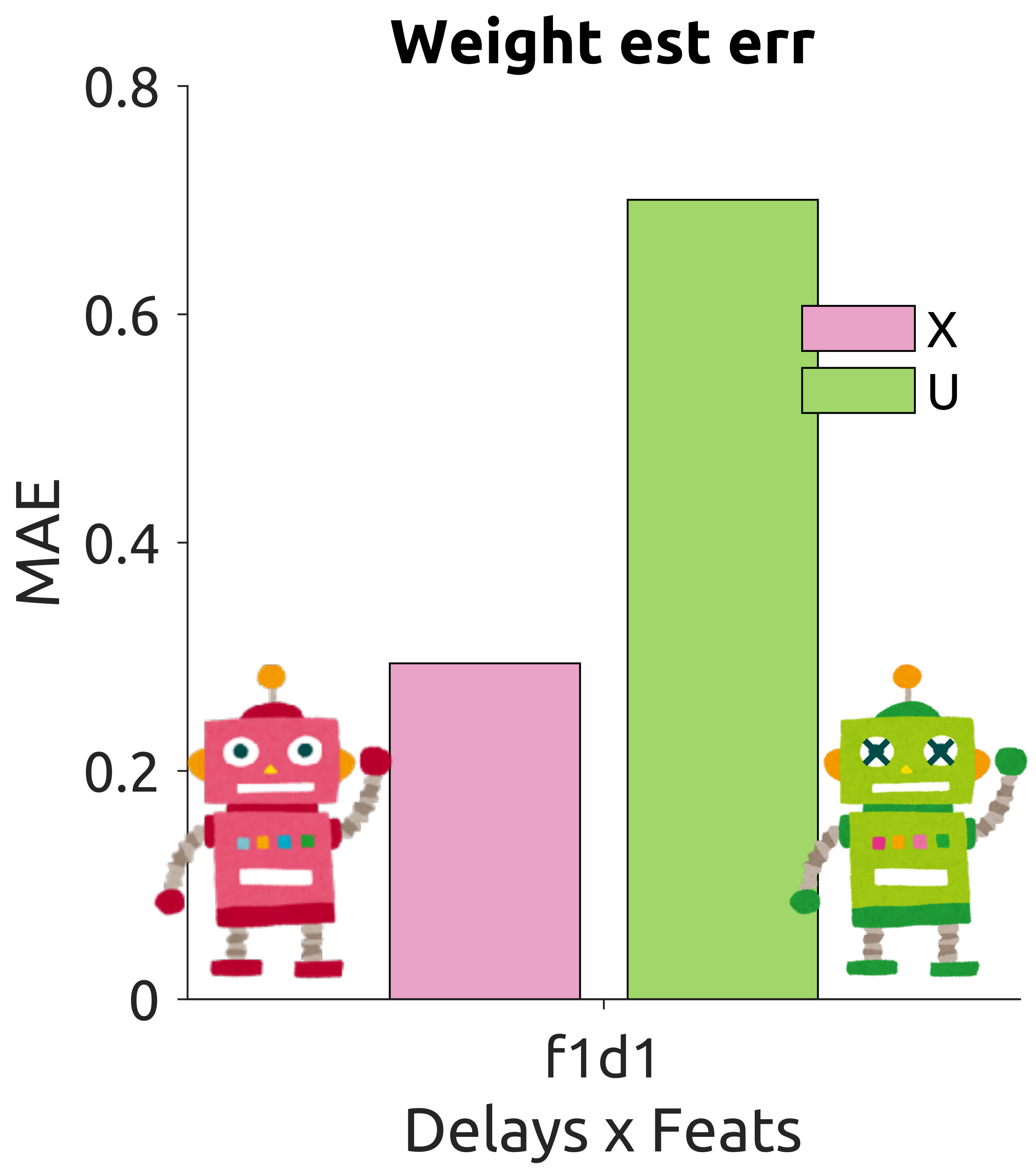

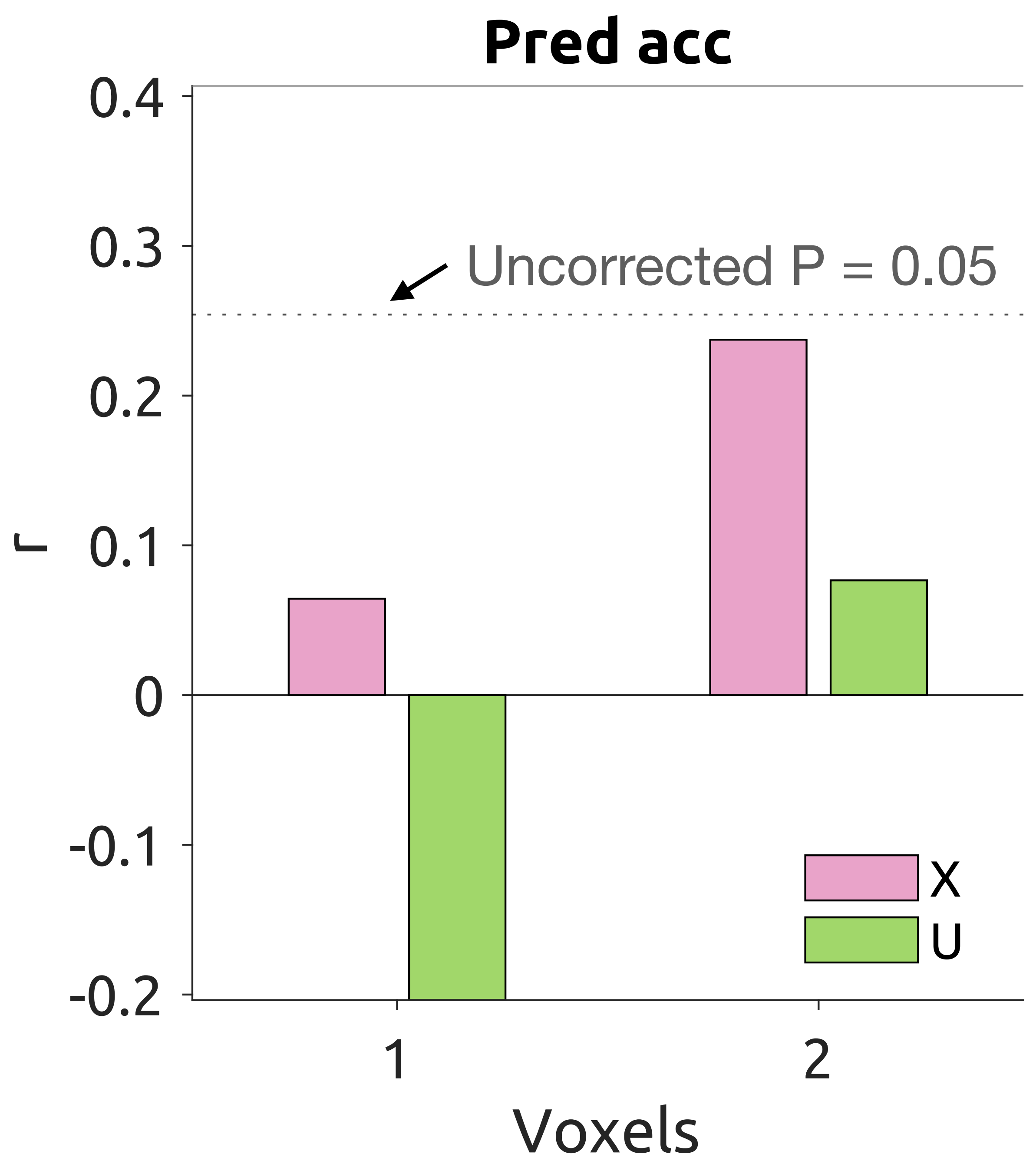

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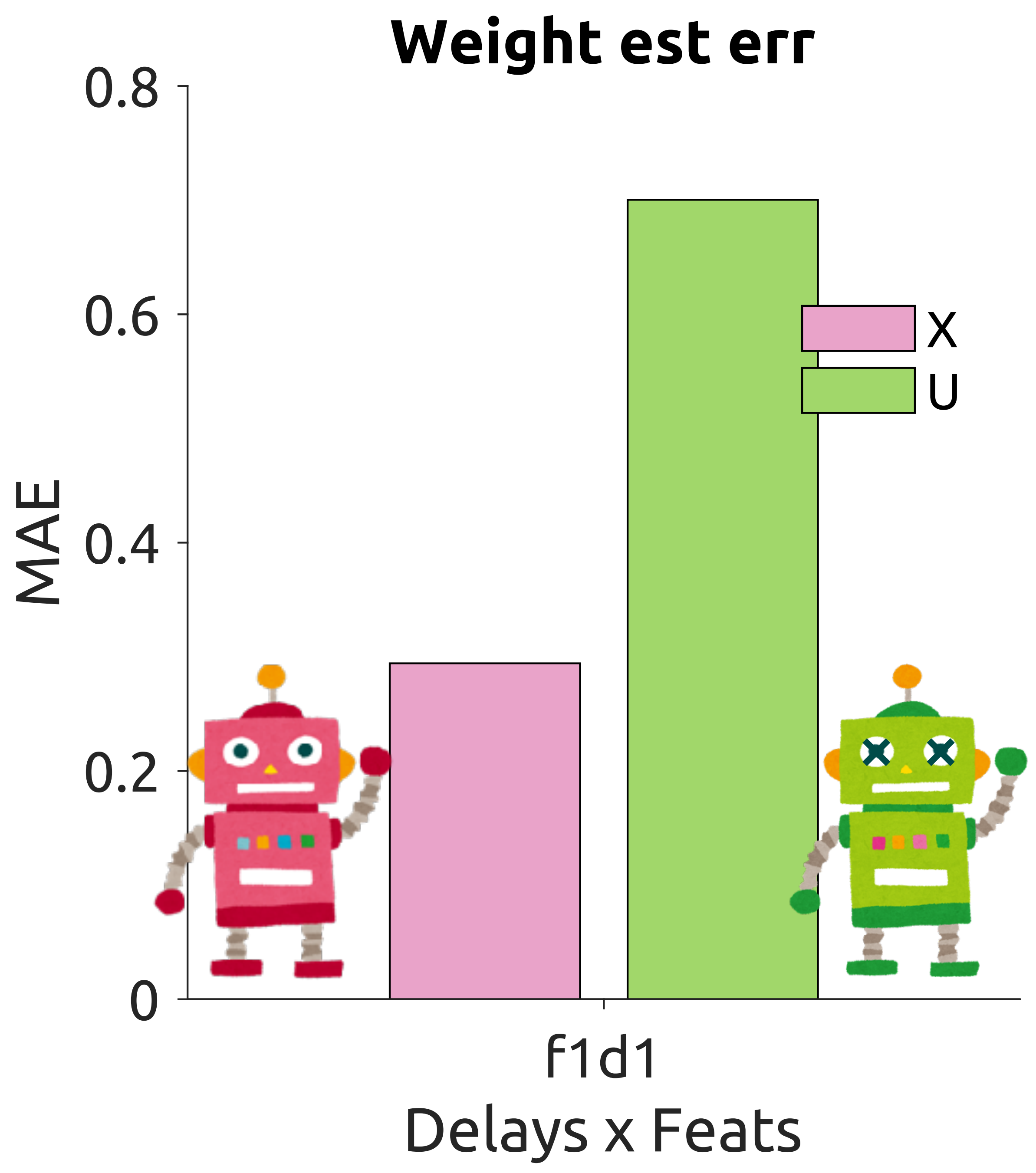

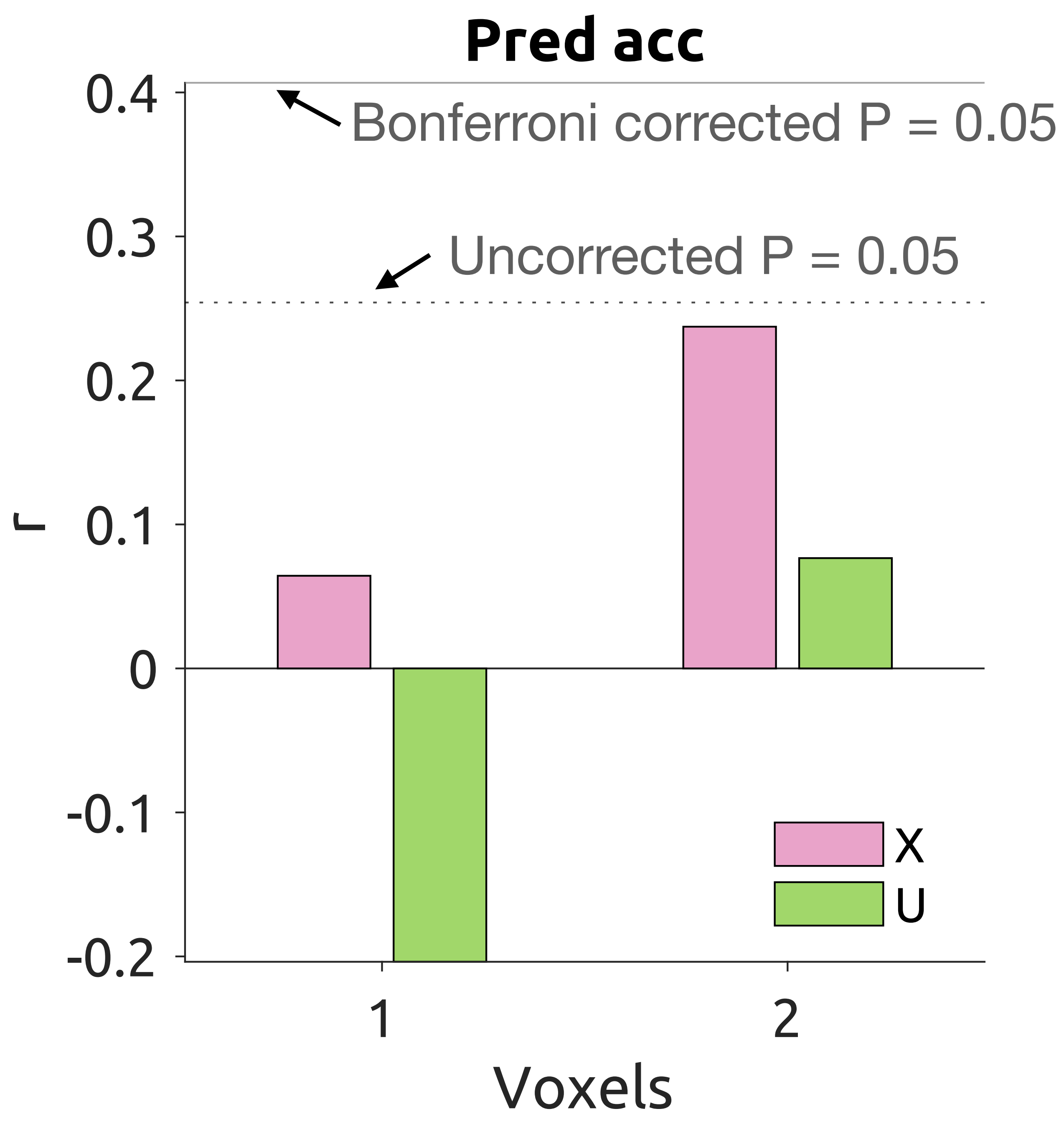

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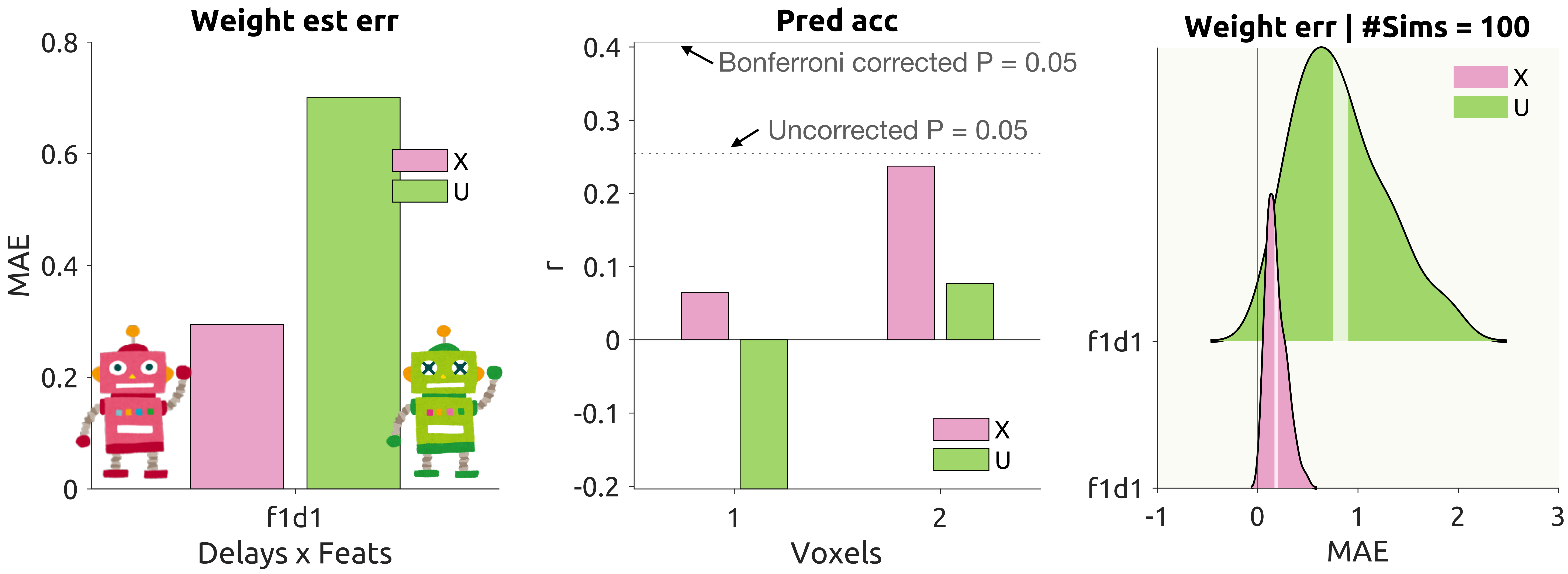

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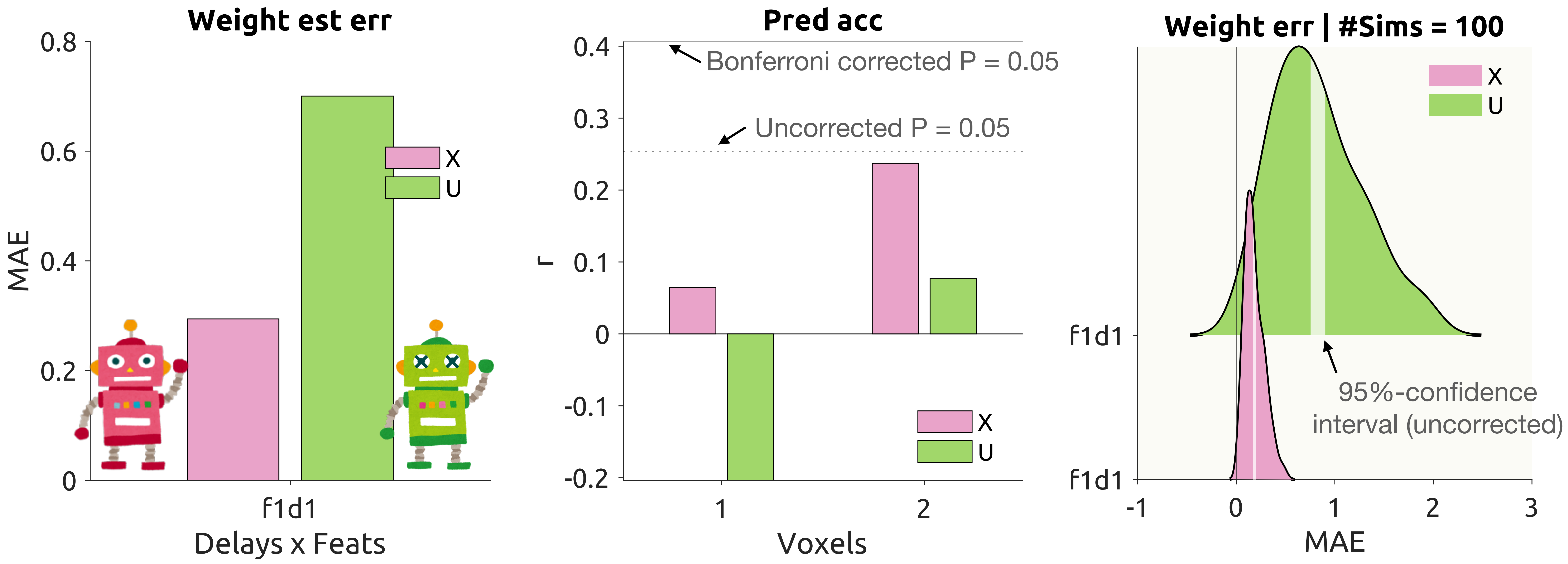

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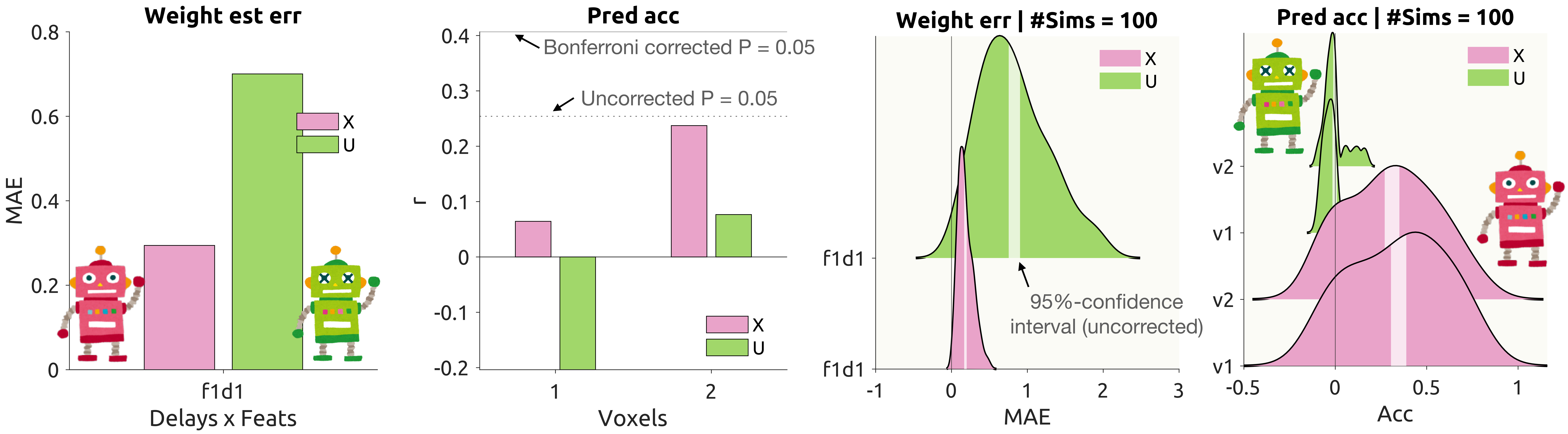

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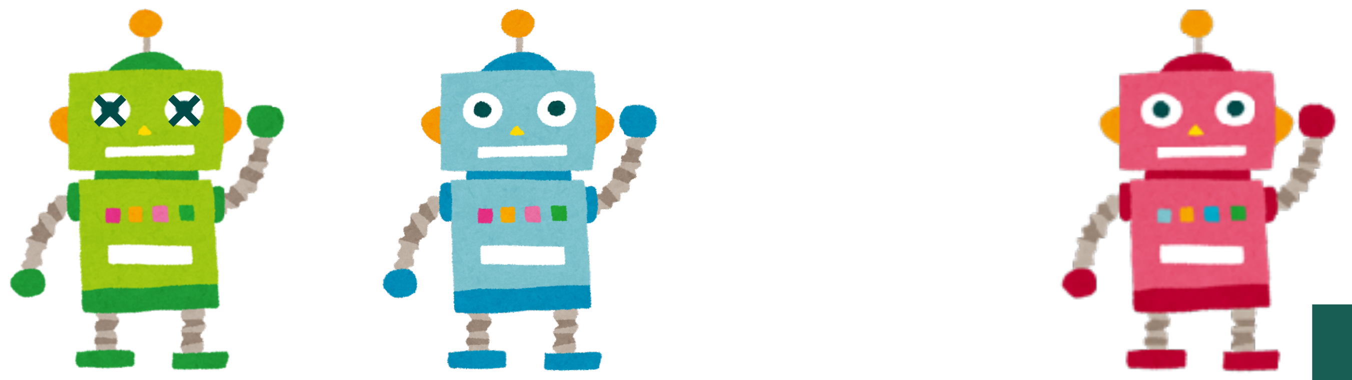

So far so good?

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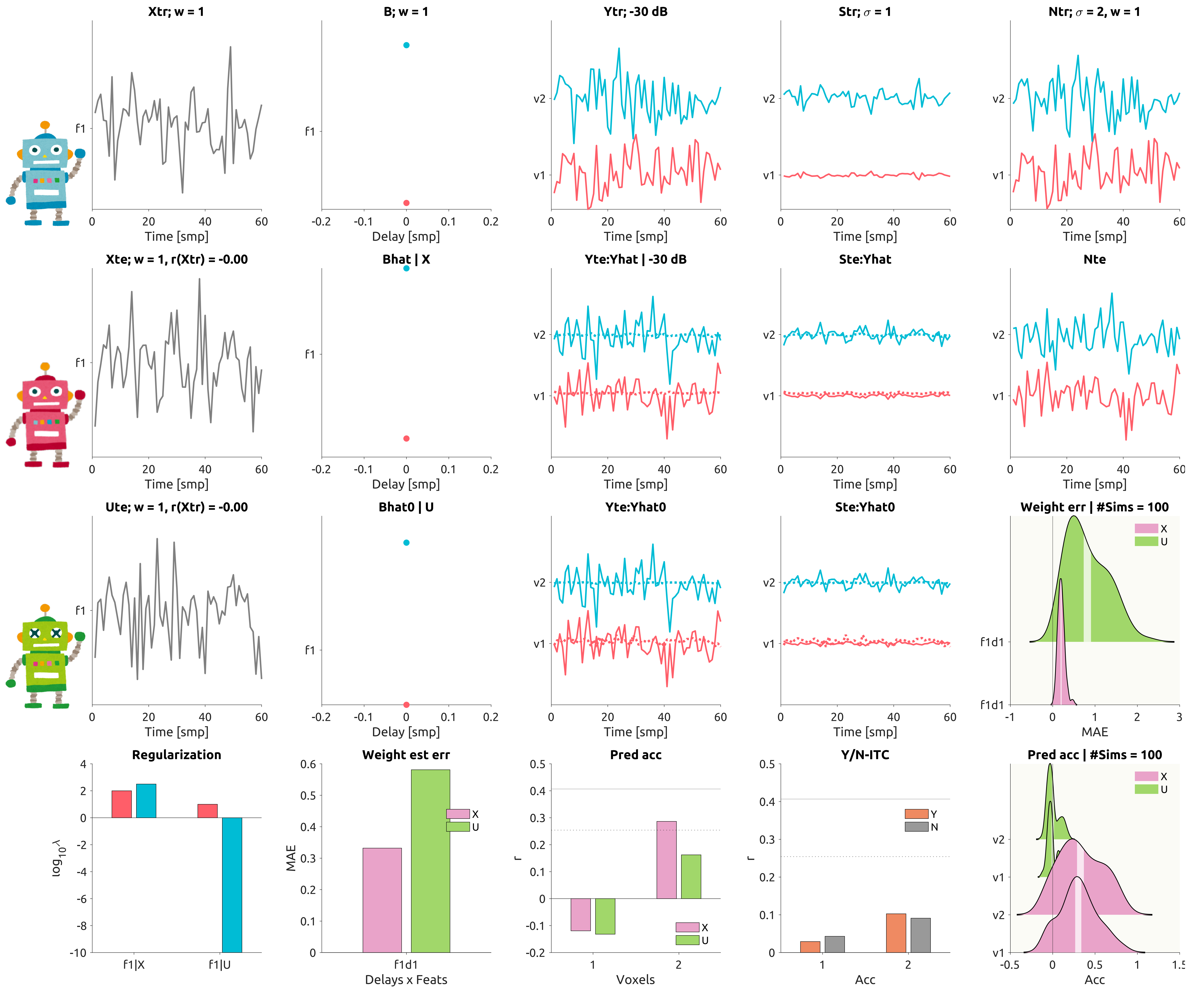
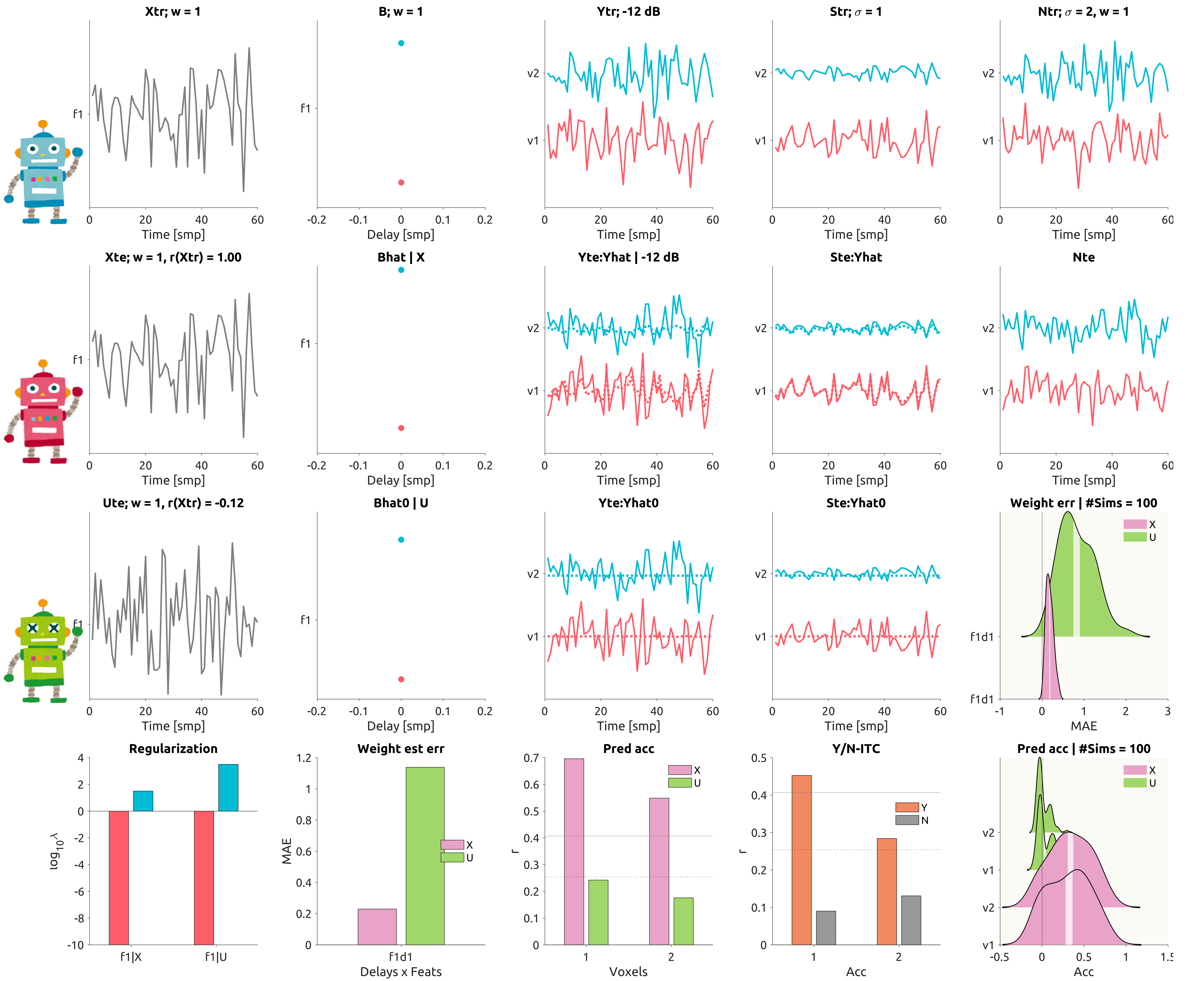
Simulation A0

- #Timepoints = 60
- #Voxels = 2
- #Features = 1
- #Delays = 1 | delay = [0]
- σ[noise] = 2
- Feature smoothness = 1
- Weight smoothness = 1
- Noise smoothness = 1
- (optimized with the 3rd dataset)



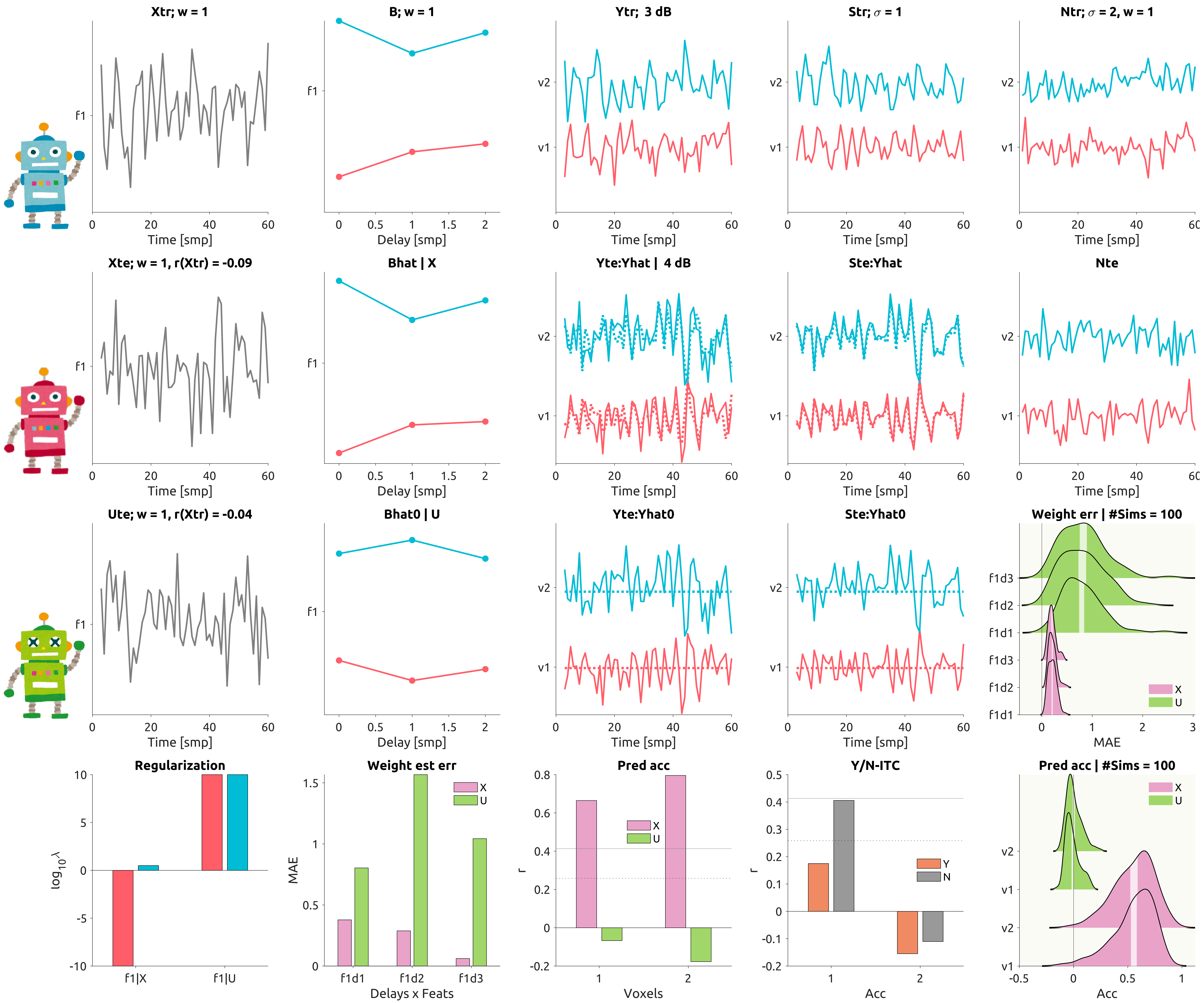
Simulation A1

- #Timepoints = 60
- #Voxels = 2
- #Features = 1
- #Delays = 1 | delay = [0]
- σ[noise] = 2
- Feature smoothness = 1
- Weight smoothness = 1
- Noise smoothness = 1
- **Repeated stimulus**



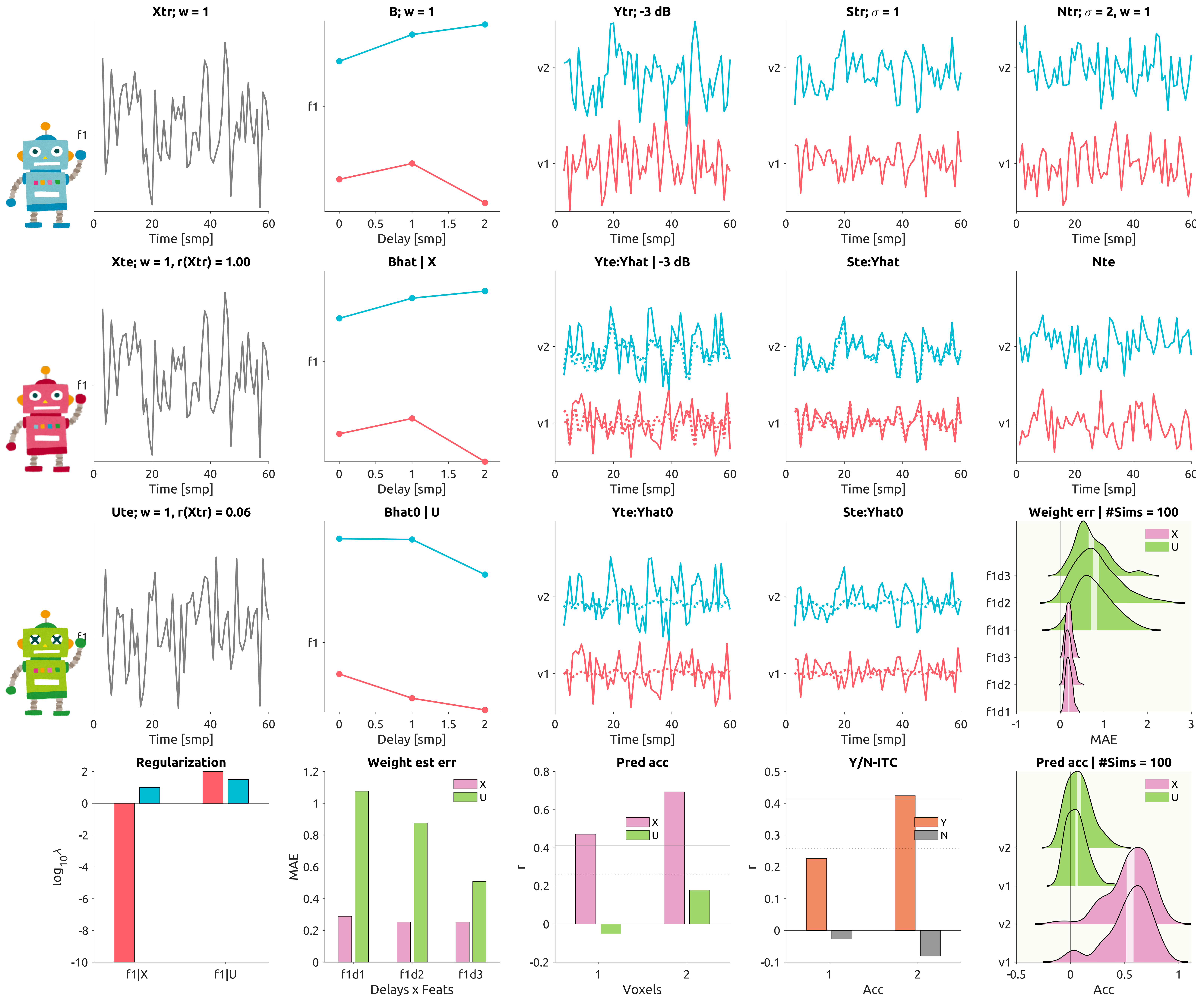
Simulation B0

- #Timepoints = 60
- #Voxels = 2
- #Features = 1
- **#Delays = 3 | [0,1,2]**
- σ[noise] = 2
- Feature smoothness = 1
- Weight smoothness = 1
- Noise smoothness = 1
- **Independent stimuli**



Simulation B1

- #Timepoints = 60
- #Voxels = 2
- #Features = 1
- #Delays = 3 | [0,1,2]
- σ[noise] = 2
- Feature smoothness = 1
- Weight smoothness = 1
- Noise smoothness = 1
- **Repeated stimulus**



Simulation B1

- #Timepoints = 60
- #Voxels = 2
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- Feature smoothness = 1
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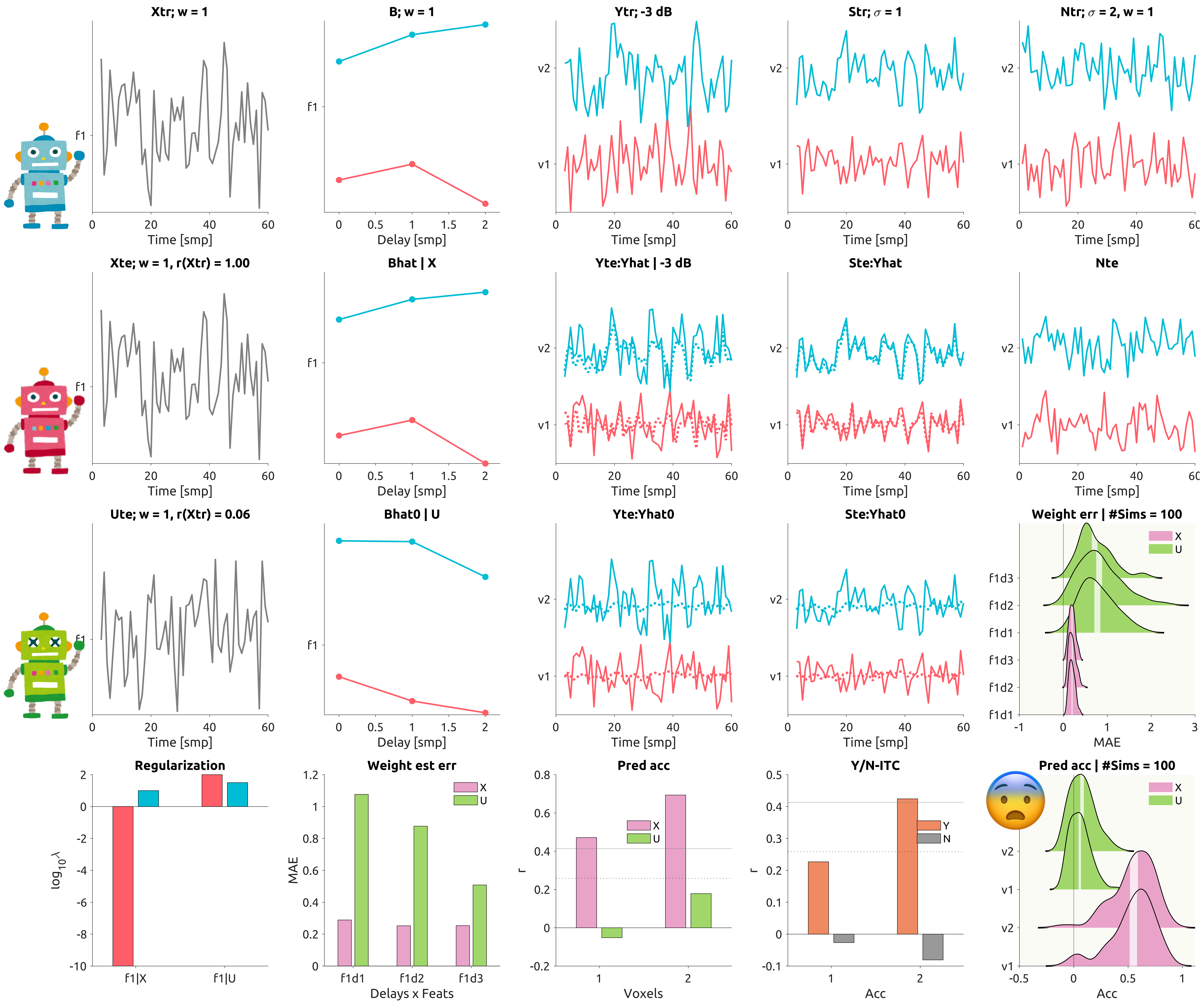
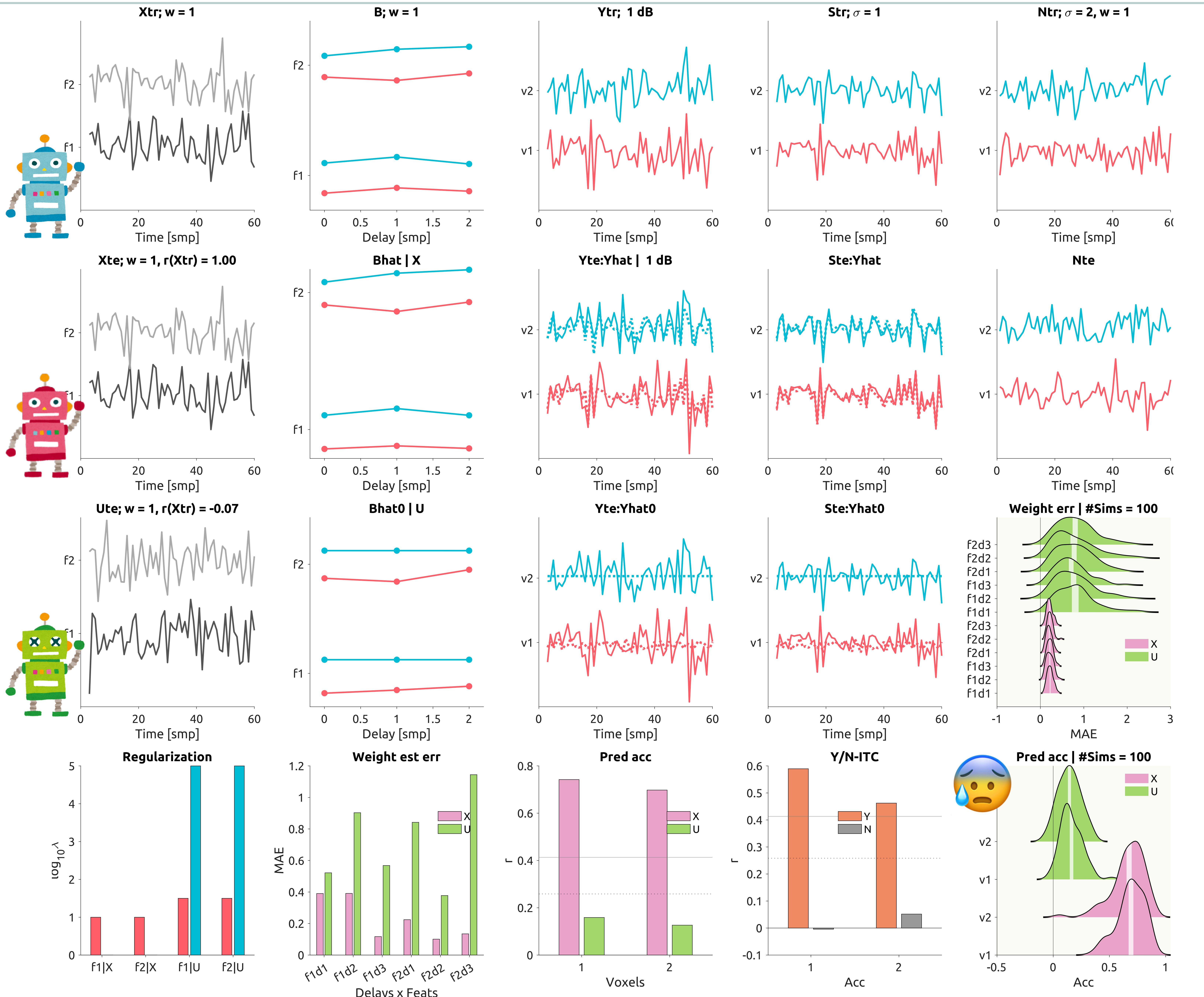
- Noise smoothness = 1
- **Repeated stimulus**



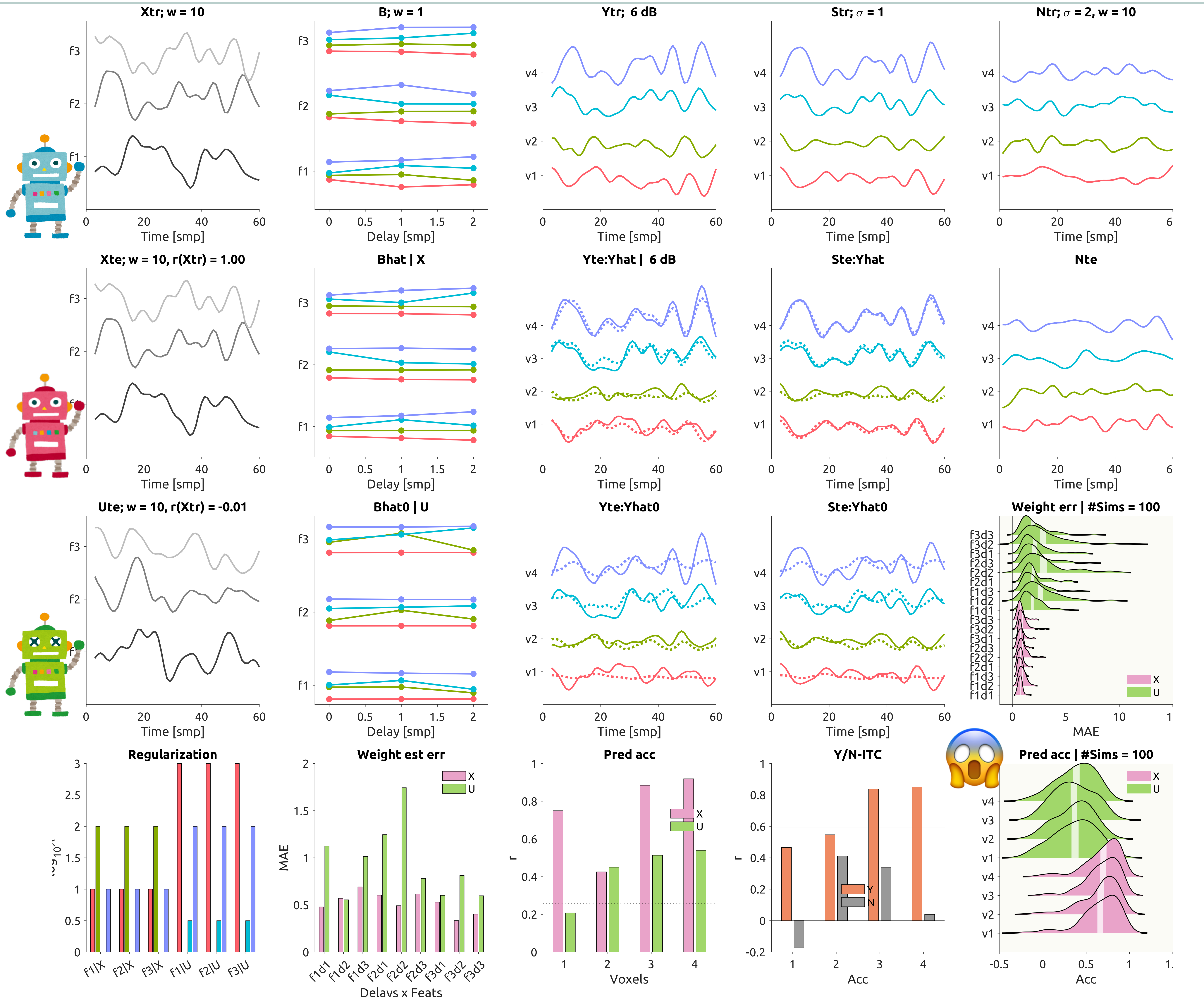
Simulation C1

- #Timepoints = 60
- #Voxels = 2
- **#Features = 2**
- #Delays = 3 | [0,1,2]
- σ[noise] = 2
- Feature smoothness = 1
- Weight smoothness = 1
- Noise smoothness = 1
- **Repeated stimulus**



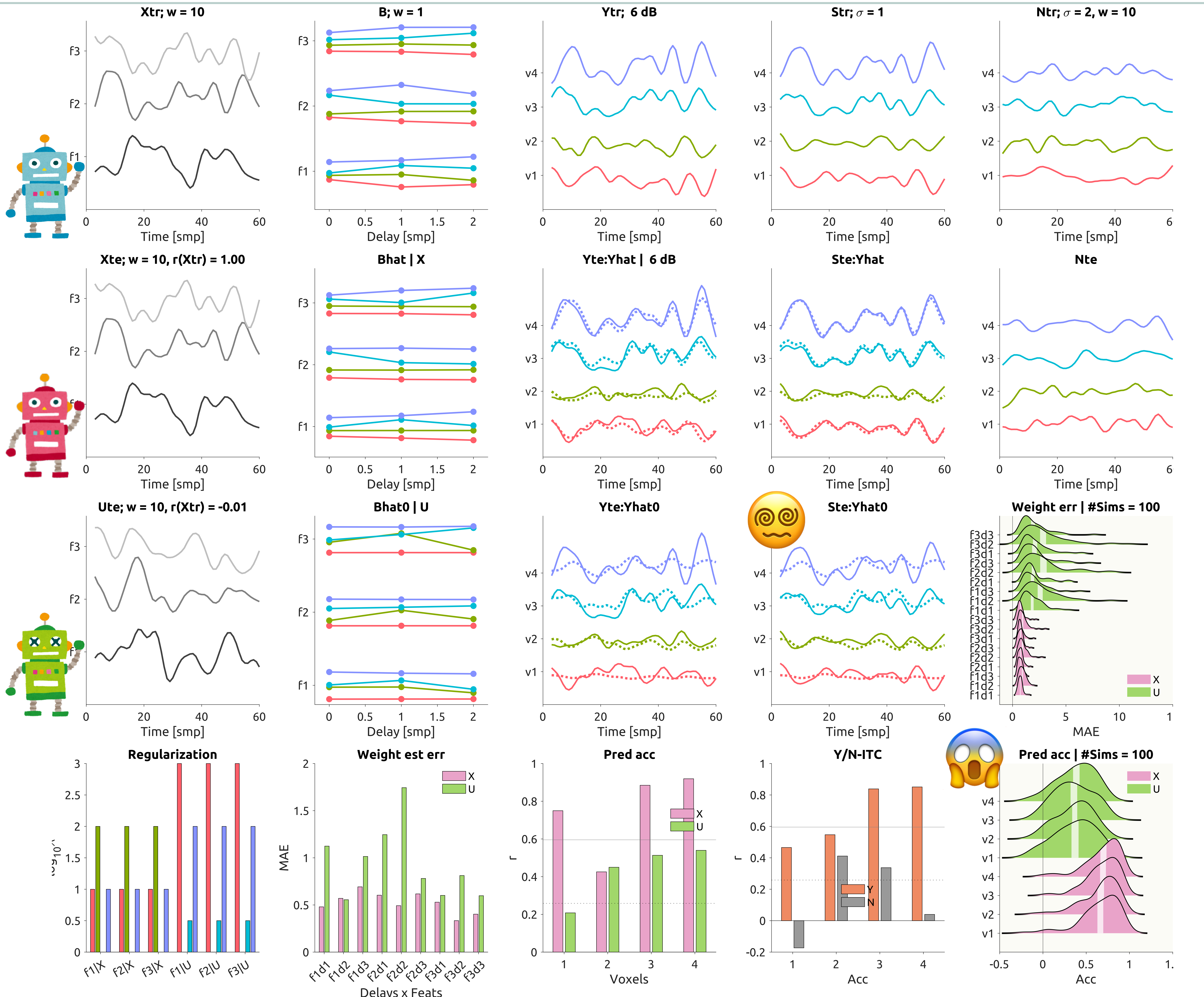
Simulation D1

- #Timepoints = 60
- **#Voxels = 4**
- **#Features = 3**
- #Delays = 3 | [0,1,2]
- σ[noise] = 2
- **Feature smoothness = 10**
- **Weight smoothness = 10**
- **Noise smoothness = 10**
- Repeated stimulus



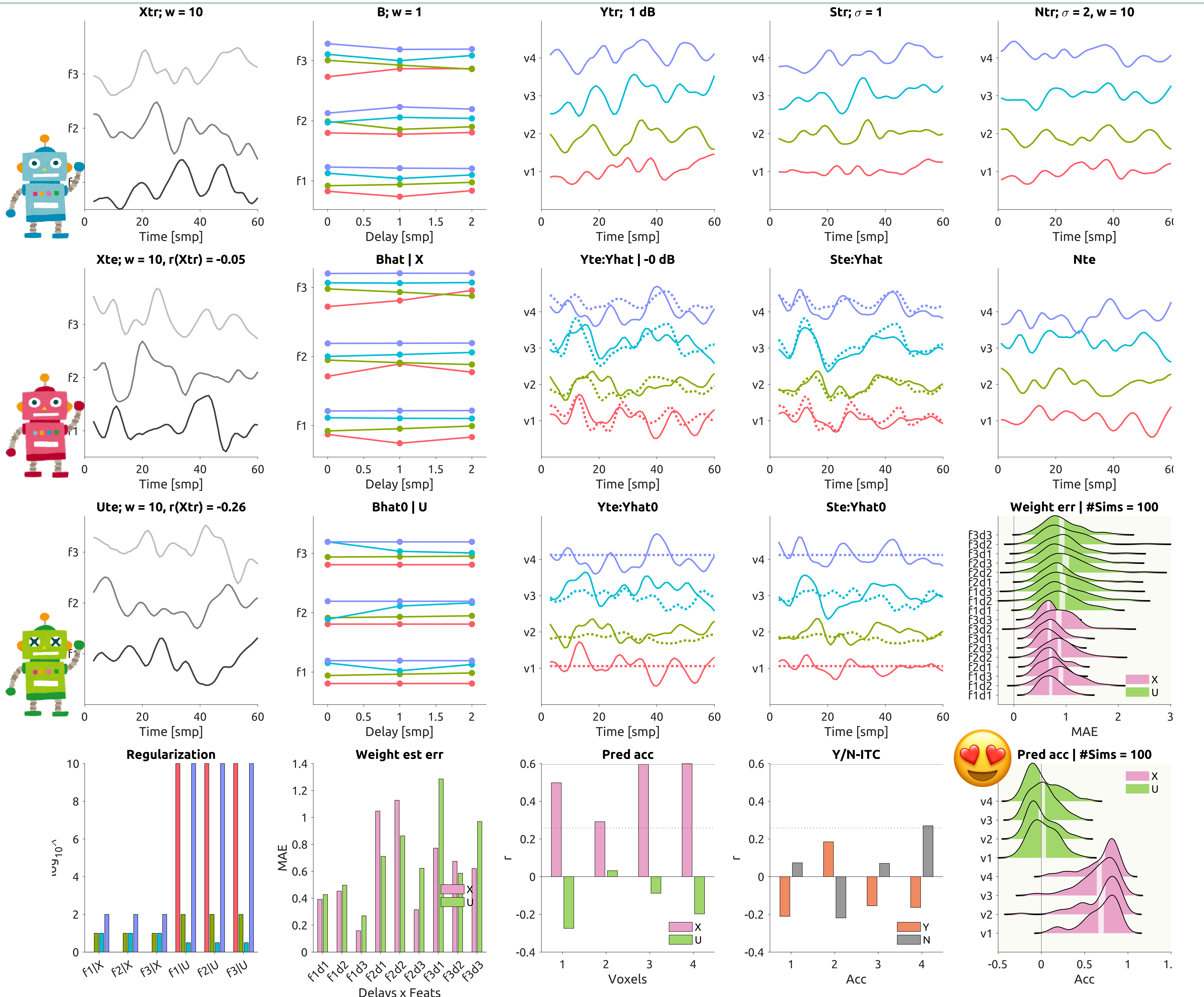
Simulation D1

- #Timepoints = 60
- **#Voxels = 4**
- **#Features = 3**
- #Delays = 3 | [0,1,2]
- σ[noise] = 2
- **Feature smoothness = 10**
- **Weight smoothness = 10**
- **Noise smoothness = 10**
- Repeated stimulus



Simulation D0

- #Timepoints = 60
- #Voxels = 4
- #Features = 3
- #Delays = 3 | [0,1,2]
- σ[noise] = 2
- Feature smoothness = 10
- Weight smoothness = 10
- Noise smoothness = 10
- **Independent stimuli**

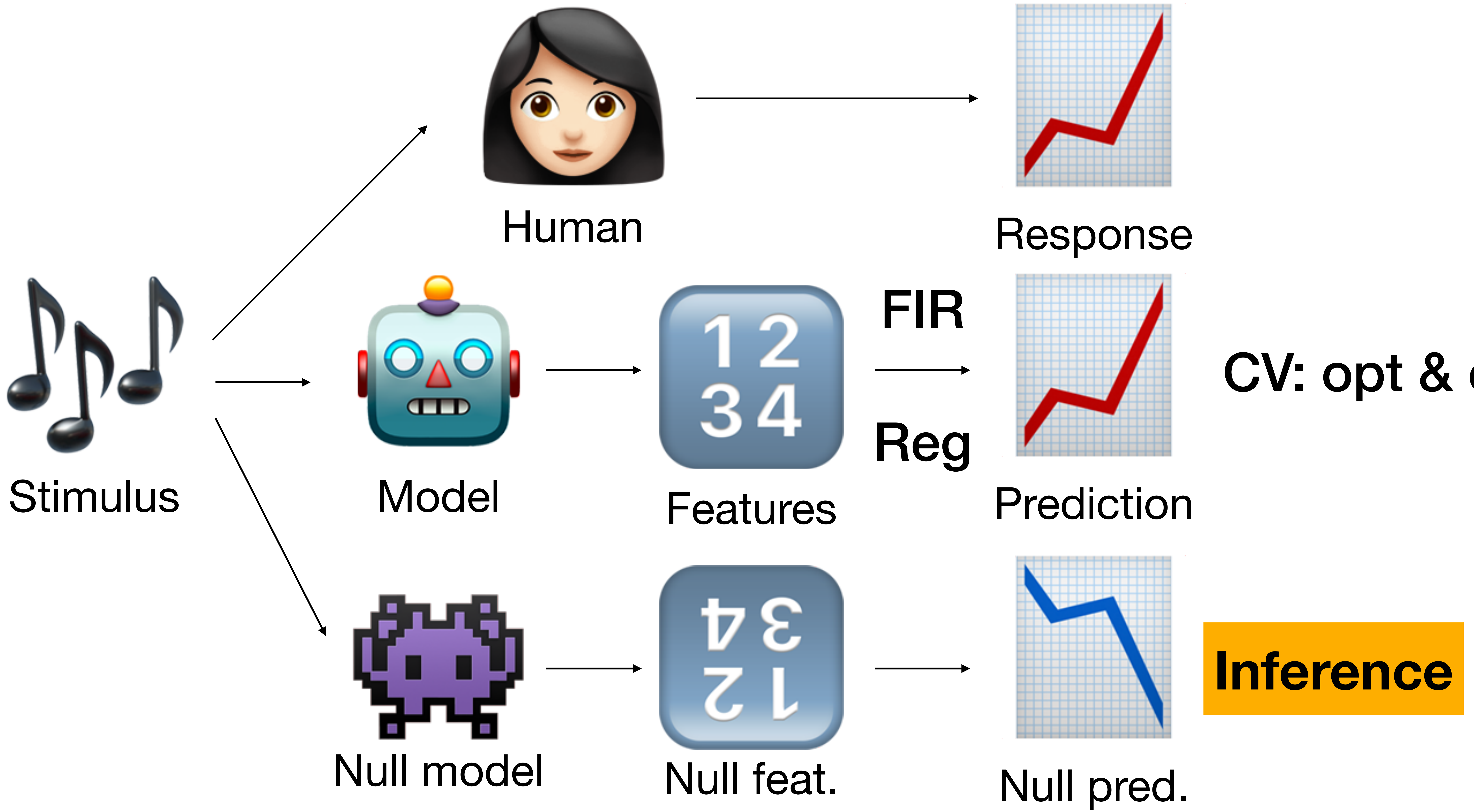


Summary [3/4]: Cross-validation

Nested cross-validation

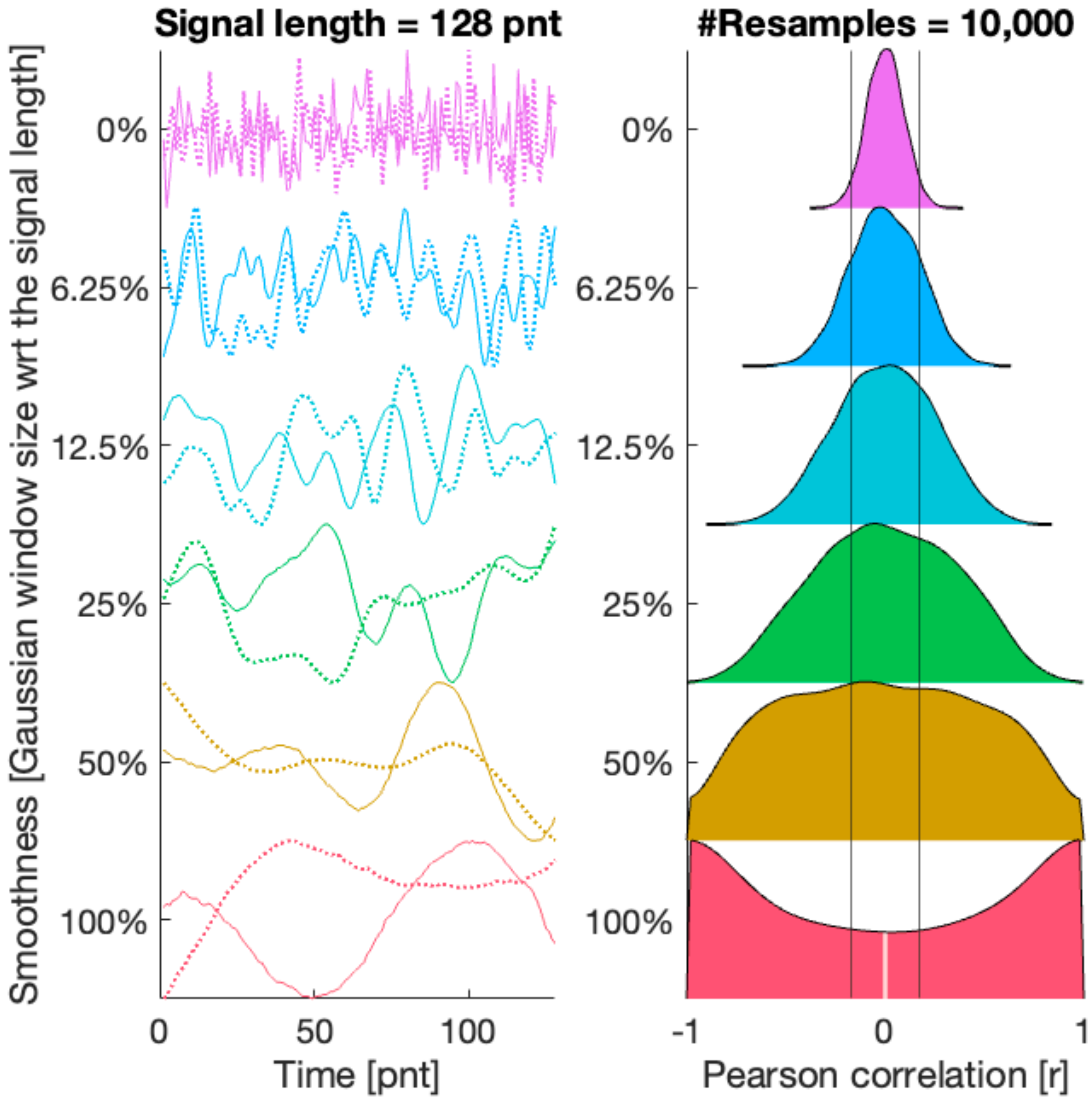
- We use an **outer** CV to evaluate the **generalizability** of a model.
- We use an **inner** CV to optimize the **hyperparameters** of a model.
- All partitions (train, optimization, and test) must be water-tightly **independent**. Otherwise, a leakage will fool you ("🤪: my model predicts 100%!").
- Note sources of leakages: **serial and spatial correlation** in the sampled data, **multicolinearity** in many self-reports, and **stimulus-driven responses**.

Linearized encoding analysis overview (HOWs)



Correlation between two time series

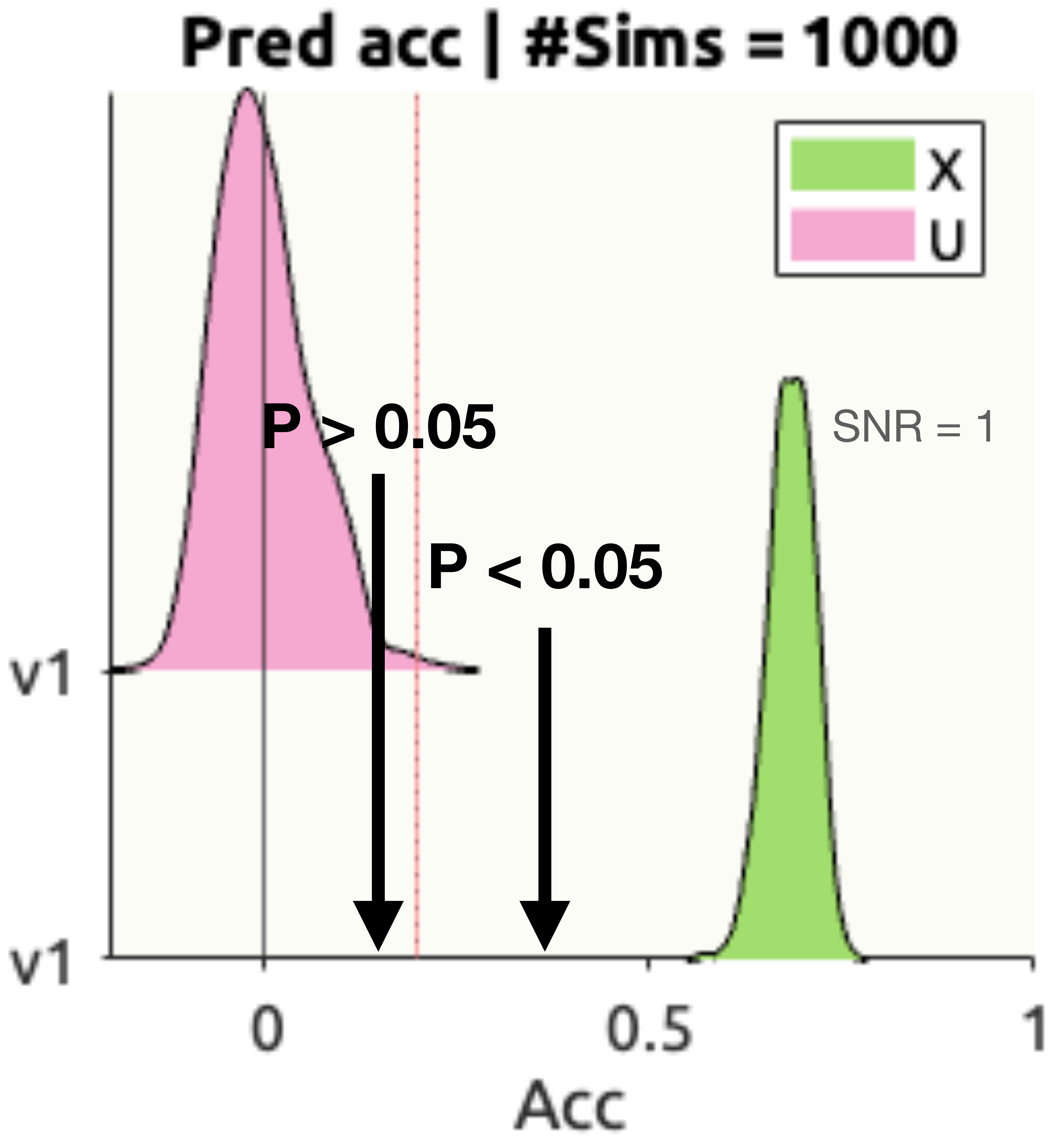
Spurious correlation in smooth (slow) time series



Noise floor & ceiling of performance

Prediction performance of time series

- **Noise floor**: $r_{null} > 0$ while $E(r_{null}) = 0$
- **Noise ceiling**: due to noise in the data, even with the perfect model, $\mathrm{E}(r_{perfect}) < 1$ ("explainable variance)
- NOTE: Sometimes people use correction using the noise ceiling (i.e., 70% of the noise ceiling of r=0.1; that is, r=0.07), and sometimes it's unclear ("r=0.7" corrected or not?)



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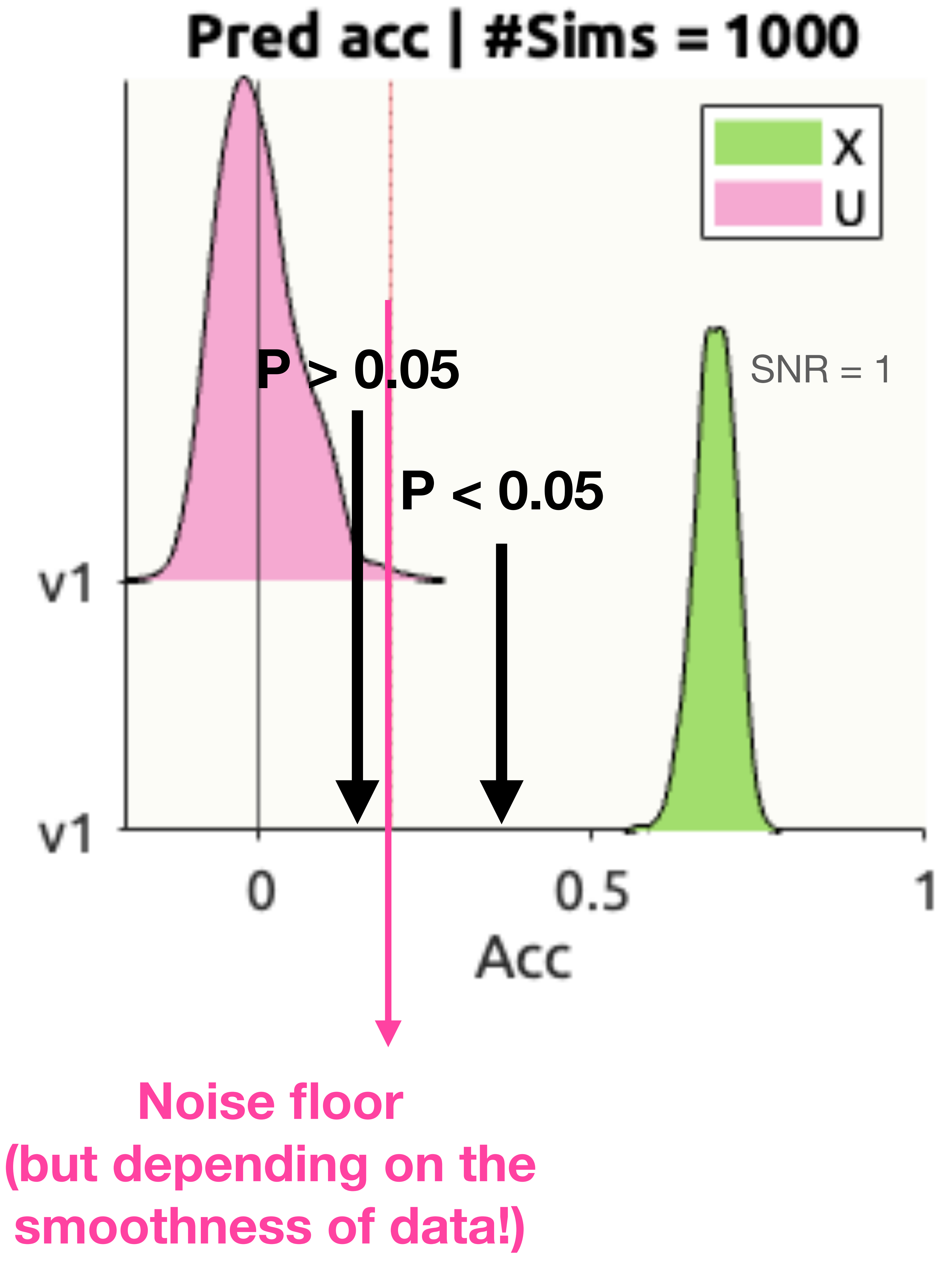

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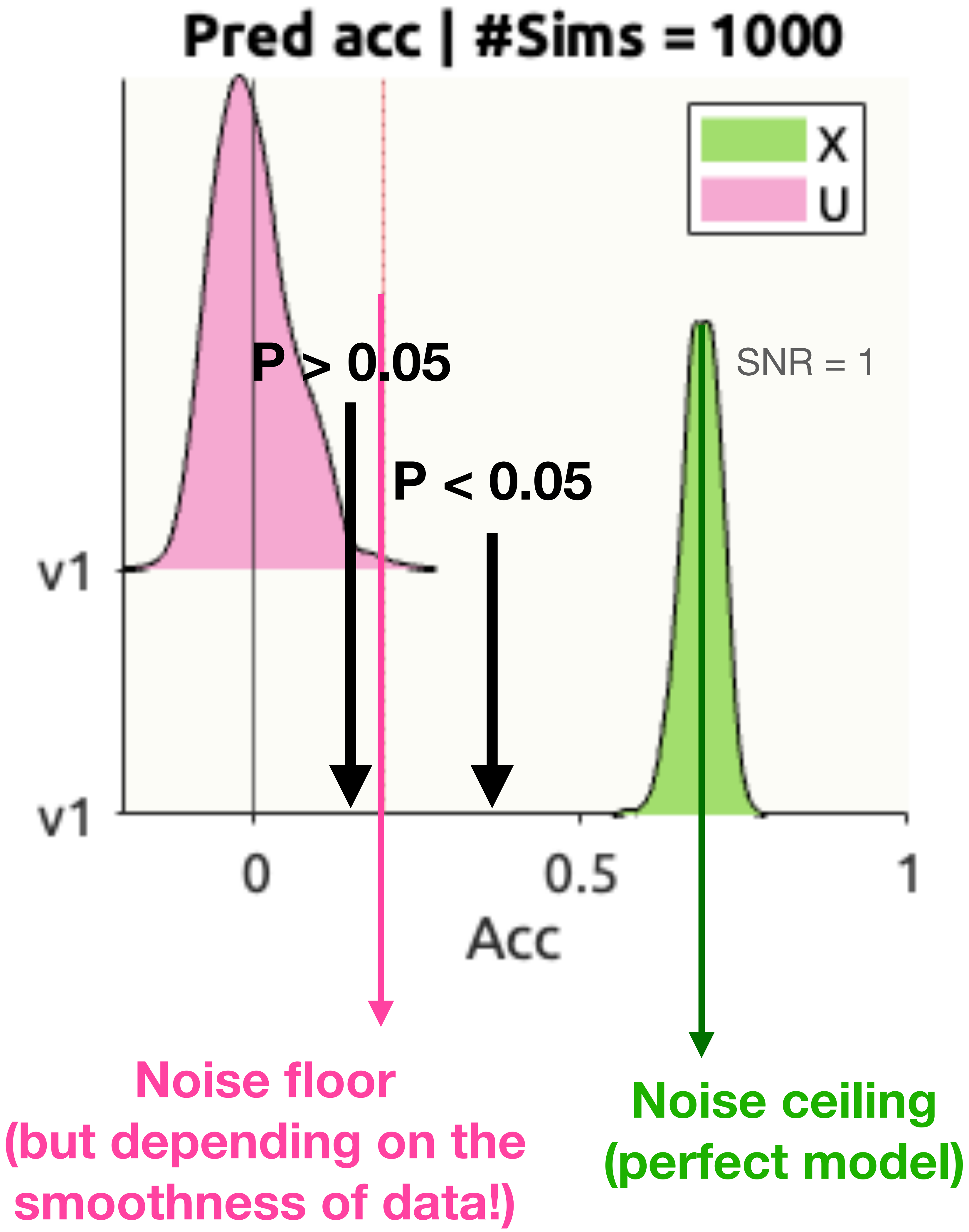


What about real data?

We don't know the correct null distribution!

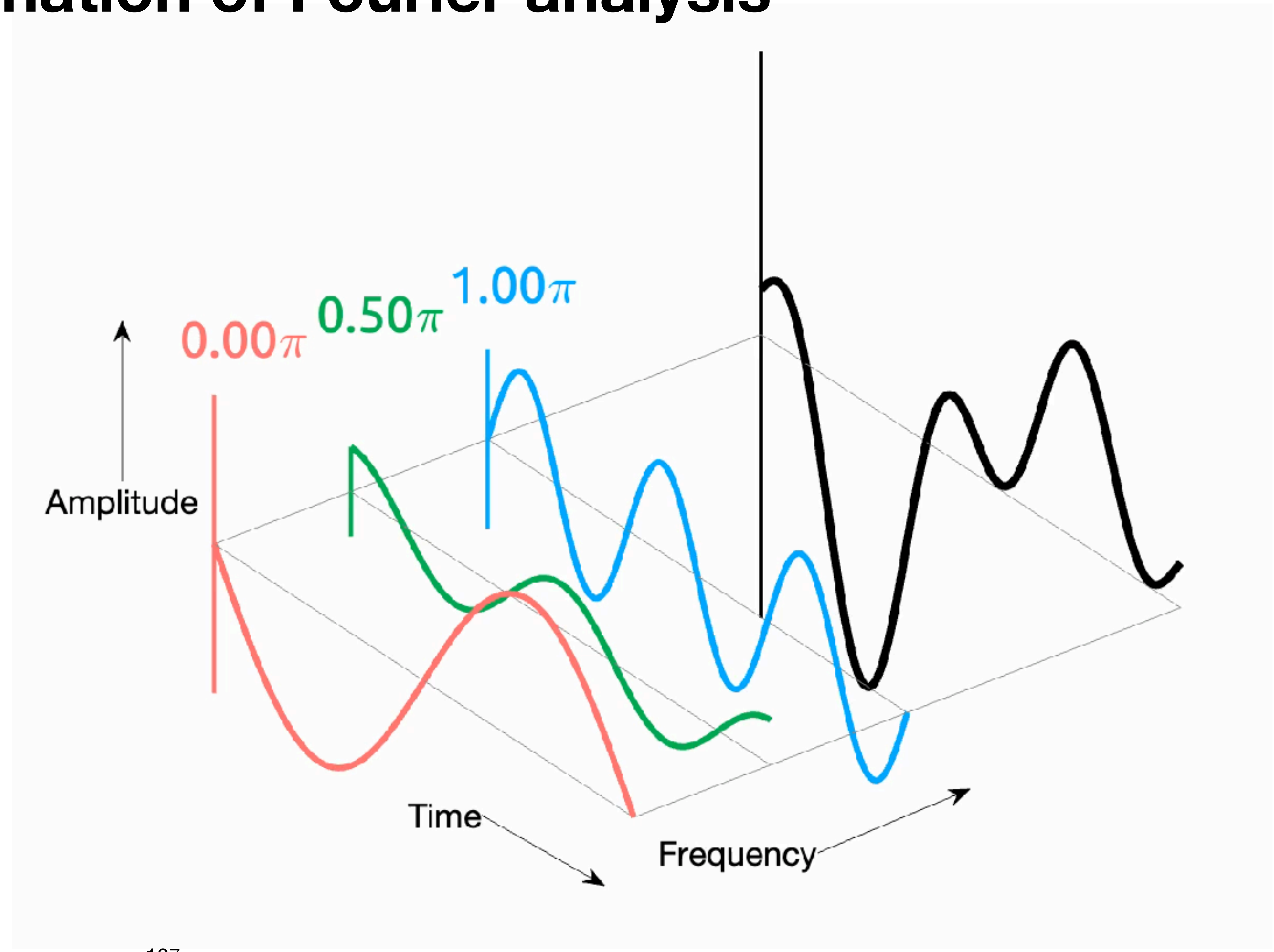
- Because we generated the data, we could also generate the null data while controlling all other properties (smoothness, SNR, ...).
- We don't know anything for sure about the real data! (We only have estimates.)
- One popular solution is to "generate" random samplings while preserving **important characteristics** of the data (e.g., autocorrelation).
  - For example, spectral magnitudes of the data, but different phases
  - Or, if you have many (1K+) time points, you can apply linear/circular shifts

What are magnitude & phase?

A (dangerously) quick explanation of Fourier analysis

- A complex waveform is a sum of simple (sine) waves at different frequencies and **phases** (is it the beginning of the cycle? in the middle? or the end?)

- Using a super cool method called "Fourier analysis" we can decompose and recompose complex waveforms! 😃



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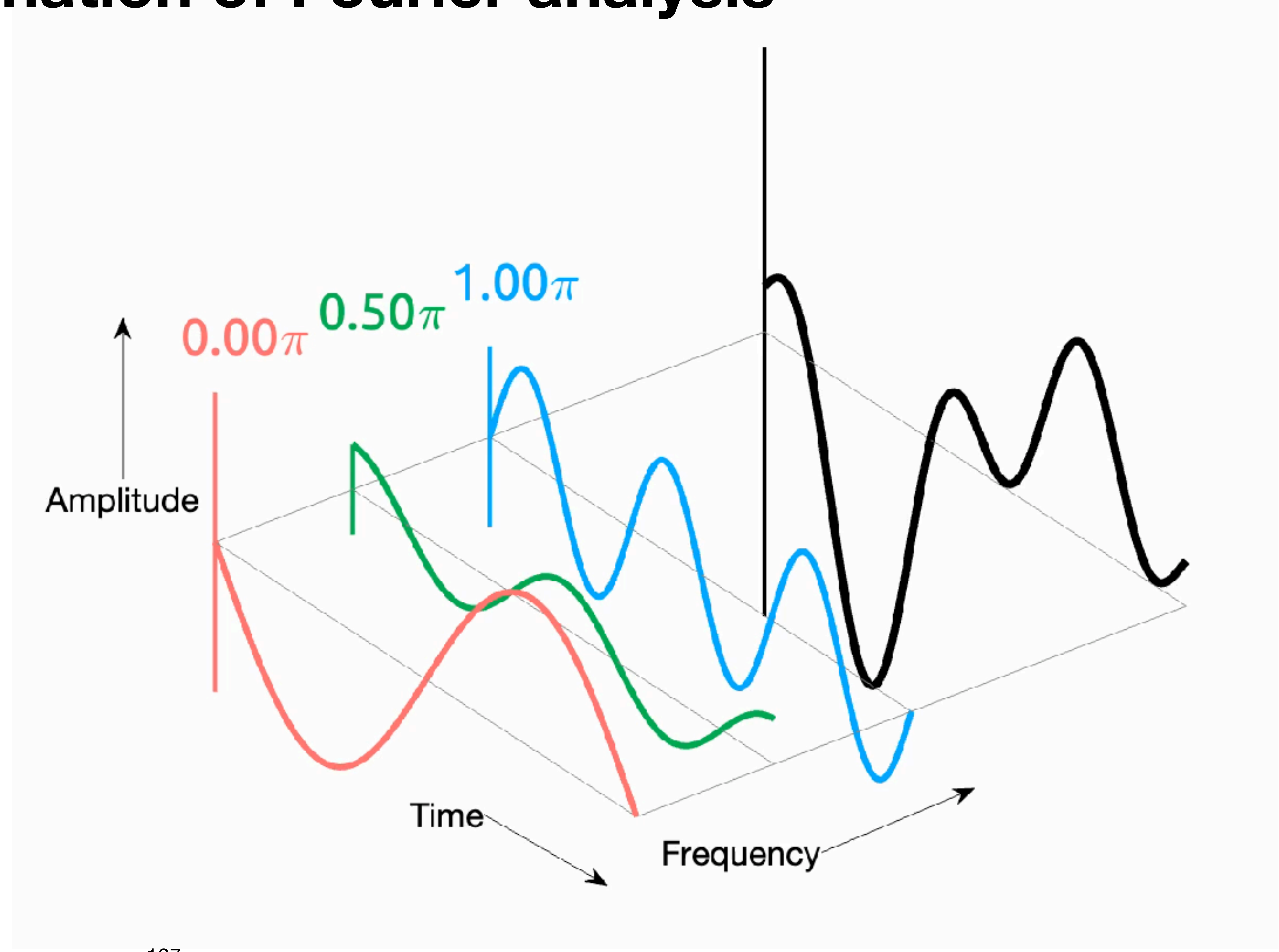
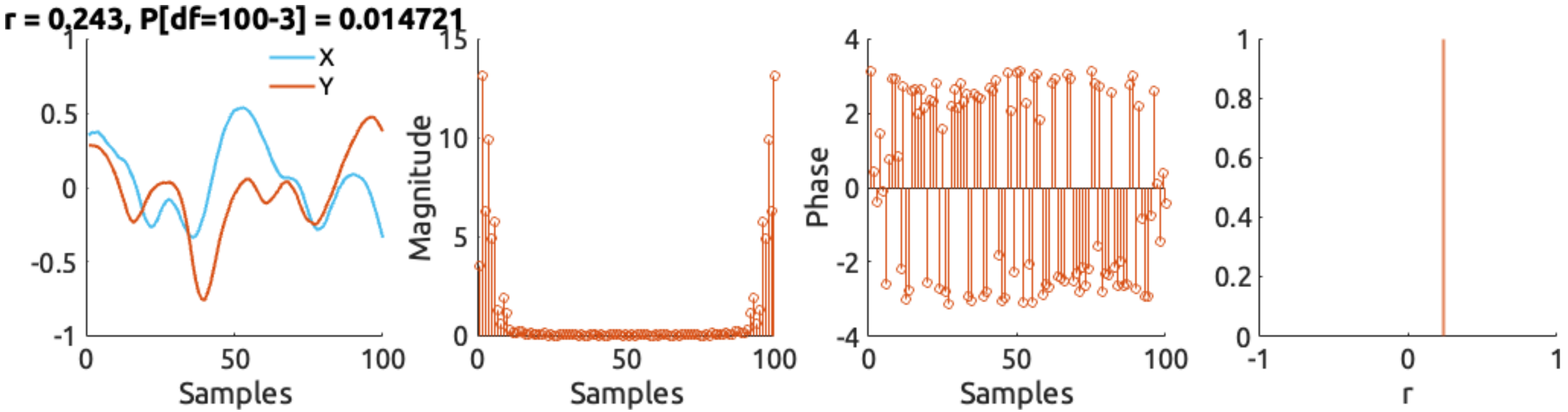


Null distribution from phase randomization



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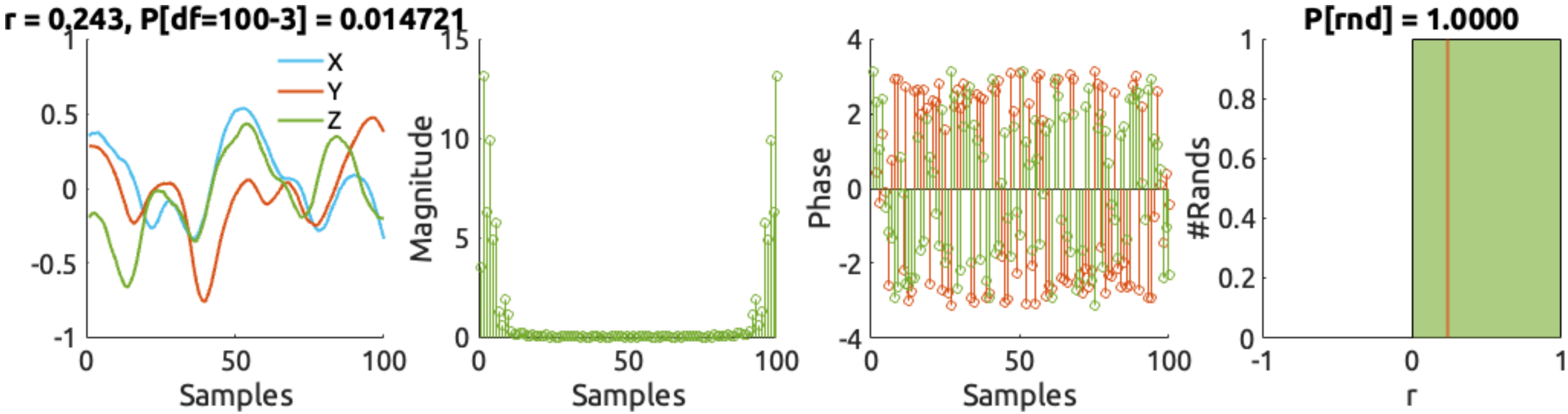

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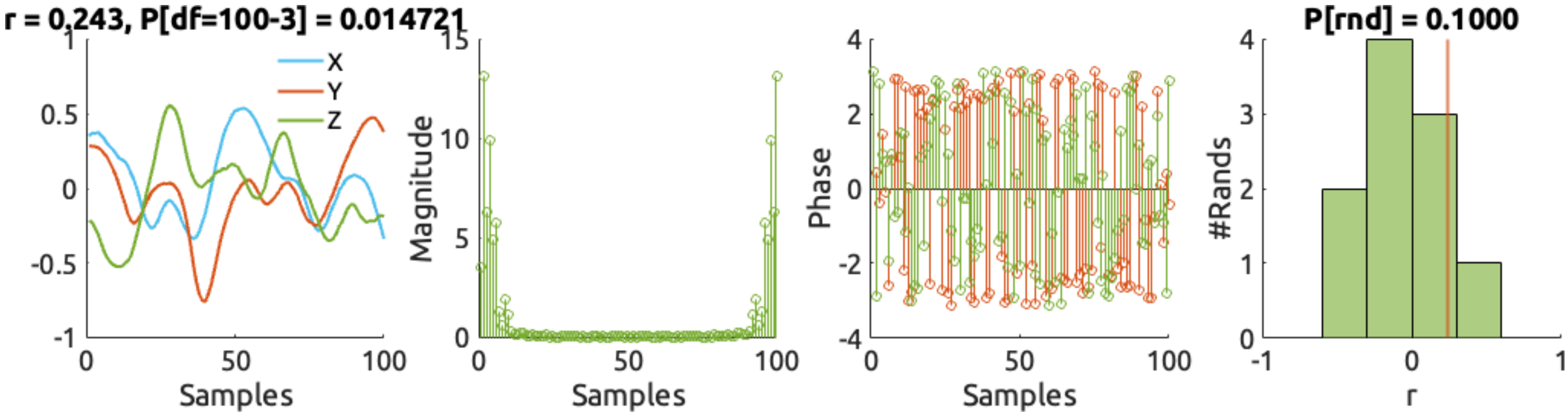

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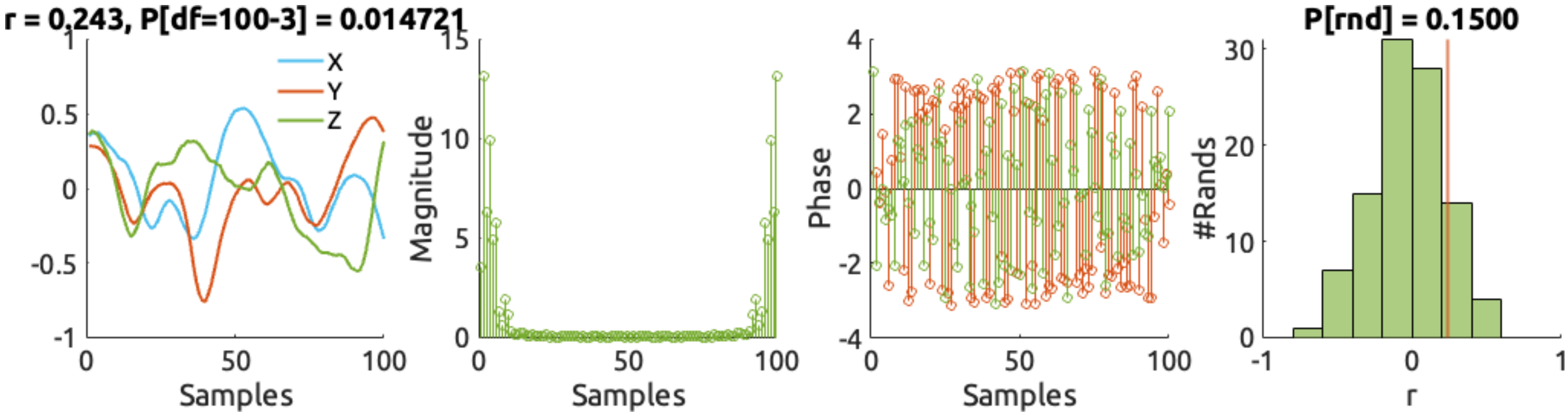

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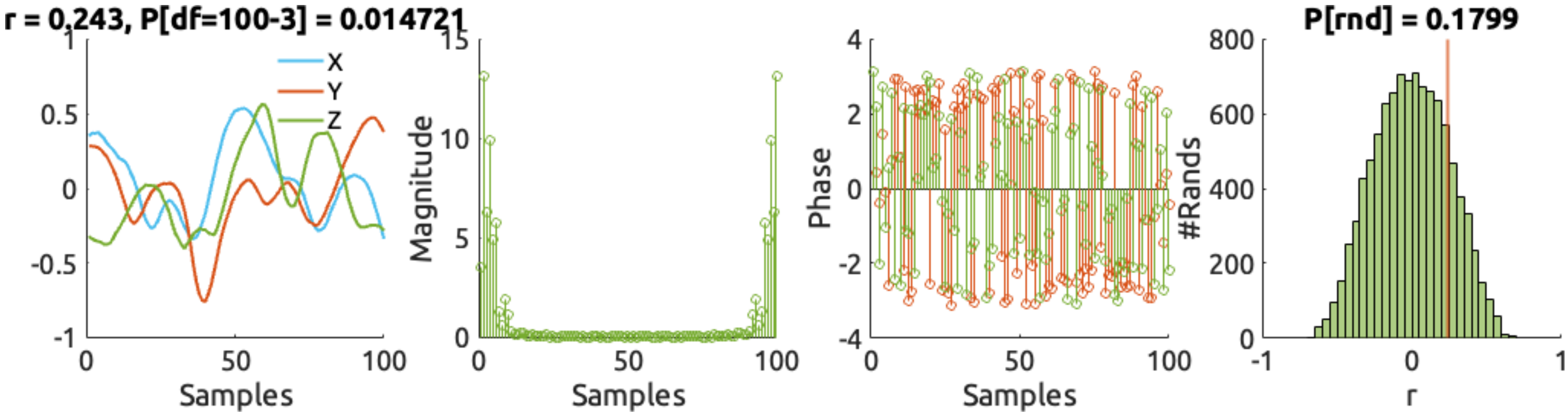

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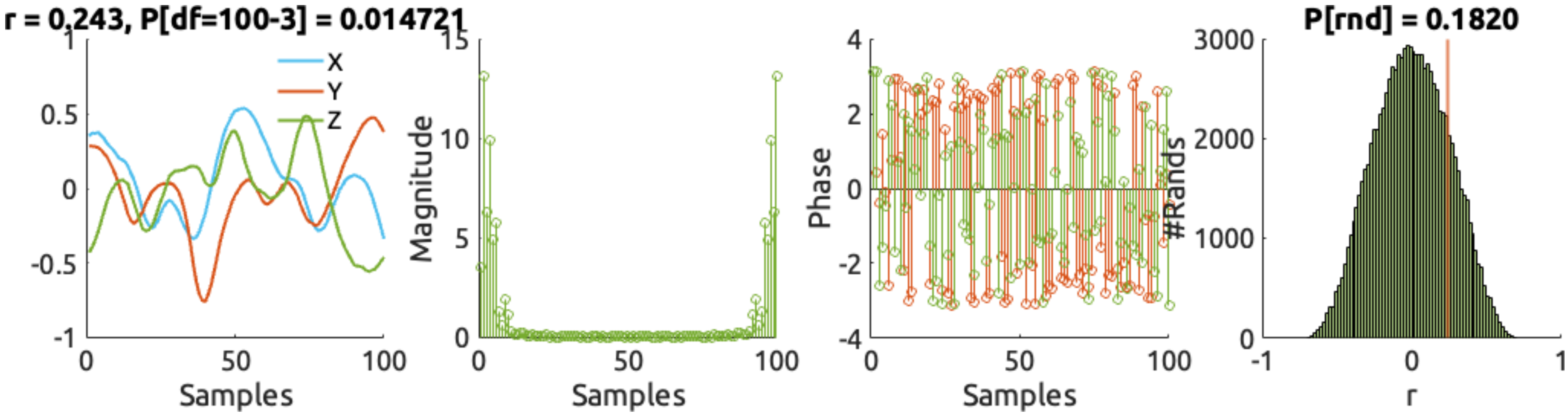

Summary [4/4]: Inference

Randomization test for time series

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Summary [4/4]: Inference

Randomization test for time series

- Some performance metric (r or R^2) may look very high for **smooth time series data** (spurious correlation).
- A parametric P-value (by default) assumes that the time series is not a time series but an independent series, which is often not true.
- **Generating null (surrogate) data** allows for approximating arbitrary noise distribution. Thus we can compute a more accurate P-value.

Summary: Methods

Linearized encoding analysis

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- (**Feature construction**: theoretical "representation" of stimuli)

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Linearized encoding analysis

- (**Feature construction**: theoretical "representation" of stimuli)
- **Delay modeling**: finite impulse response modeling
- **Regularized estimation**: ridge regression
- **Optimization & Evaluation**: nested cross-validation
- **Statistical inference**: non-parametric inference using null data generation

Any questions so far?

(Or I'll ask one 😈)

Go back to SESSION PLAN

Hands-on -1: MATLAB ONLINE

How to accept the SHARE INVITATION?

Hands-on -1: MATLAB ONLINE

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1. log in to HTTPS://MATLAB.MATHWORKS.COM

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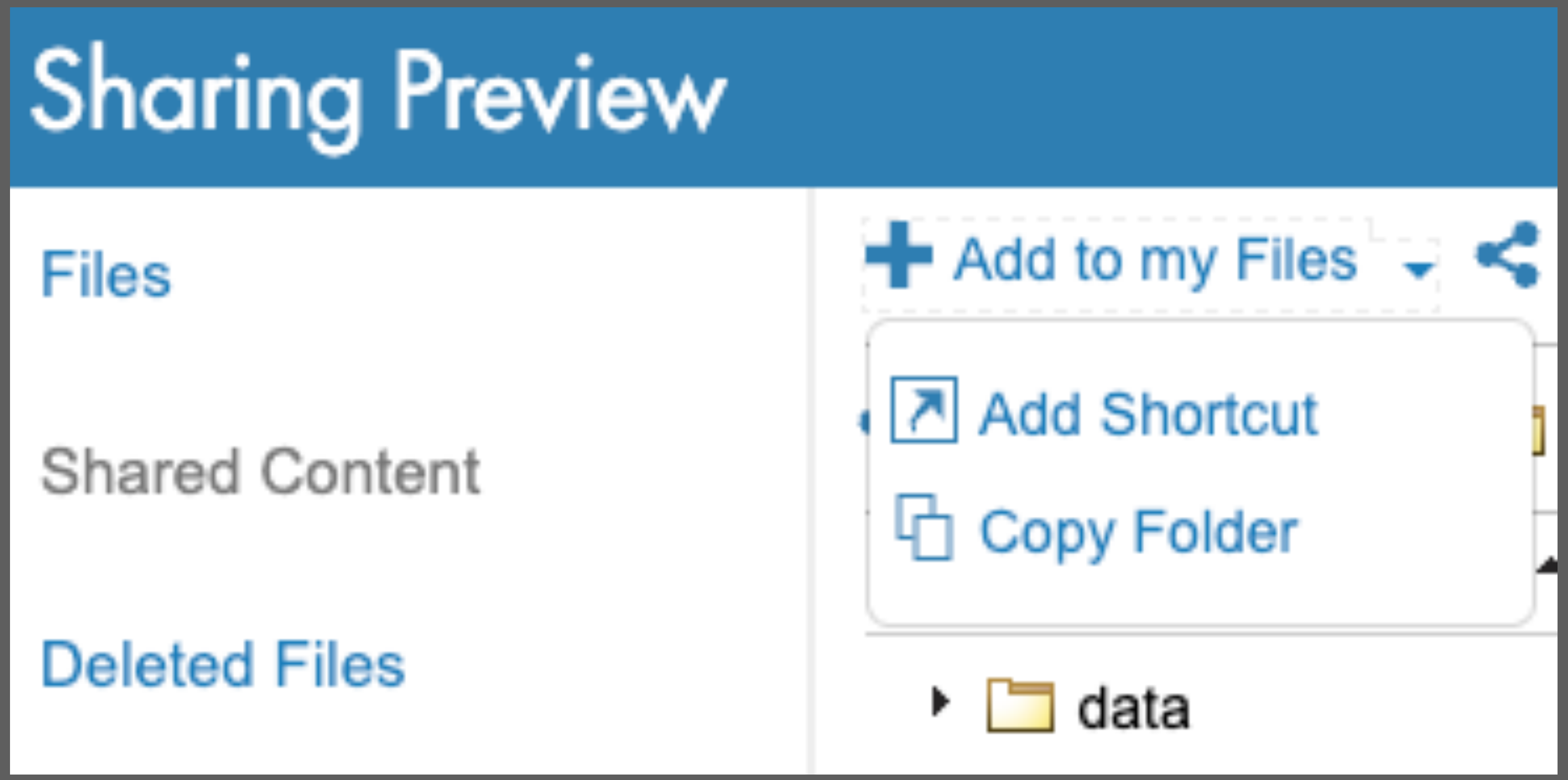
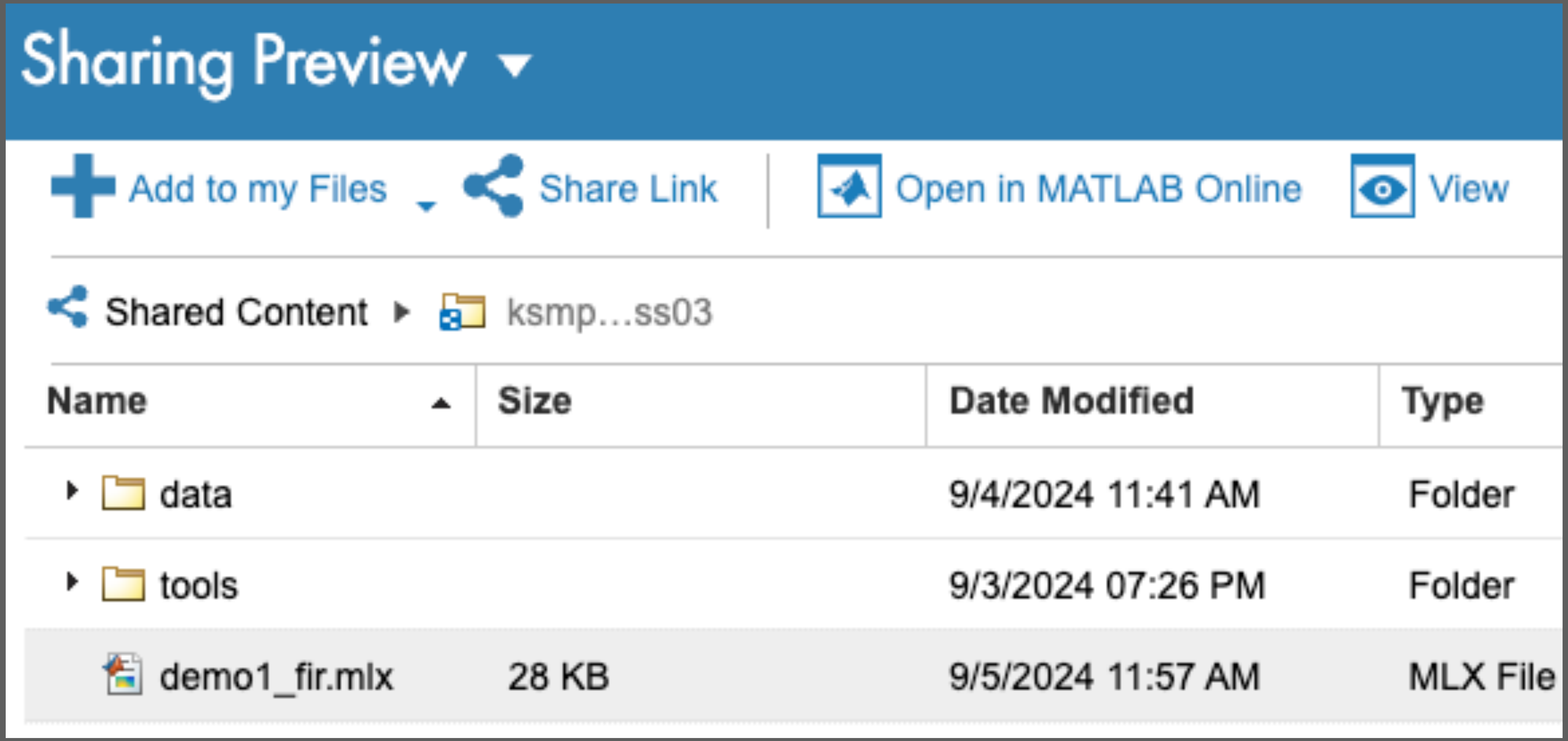
3. Clink on "Add to my Files" and "Copy Folder"



Hands-on -1: MATLAB ONLINE

How to open a MLX (matlab live script) file?

- From your MATLAB Drive, select a file to open (highlighted) and click on Open in MATLAB Online



https://drive.mathworks.com/sharing/6852c95a-b53f-4be0-bbe5-b6e4f7f8c6ae/

Hands-on 0:
🚀 Launch MATLAB Online

`todo0_matlab.mlx`

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Hands-on 1: 🧸 Toy Example

`todo1_toy.mlx`

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Hands-on 2:
🌟 Real data analysis

todo2_real.mlx

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Summary of the session

Music and the Brain 🎶🧠

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- **Predictive modeling** is used to verify **encoded information** in the response.
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Music and the Brain 🎶🧠

- Behavioral/physiological responses to **naturalistic music** can be analyzed using computational models of music information.
- **Predictive modeling** is used to verify **encoded information** in the response.
- **Data leakage** and/or **over-optimization** may lead to circular reasoning fallacy (forward and reverse double-dipping).
- Statistical inference must account for **dependency structure** of the data (time series, N-D images, ...)

Resources

https://github.com/seunggookim/ksmpc-ss24-sess3

https://seunggookim.github.io/

Time for more questions! 🤓

Go back to SESSION PLAN

Thank you for your attention! 😎