

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	<u>Introduction: Naturalistic Stimuli for Music Research</u>	30m
15:55	16:10	<u>Motivations (WHYs)</u>	15m
16:10	16:15	Short break	5m
16:15	16:55	<u>Methods (HOWs)</u>	40m
16:55	17:05	Long break	10m
17:05	18:15	<u>Hands-on (MATLAB Online)</u>	1h 10m
		SUM	3h



🤔: 이 사람은 누구지?

Seung-Goo Kim

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



2016, Leipzig



2019, Jeju



Song
Instrument
Order
Pattern

Armani Showers
01: (C) Edge / EMF 1994
000/010
00

Row 00

Channel 01

File
Chord
C. Tempo
C. Speed

armani.s3m (S3M)
none
7D
06

Baseoctave | 3

ESC Main Menu
F10 Quick-Help
CTRL-Q Quit to DOS

F1 . F4 . . . Edit Screen
CTRL-L . . . Load Module
F5/F8 . . . Play / Stop

FreeMem: 281K
FreeEMS: 31280K
FreeGUS: 1018K

Pattern Editor (F2)

01: L1

02: R1

03: L2

04: R2

05: L3

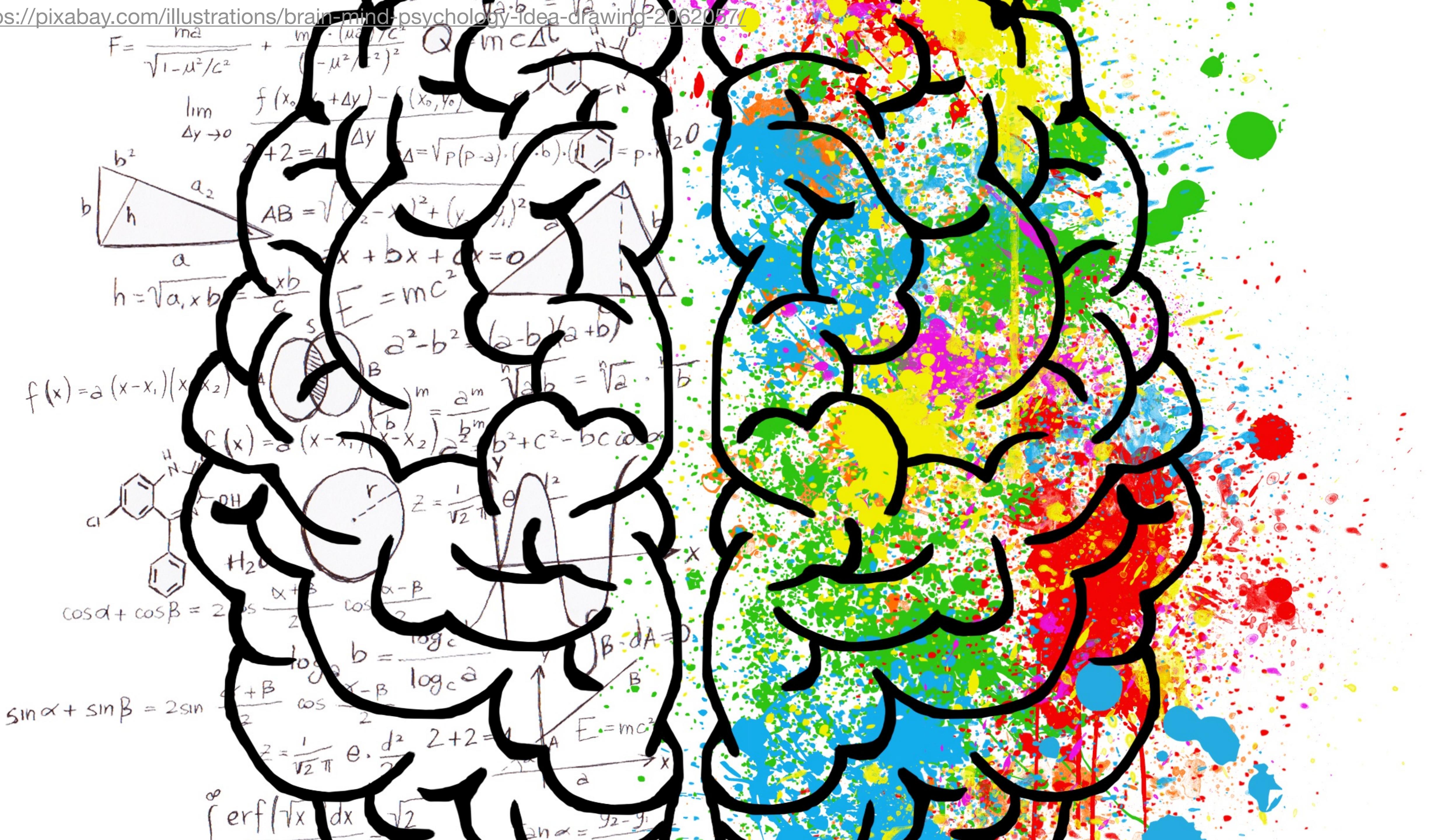
00	E-3	01	01	S85
01	A-3		01	GAF
02	B-3		02	G00
03	E-3		02	G00
04	B-3		03	G00
05	C-4		03	G00
06	E-3		04	G00
07	D-4		05	G00
08	E-3		05	G00
09	A-3		06	G00
10	B-3		06	G00
11	E-3		07	G00
12	B-3		07	G00
13	C-4		08	G00
14	E-3		09	G00
15	E-4		09	G00
16	E-3		10	G00
17	A-3		10	G00
18	B-3		11	G00
19	E-3		11	G00
20	B-3		12	G00
21	C-4		13	G00
22	E-3		13	G00
23	D-4		14	G00
24	E-3		14	G00
25	A-3		15	G00
26	B-3		15	G00
27	E-3		16	G00
28	B-3		17	G00

E-4 01 00 S8F

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02	.	.	.	00
03	.	.	.	00
04	.	.	.	00

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03	B-3			G00
04	E-3			G00
05	D-4			G00
06	E-3			G00
07	A-3			G00
08	B-3			G00
09	E-3			G00
10	D-4			G00
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12	B-3			G00
13	C-4			G00
14	E-3			G00
15	E-4			G00
16	E-3			G00
17	A-3			G00
18	E-4			G00
19	E-3			G00
20	B-3			G00
21	E-3			G00
22	B-3			G00
23	C-4			G00
24	E-3			G00
25	D-4			G00
26	E-3			G00
27	A-3			G00
28	B-3			G00

00	.	00	.	00
01	E-3	01	01	.00
02	A-3			GAF
03	B-3			G00
04	E-3			G00
05	D-4			G00
06	E-3			G00
07	A-3			G00
08	B-3			G00
09	E-3			G00
10	D-4			G00
11	E-3			G00
12	B-3			G00
13	C-4			G00
14	E-3			G00
15	E-4			G00
16	E-3			G00
17	A-3			G00
18	E-4			G00
19	E-3			G00
20	B-3			G00
21	E-3			G00
22	B-3			G00
23	C-4			G00
24	E-3			G00
25	D-4			G00
26	E-3			G00
27	A-3			G00
28	B-3			G00



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!



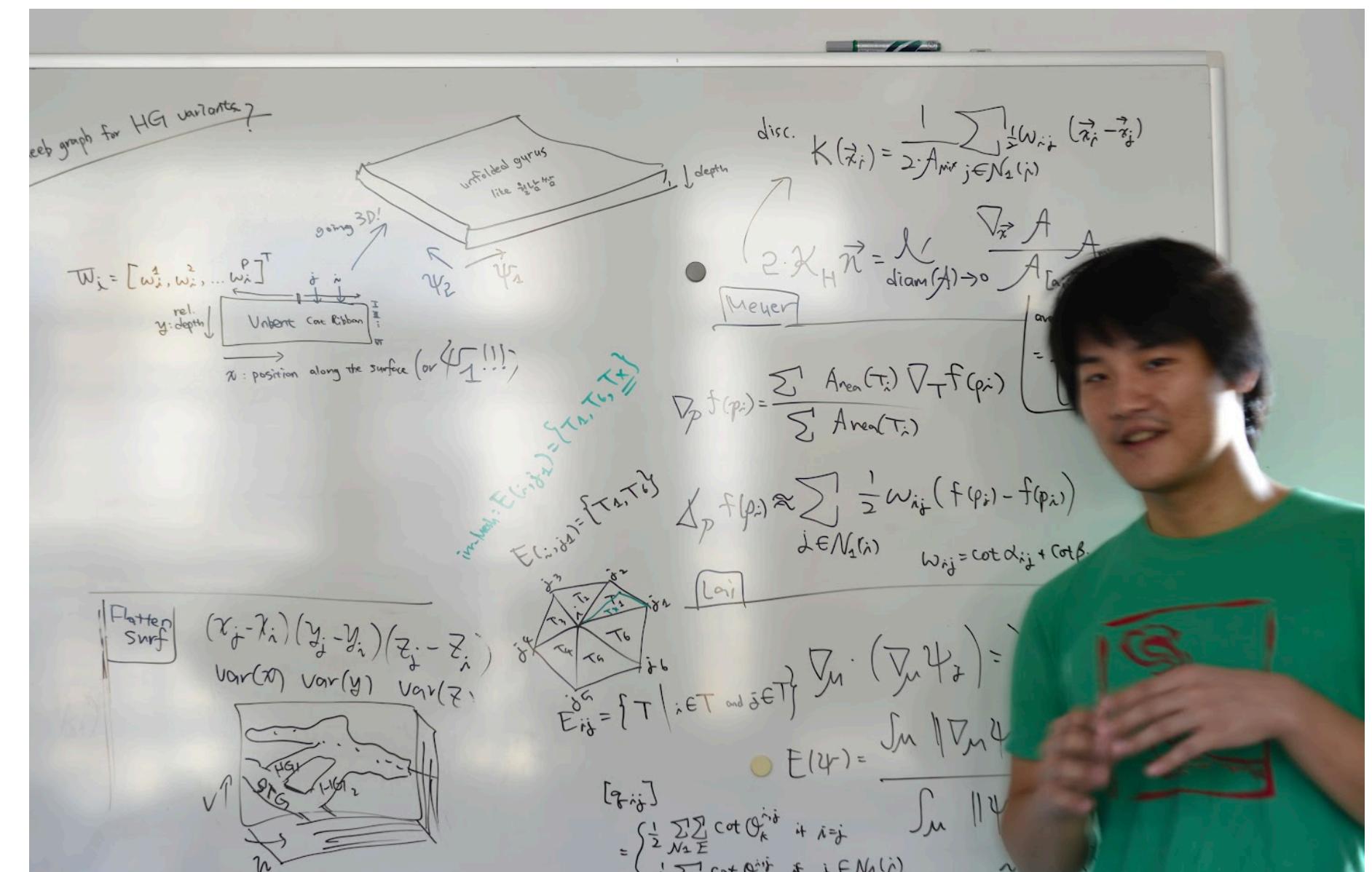
2017, Leipzig



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 [프랑크푸르트, 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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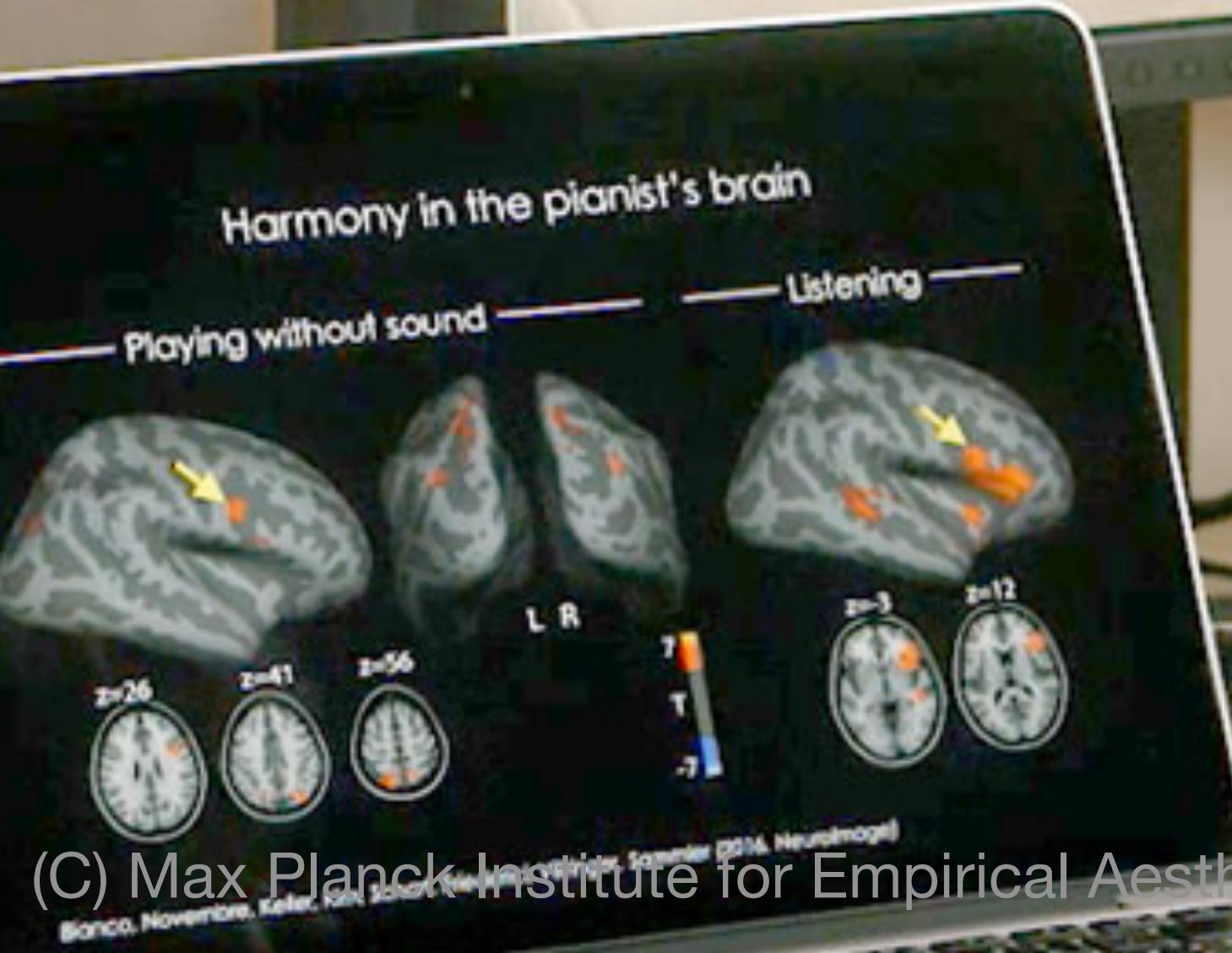
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South Korea)



MAX PLANCK INSTITUTE FOR EMPIRICAL AESTHETICS











Zeit für Musik

Eine Studie über Musik und
das motorische System



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.

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

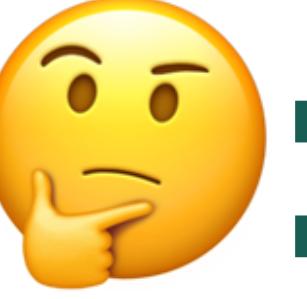
Human Resources
+49 69 8300479-507

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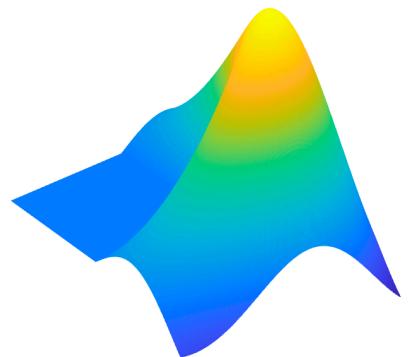
- **Introduction:** Why do we need a predictive analysis for music research?



Overview of the session

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- **Methods:** Linearized encoding analysis = Finite impulse response modeling + Regularization + Cross-validation + Inference

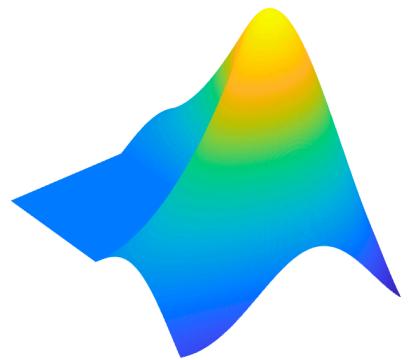




Overview of the session

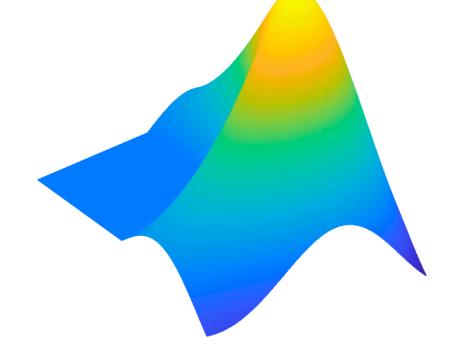
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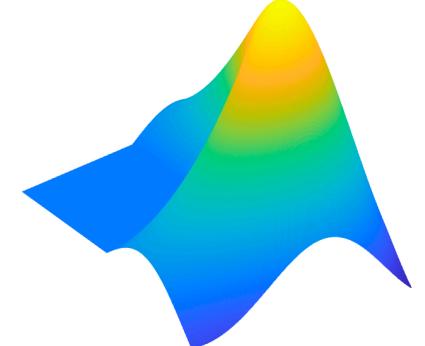
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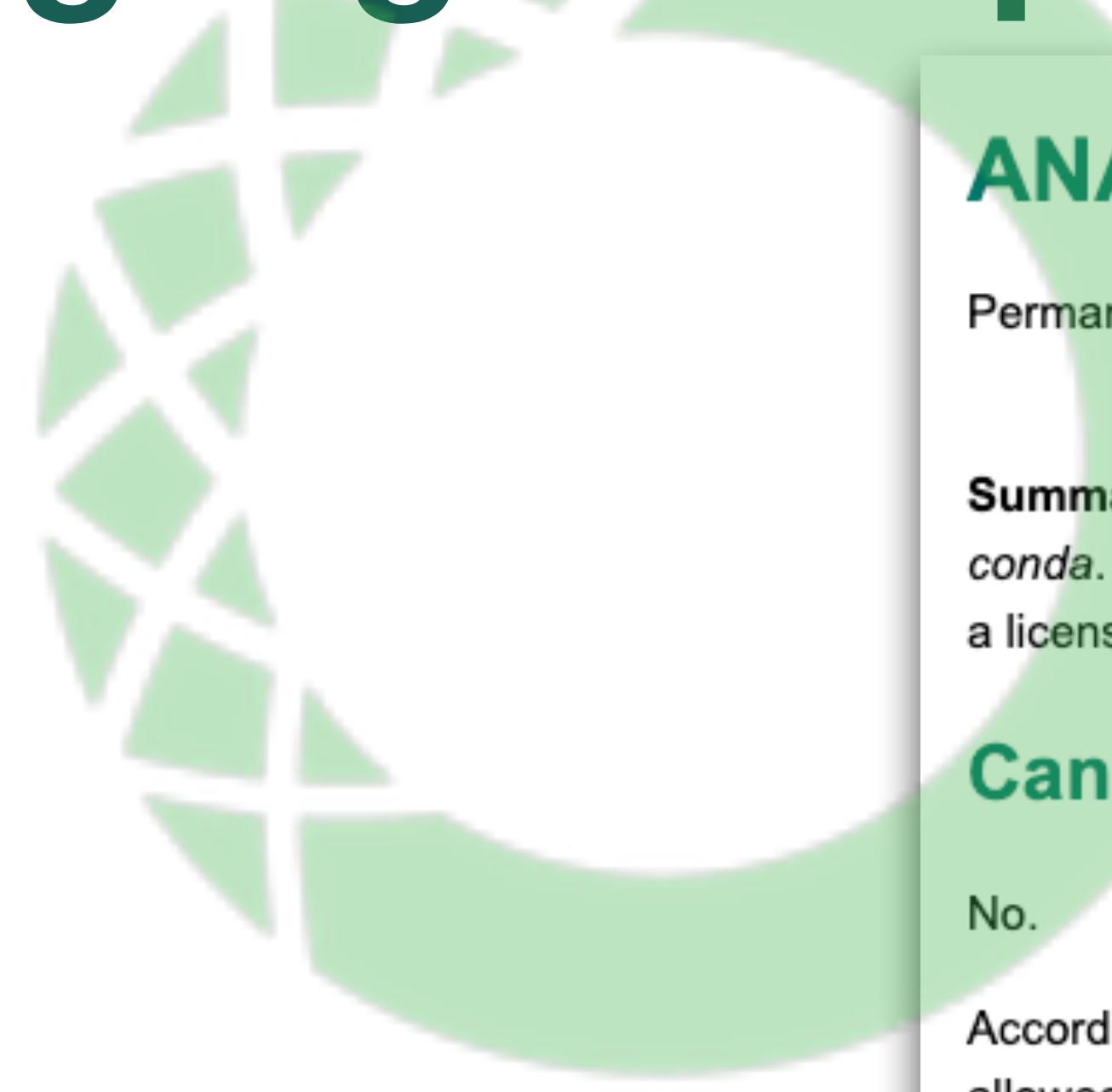
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- 😳: 그런데 왜 슬라이드는 영어고 말은 판교 사투리지? English is currently the lingua franca of science & engineering.

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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: [!\[\]\(77e670be72de63f664b9f3cf25895195_img.jpg\)](#)

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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 - **Cybersocialism:** "Californian Ideology" or the Hacker culture (e.g., GNU manifesto [1983/1985])



Richard Stallman (circa 2002)

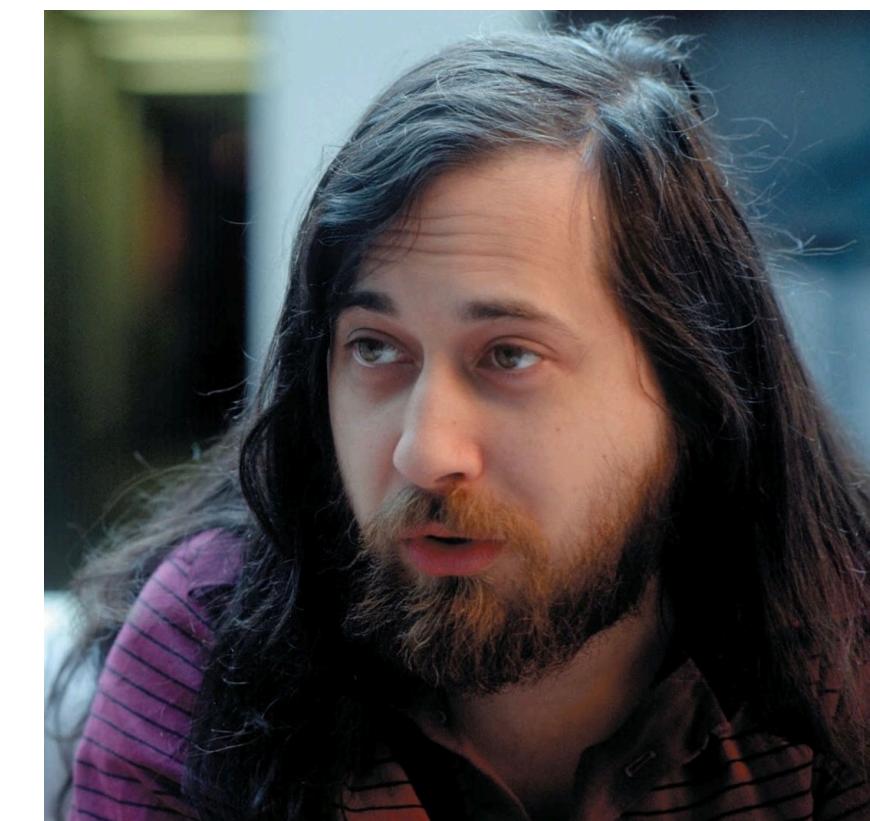


St. IGNUcius, the Church
of EMACS (2012)

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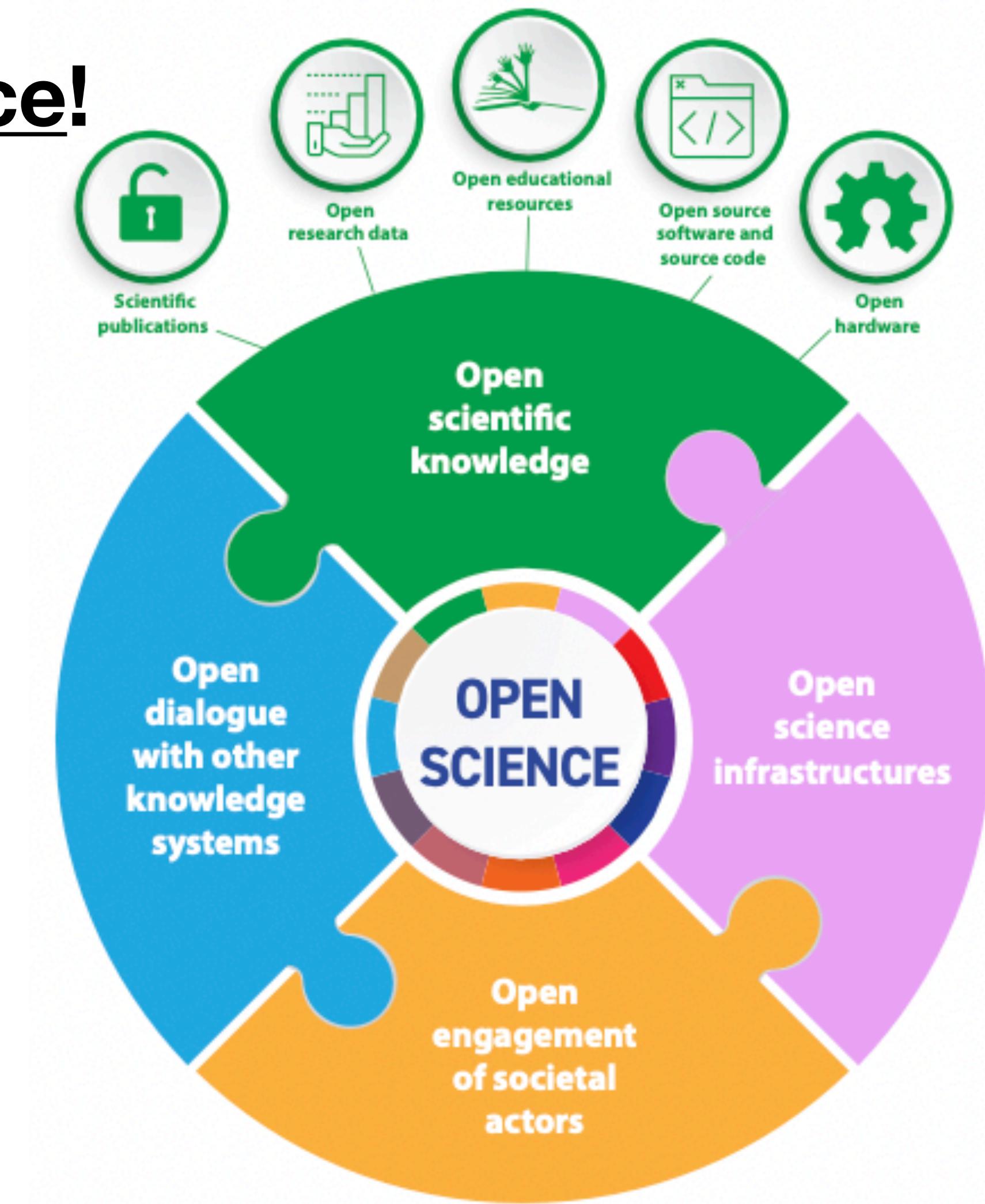
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- **Why?**
 - **Public finance:** (Many) scientists produce knowledge using tax money.
 - **Cybersocialism:** "Californian Ideology" or the Hacker culture (e.g., GNU manifesto [1983/1985])
 - **Reproducibility crisis:** ~40% psychology studies did not replicated (OSC, 2015, *Science*).



Richard Stallman (circa 2002)



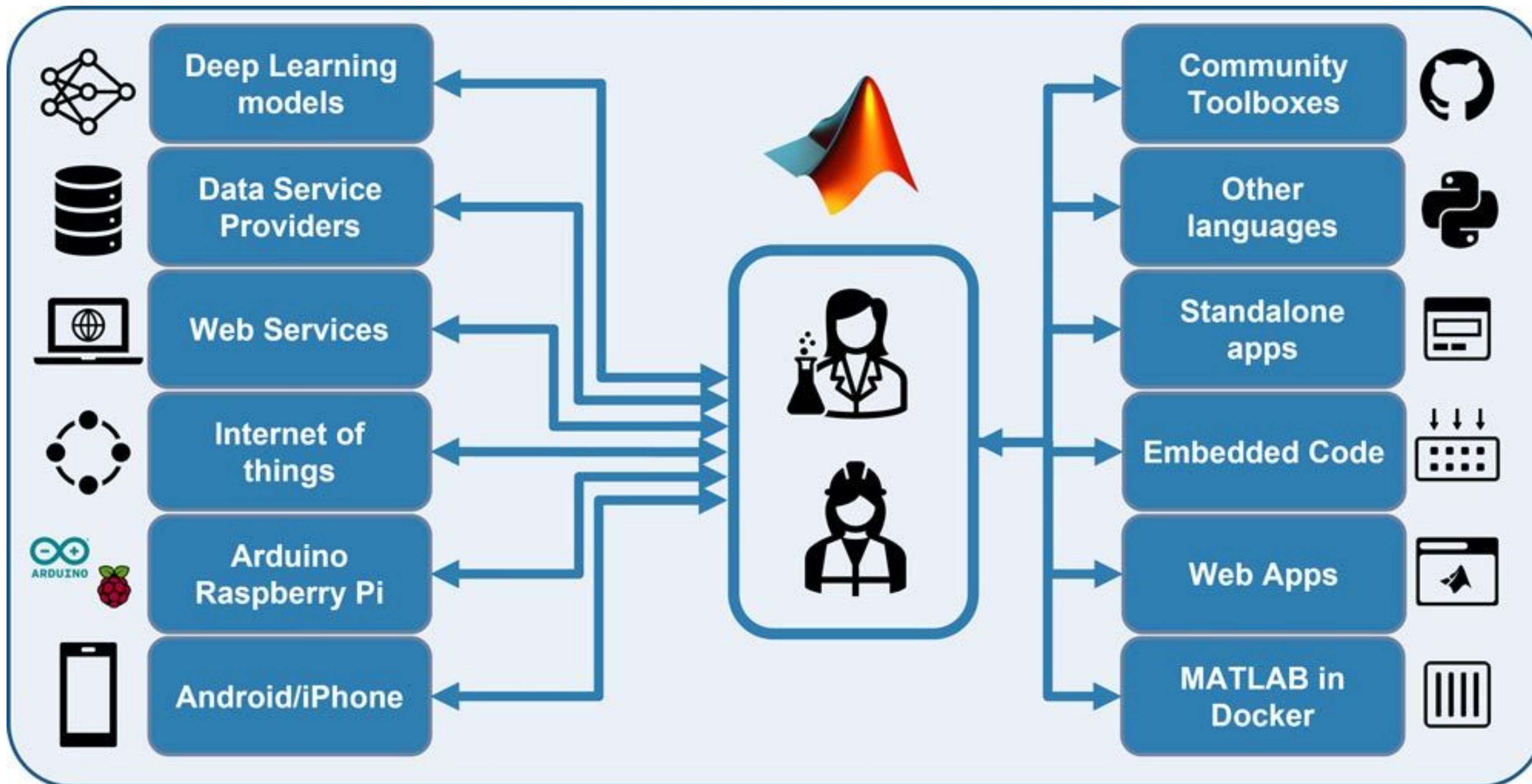
St. IGNUcius, the Church
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UNESCO, 2022, *Recommendation
on Open Science*.

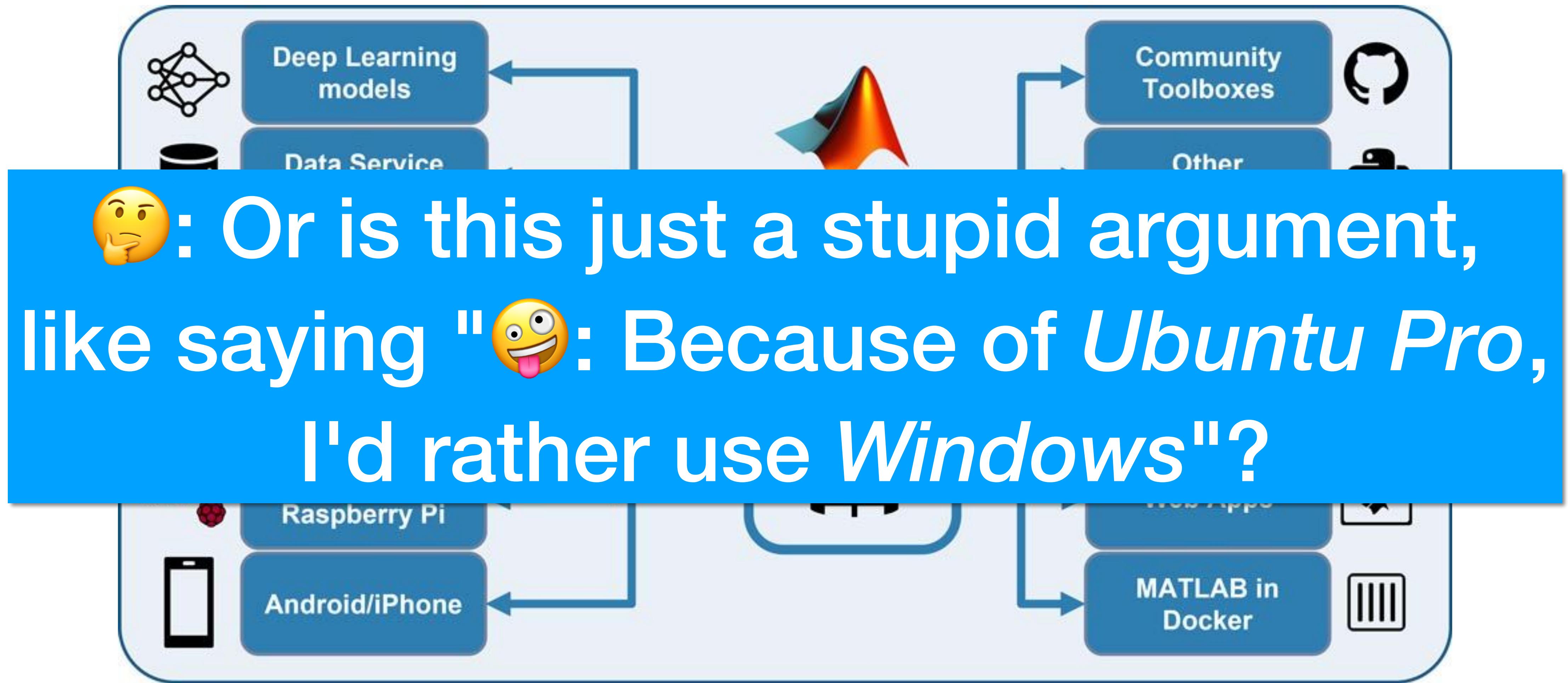
MATLAB for Open Science?

At least they know it sells for now...



MATLAB for Open Science?

At least they know it sells for now...



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

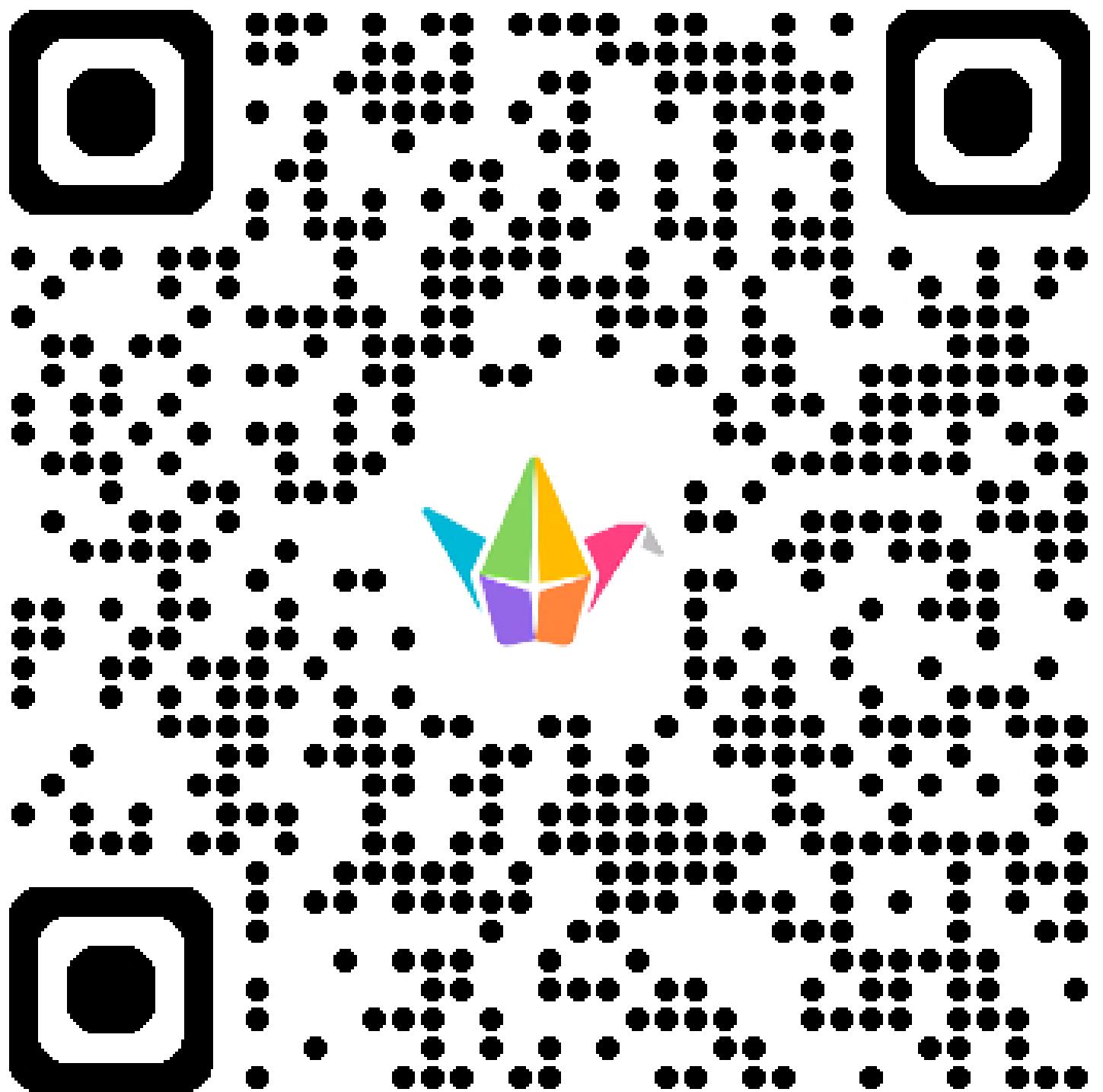
"Don't be evil" my a\$\$...

- 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 you are the product.*" (Tristan Harris)



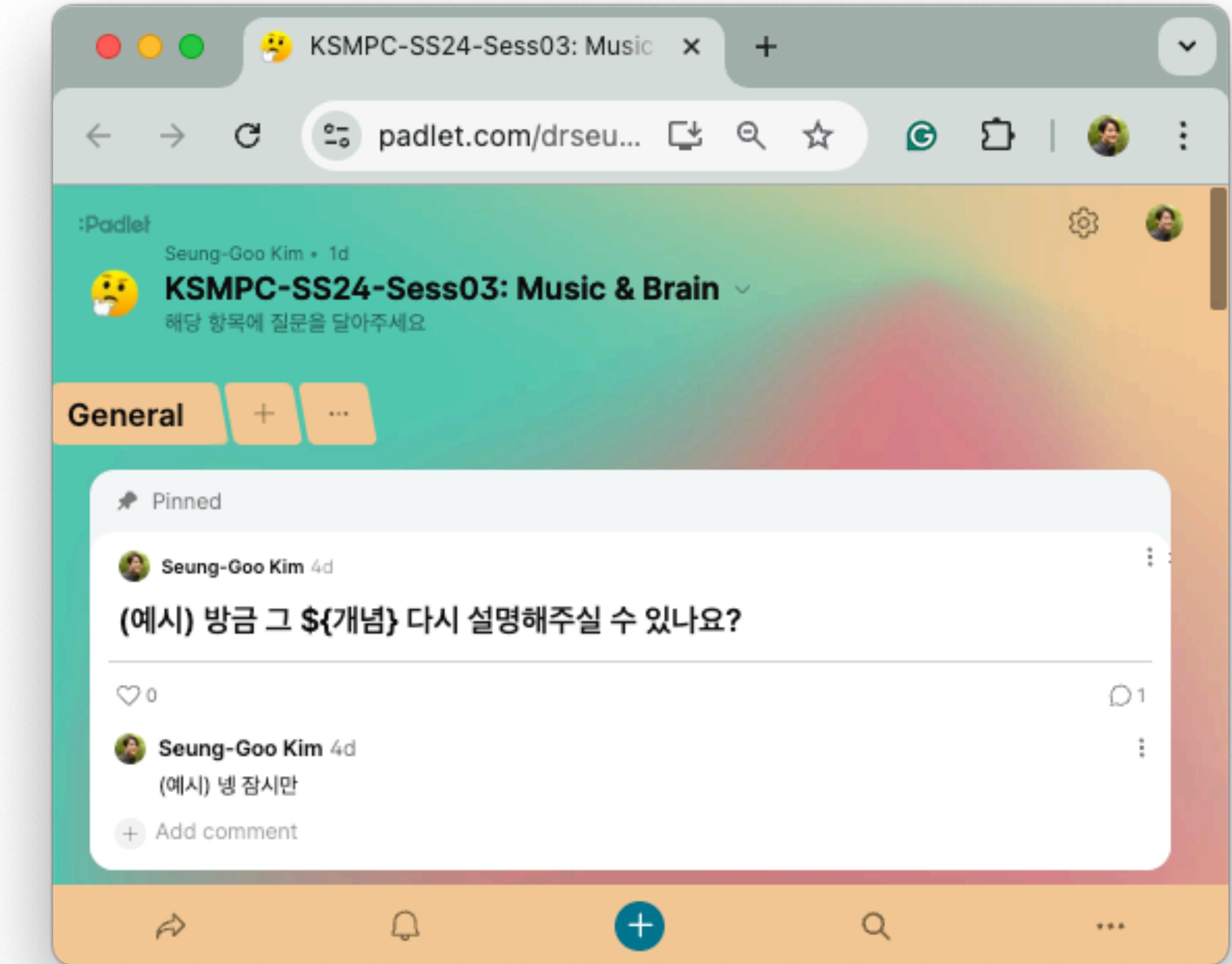
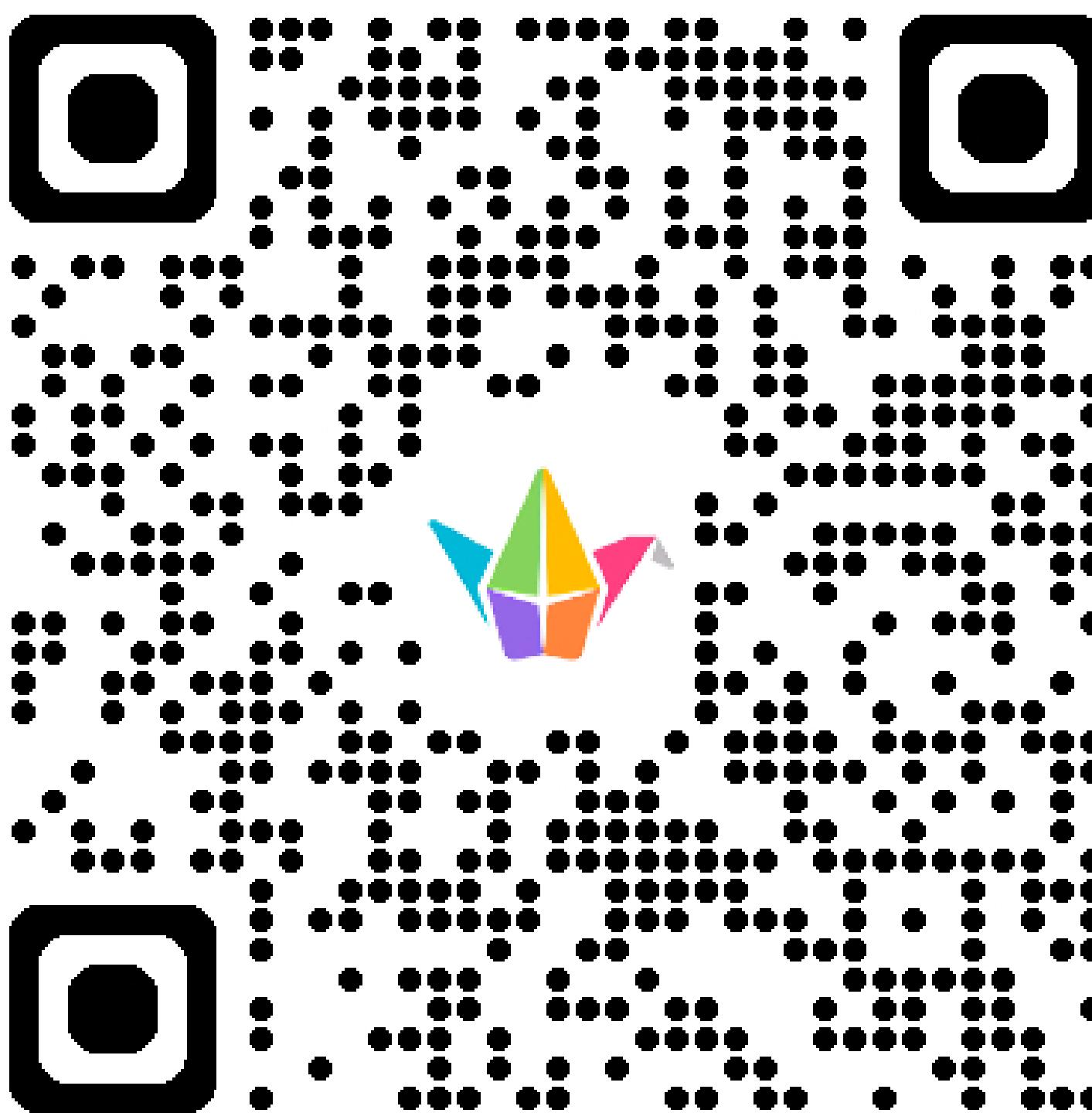
How to communicate

Use Padlet board!



How to communicate

Use Padlet board!



KSMPC-SS24-Sess03: Music & Brain

Seung-Goo Kim • 1d

KSMPC-SS24-Sess03: Music & Brain

해당 항목에 질문을 달아주세요

General

Pinned

Seung-Goo Kim 4d

(예시) 방금 그 \${개념} 다시 설명해주실 수 있나요?

Seung-Goo Kim 4d

(예시) 네! 잠시만

Add comment

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"?



How does music evoke emotions *via* the brain?

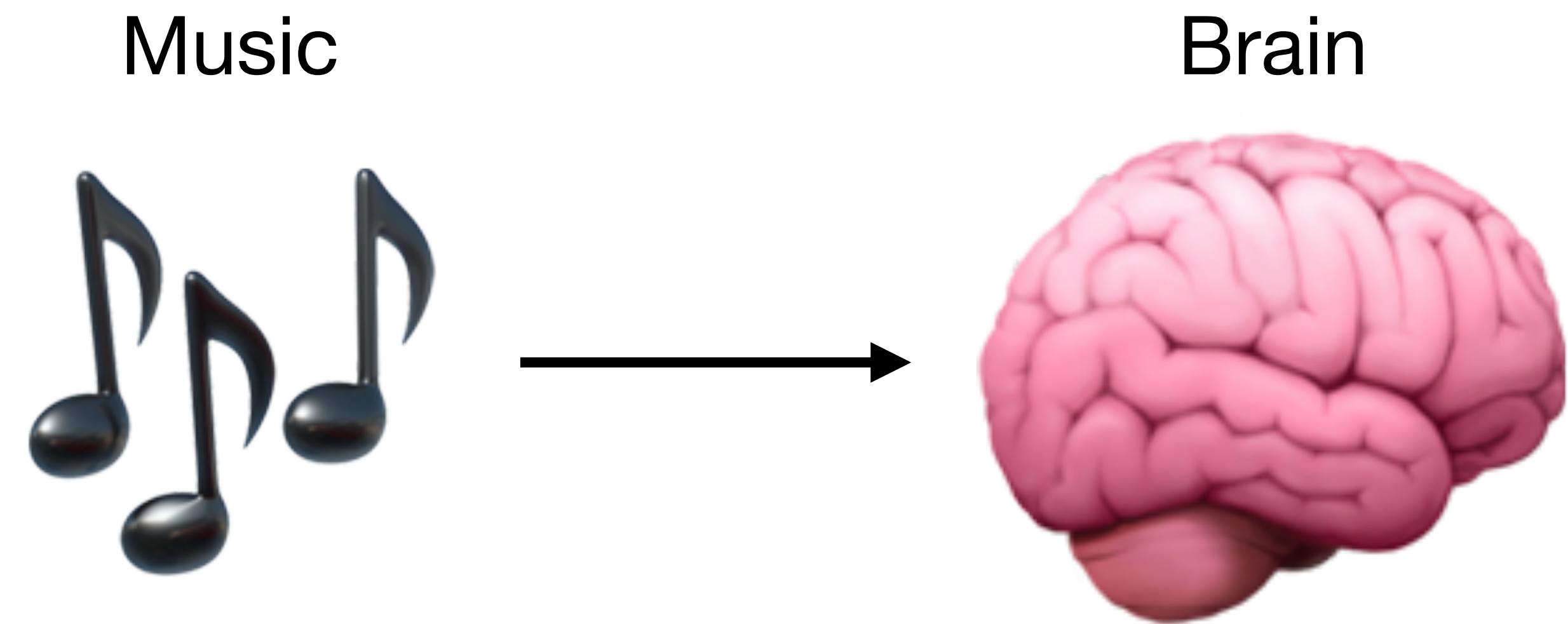
Neuroscientific view

Music



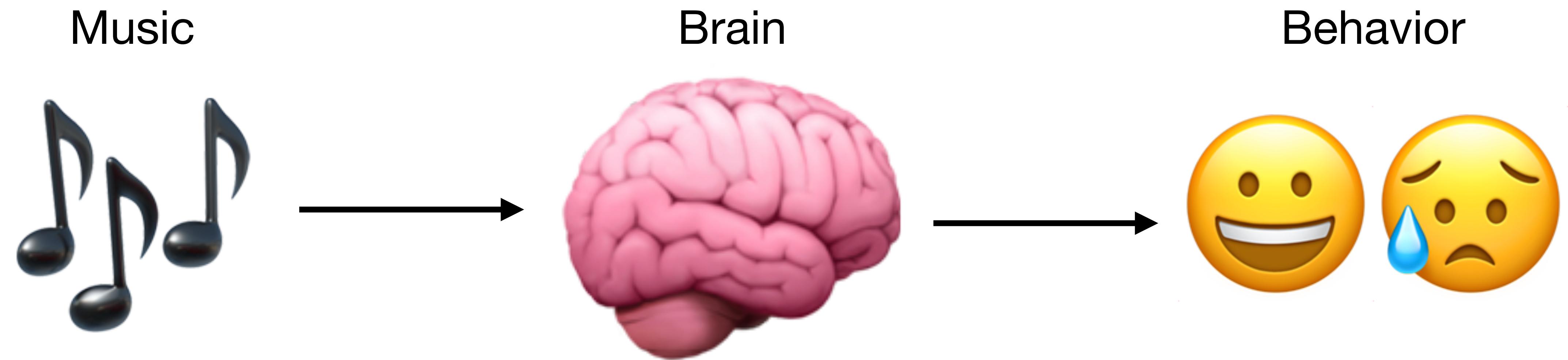
How does music evoke emotions *via* the brain?

Neuroscientific view

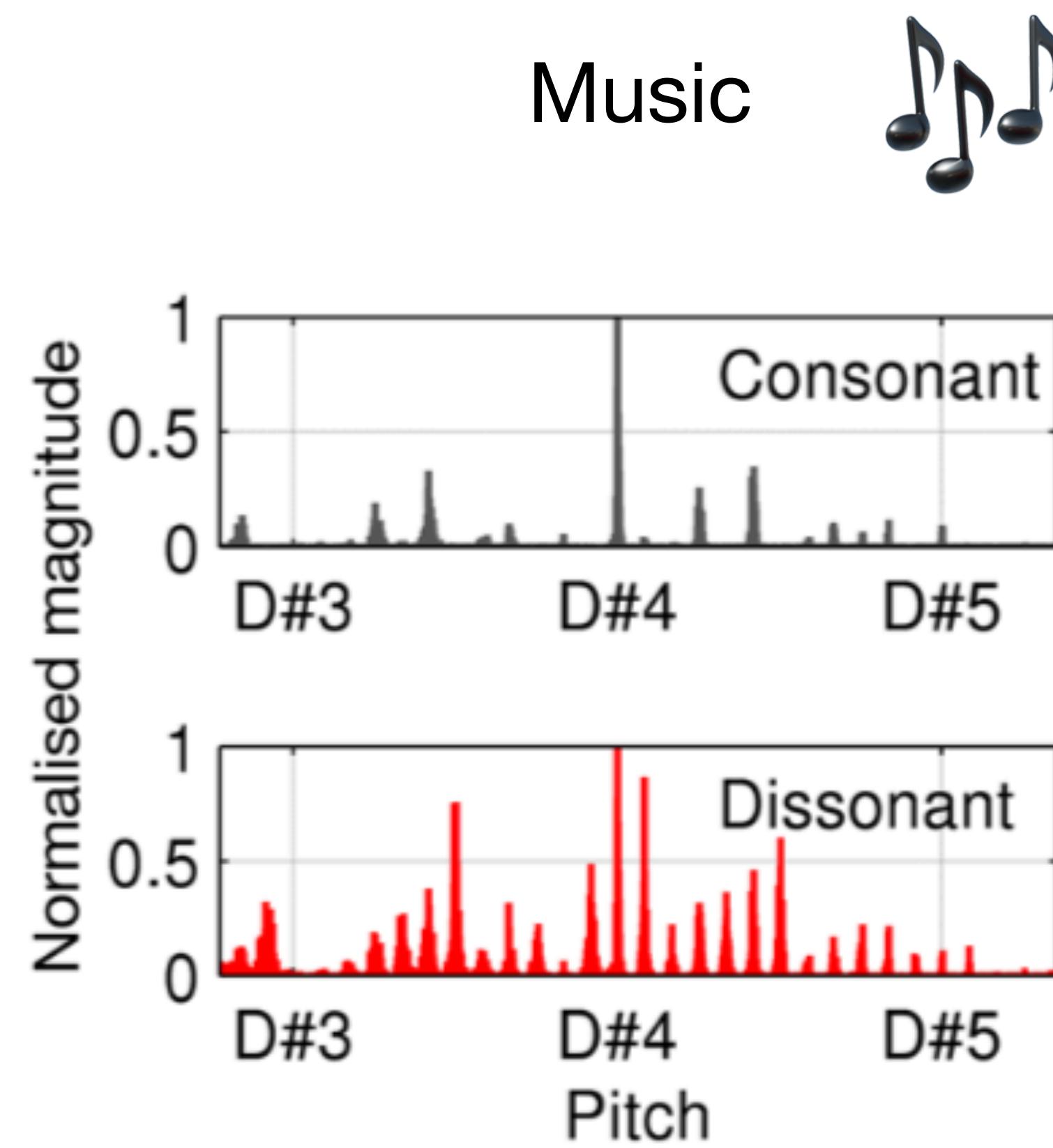


How does music evoke emotions *via* the brain?

Neuroscientific view

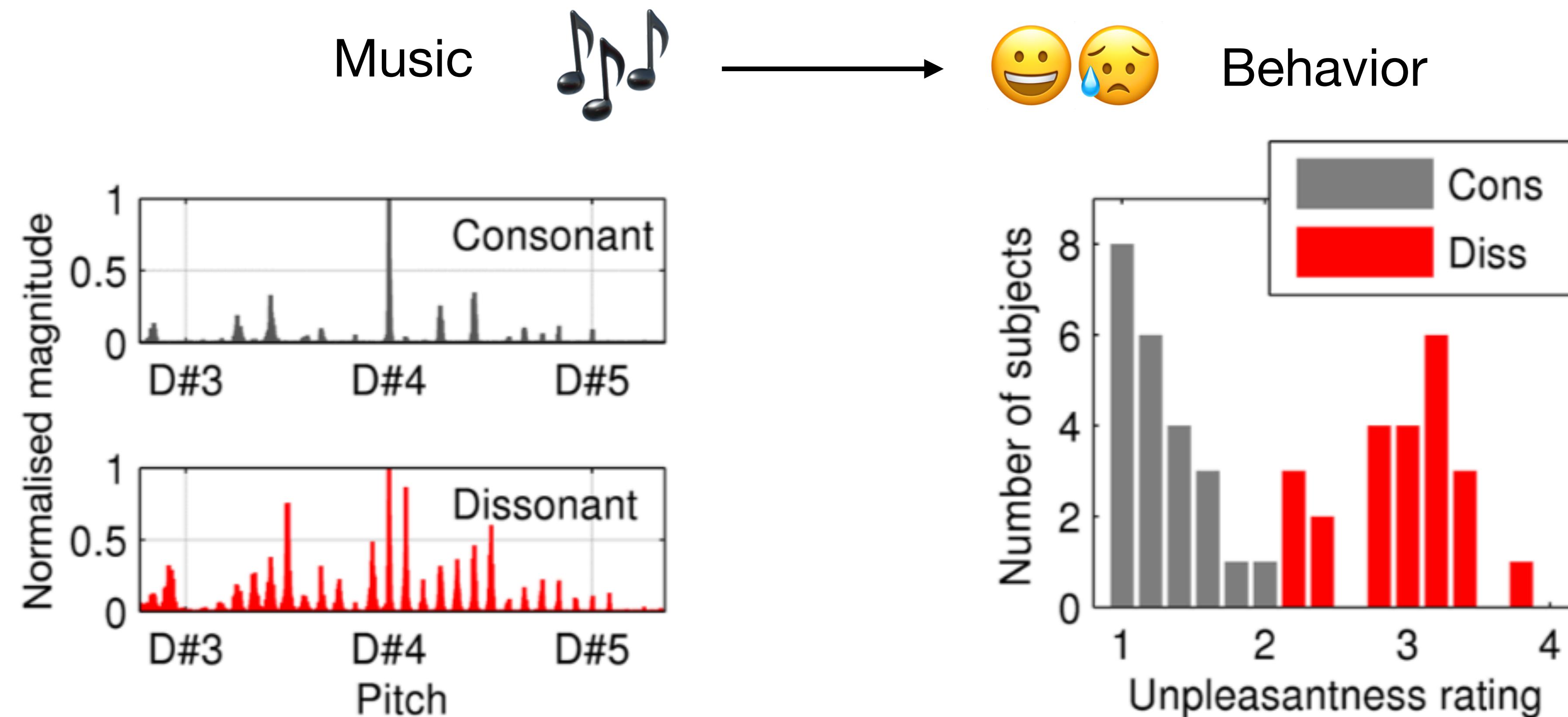


Traditional approach: music vs. "non-music"



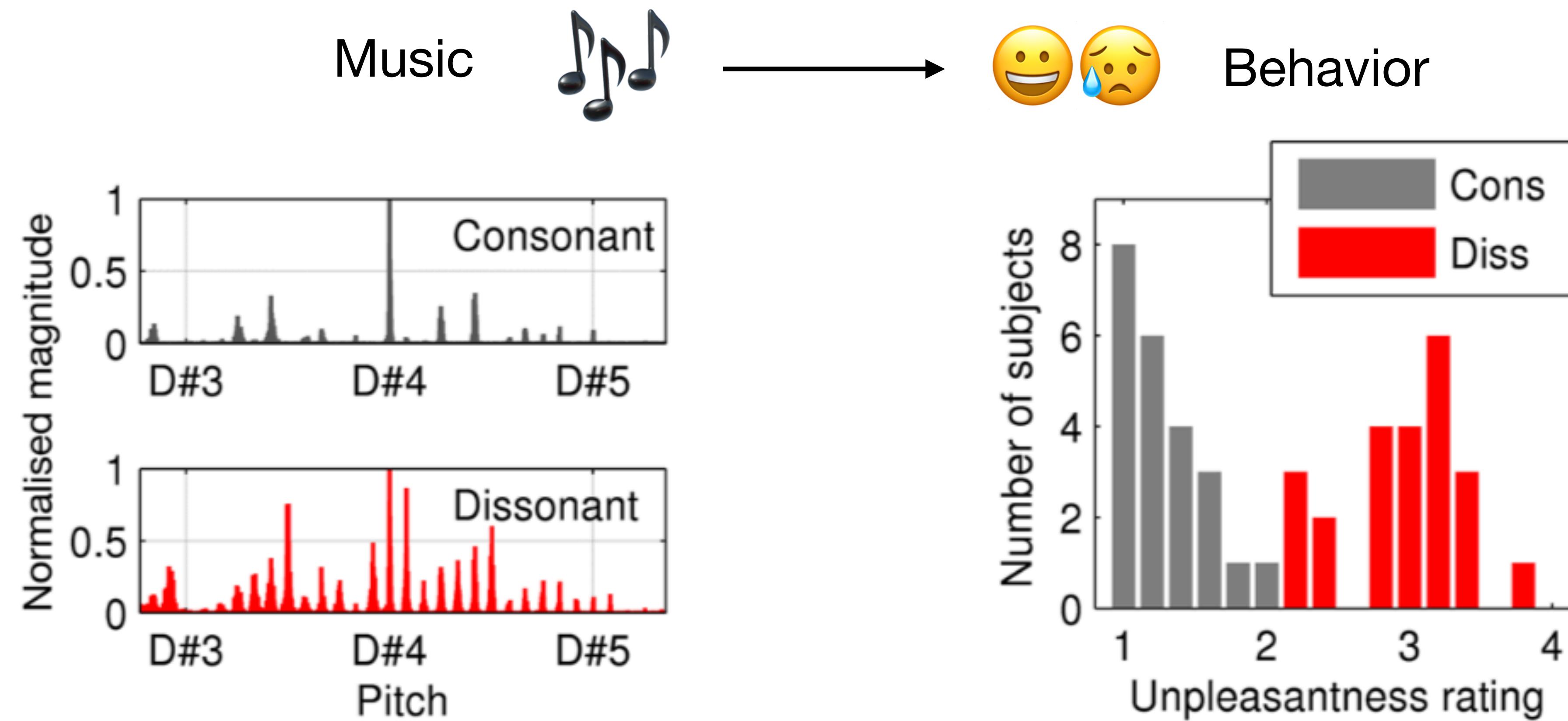
stimuli per condition = 20, stimulus duration = 30 s, # subjects = 23 (25.9 yo; 13 F)

Traditional approach: music vs. "non-music"



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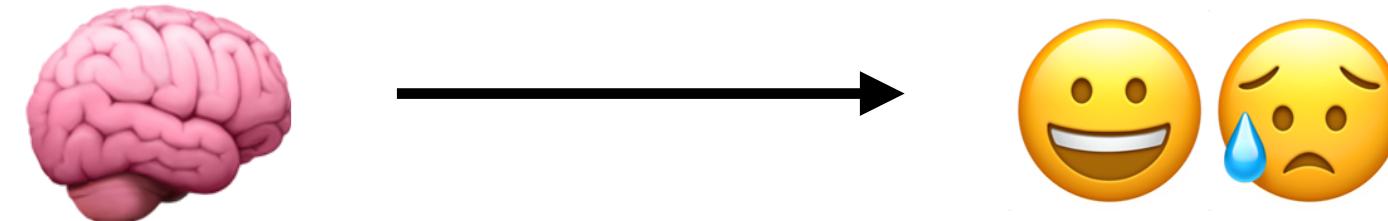
Traditional approach: music vs. "non-music"



"Dissonant" stimuli were rated more unpleasant.

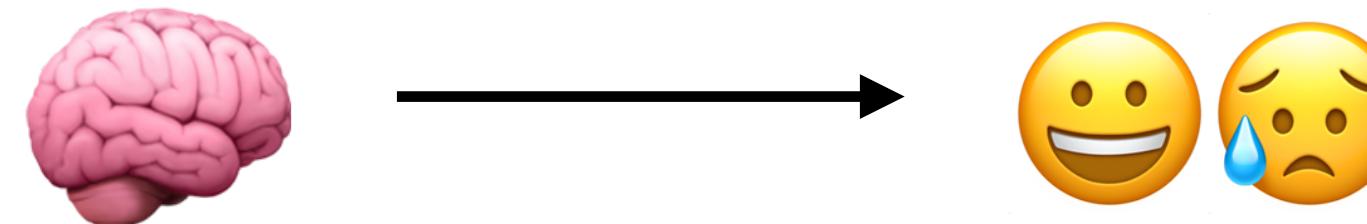
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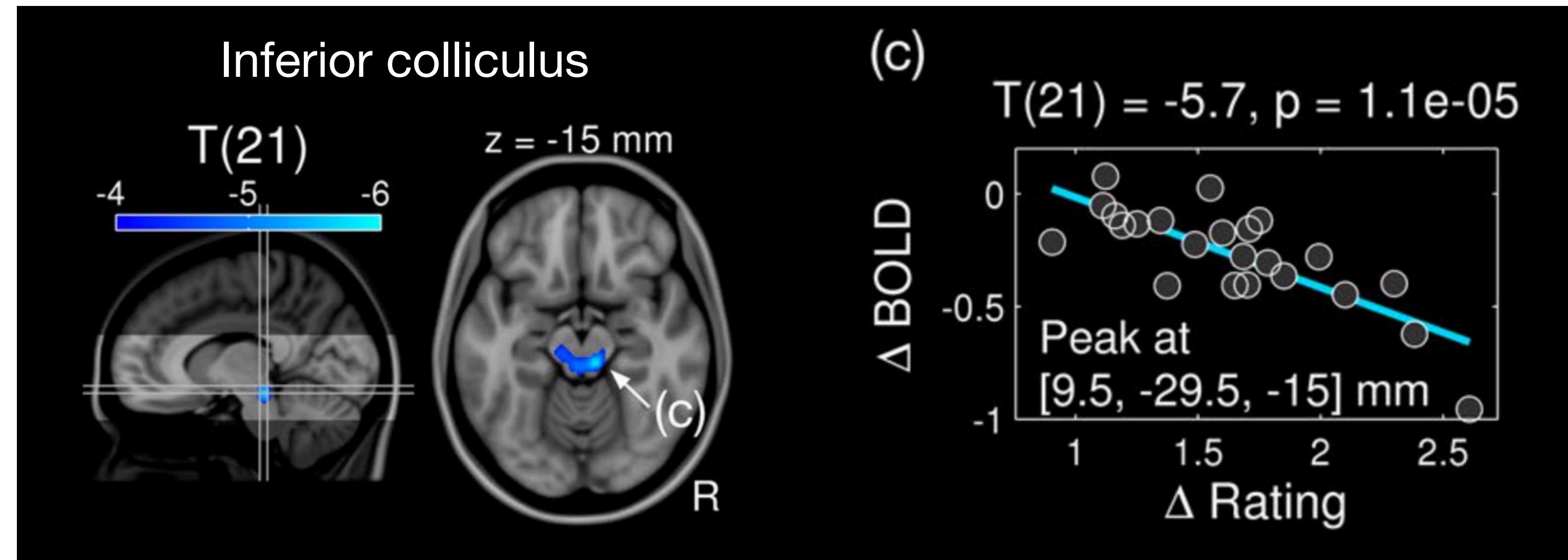


$$\Delta BOLD = \beta_0 + \beta_1 \Delta Rating + error$$

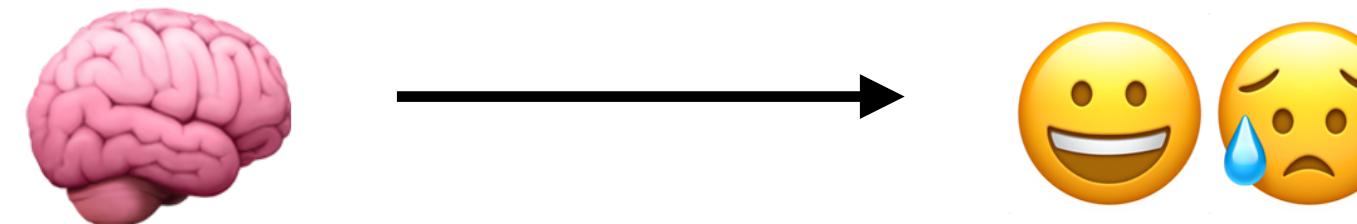
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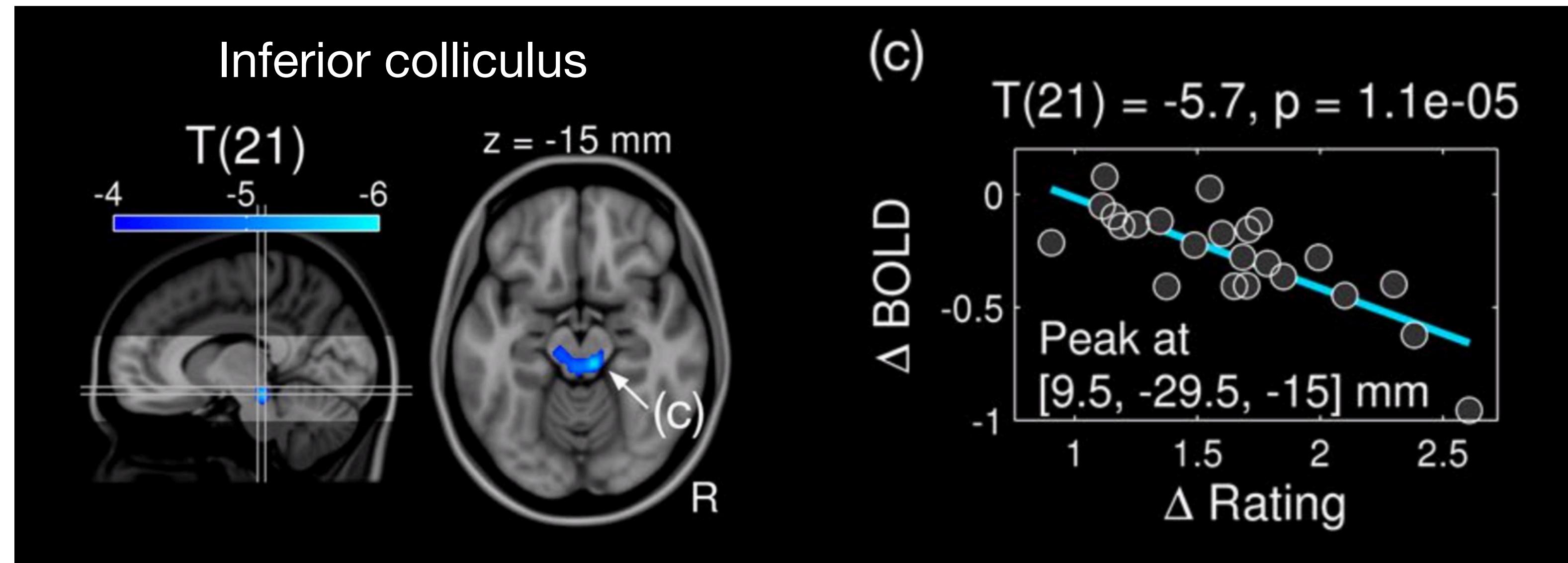
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Traditional approach: music vs. "non-music"



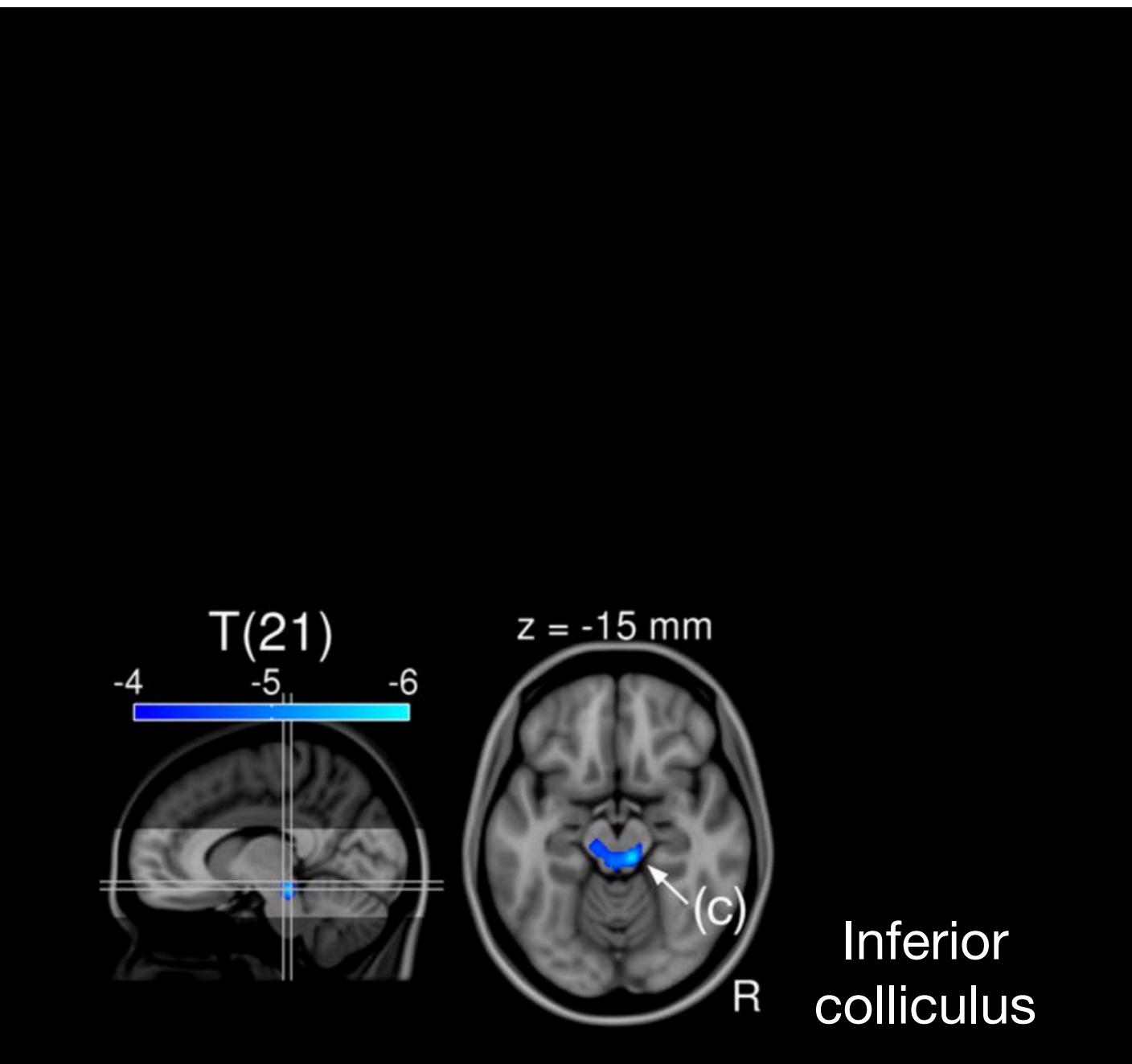
$$\Delta BOLD = \beta_0 + \beta_1 \Delta Rating + error$$



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

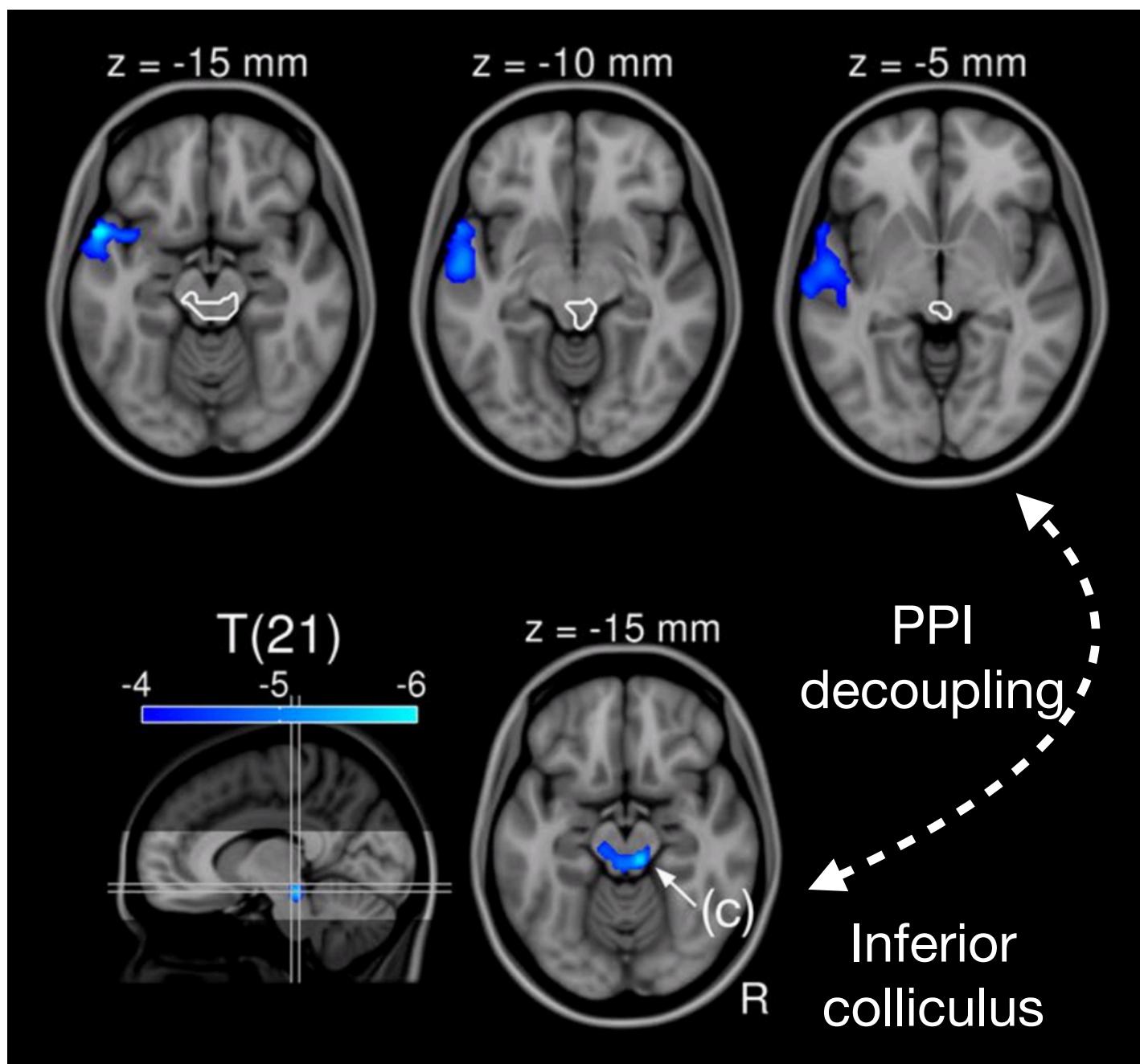
Traditional approach: music vs. "non-music"

Psycho-Physiological Interaction (PPI)



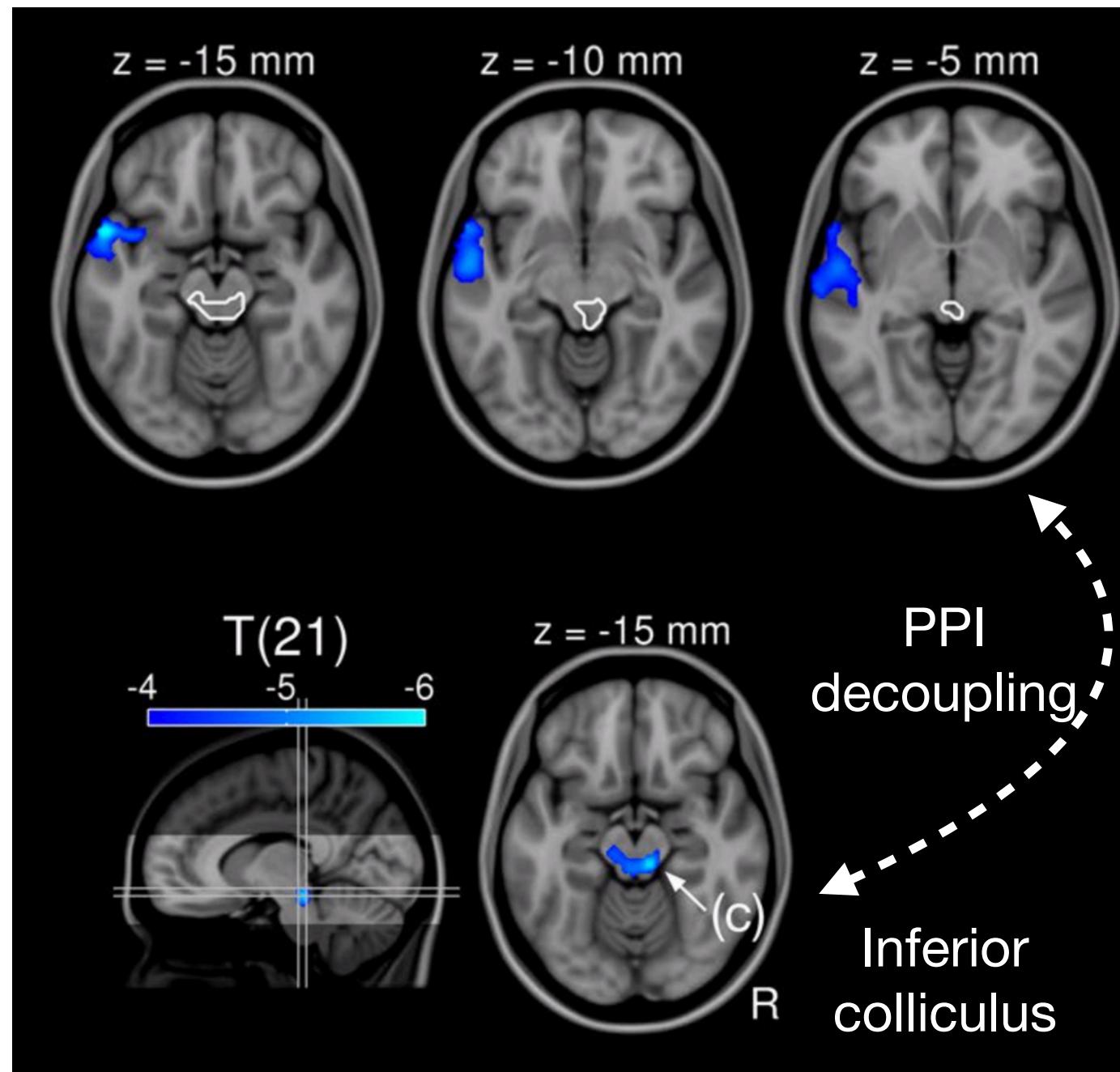
Traditional approach: music vs. "non-music"

Psycho-Physiological Interaction (PPI)

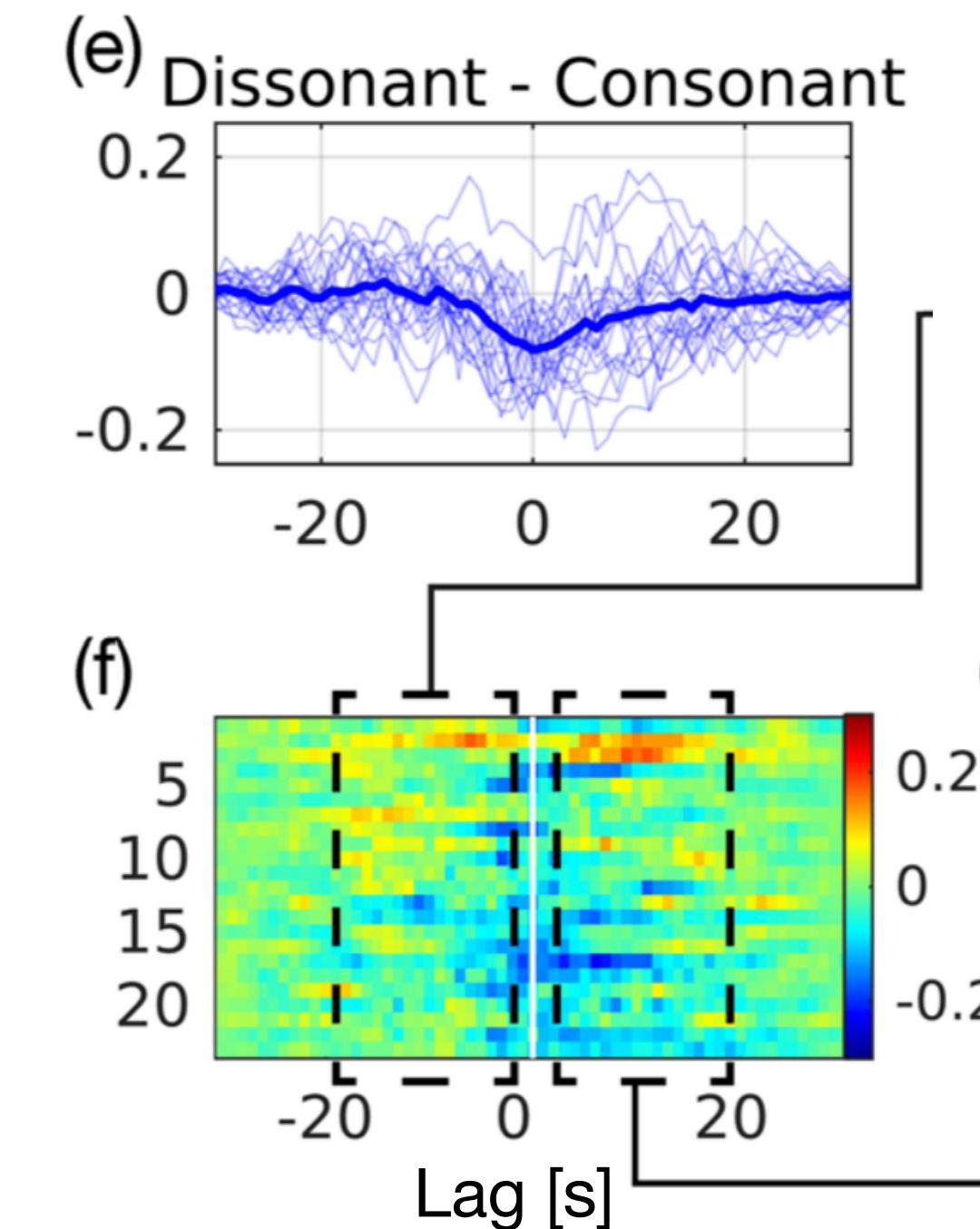


Traditional approach: music vs. "non-music"

Psycho-Physiological Interaction (PPI)

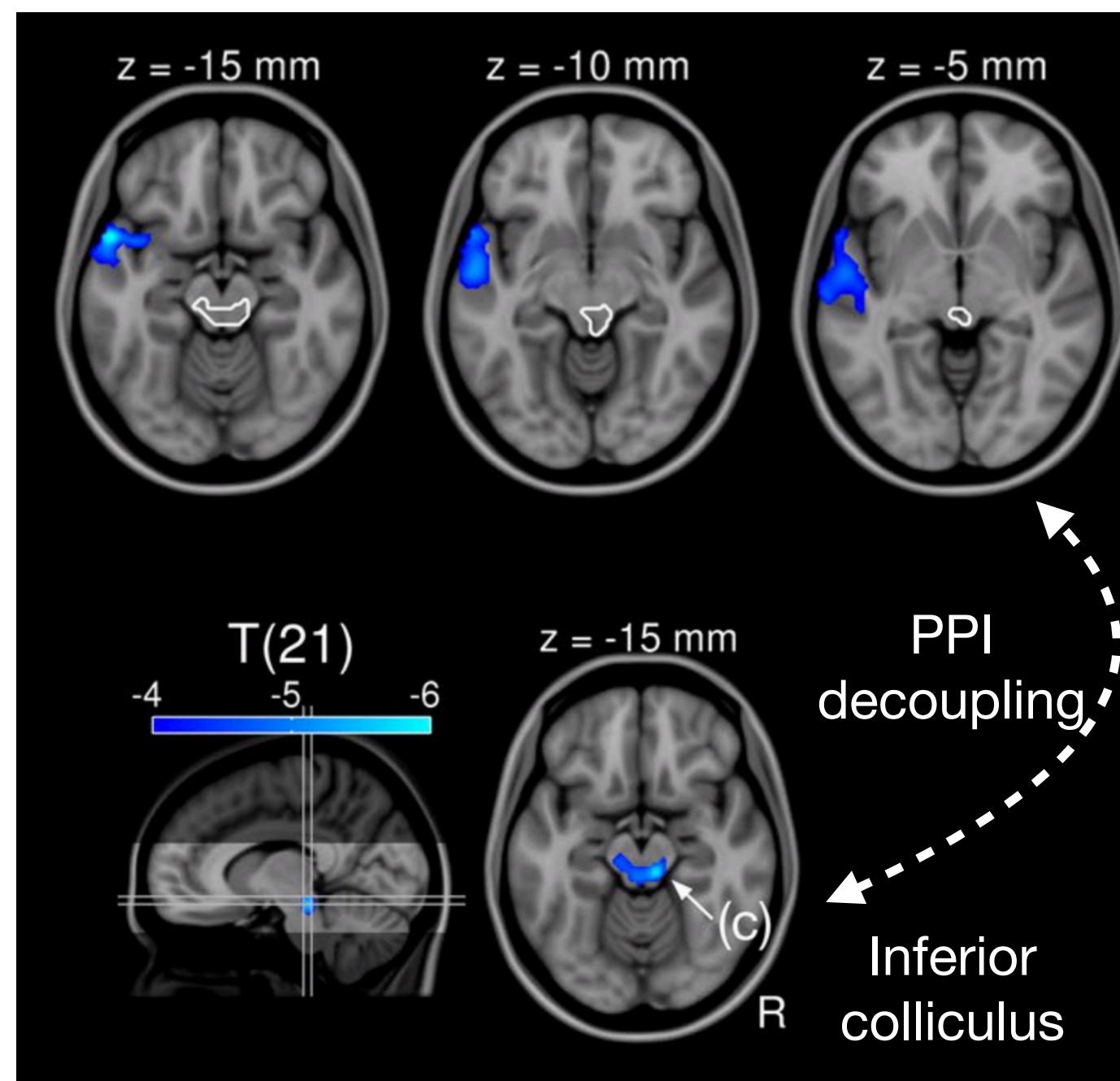


Cross-correlation

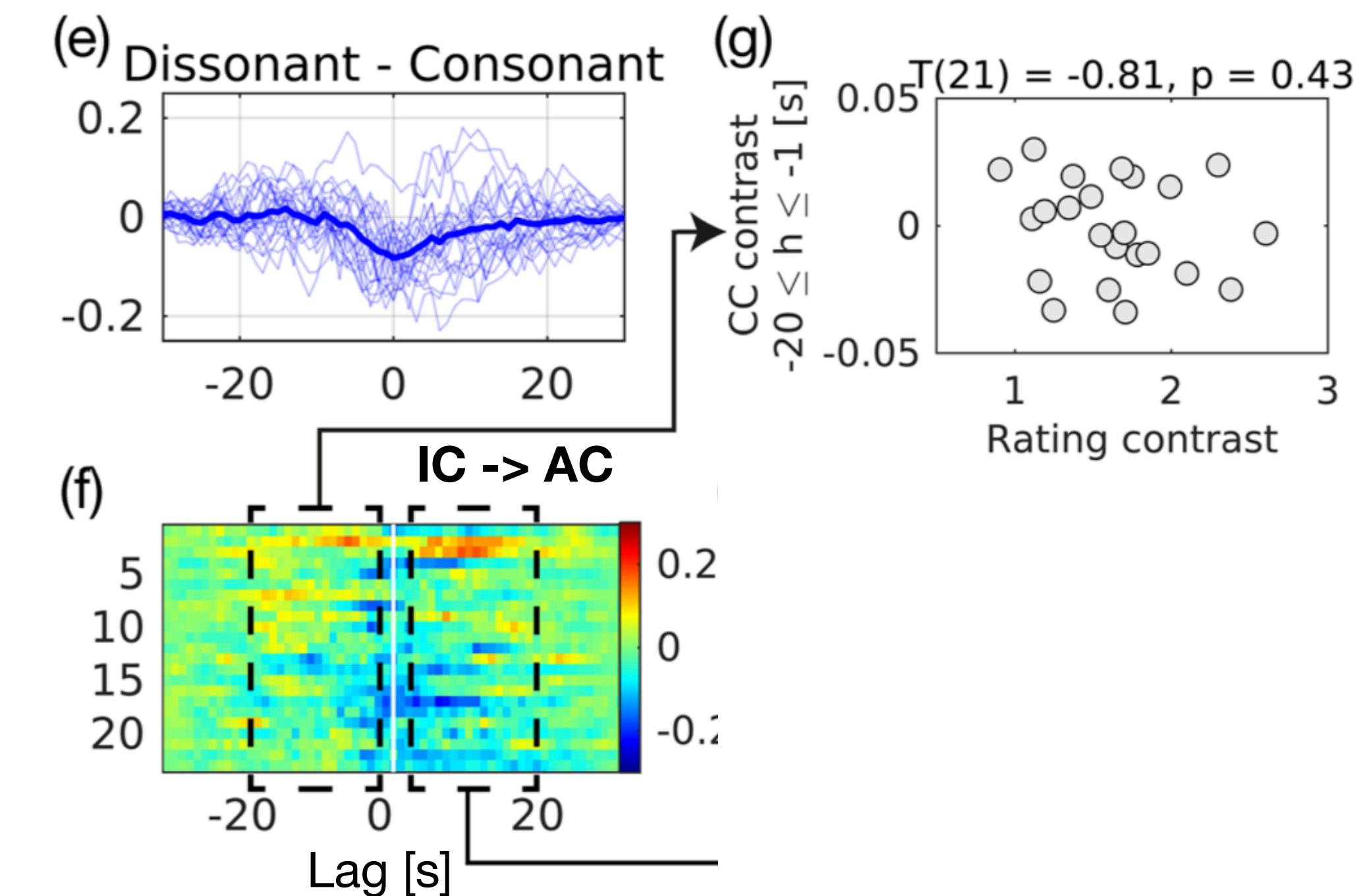


Traditional approach: music vs. "non-music"

Psycho-Physiological Interaction (PPI)

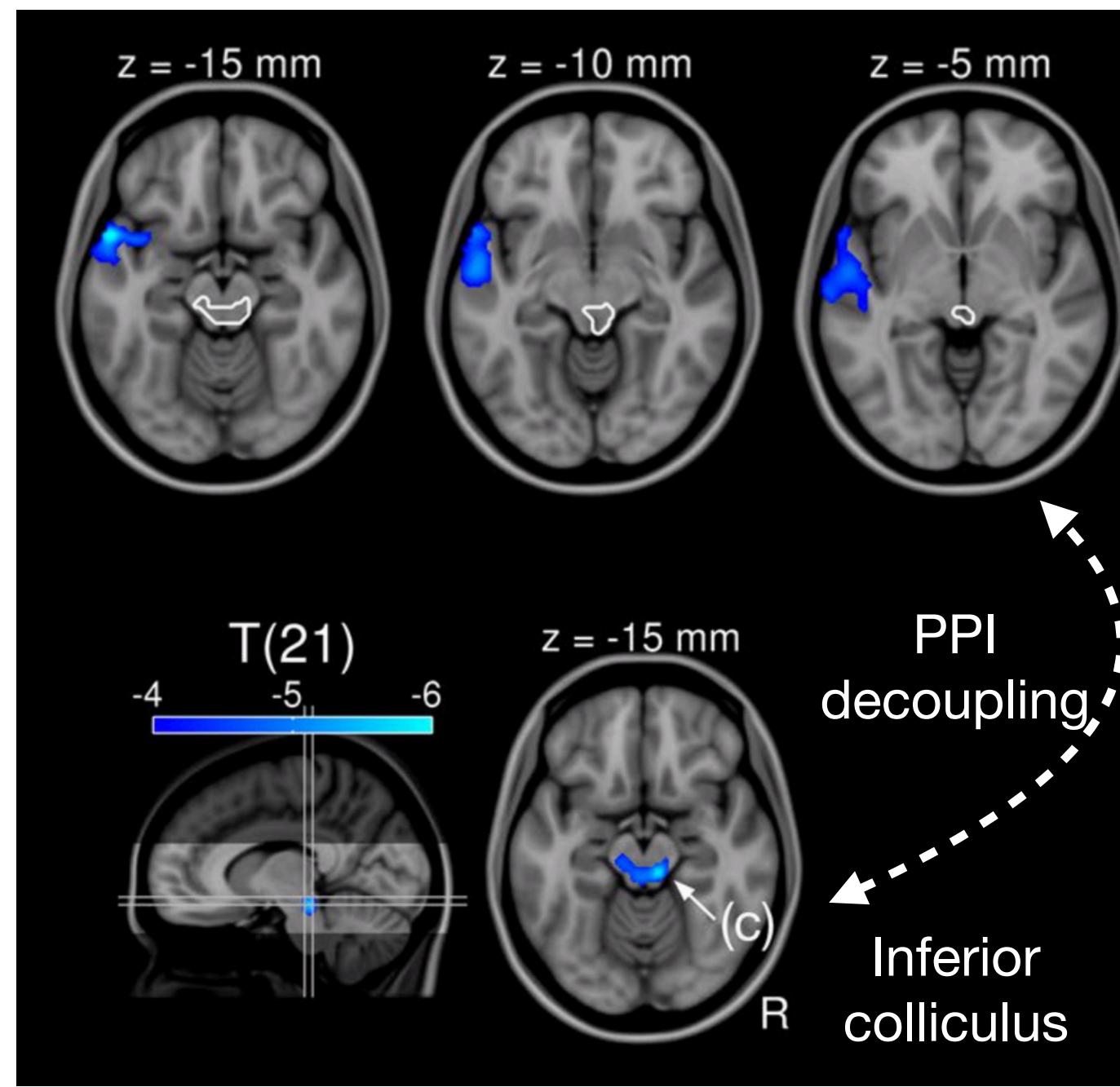


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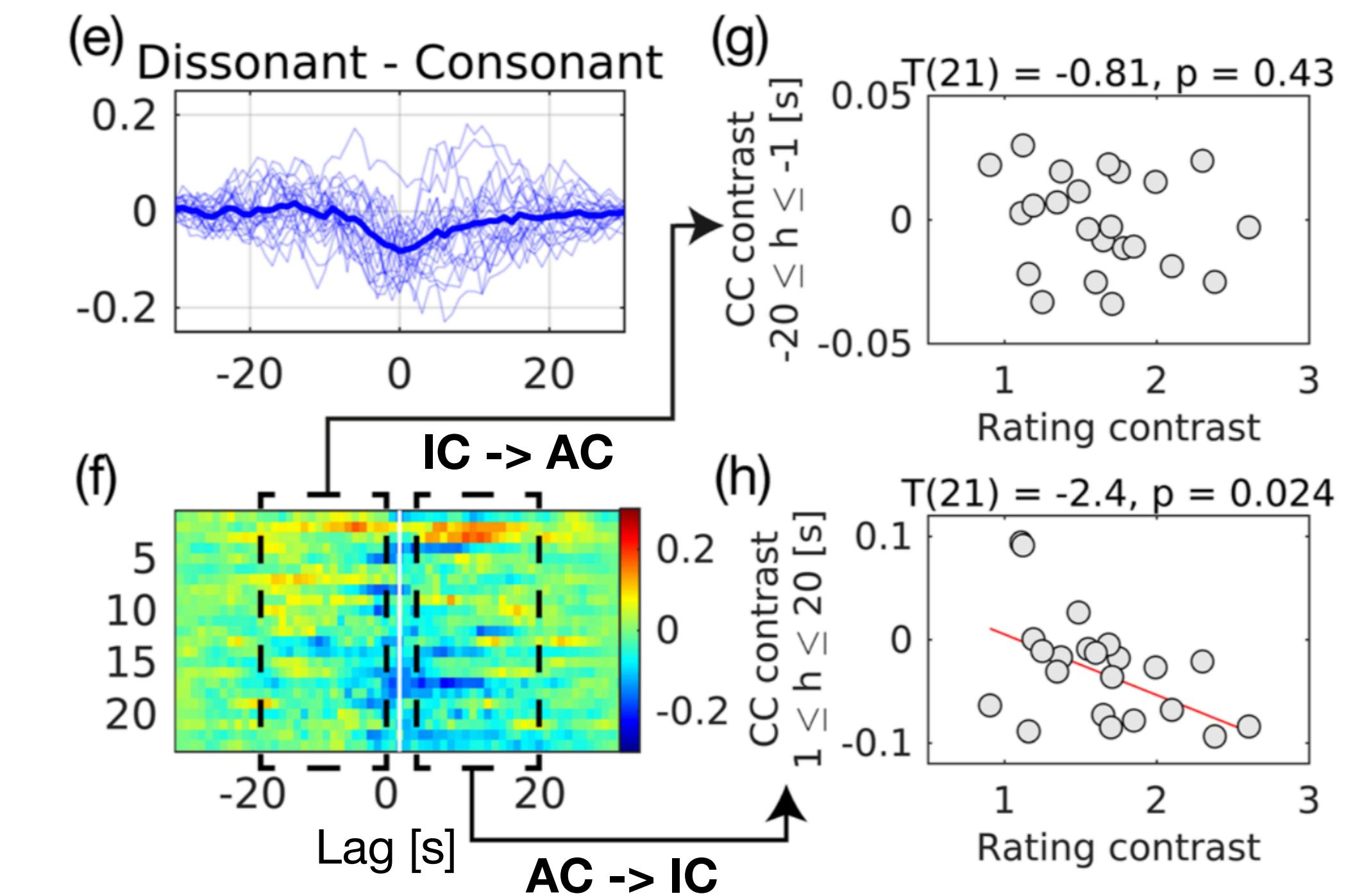


Traditional approach: music vs. "non-music"

Psycho-Physiological Interaction (PPI)

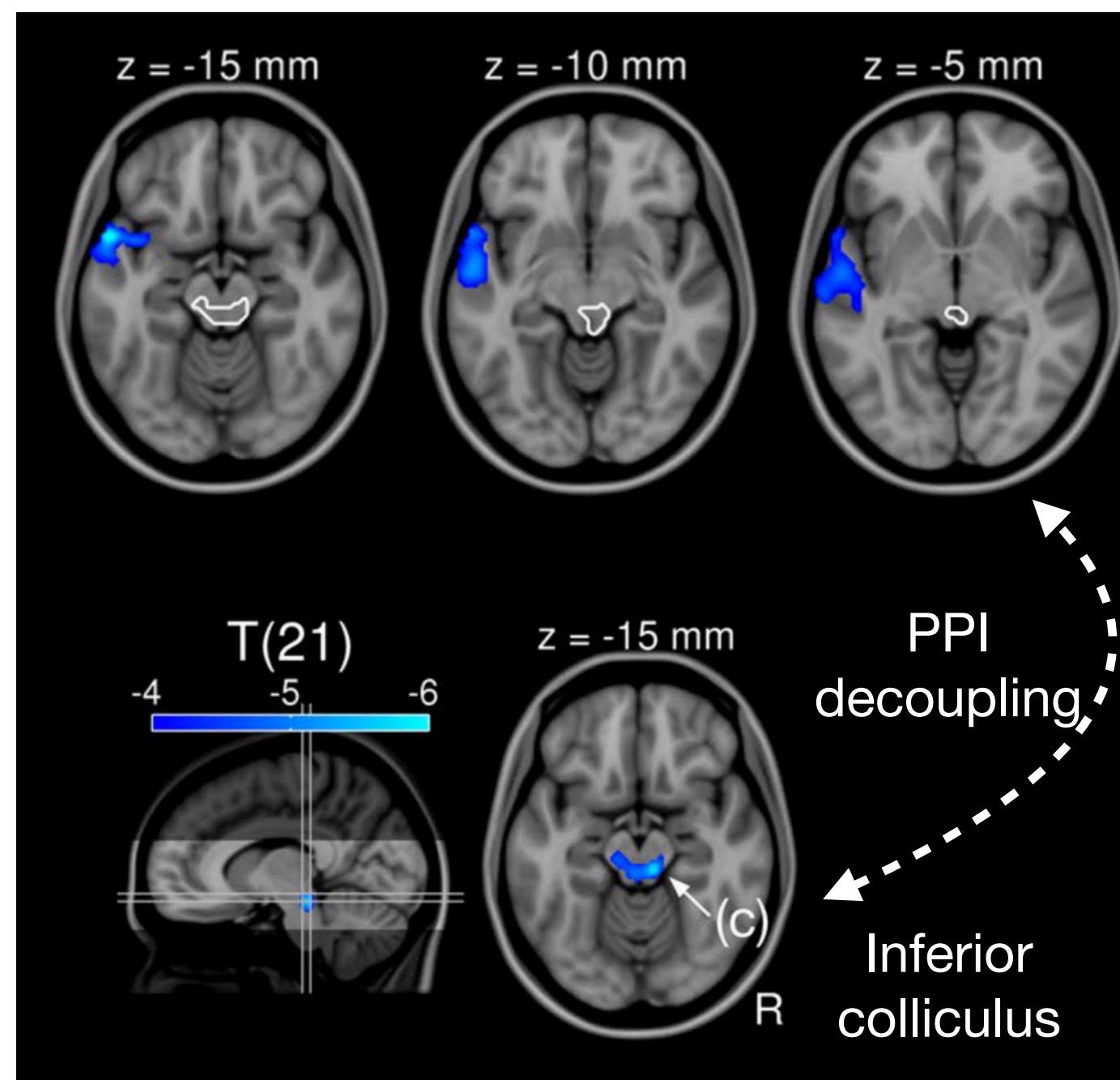


Cross-correlation

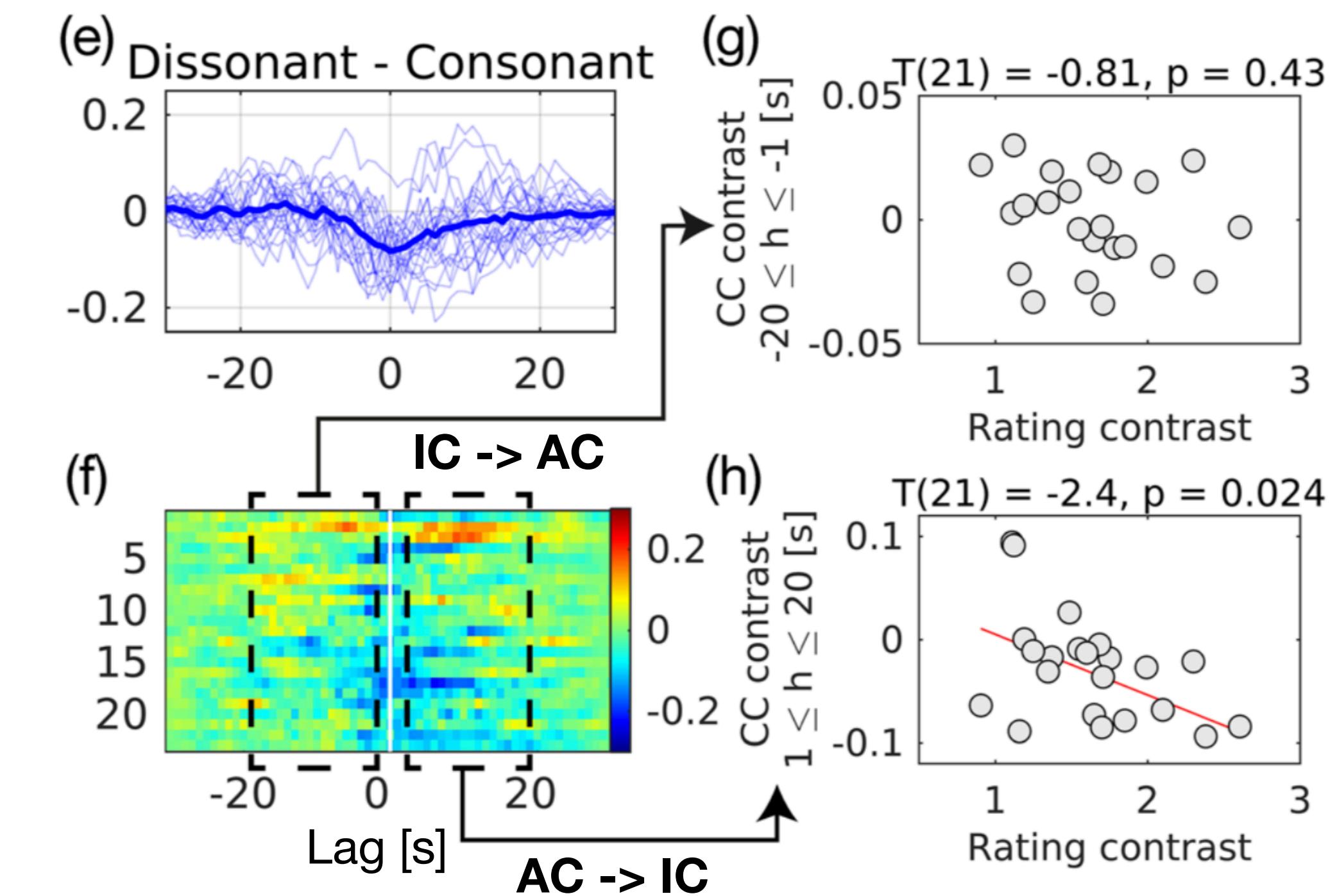


Traditional approach: music vs. "non-music"

Psycho-Physiological Interaction (PPI)



Cross-correlation

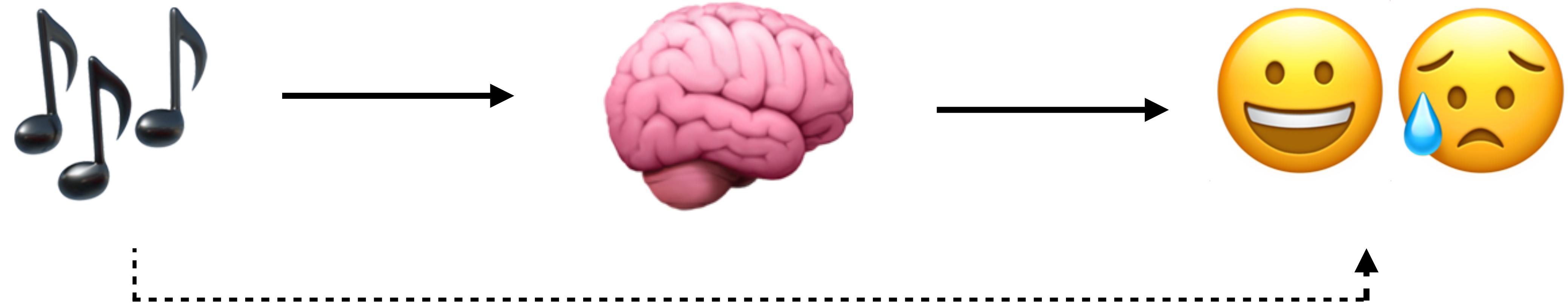


The IC decoupled more from the left auditory cortex (top-down) in individuals who rated dissonant versions worse.

Limitations of controlled stimuli

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

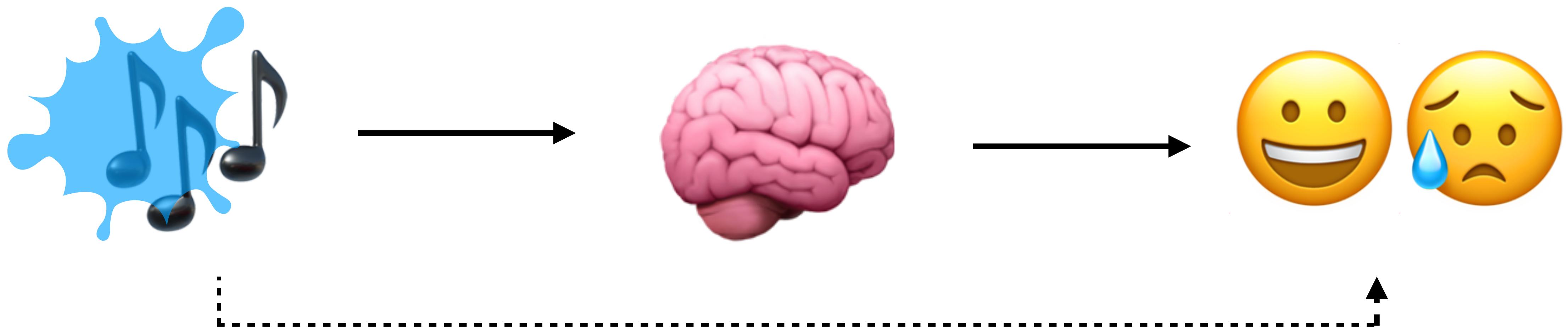
Disruptive manipulations: validity, generalizability, & specificity?



Limitations of controlled stimuli

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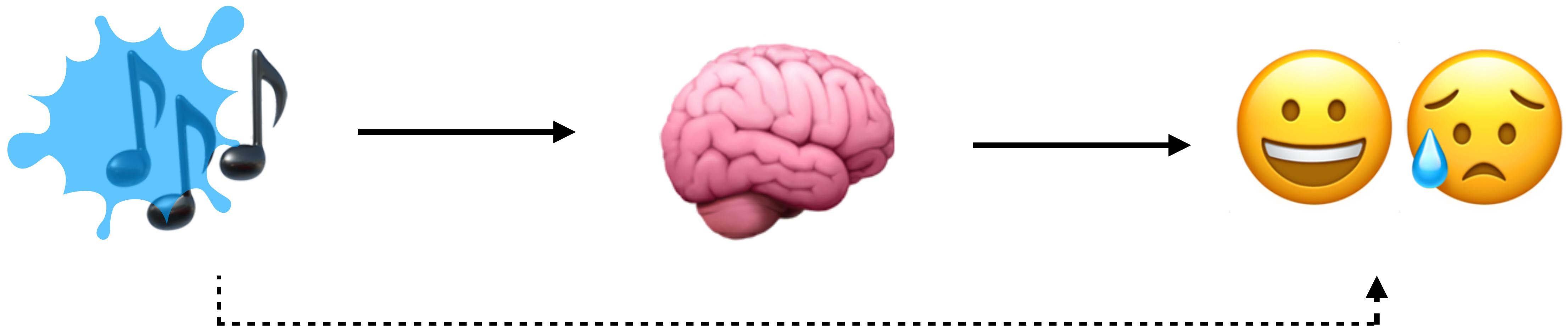
Disruptive manipulations: validity, generalizability, & specificity?



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

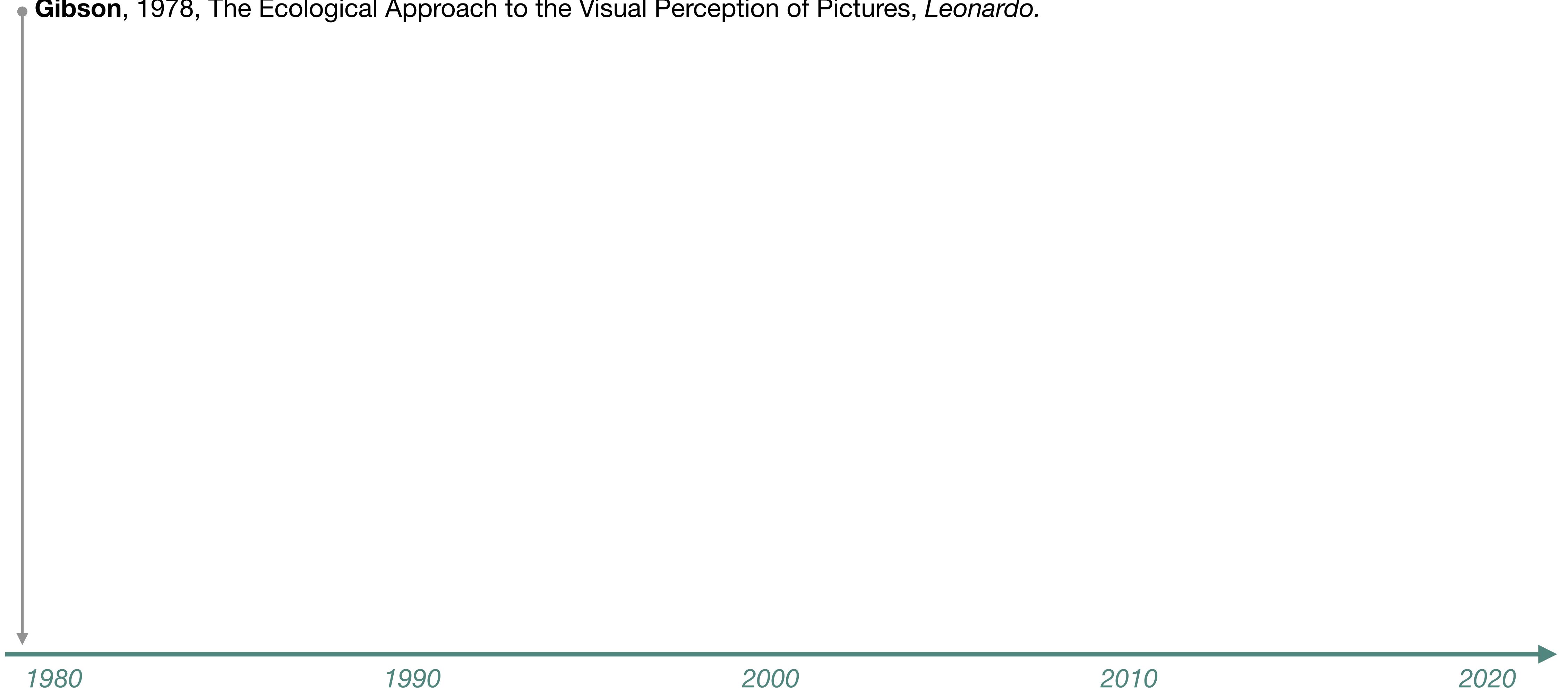
2010

2020

Alternative approach: "naturalistic neuroimaging"

Embracing complexity for ecological validity

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



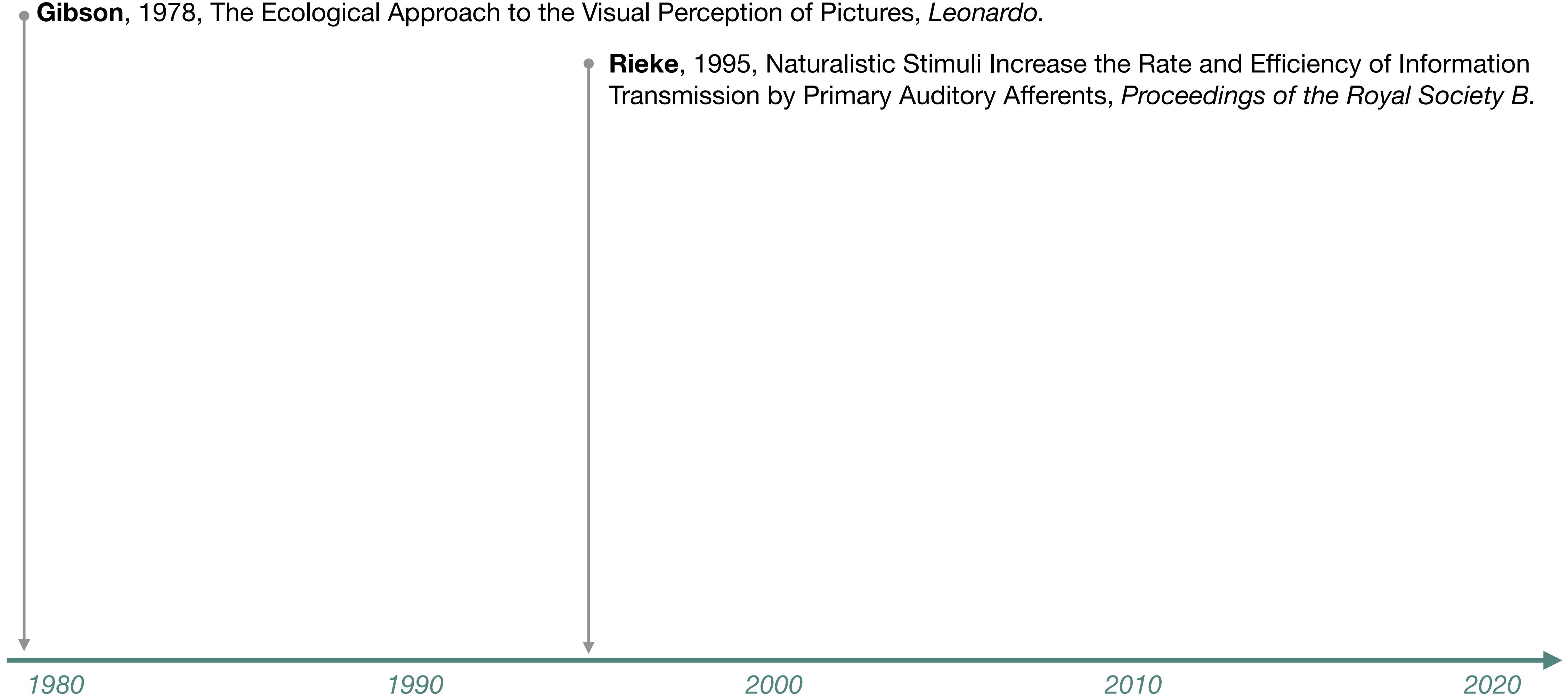


Alternative approach: "naturalistic neuroimaging"

Embracing complexity for ecological validity

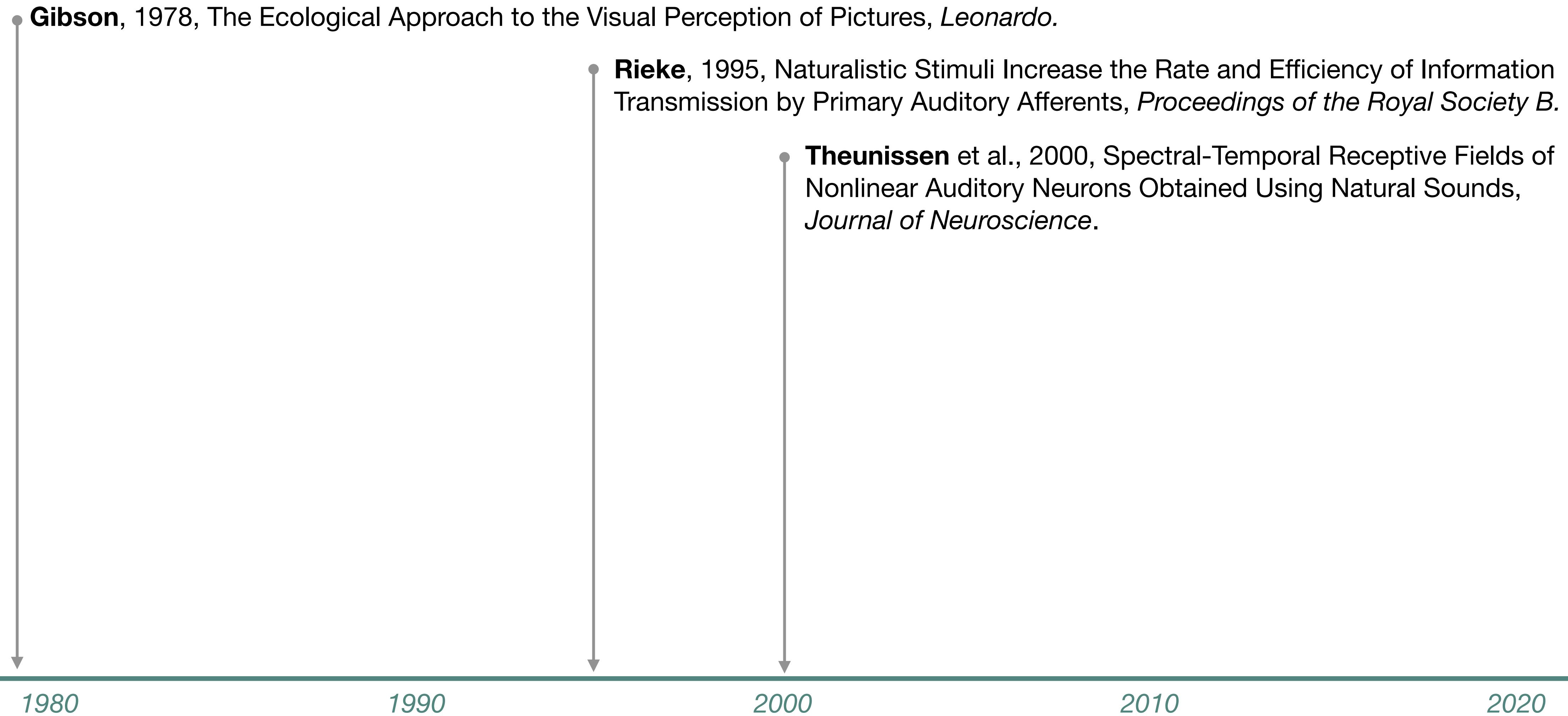
Gibson, 1978, The Ecological Approach to the Visual Perception of Pictures, *Leonardo*.

Rieke, 1995, Naturalistic Stimuli Increase the Rate and Efficiency of Information Transmission by Primary Auditory Afferents, *Proceedings of the Royal Society B*.



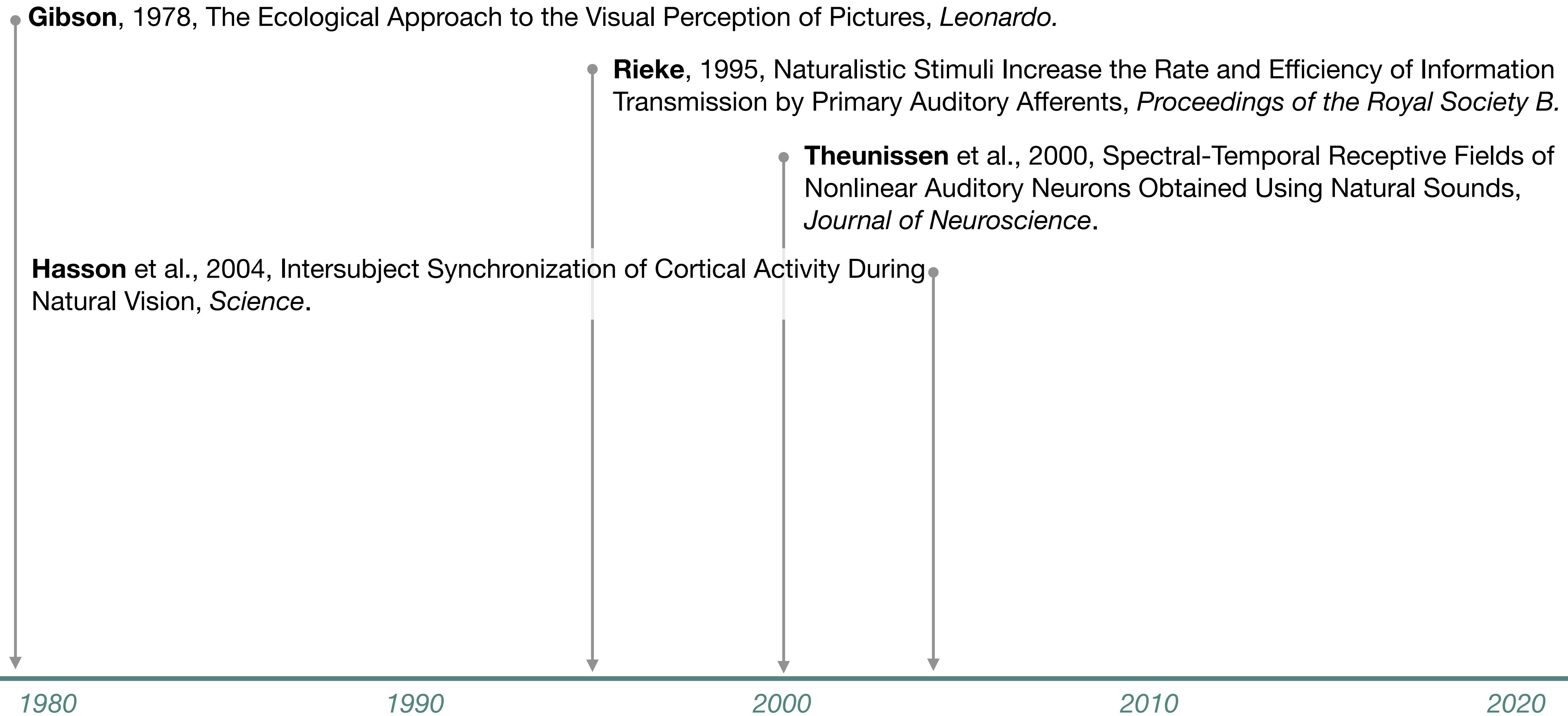
Alternative approach: "naturalistic neuroimaging"

Embracing complexity for ecological validity



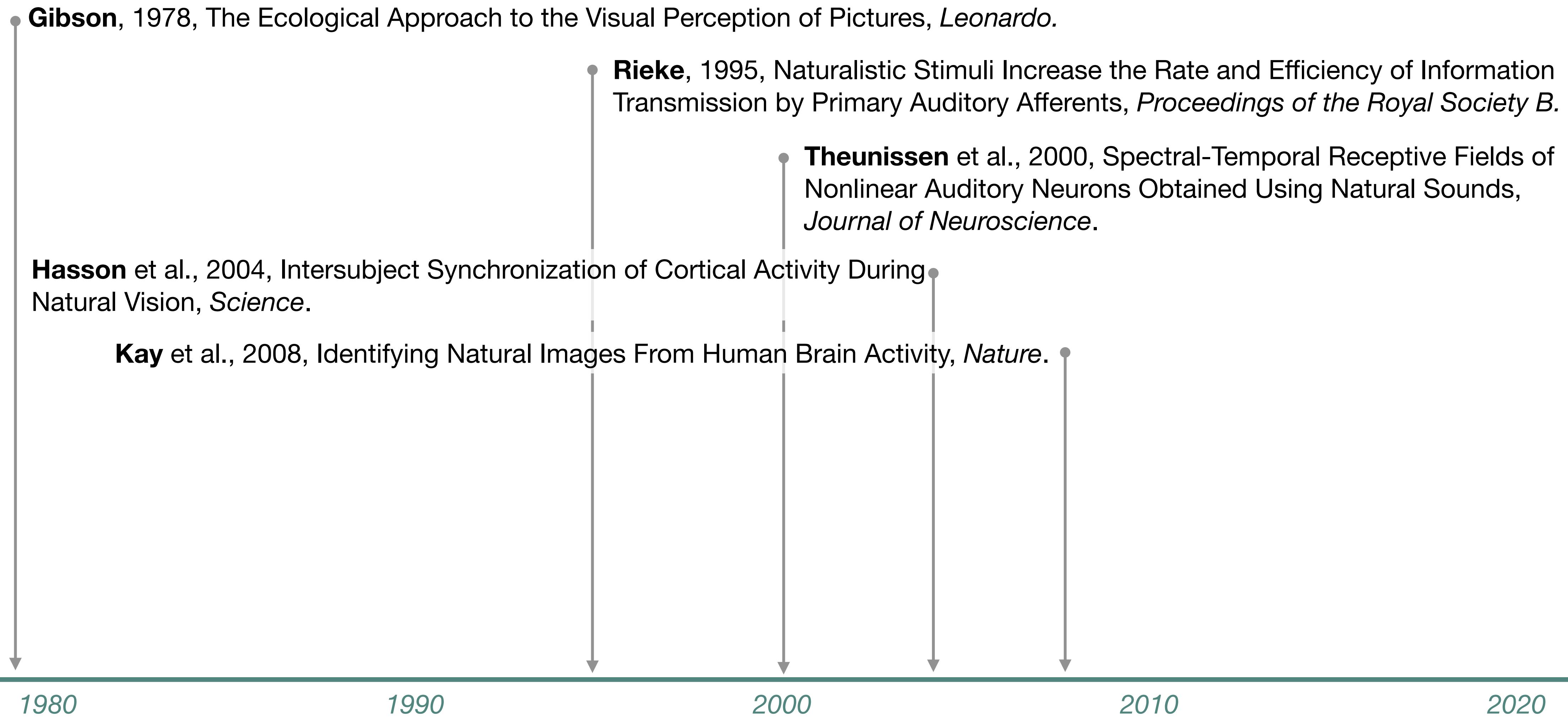
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Embracing complexity for ecological validity



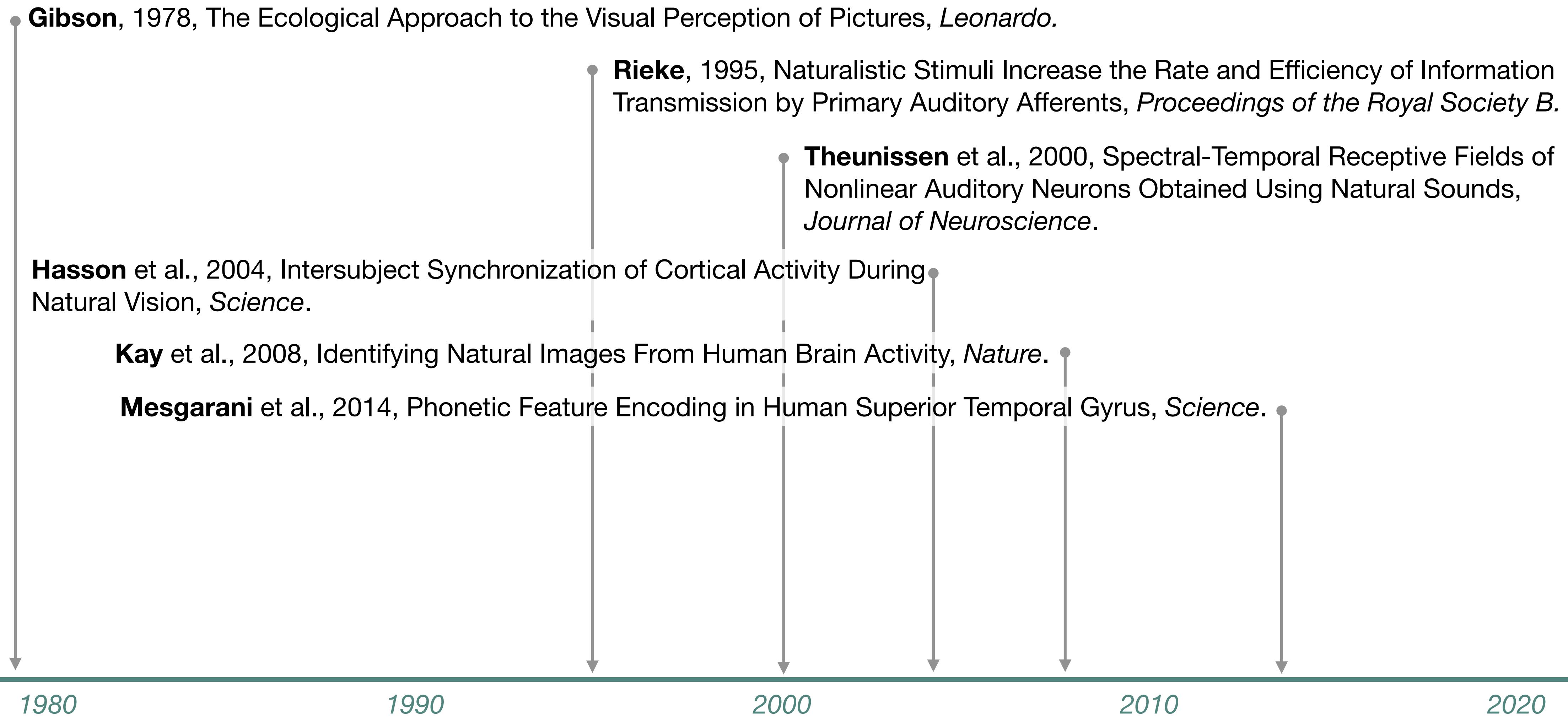
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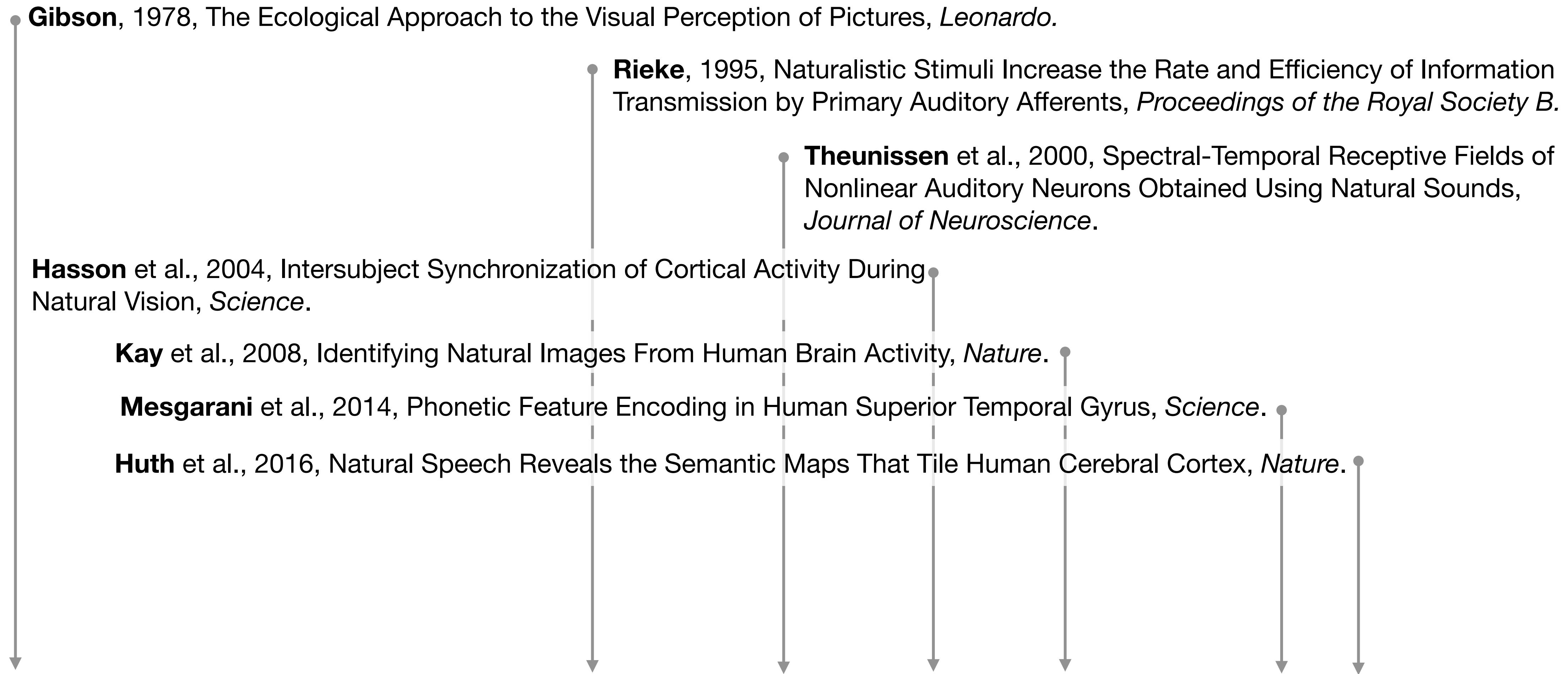
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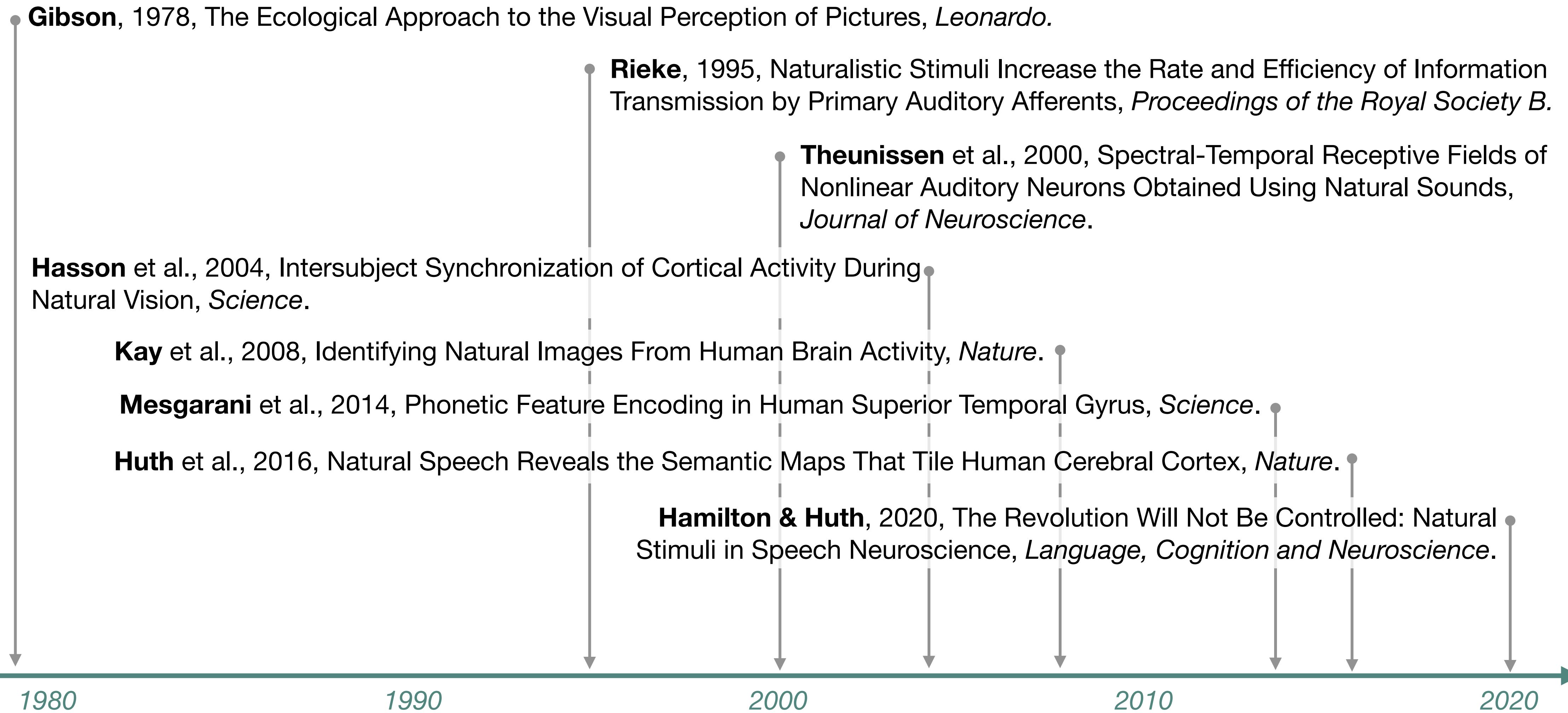
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Embracing complexity for ecological validity

- 
- A vertical timeline on the left lists seven research papers, each marked with a grey dot and a downward arrow. The timeline is represented by a horizontal green arrow at the bottom, with major tick marks for the years 1980, 1990, 2000, 2010, and 2020.
- Gibson, 1978, The Ecological Approach to the Visual Perception of Pictures, *Leonardo*.
 - Rieke, 1995, Naturalistic Stimuli Increase the Rate and Efficiency of Information Transmission by Primary Auditory Afferents, *Proceedings of the Royal Society B*.
 - Theunissen et al., 2000, Spectral-Temporal Receptive Fields of Nonlinear Auditory Neurons Obtained Using Natural Sounds, *Journal of Neuroscience*.
 - Hasson et al., 2004, Intersubject Synchronization of Cortical Activity During Natural Vision, *Science*.
 - Kay et al., 2008, Identifying Natural Images From Human Brain Activity, *Nature*.
 - Mesgarani et al., 2014, Phonetic Feature Encoding in Human Superior Temporal Gyrus, *Science*.
 - Huth et al., 2016, Natural Speech Reveals the Semantic Maps That Tile Human Cerebral Cortex, *Nature*.

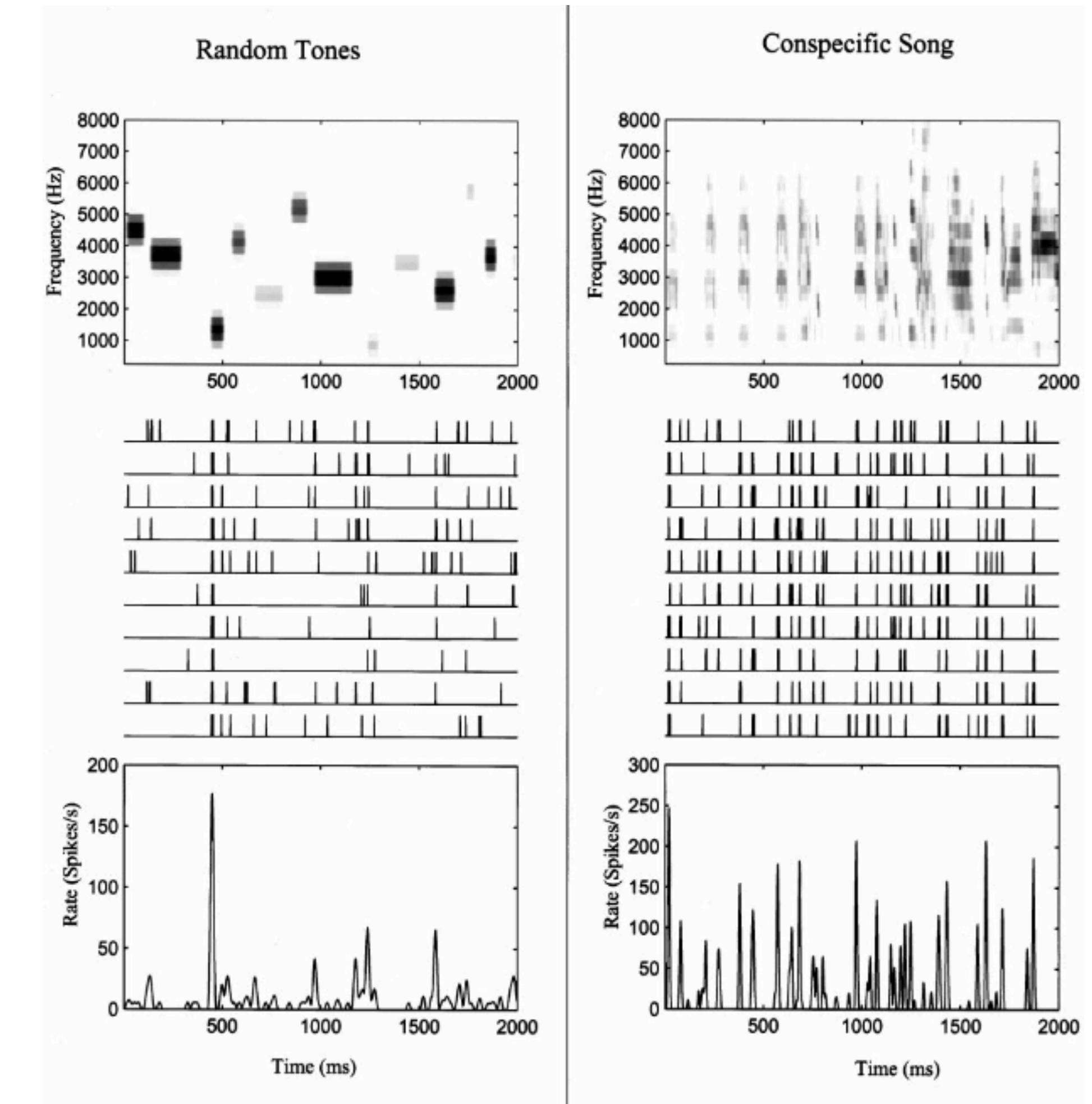
Alternative approach: "naturalistic neuroimaging"

Embracing complexity for ecological validity



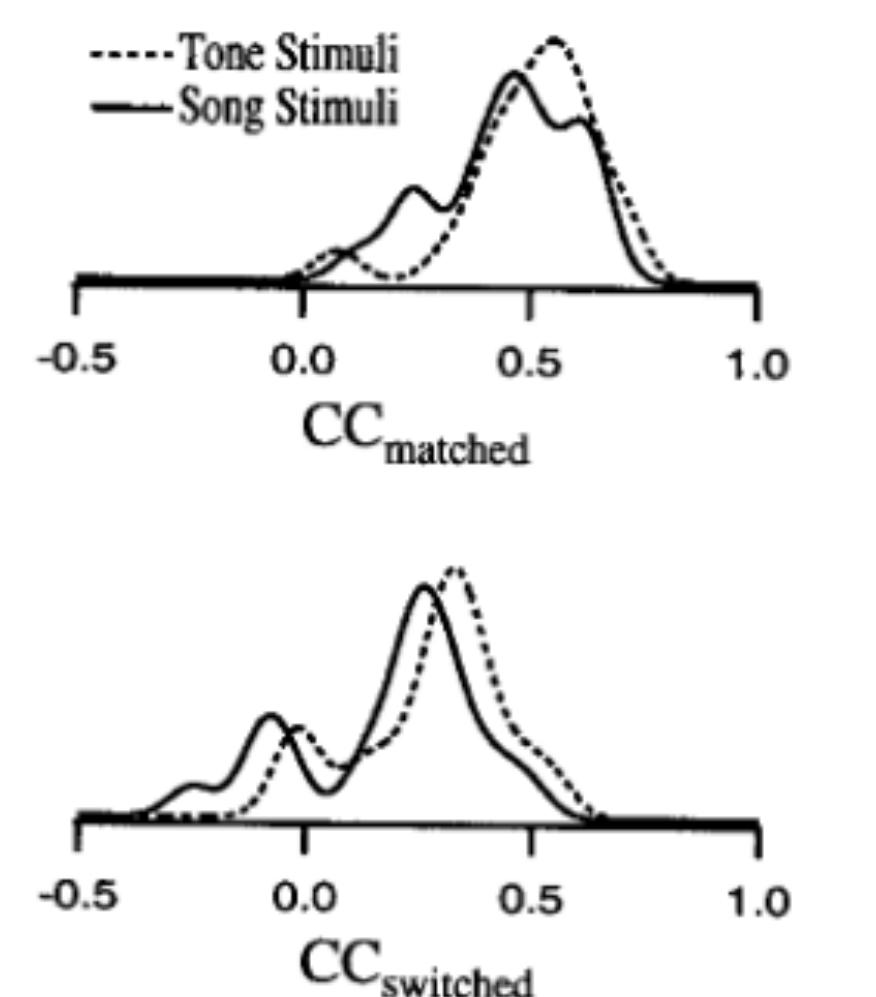
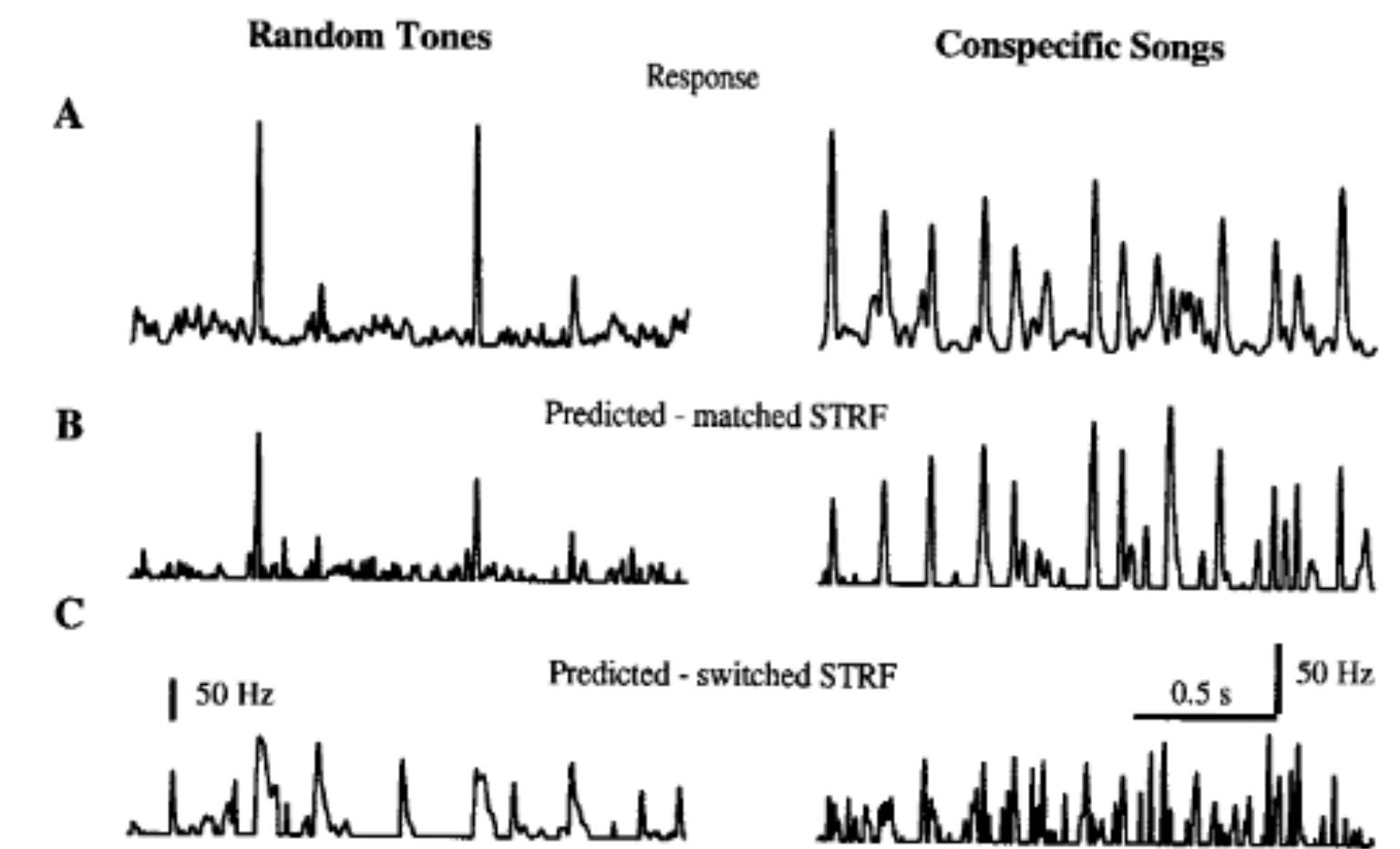
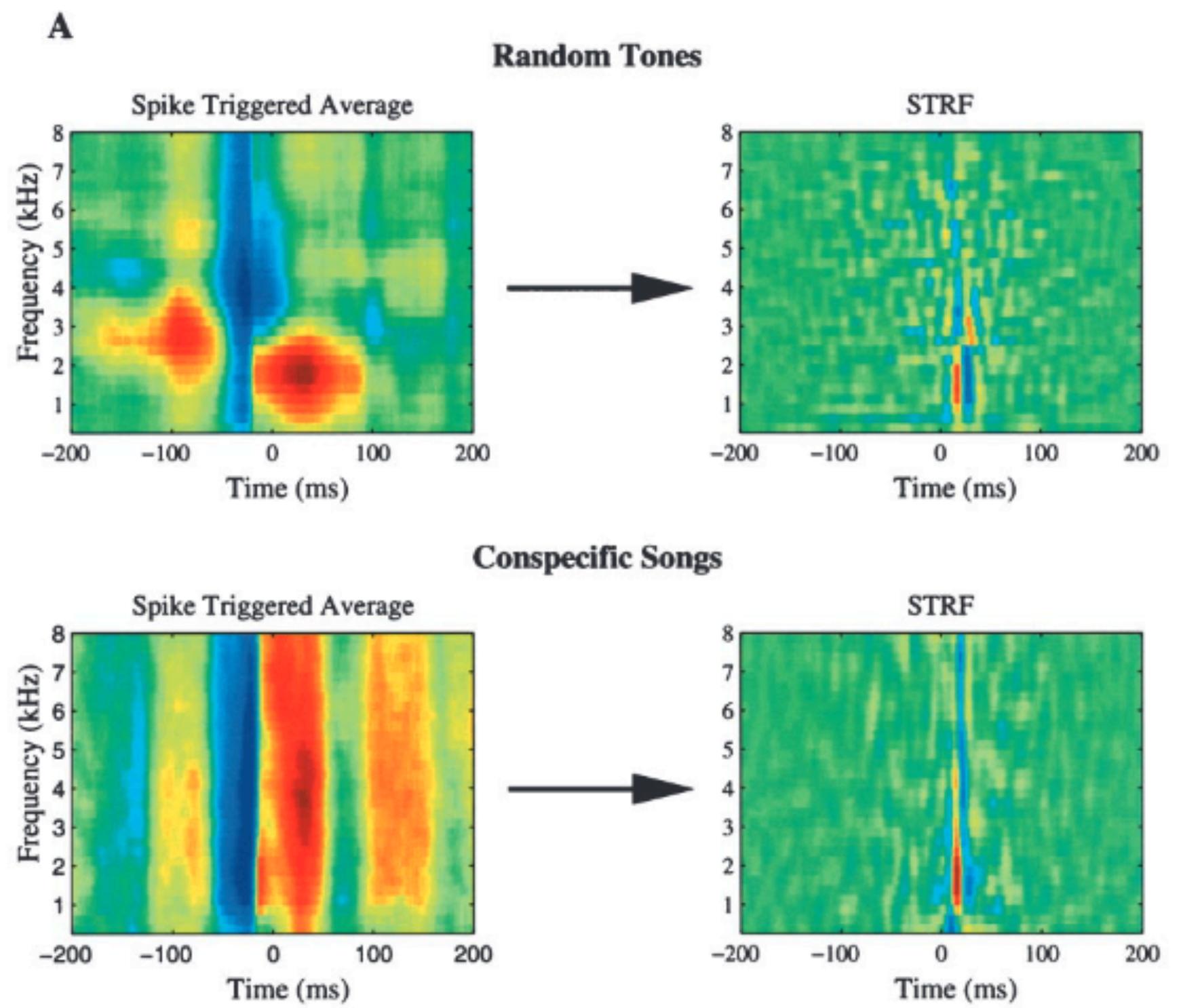
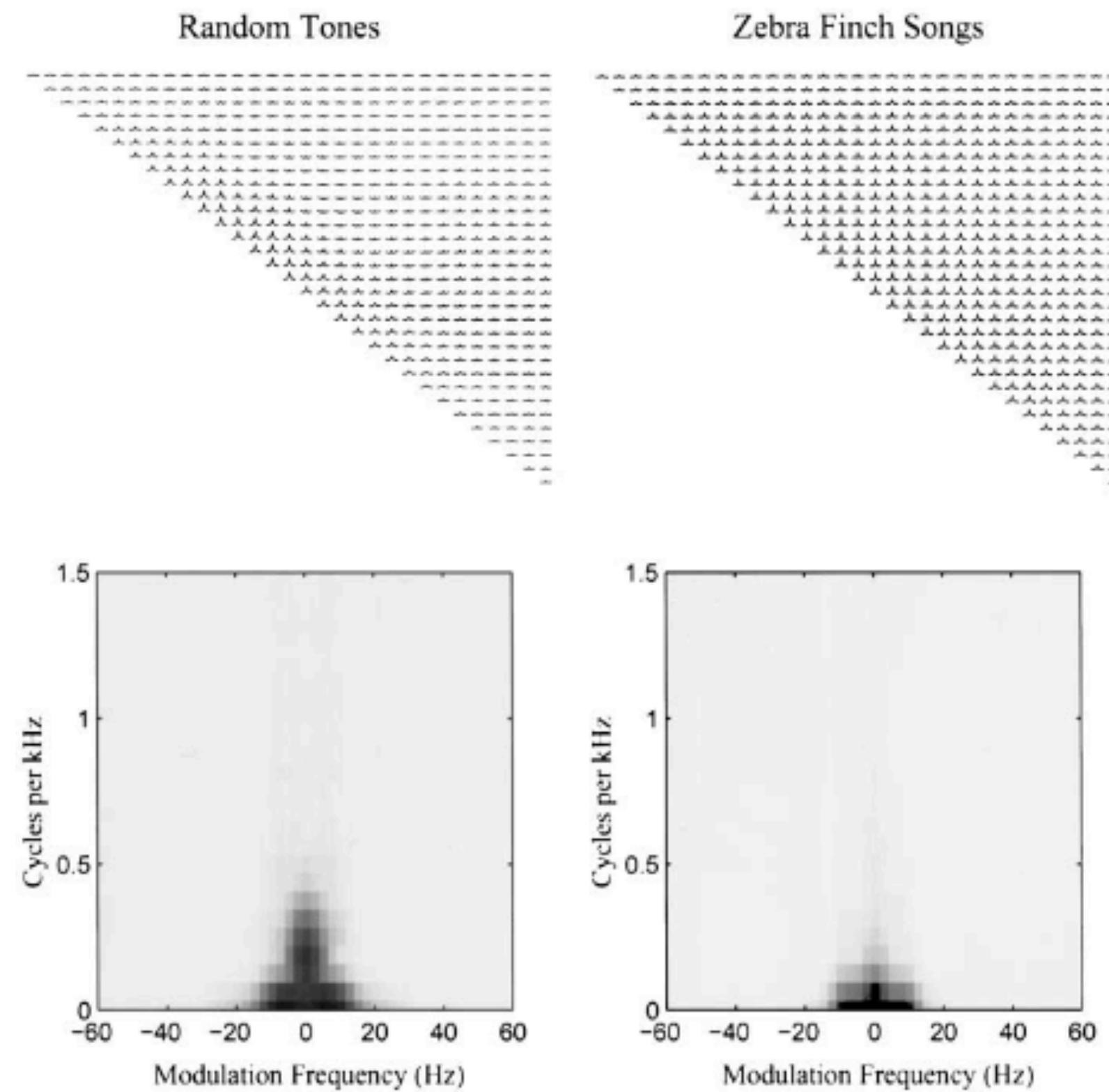
Receptive field mapping of a conspecific calls

Invasive recording of local field potential of neurons



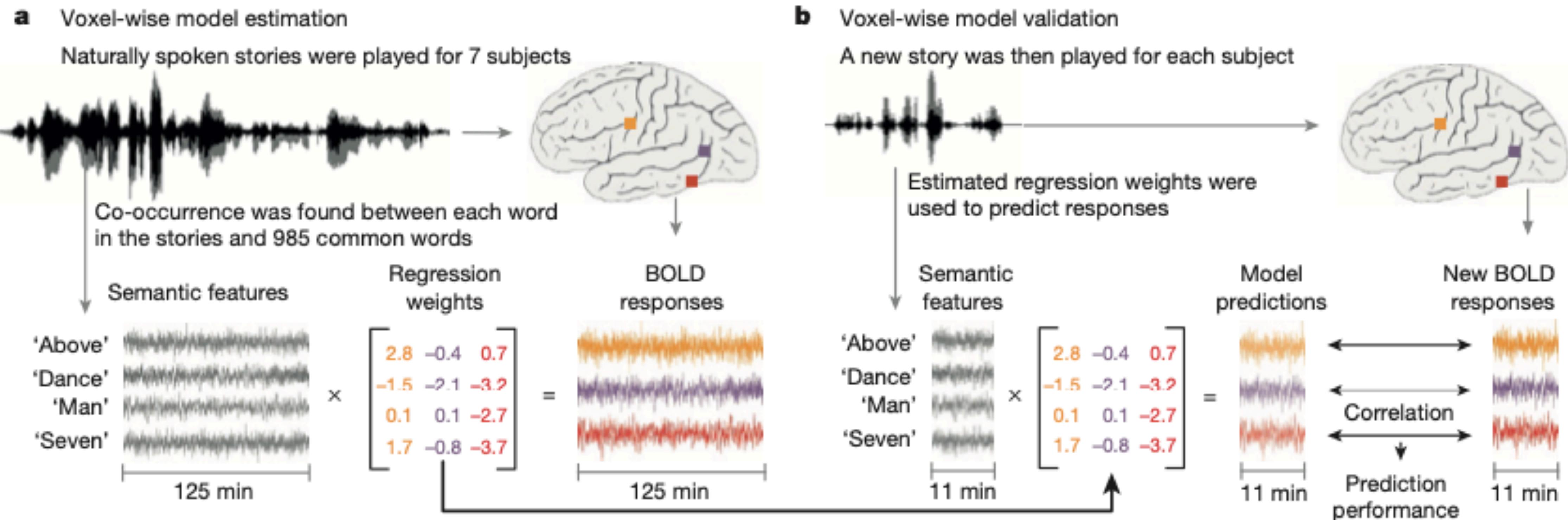
Receptive field mapping of a conspecific calls

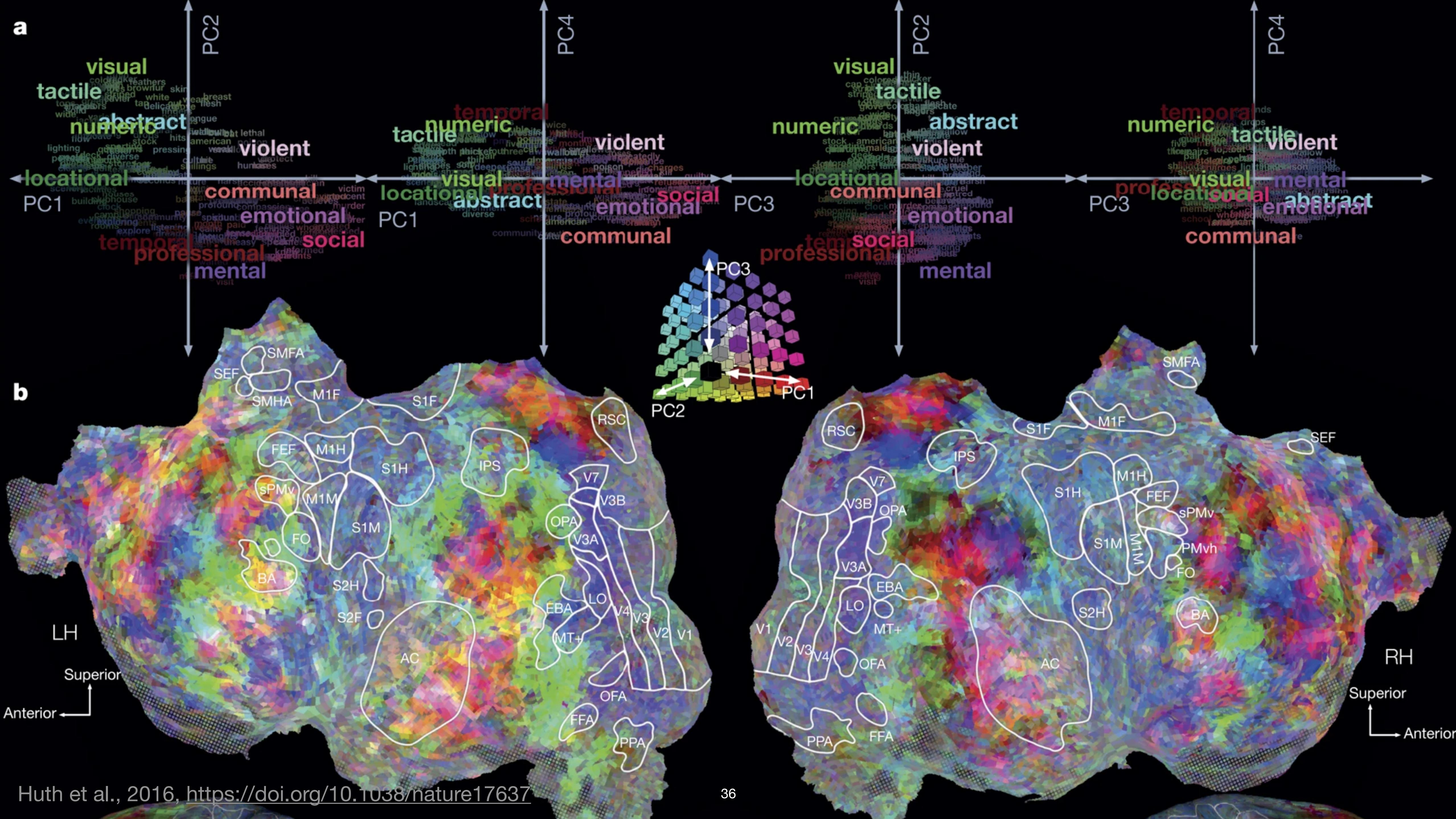
Invasive recording of local field potential of neurons



Semantic representation in the whole cortex

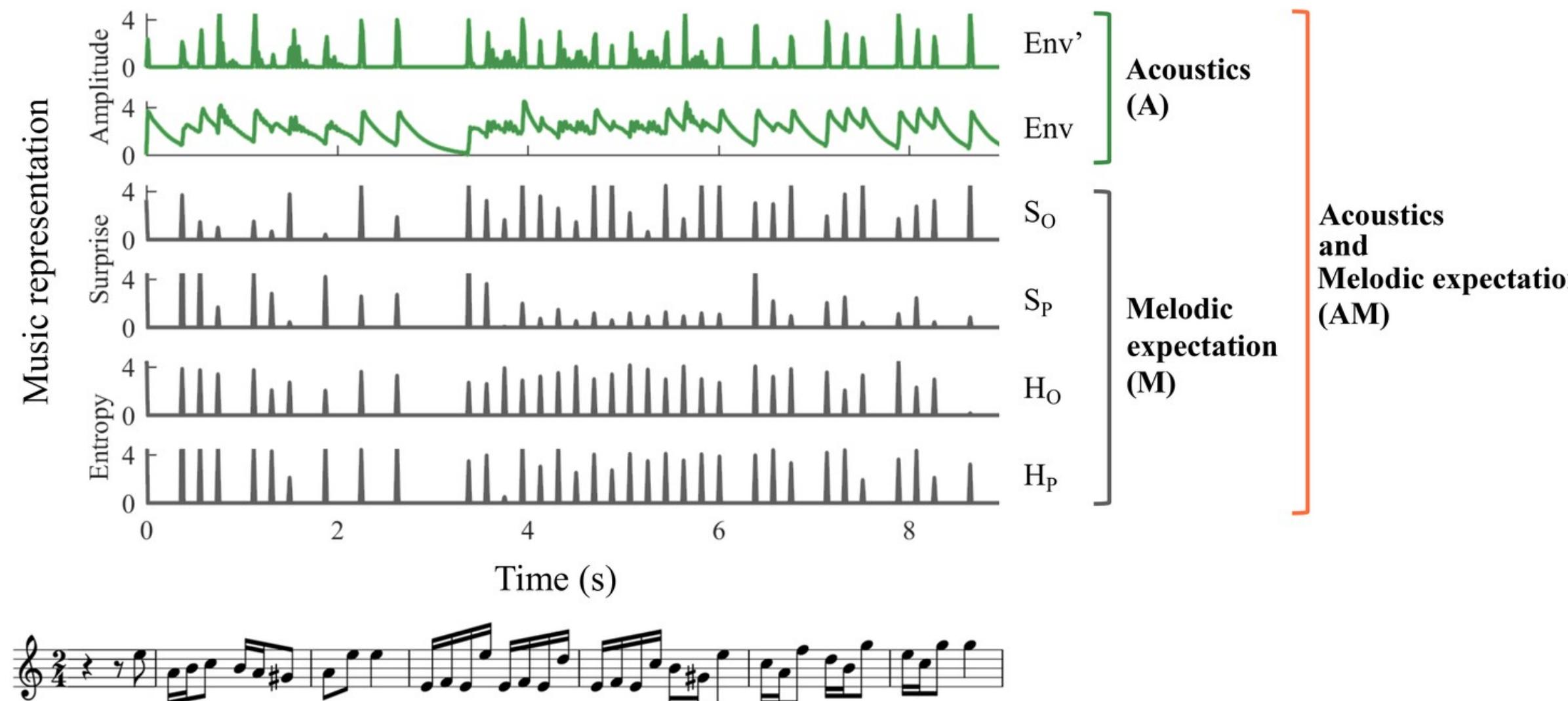
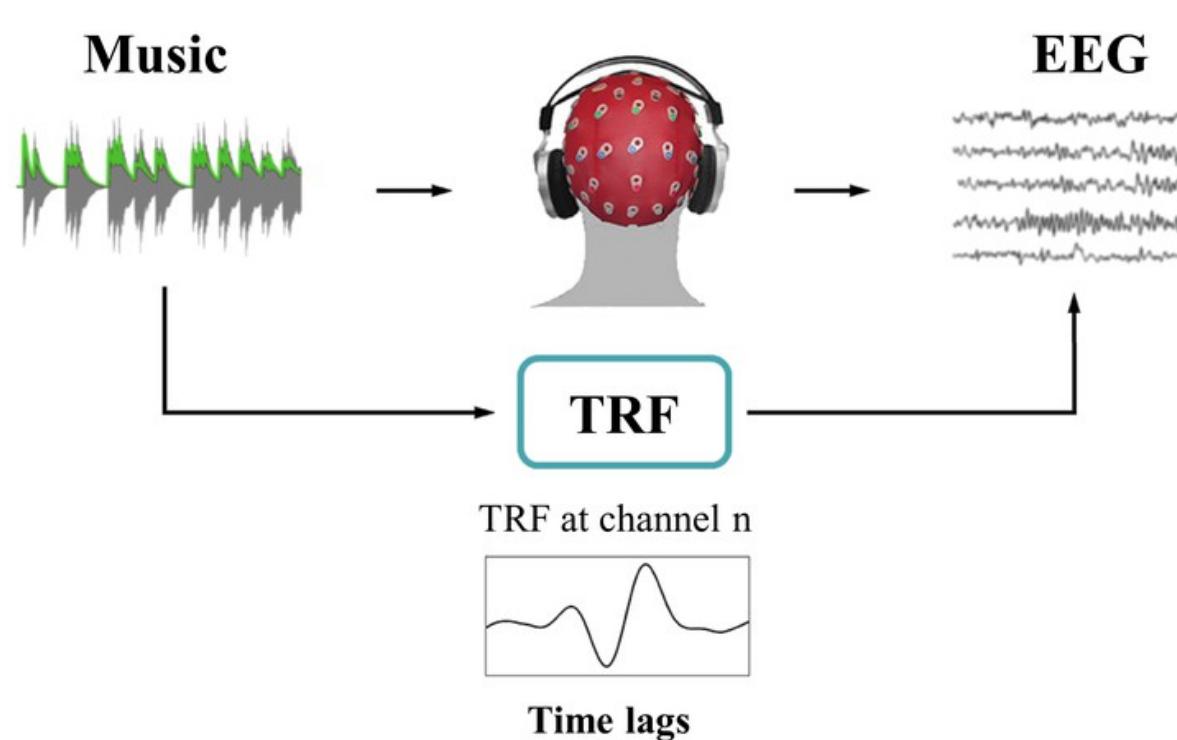
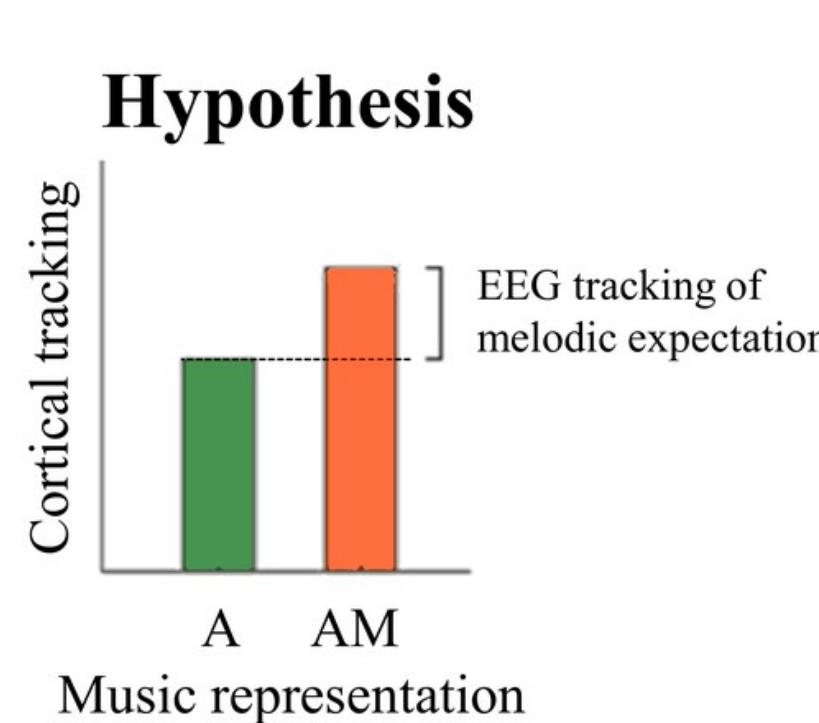
Non-invasive scanning of functional MRI (local paramagnetism)





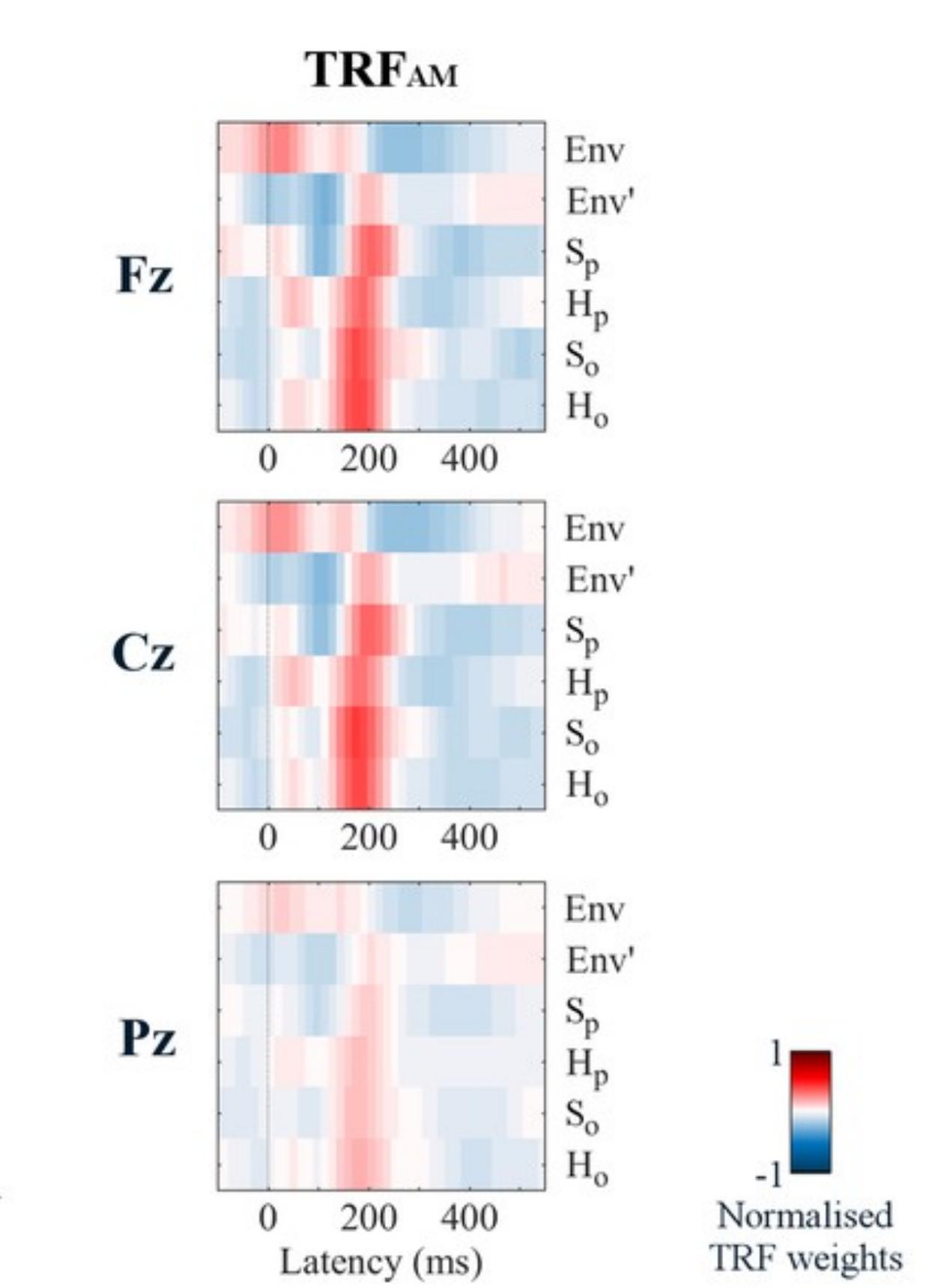
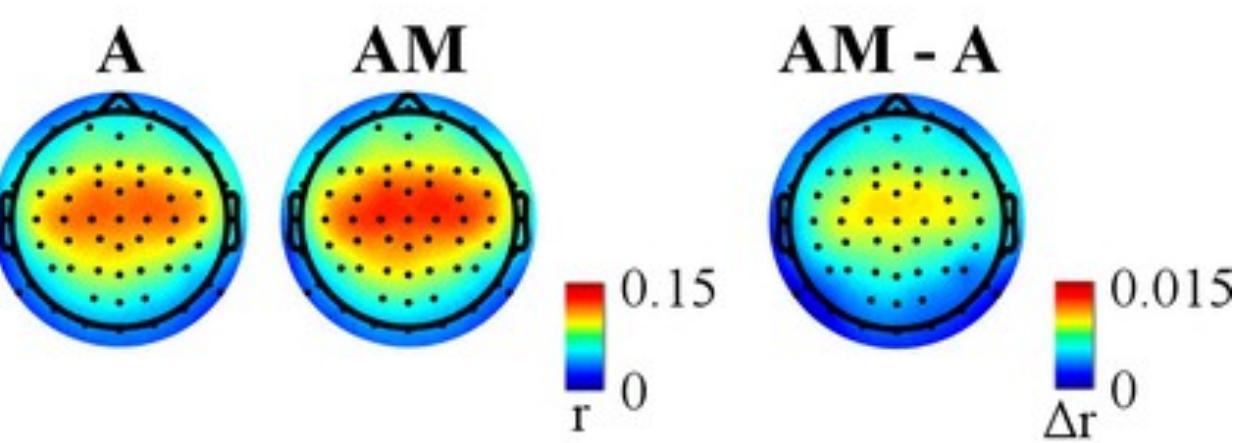
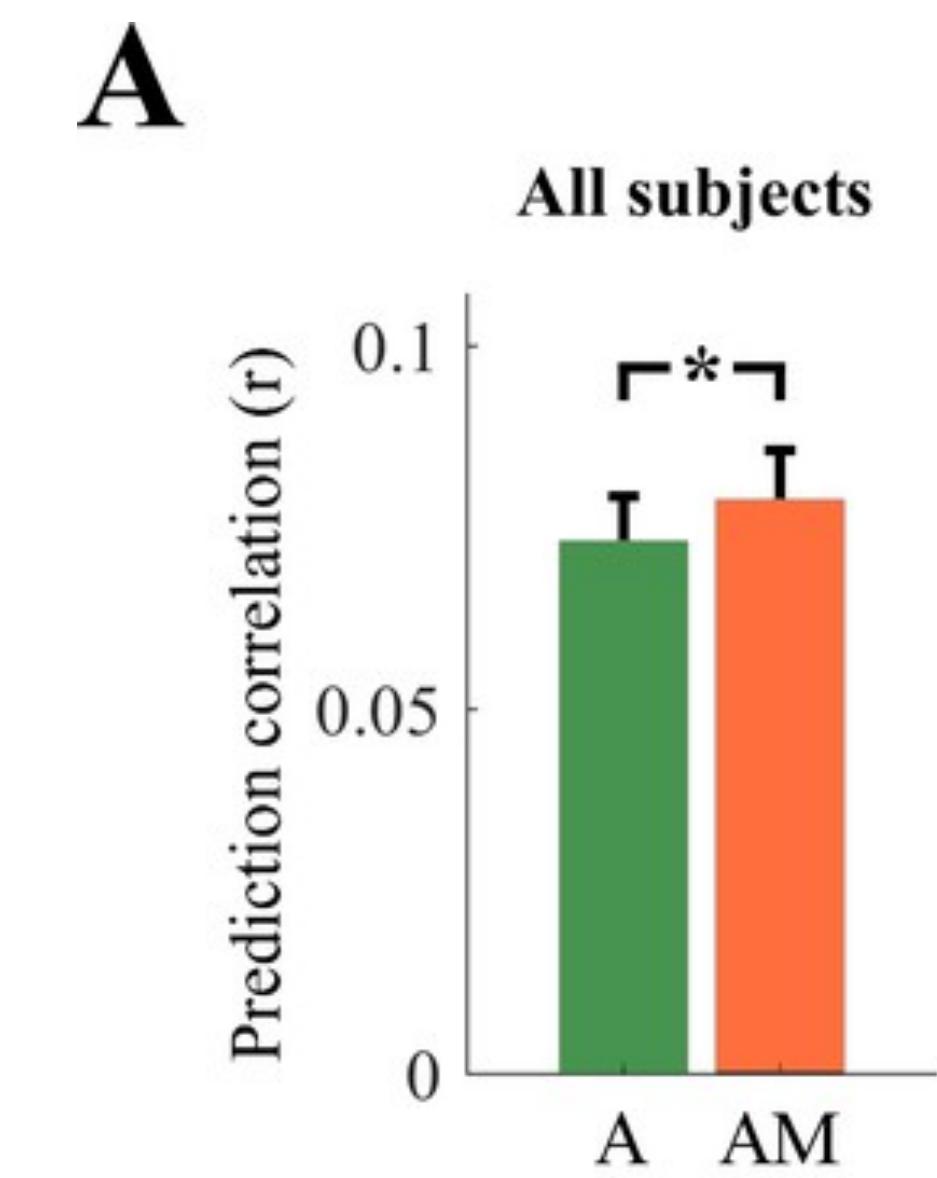
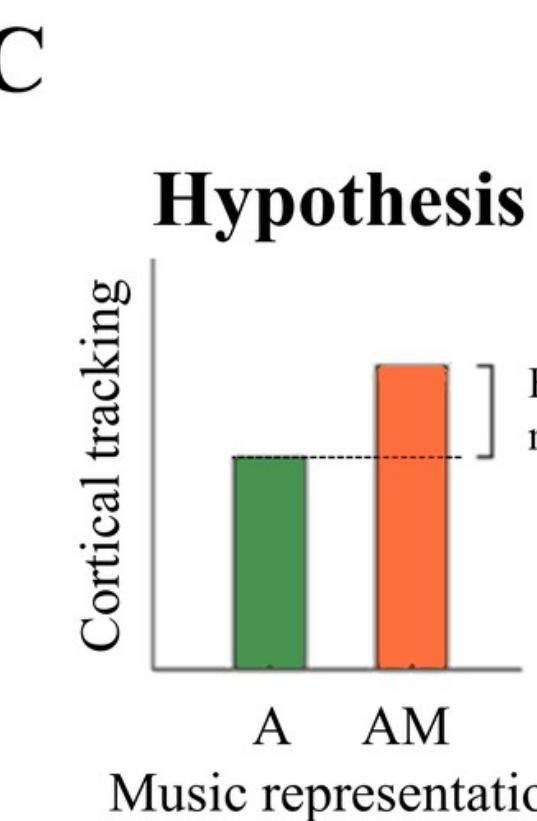
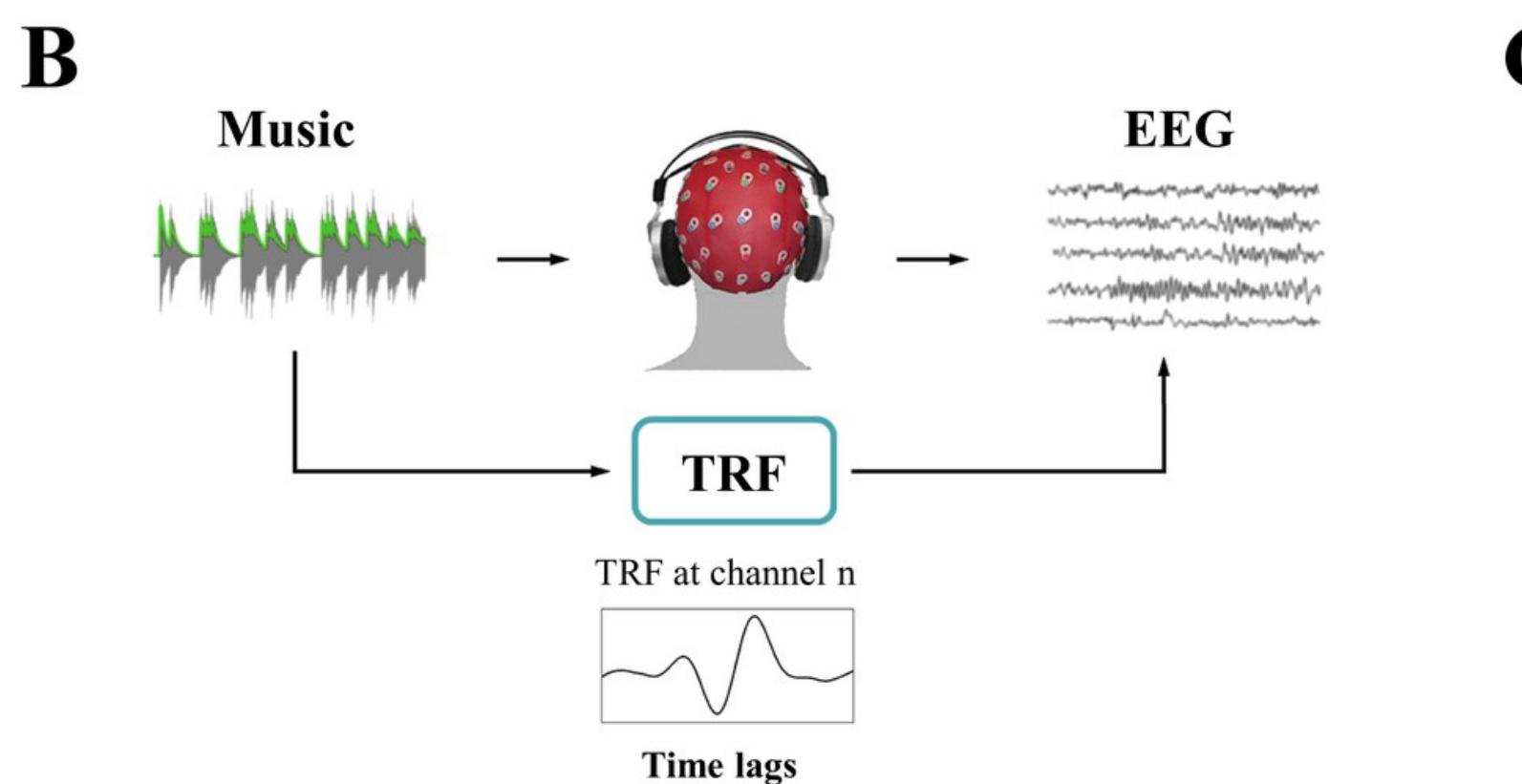
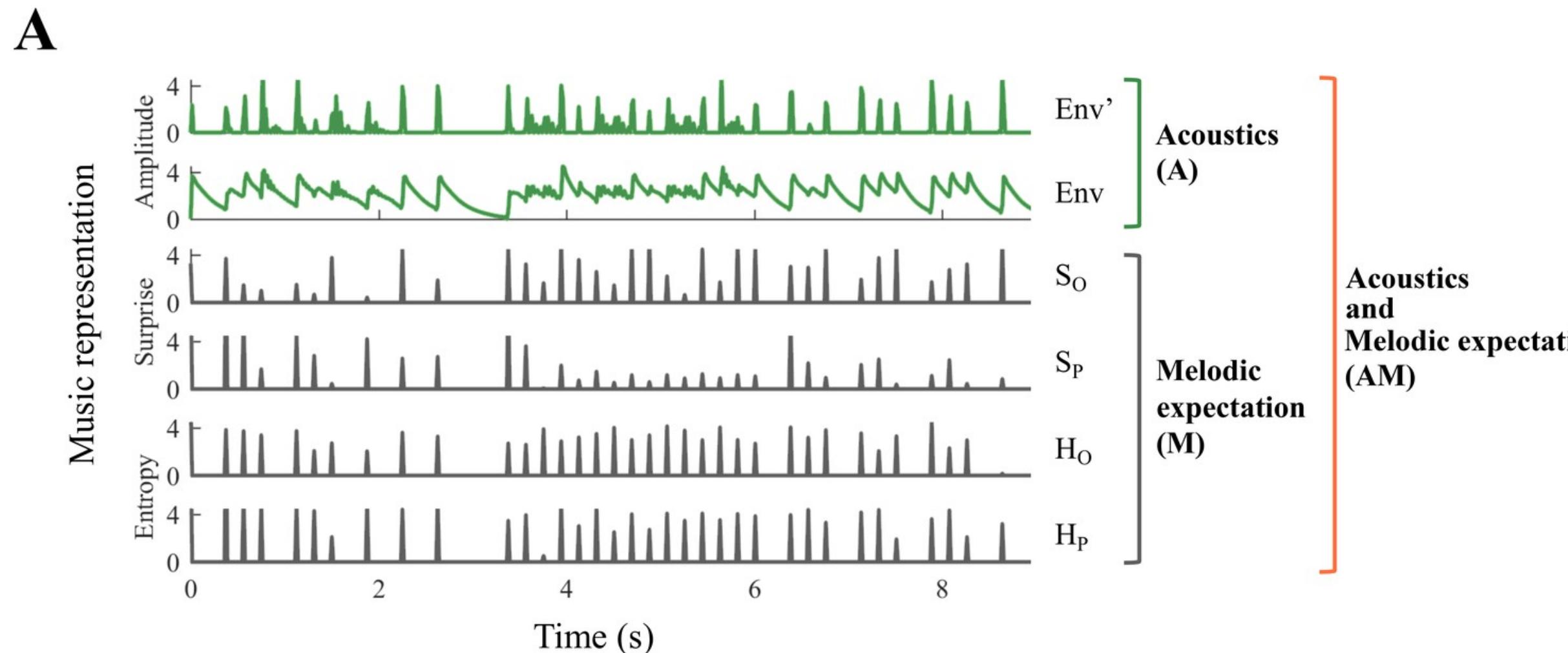
Temporal response function of melodic surprisal

Non-invasive recording of EEG (scalp potential)

A**B****C**

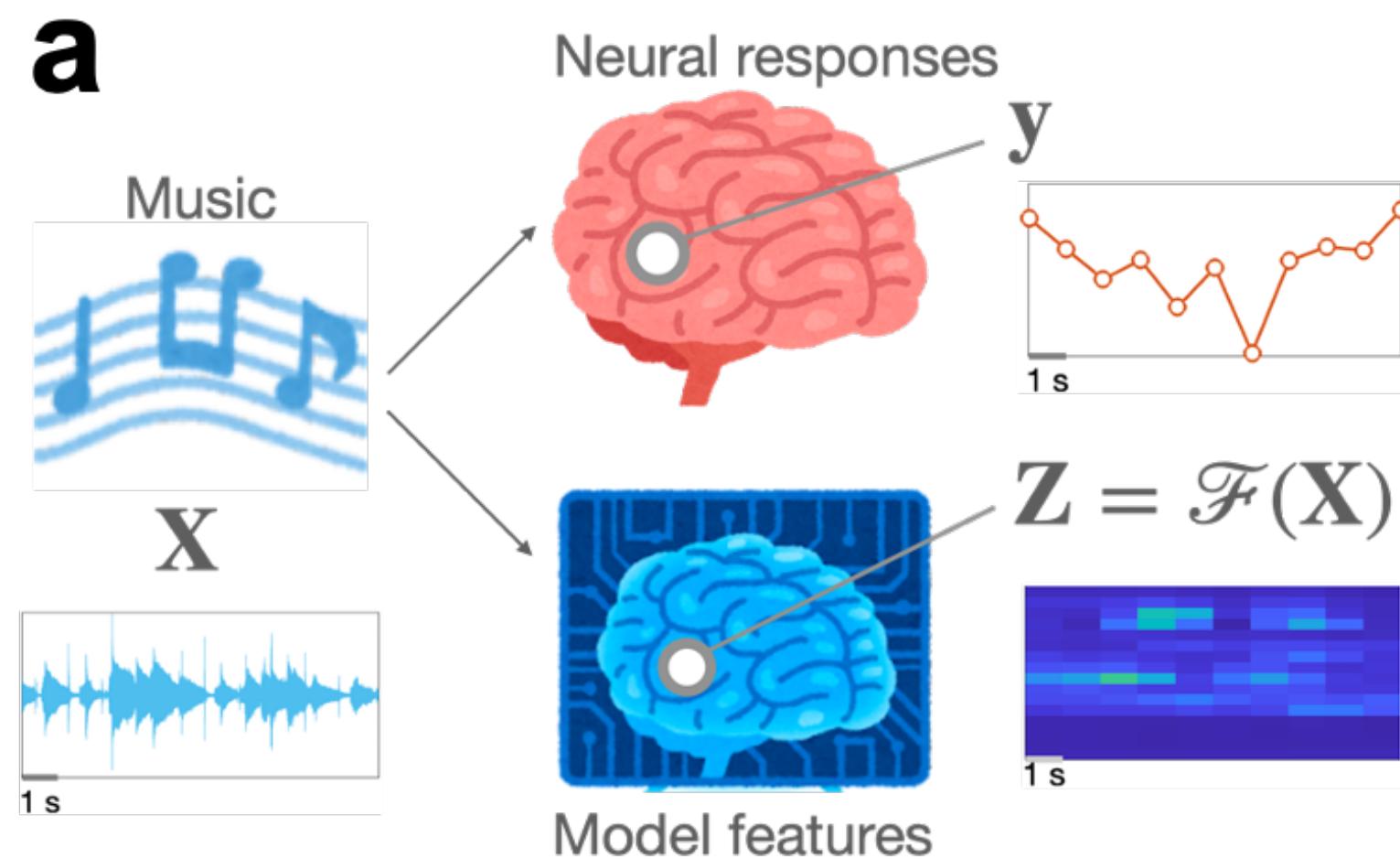
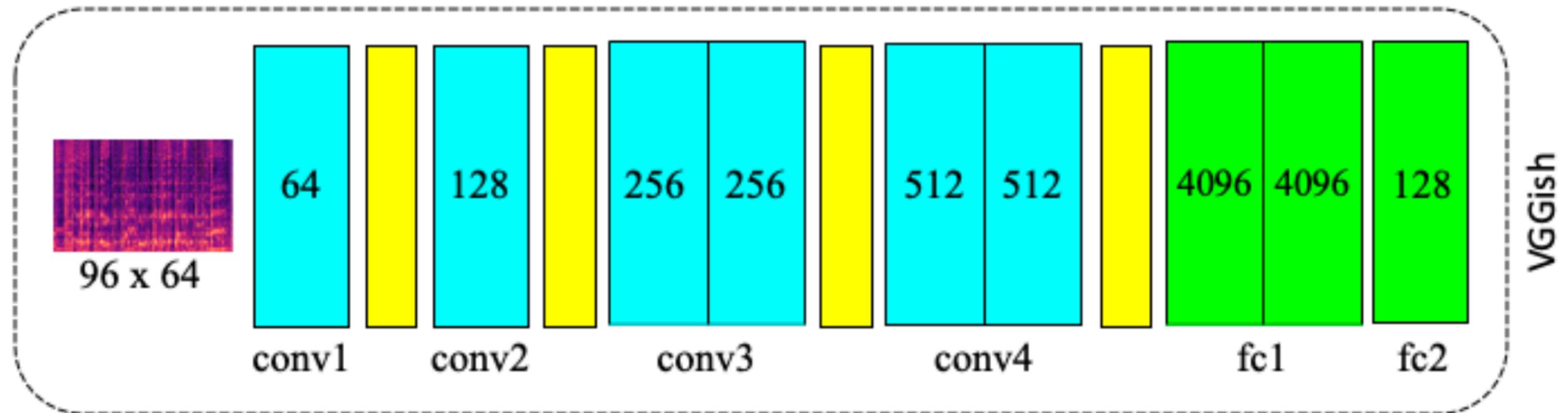
Temporal response function of melodic surprisal

Non-invasive recording of EEG (scalp potential) D



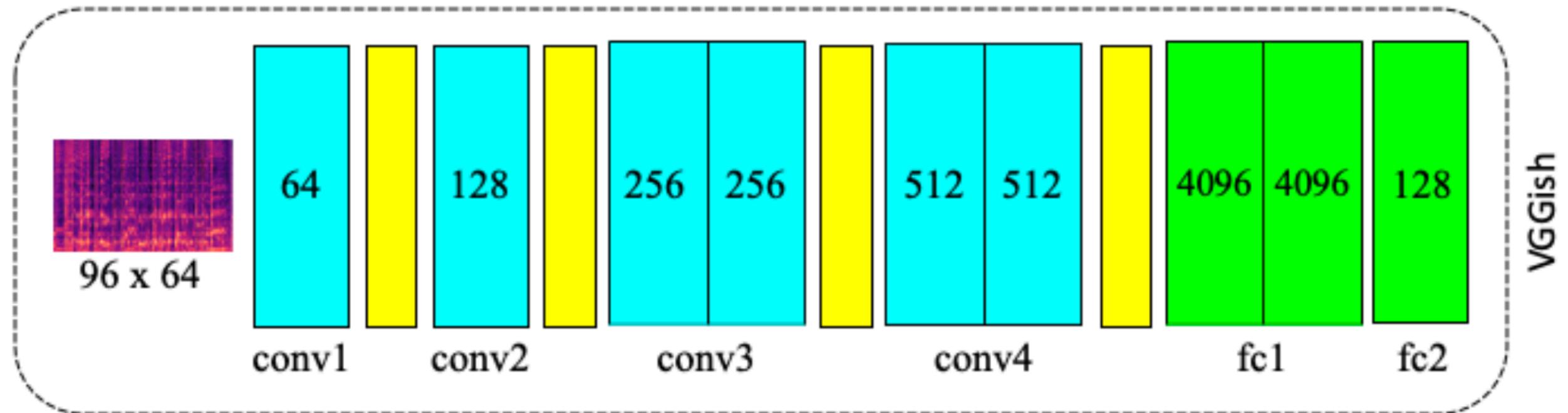
Representational gradient of musical emotions in fMRI

Non-invasive scanning of functional MRI (local paramagnetism)

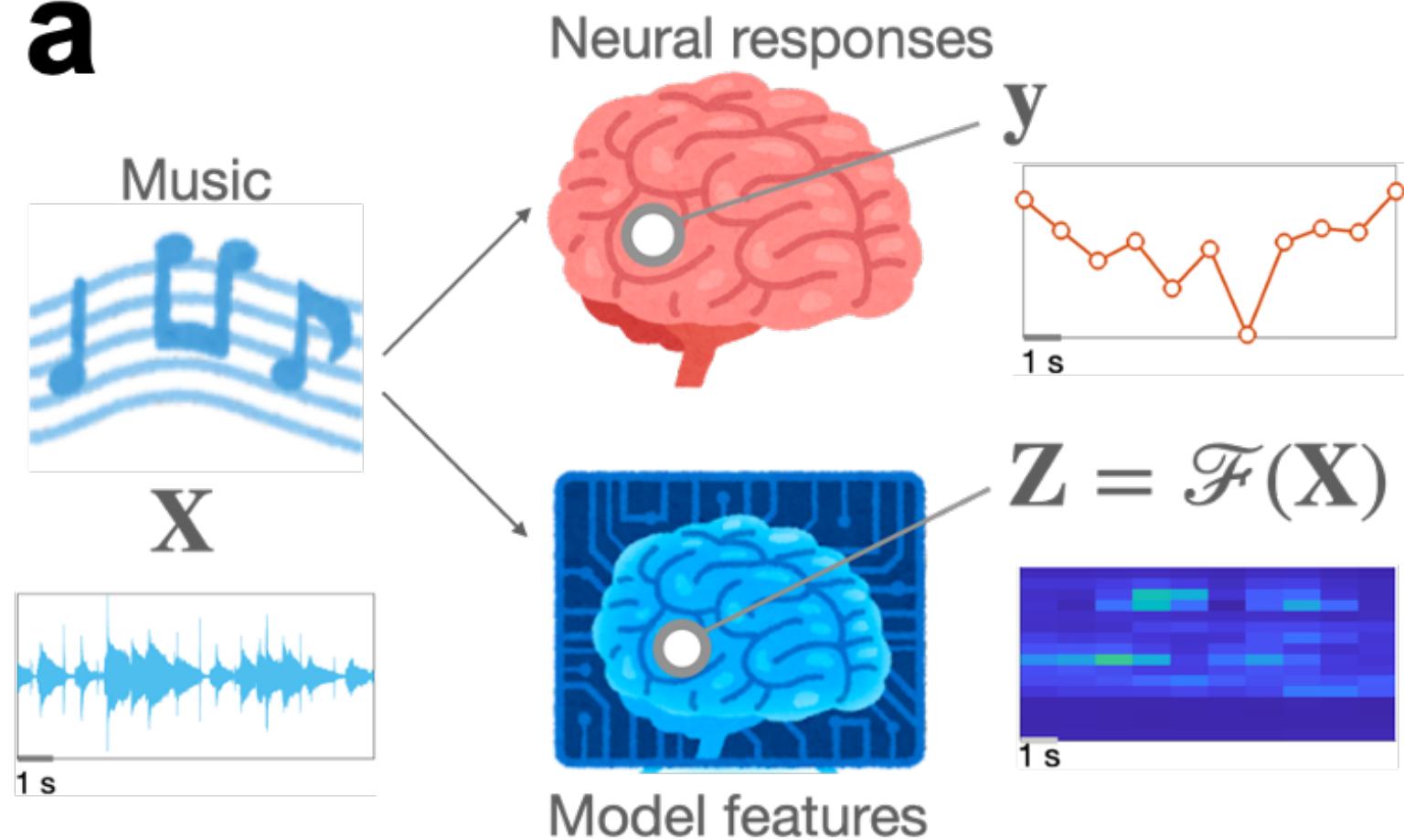


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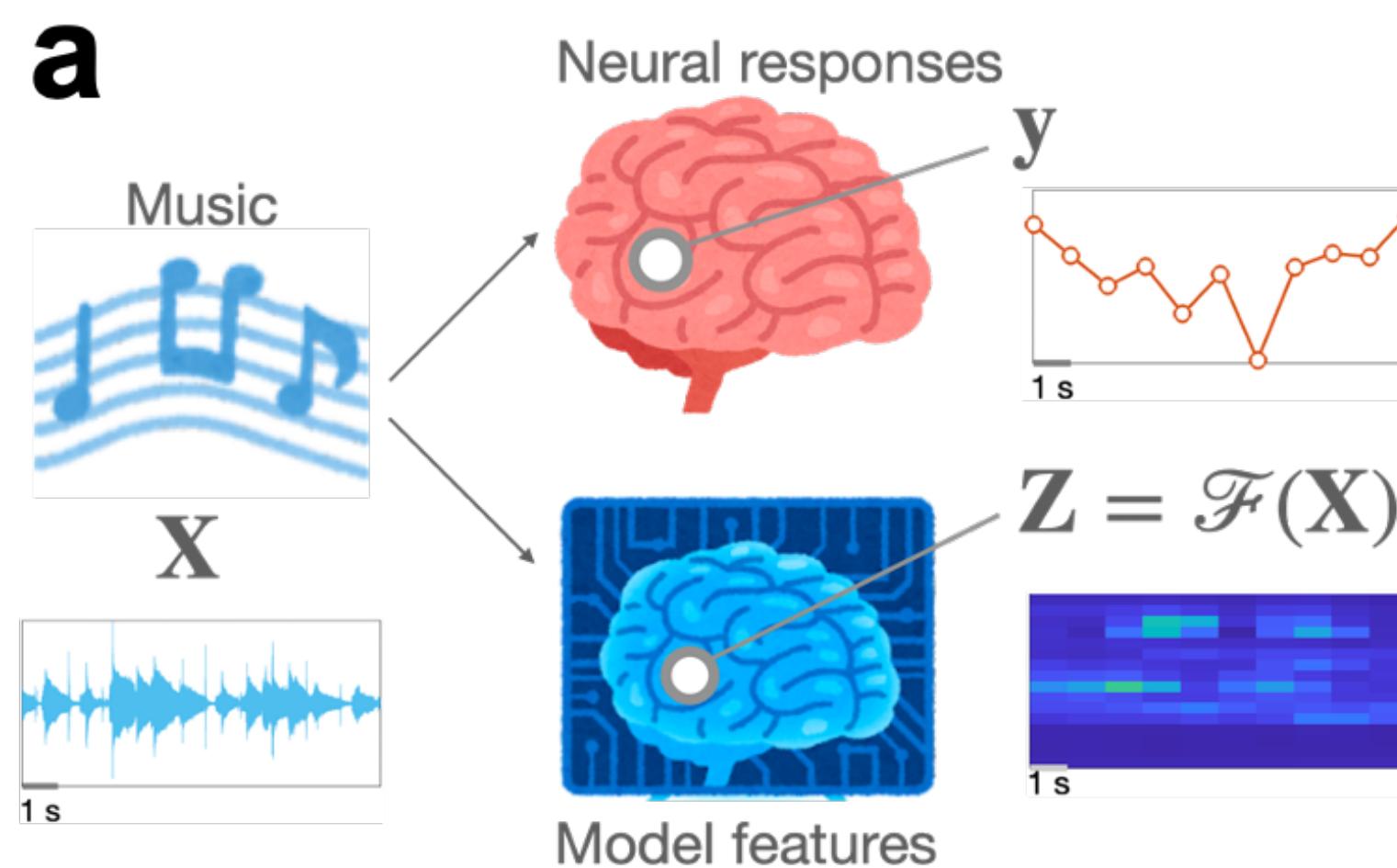
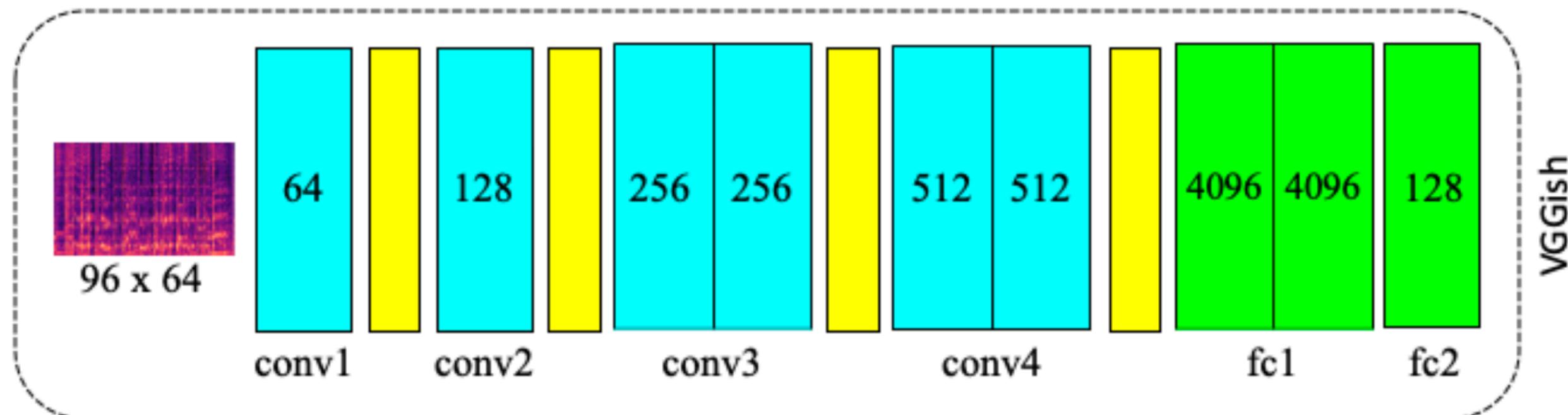
a



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)



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

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

$$\mathbf{y}^{(1)} = \mathcal{F}_2(\mathbf{X}^{(1)})\mathbf{b}_2 + \varepsilon \rightarrow \mathbf{r}_2 = \text{corr}(\hat{\mathbf{y}}_2^{(2)}, \mathbf{y}^{(2)})$$

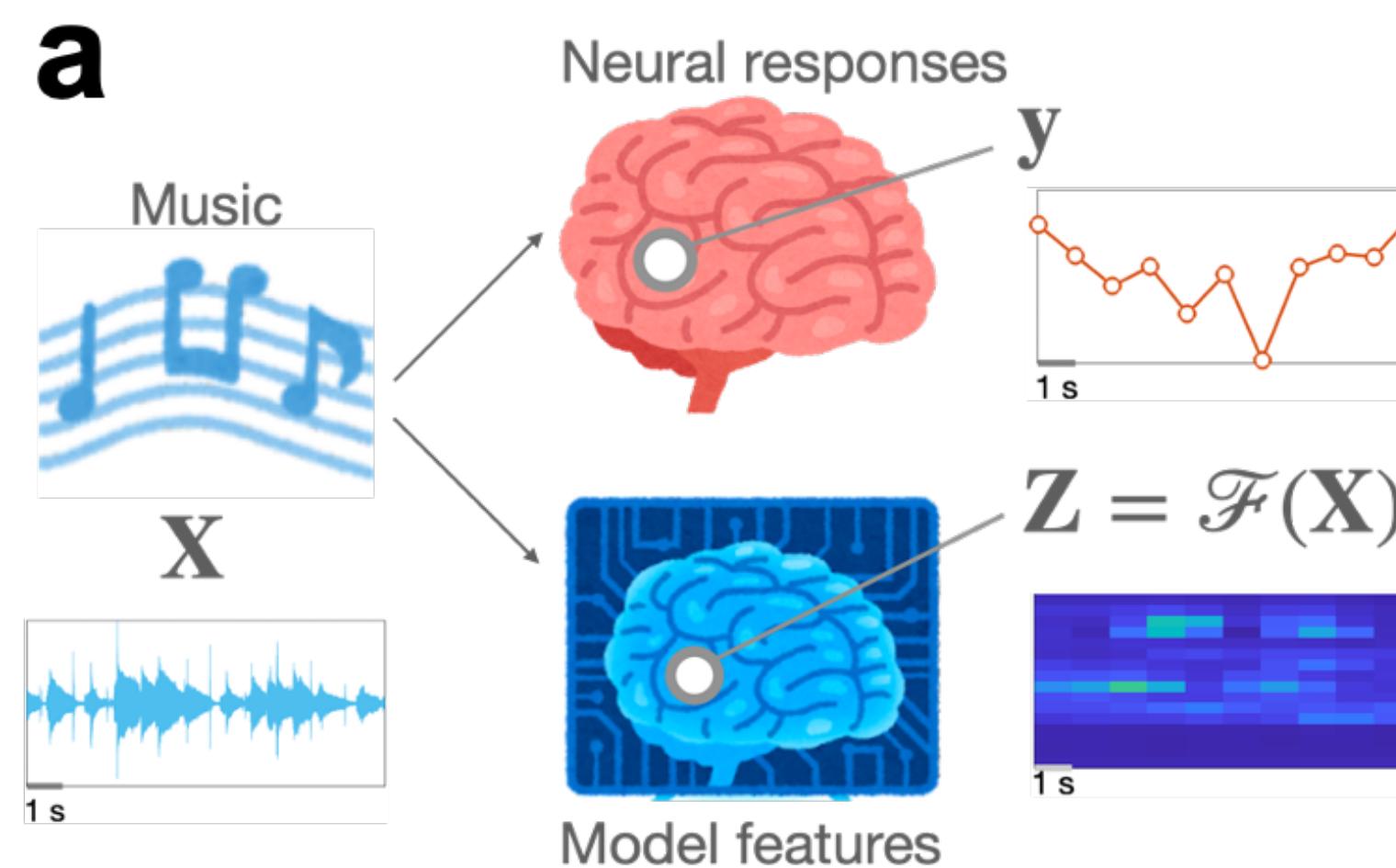
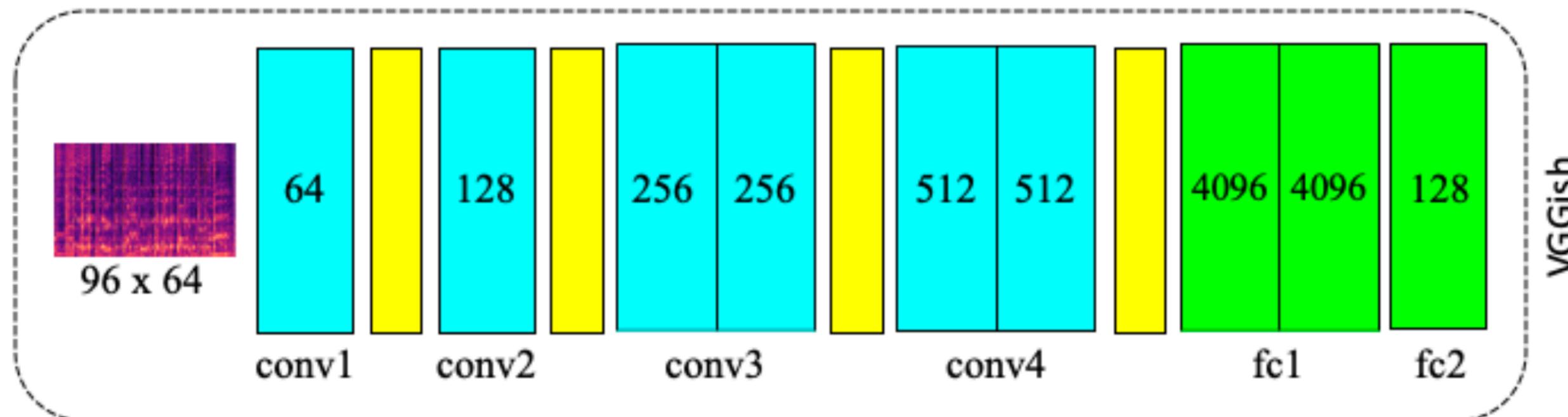
$$\mathbf{y}^{(1)} = \mathcal{F}_3(\mathbf{X}^{(1)})\mathbf{b}_3 + \varepsilon \rightarrow \mathbf{r}_3 = \text{corr}(\hat{\mathbf{y}}_3^{(2)}, \mathbf{y}^{(2)})$$

:

$$\mathbf{y}^{(1)} = \mathcal{F}_{24}(\mathbf{X}^{(1)})\mathbf{b}_{24} + \varepsilon \rightarrow \mathbf{r}_{24} = \text{corr}(\hat{\mathbf{y}}_{24}^{(2)}, \mathbf{y}^{(2)})$$

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?

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

$$\mathbf{y}^{(1)} = \mathcal{F}_2(\mathbf{X}^{(1)})\mathbf{b}_2 + \varepsilon \rightarrow \mathbf{r}_2 = \text{corr}(\hat{\mathbf{y}}_2^{(2)}, \mathbf{y}^{(2)})$$

$$\mathbf{y}^{(1)} = \mathcal{F}_3(\mathbf{X}^{(1)})\mathbf{b}_3 + \varepsilon \rightarrow \mathbf{r}_3 = \text{corr}(\hat{\mathbf{y}}_3^{(2)}, \mathbf{y}^{(2)})$$

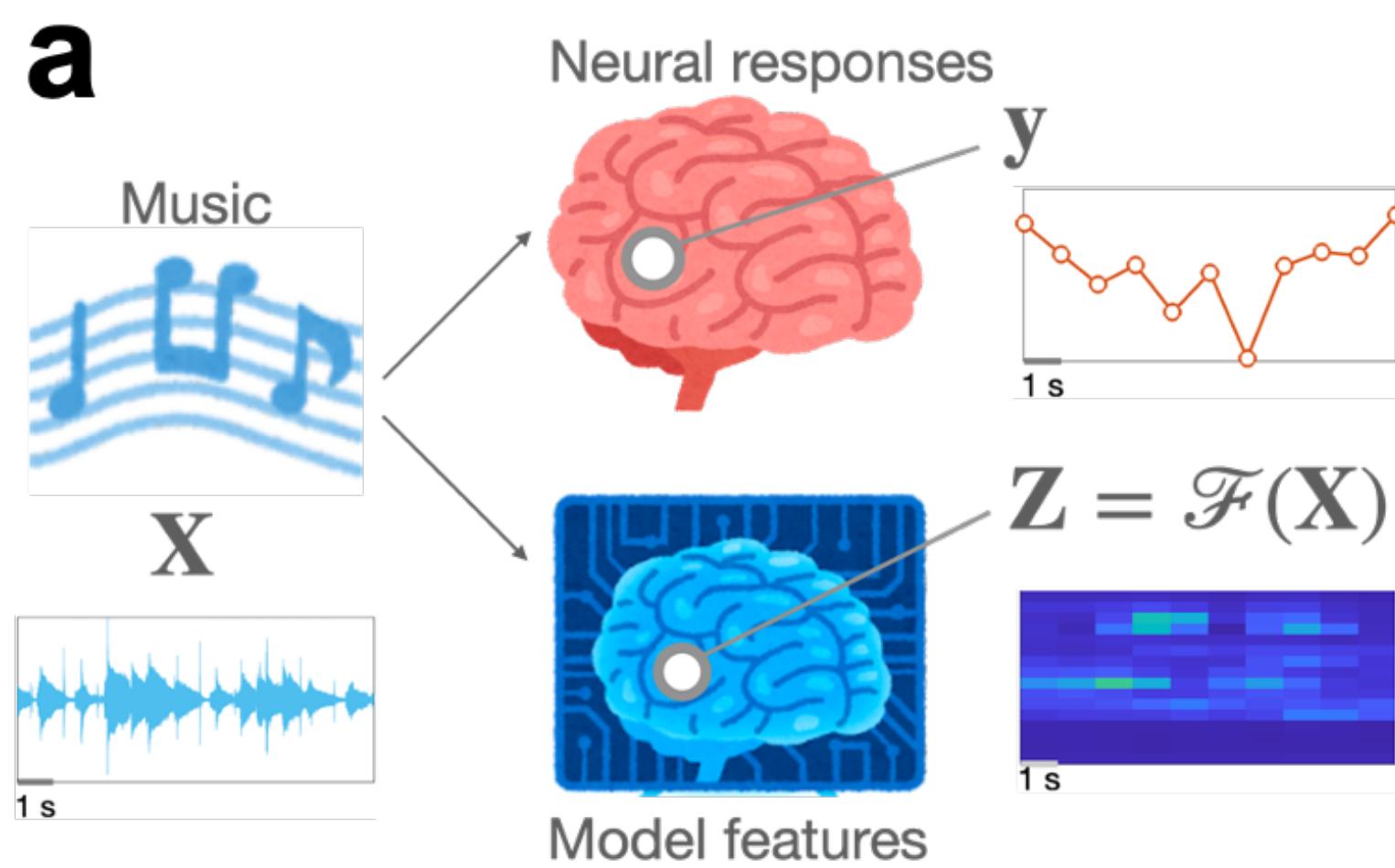
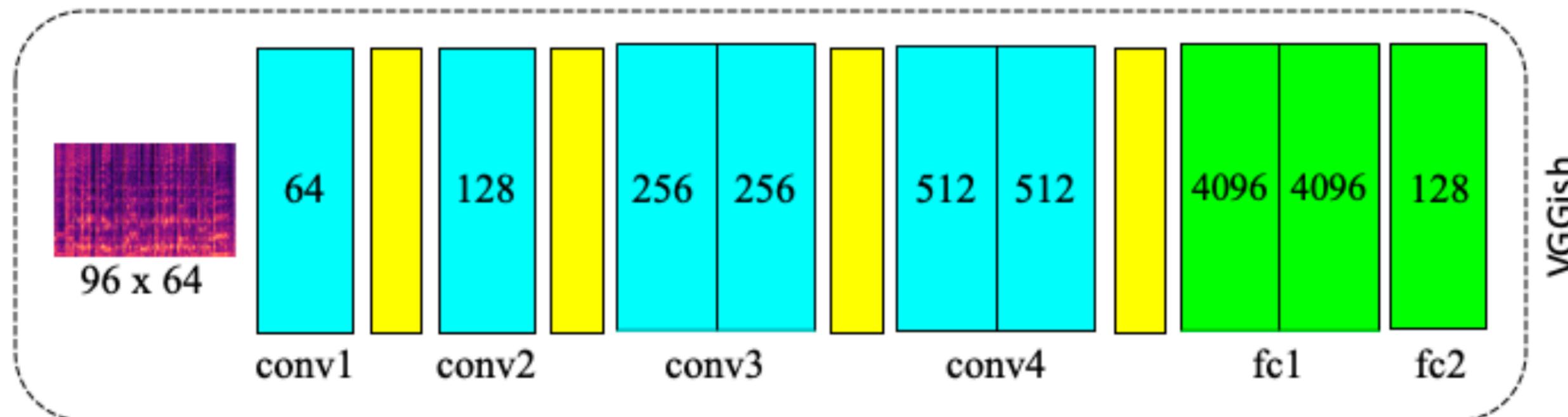
:

$$\mathbf{y}^{(1)} = \mathcal{F}_{24}(\mathbf{X}^{(1)})\mathbf{b}_{24} + \varepsilon \rightarrow \mathbf{r}_{24} = \text{corr}(\hat{\mathbf{y}}_{24}^{(2)}, \mathbf{y}^{(2)})$$

A "profile" of layer-specific prediction accuracies

Representational gradient of musical emotions in fMRI

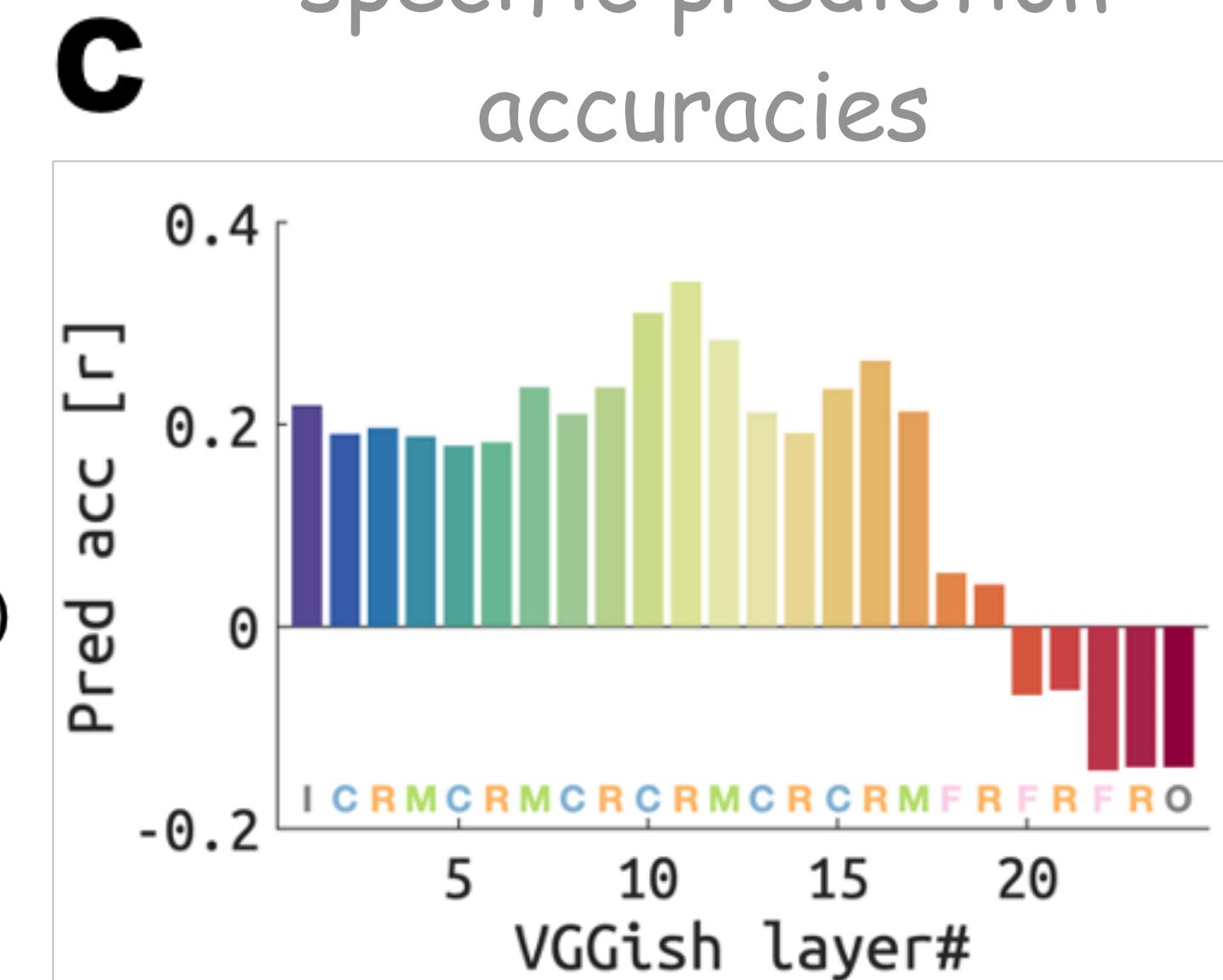
Non-invasive scanning of functional MRI (local paramagnetism)



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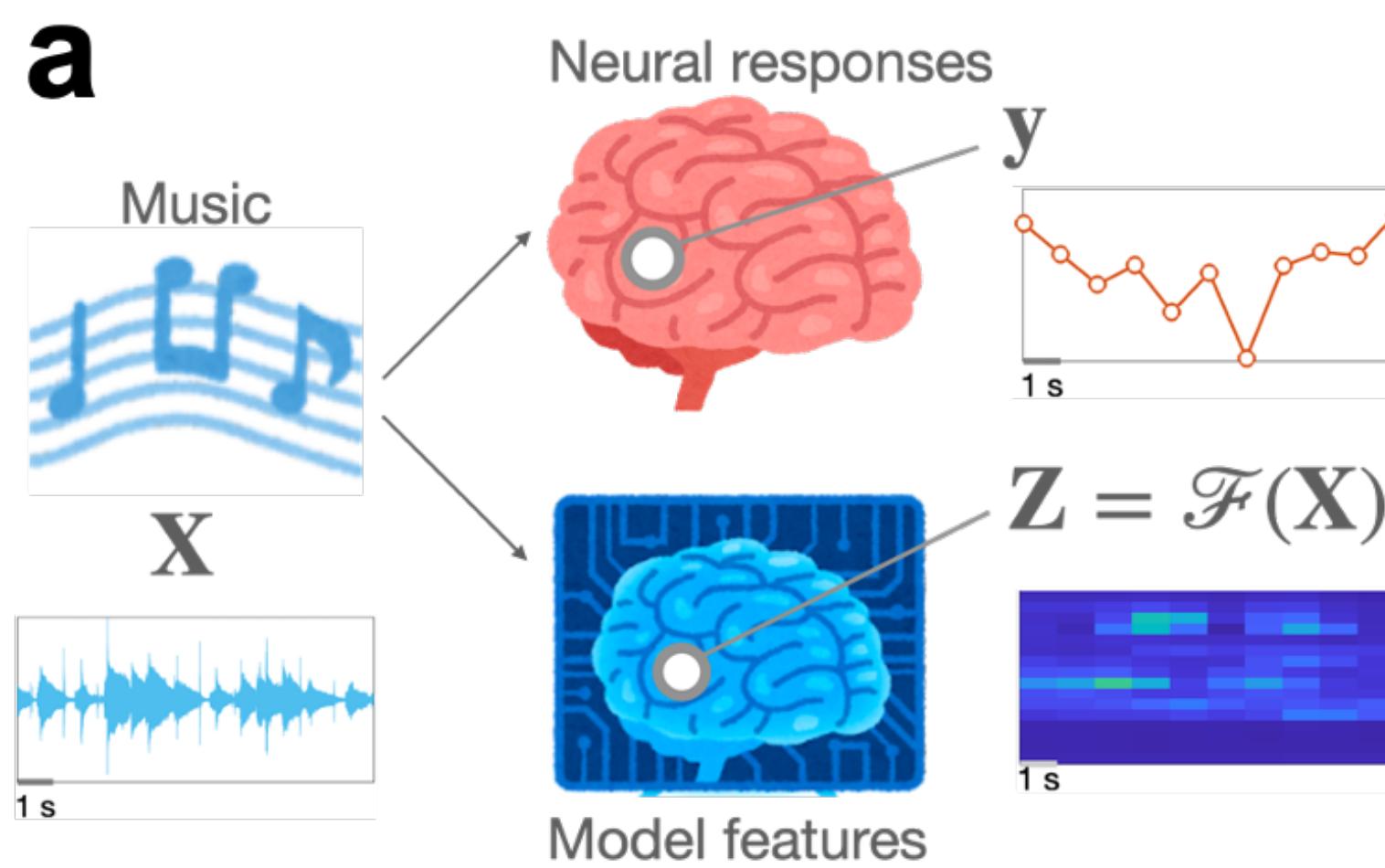
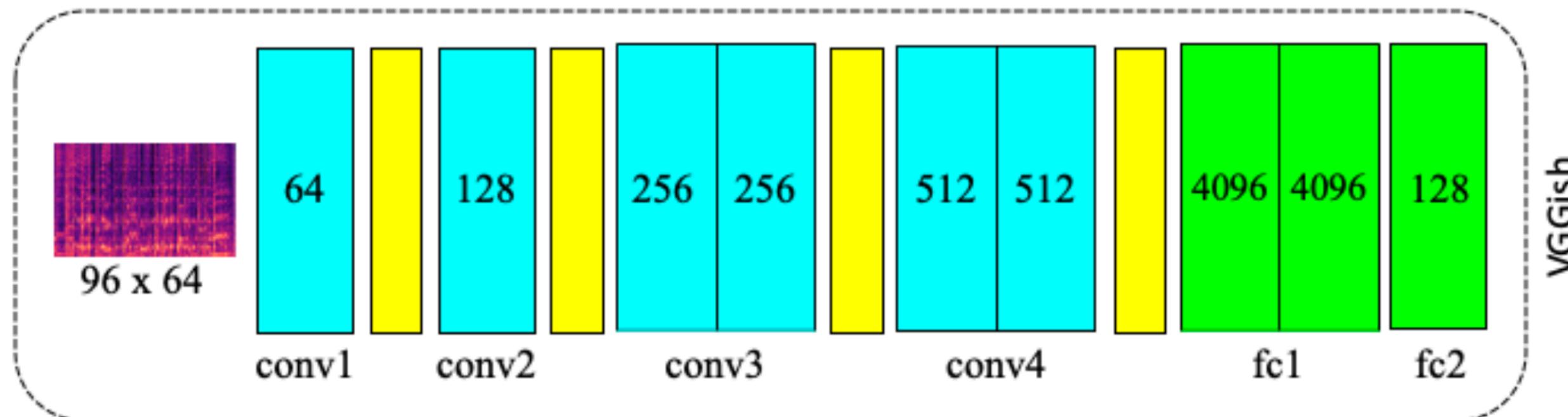
$$\begin{aligned}
 \mathbf{y}^{(1)} &= \mathcal{F}_1(\mathbf{X}^{(1)})\mathbf{b}_1 + \varepsilon \rightarrow \mathbf{r}_1 = \text{corr}(\hat{\mathbf{y}}_1^{(2)}, \mathbf{y}^{(2)}) \\
 \mathbf{y}^{(1)} &= \mathcal{F}_2(\mathbf{X}^{(1)})\mathbf{b}_2 + \varepsilon \rightarrow \mathbf{r}_2 = \text{corr}(\hat{\mathbf{y}}_2^{(2)}, \mathbf{y}^{(2)}) \\
 \mathbf{y}^{(1)} &= \mathcal{F}_3(\mathbf{X}^{(1)})\mathbf{b}_3 + \varepsilon \rightarrow \mathbf{r}_3 = \text{corr}(\hat{\mathbf{y}}_3^{(2)}, \mathbf{y}^{(2)}) \\
 &\vdots \\
 \mathbf{y}^{(1)} &= \mathcal{F}_{24}(\mathbf{X}^{(1)})\mathbf{b}_{24} + \varepsilon \rightarrow \mathbf{r}_{24} = \text{corr}(\hat{\mathbf{y}}_{24}^{(2)}, \mathbf{y}^{(2)})
 \end{aligned}$$

A "profile" of layer-specific prediction accuracies



Representational gradient of musical emotions in fMRI

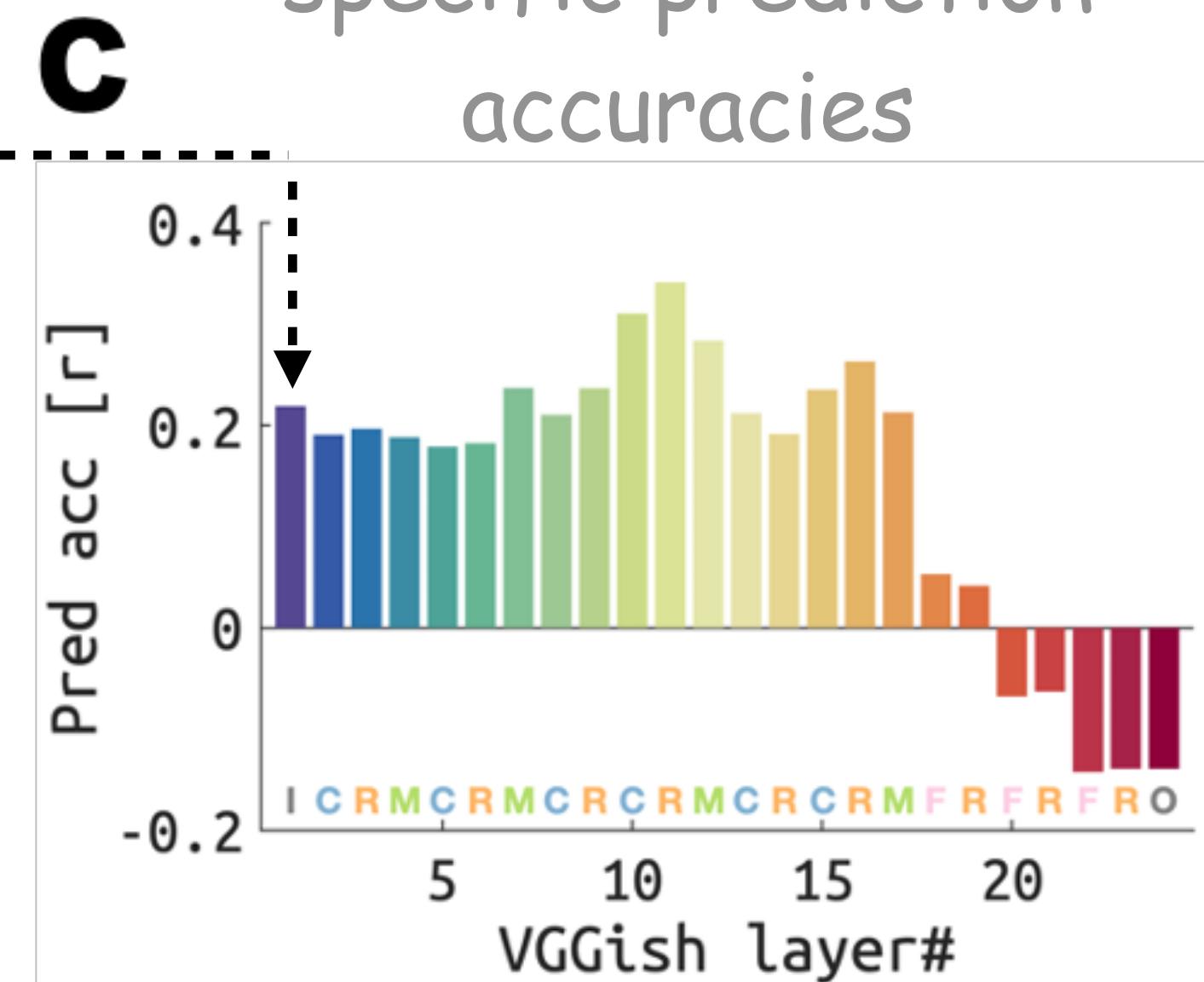
Non-invasive scanning of functional MRI (local paramagnetism)



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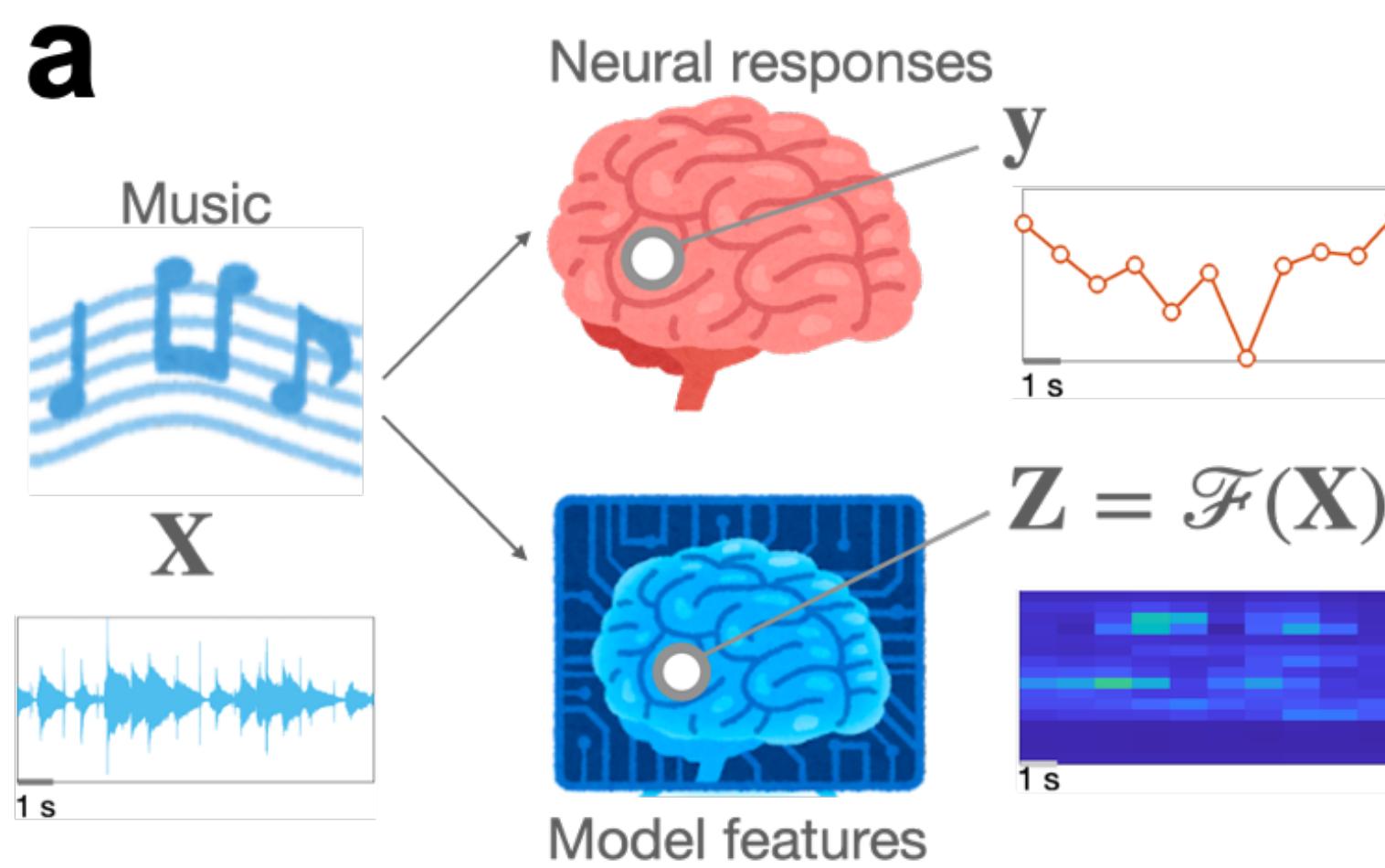
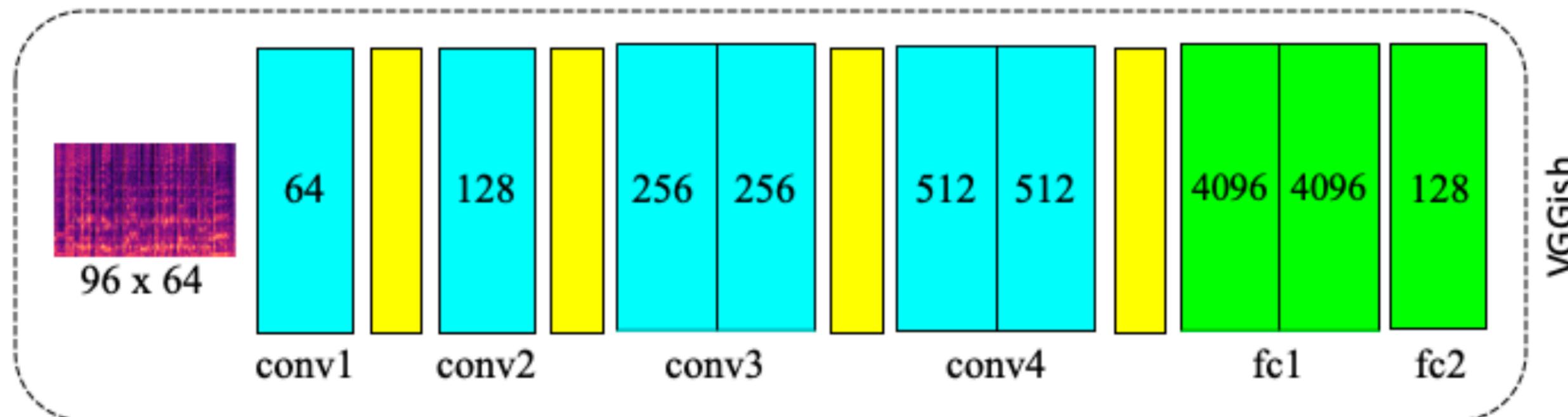
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 \end{aligned}$$

A "profile" of layer-specific prediction accuracies



Representational gradient of musical emotions in fMRI

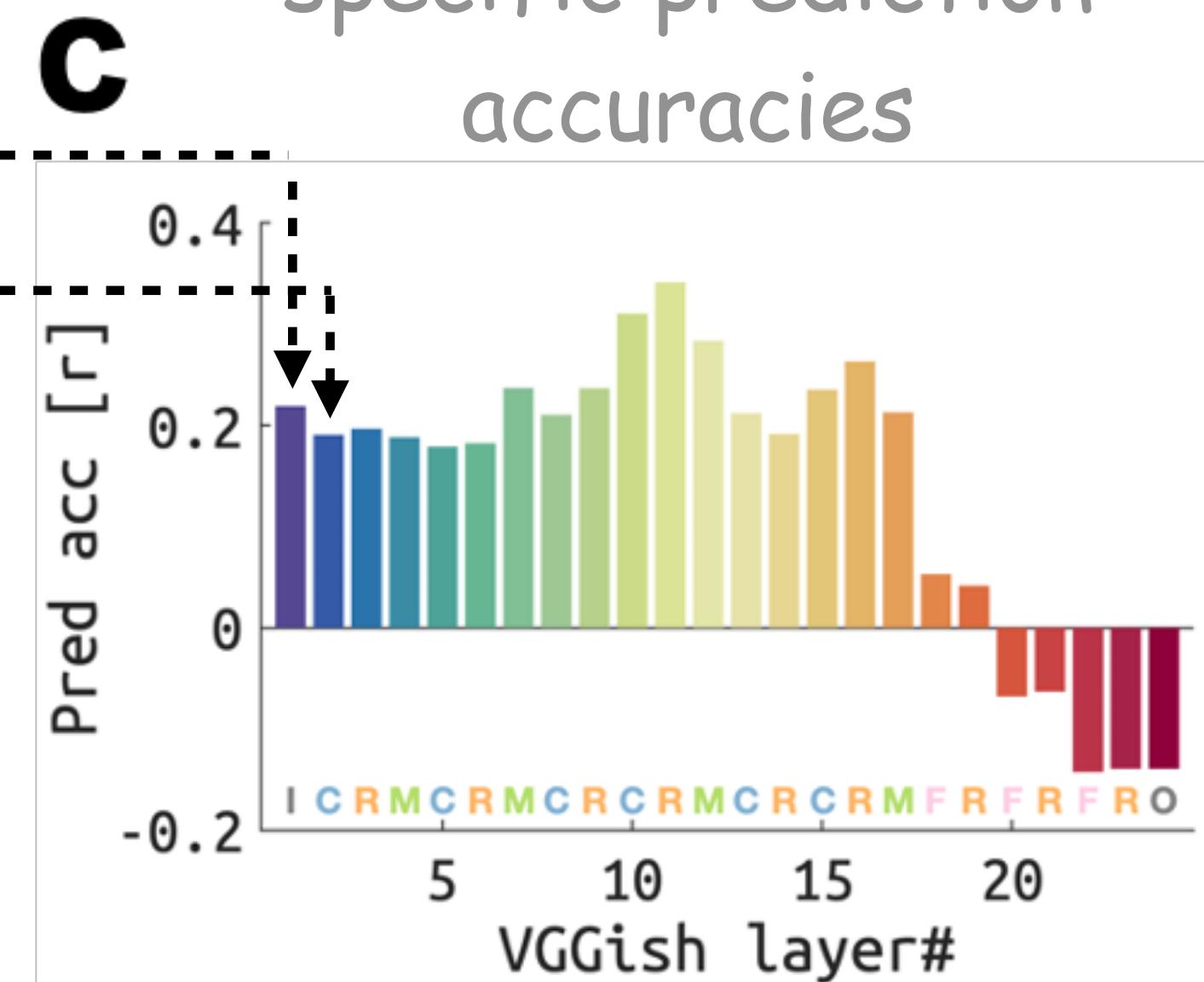
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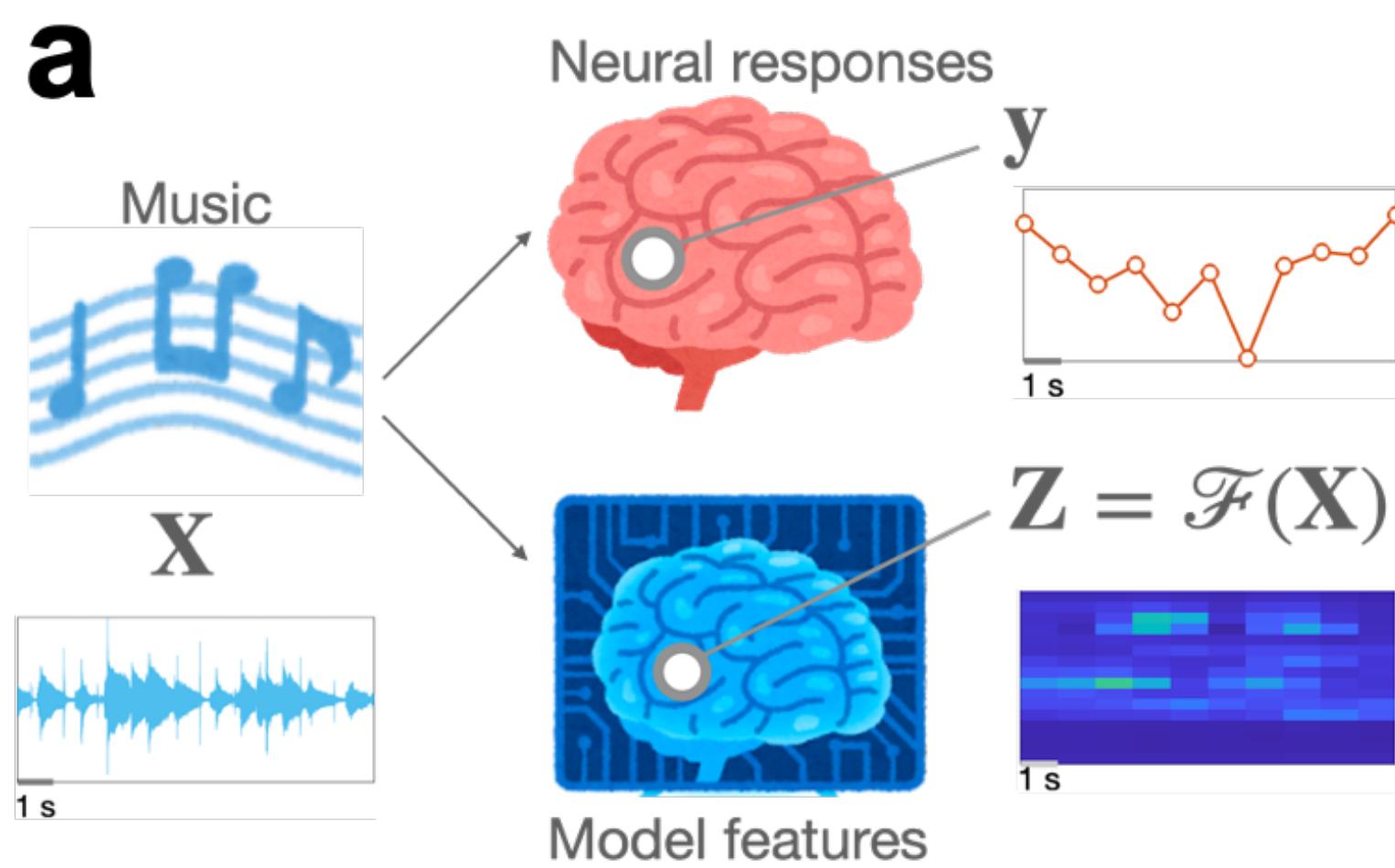
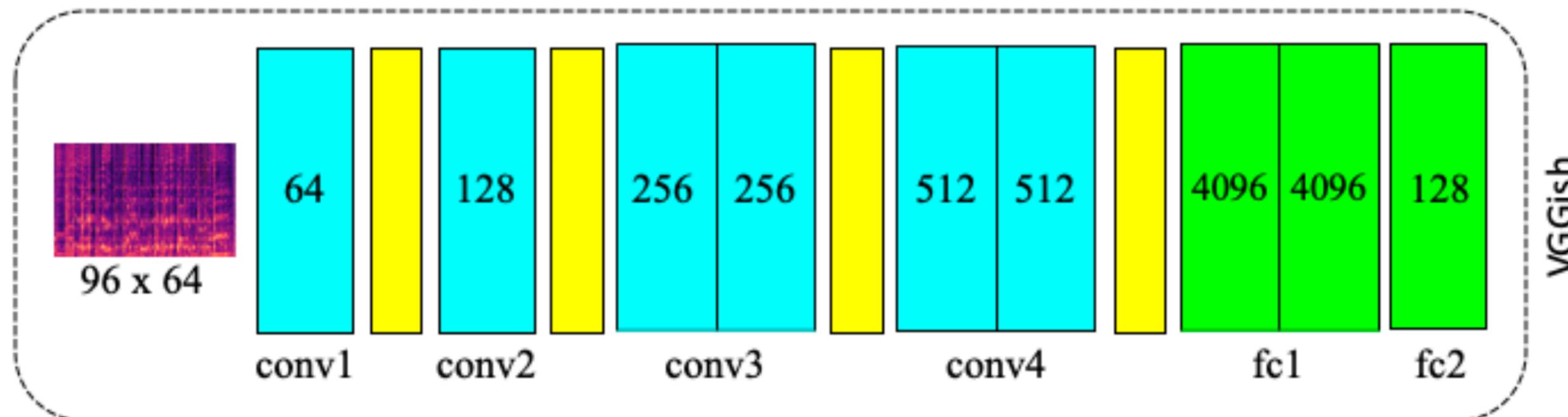
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 \mathbf{y}^{(1)} &= \mathcal{F}_3(\mathbf{X}^{(1)})\mathbf{b}_3 + \varepsilon \rightarrow \mathbf{r}_3 = \text{corr}(\hat{\mathbf{y}}_3^{(2)}, \mathbf{y}^{(2)}) \\
 &\vdots \\
 \mathbf{y}^{(1)} &= \mathcal{F}_{24}(\mathbf{X}^{(1)})\mathbf{b}_{24} + \varepsilon \rightarrow \mathbf{r}_{24} = \text{corr}(\hat{\mathbf{y}}_{24}^{(2)}, \mathbf{y}^{(2)})
 \end{aligned}$$

A "profile" of layer-specific prediction accuracies



Representational gradient of musical emotions in fMRI

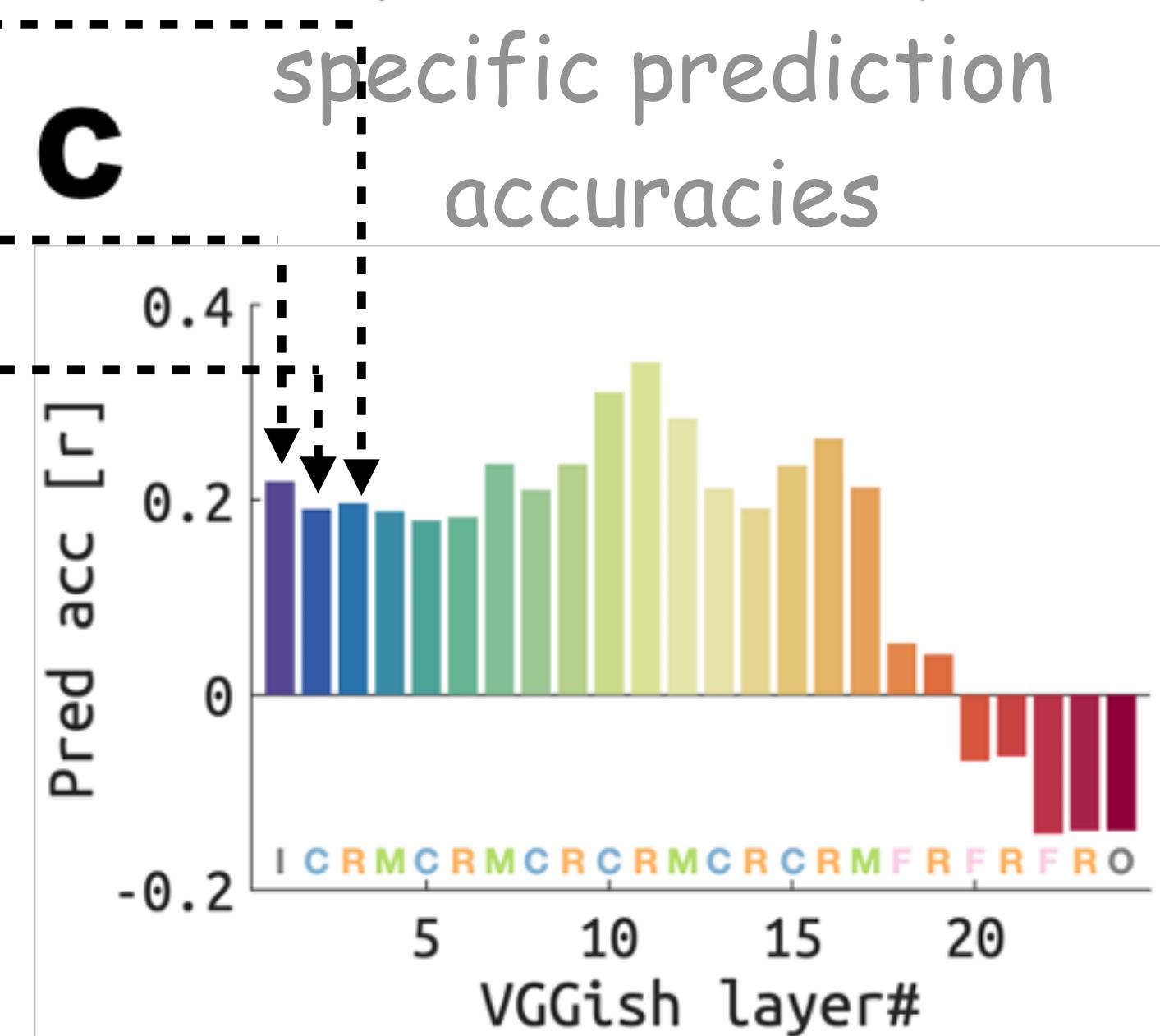
Non-invasive scanning of functional MRI (local paramagnetism)



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

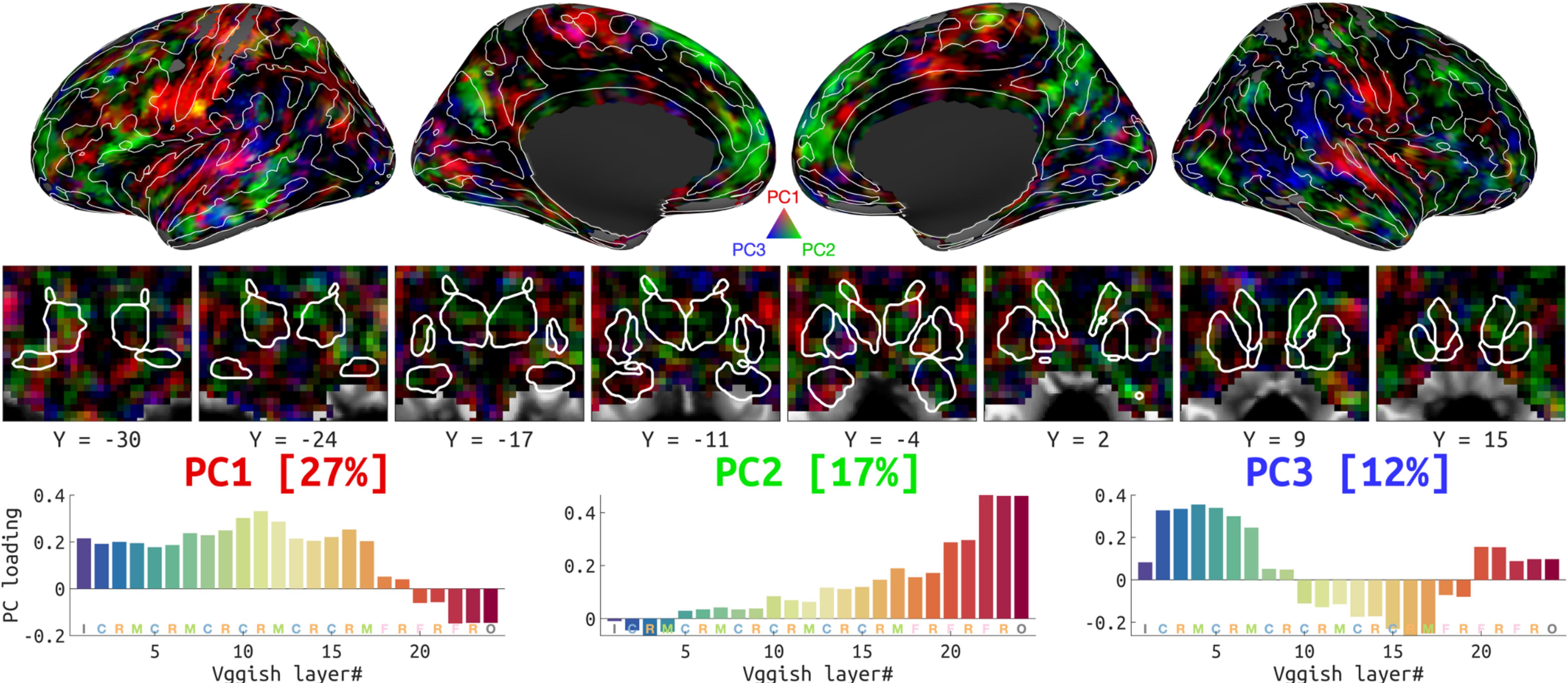
$$\begin{aligned} \mathbf{y}^{(1)} &= \mathcal{F}_1(\mathbf{X}^{(1)})\mathbf{b}_1 + \varepsilon \rightarrow \mathbf{r}_1 = \text{corr}(\hat{\mathbf{y}}_1^{(2)}, \mathbf{y}^{(2)}) \\ \mathbf{y}^{(1)} &= \mathcal{F}_2(\mathbf{X}^{(1)})\mathbf{b}_2 + \varepsilon \rightarrow \mathbf{r}_2 = \text{corr}(\hat{\mathbf{y}}_2^{(2)}, \mathbf{y}^{(2)}) \\ \mathbf{y}^{(1)} &= \mathcal{F}_3(\mathbf{X}^{(1)})\mathbf{b}_3 + \varepsilon \rightarrow \mathbf{r}_3 = \text{corr}(\hat{\mathbf{y}}_3^{(2)}, \mathbf{y}^{(2)}) \\ &\vdots \\ \mathbf{y}^{(1)} &= \mathcal{F}_{24}(\mathbf{X}^{(1)})\mathbf{b}_{24} + \varepsilon \rightarrow \mathbf{r}_{24} = \text{corr}(\hat{\mathbf{y}}_{24}^{(2)}, \mathbf{y}^{(2)}) \end{aligned}$$

A "profile" of layer-specific prediction accuracies



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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:**

X

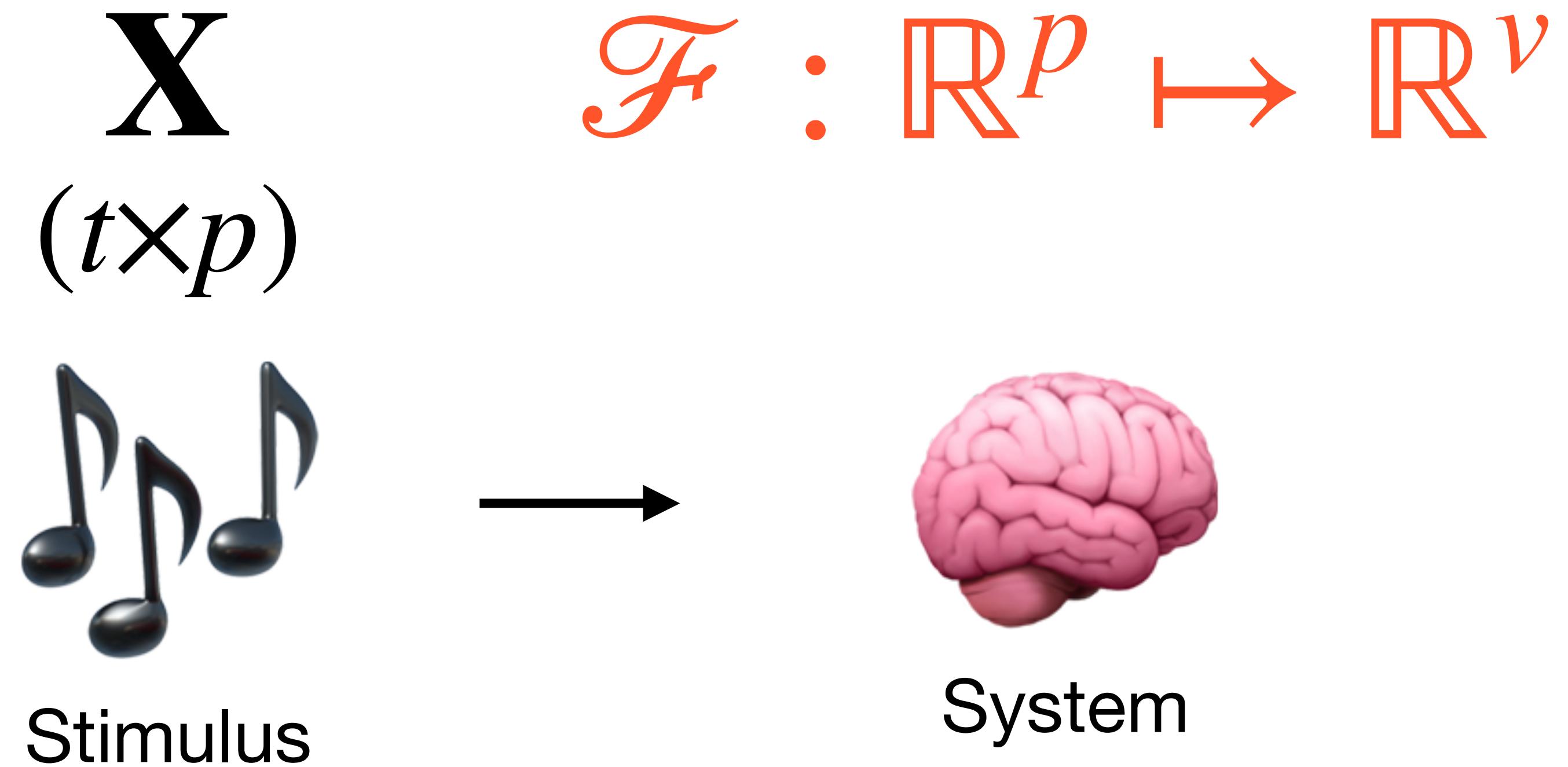
($t \times p$)



Stimulus

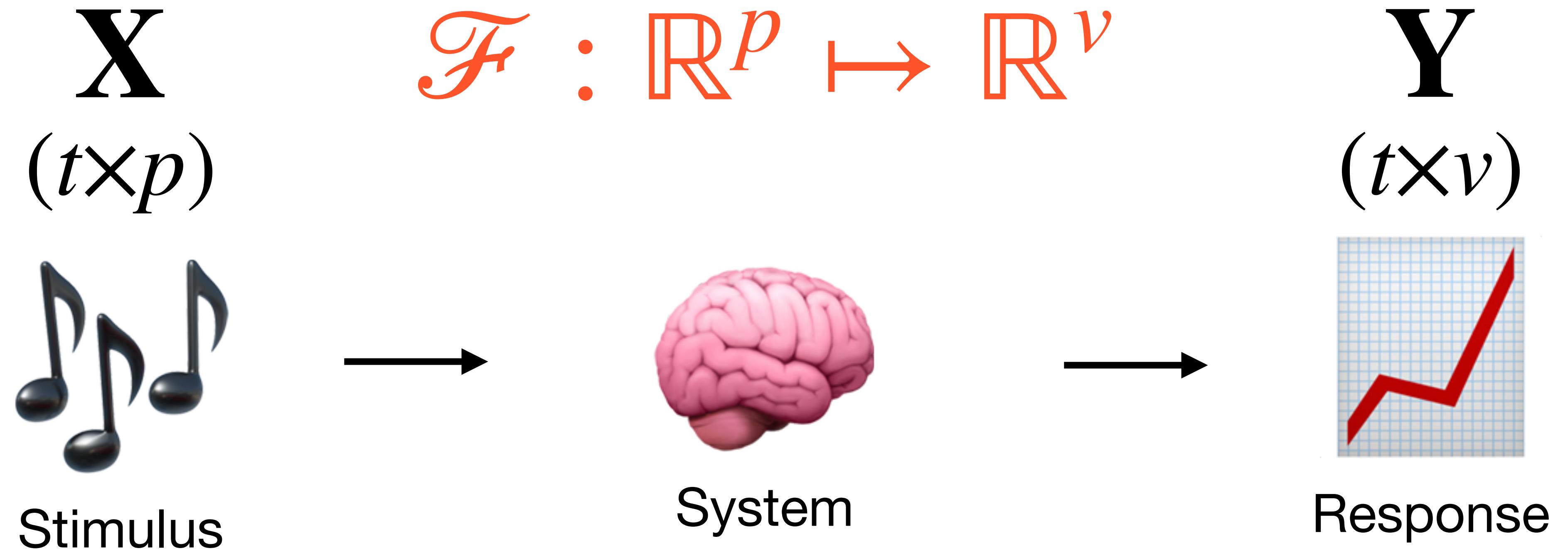
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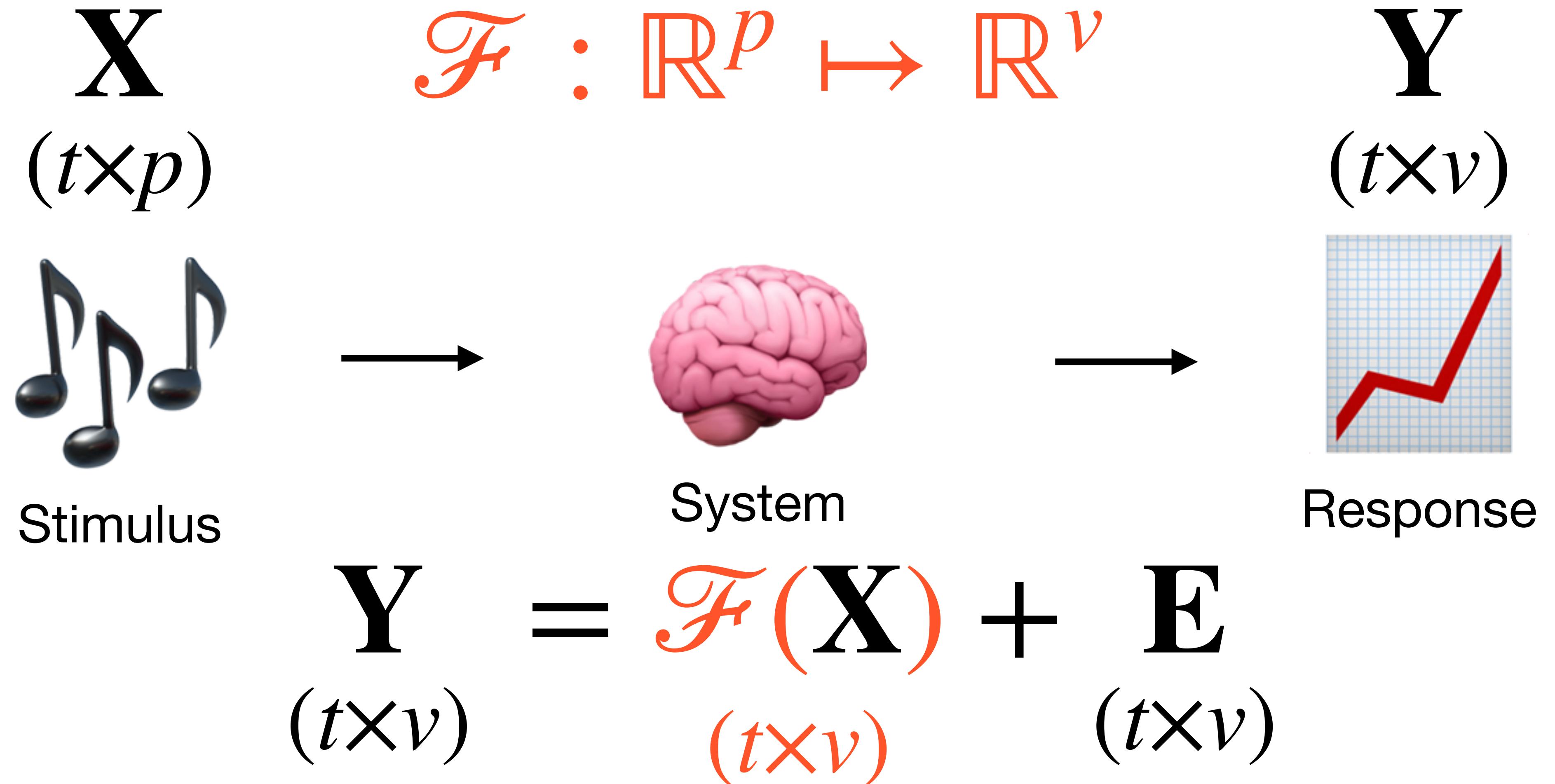
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How can we understand a nonlinear system?

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How can we understand a nonlinear system?

Let's say we somehow know **a function** that gives us **a linear mapping**

X

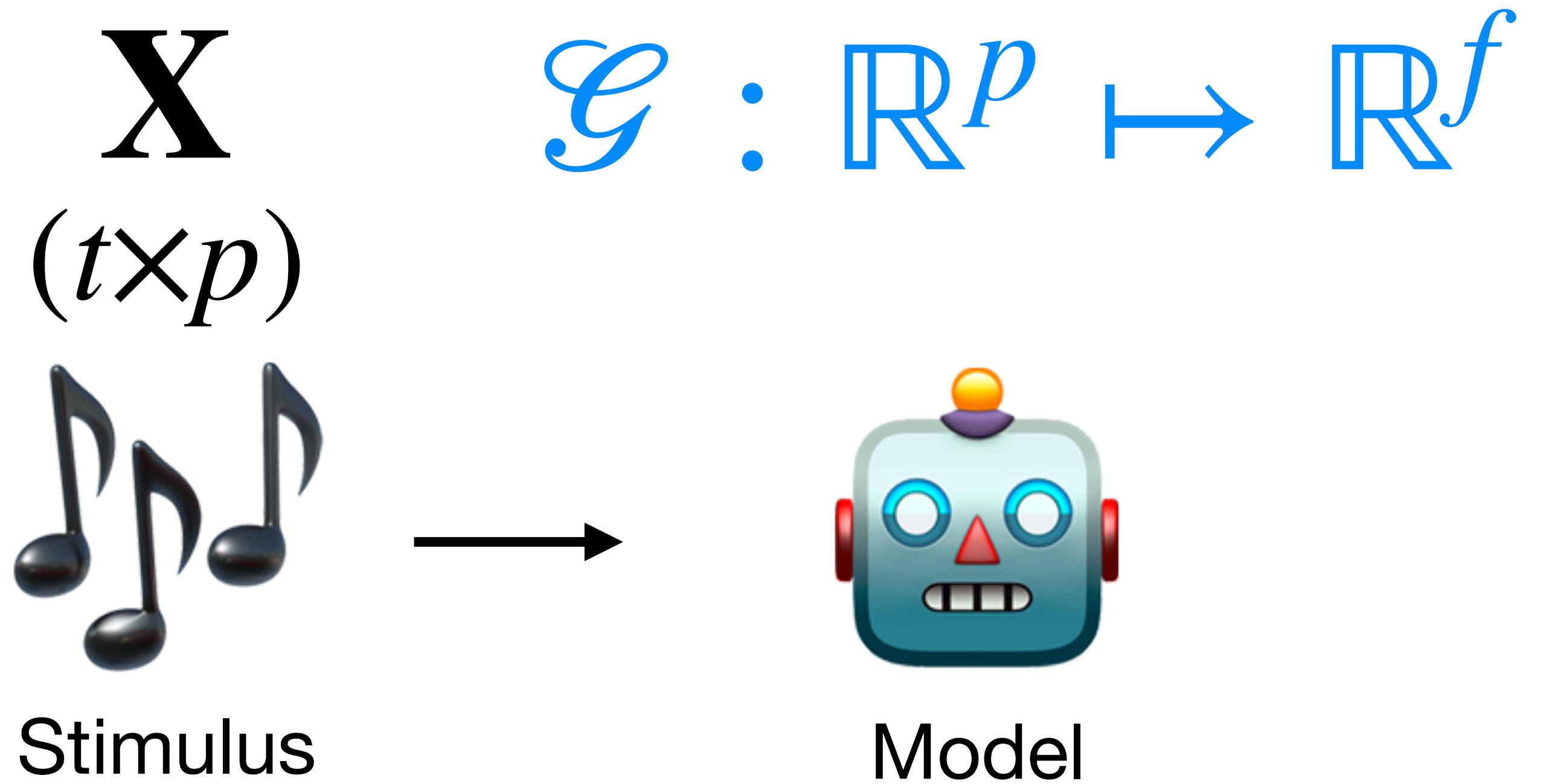
($t \times p$)



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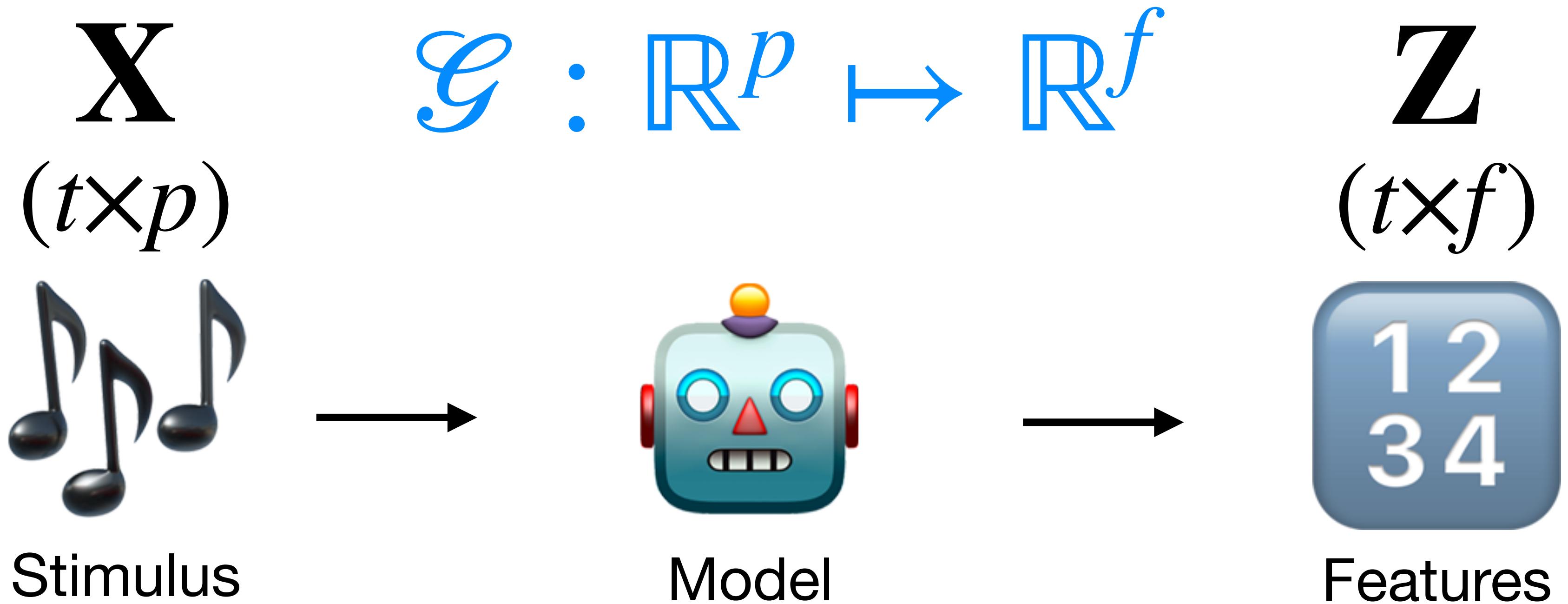
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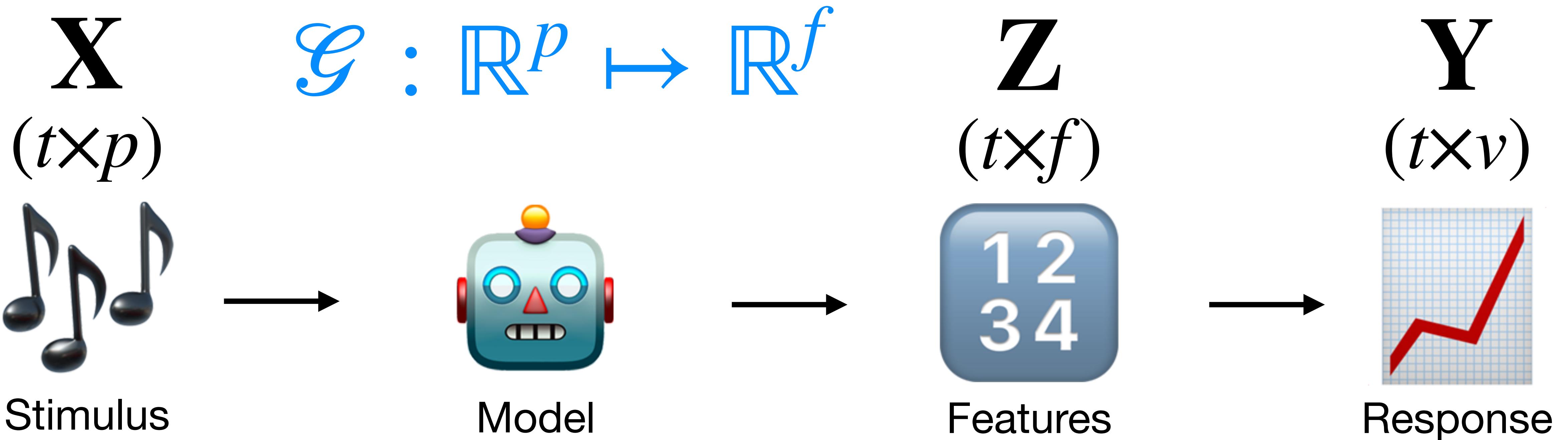
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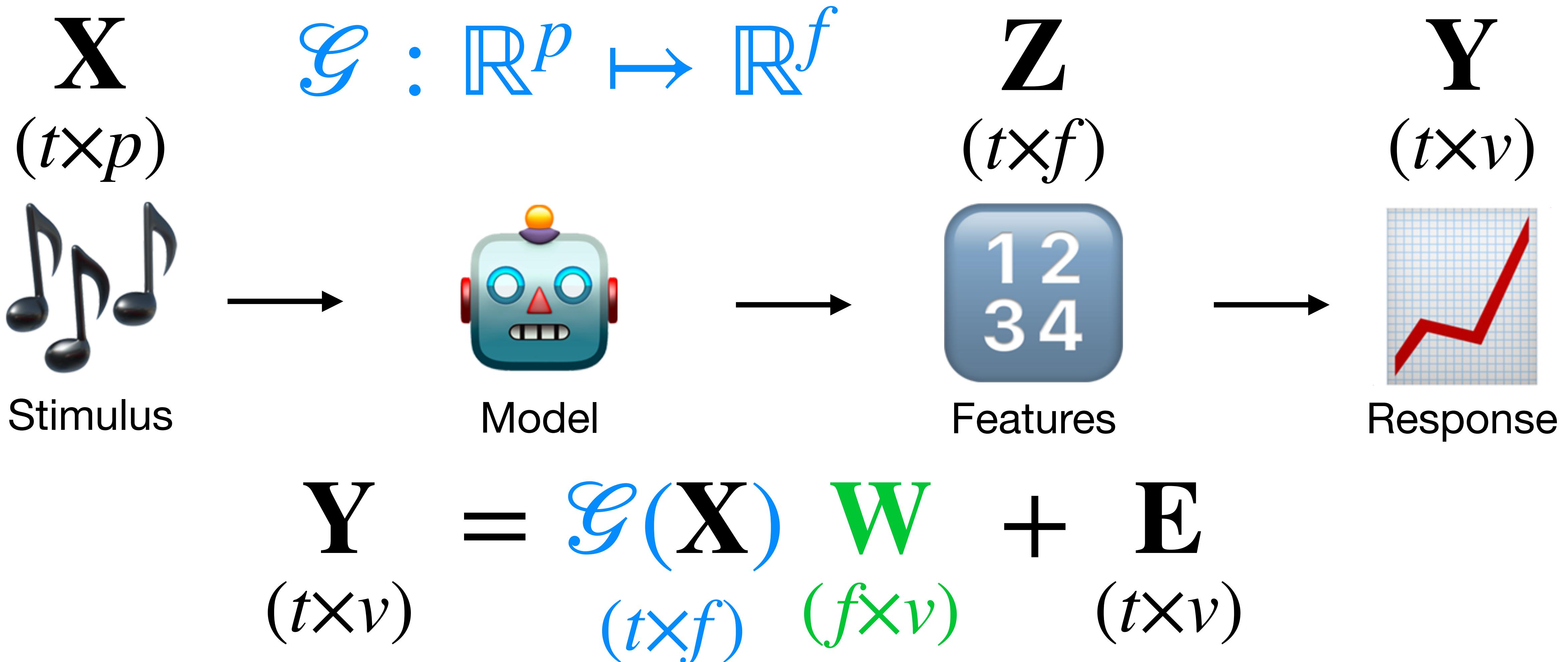
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How can we understand a nonlinear system?

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Linearized encoding analysis

A linear time-invariant system identification

Linearized encoding analysis

A linear time-invariant system identification

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

Linearized encoding analysis

A linear time-invariant system identification

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

$$\mathbf{Y} = \mathcal{G}(\mathbf{X})\mathbf{W} + \boldsymbol{\varepsilon}$$

Linearized encoding analysis

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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Linearized encoding analysis

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- 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)**.
- How the stimulus is *linearized* (by which function) is your hypothesis.

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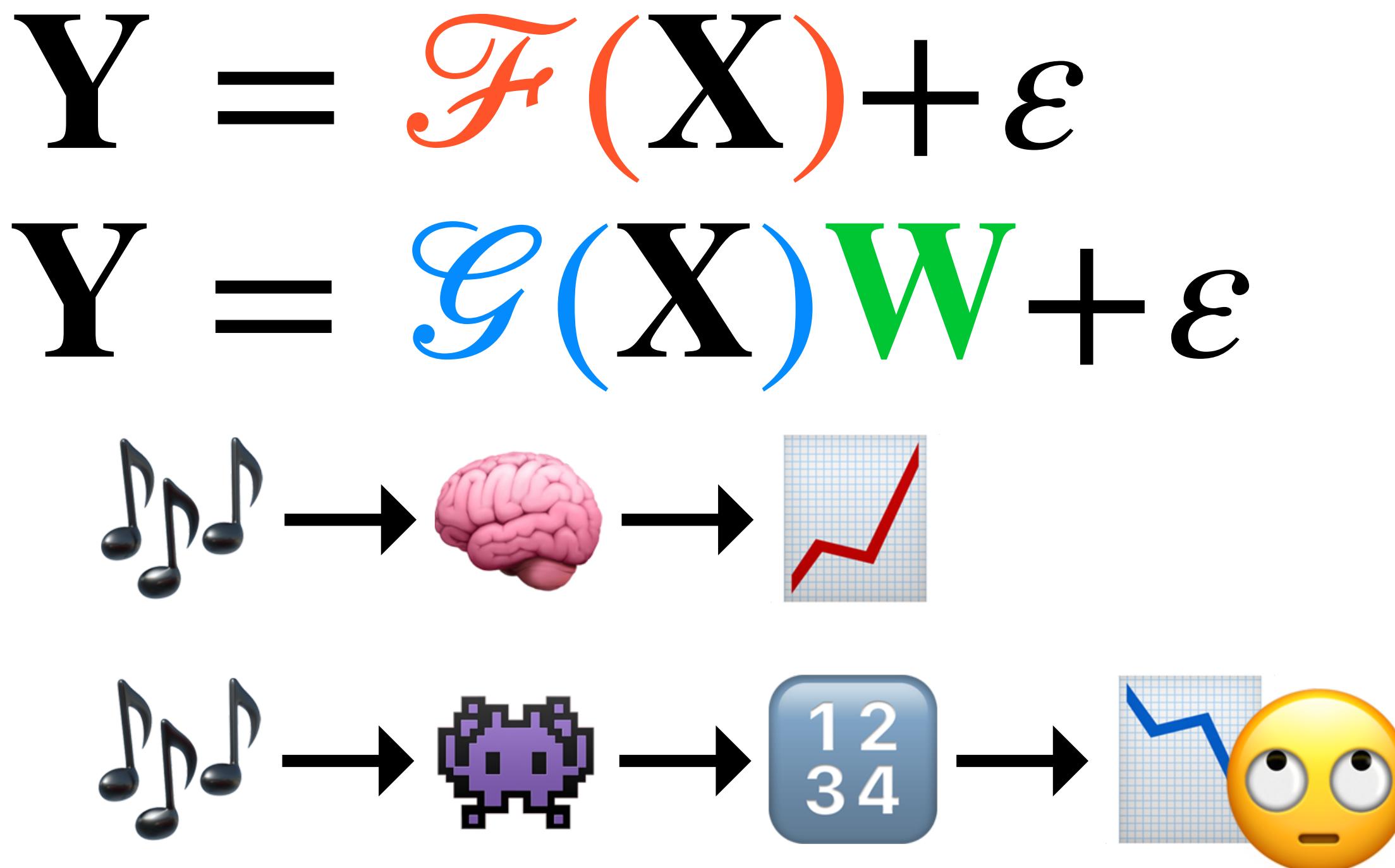
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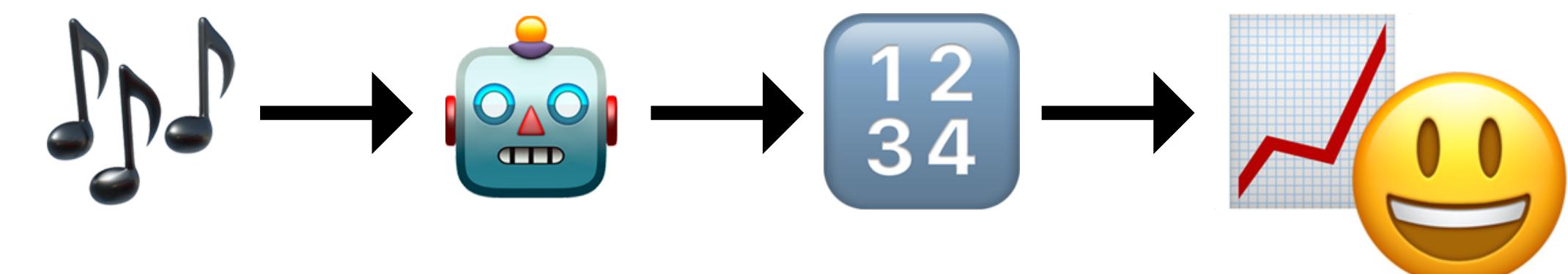
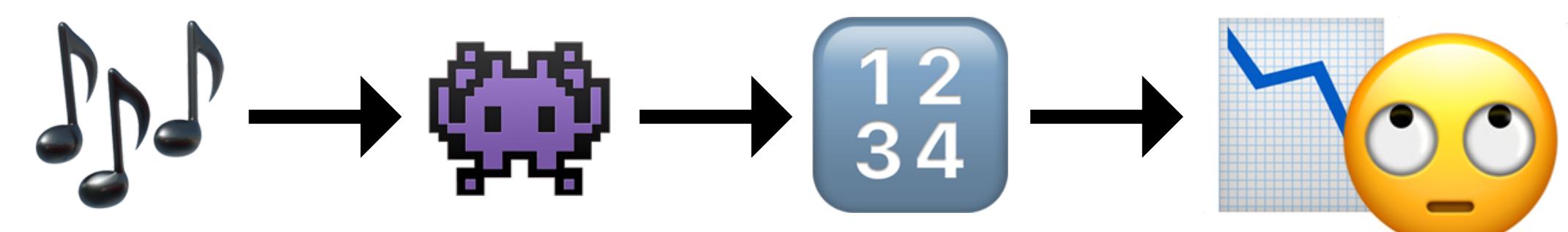


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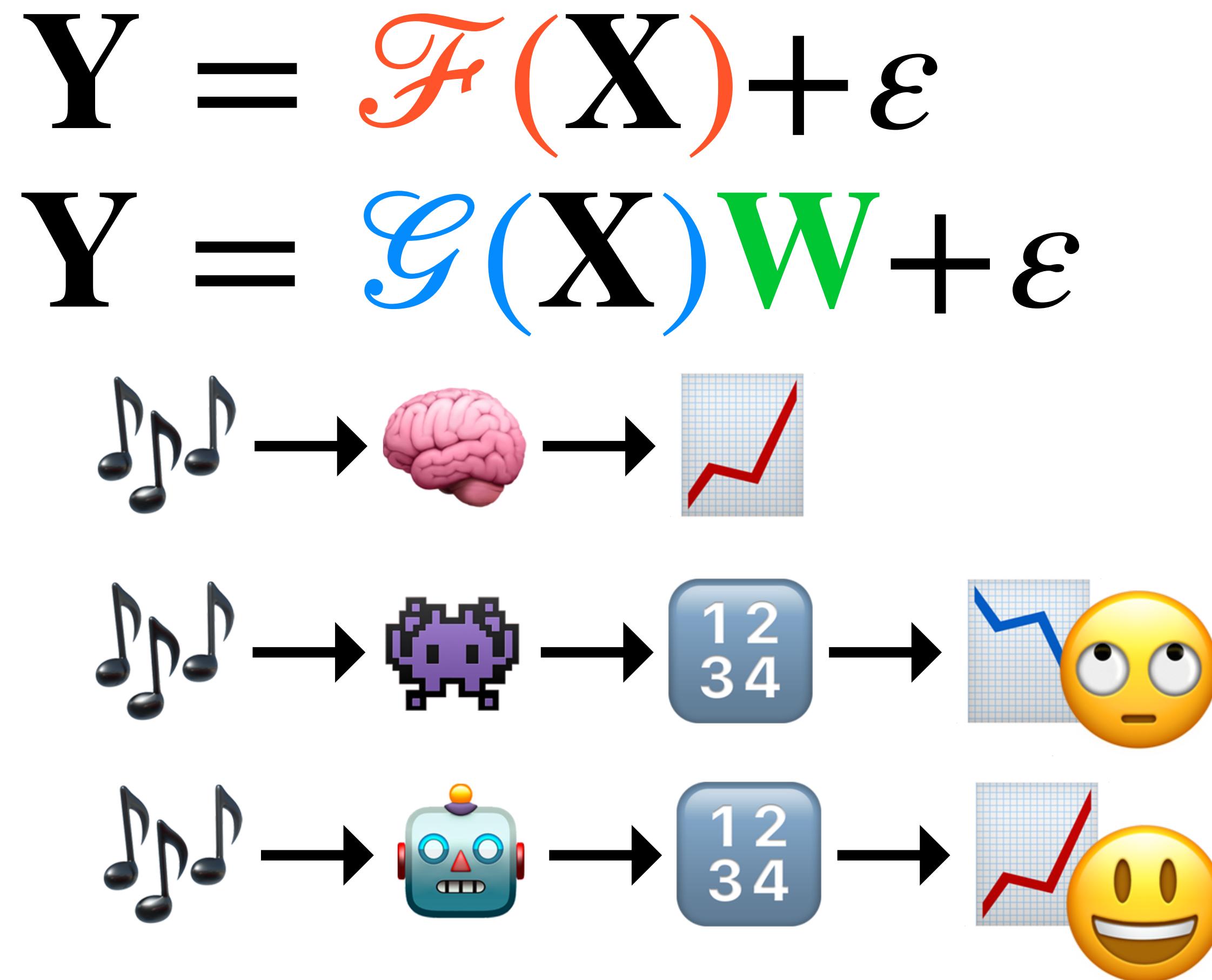
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Linearized encoding analysis

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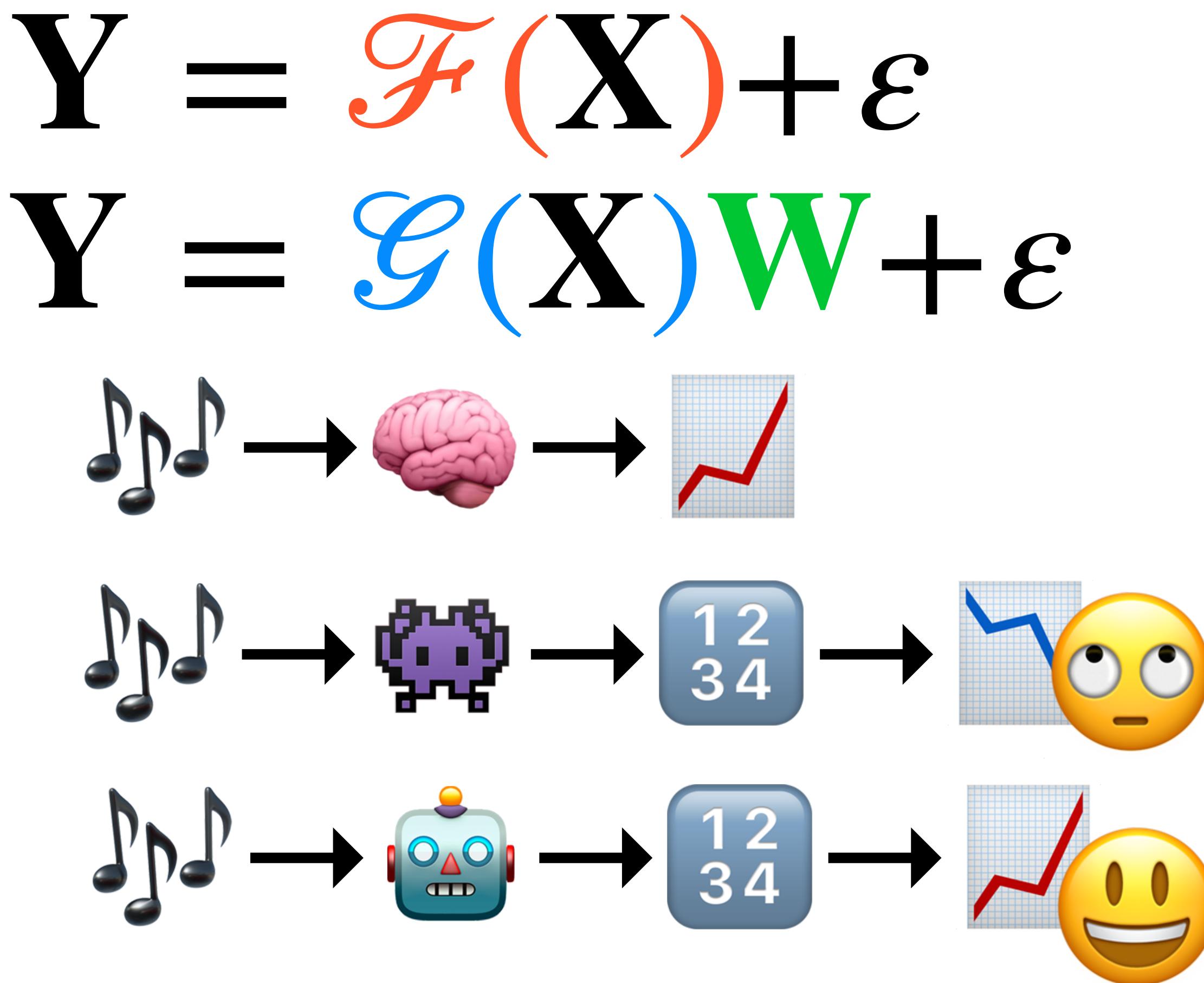
This means the hypothesis is **FALSIFIABLE!**

Pixelated brain: ✗ but Robot: ✓

Linearized encoding analysis

A linear time-invariant system identification

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



This means the hypothesis is **FALSIFIABLE!**

👾: ✘ but 🤖: ✓



: 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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$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_0 \\ 1 & x_2 & x_1 \\ \vdots & \vdots & \vdots \\ 1 & x_n & x_{n-1} \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ b_2 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

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- This is a discrete equivalent of convolution (thus, the vector **b** is also called a "filter" or a "kernel").
- "**Finite**": Because we model the impulse response up to #delay.
- "**Impulse response**

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<#Timepoints x 1>

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<[#delays+1] x 1>

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: But does it work for the other case?

Topic 2 & 3: Predictive modeling

Training set

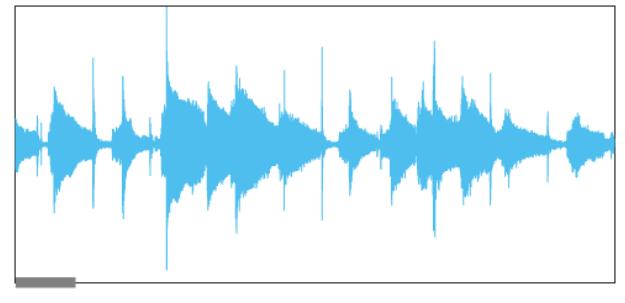
Topic 2 & 3: Predictive modeling

Training set

Music #1



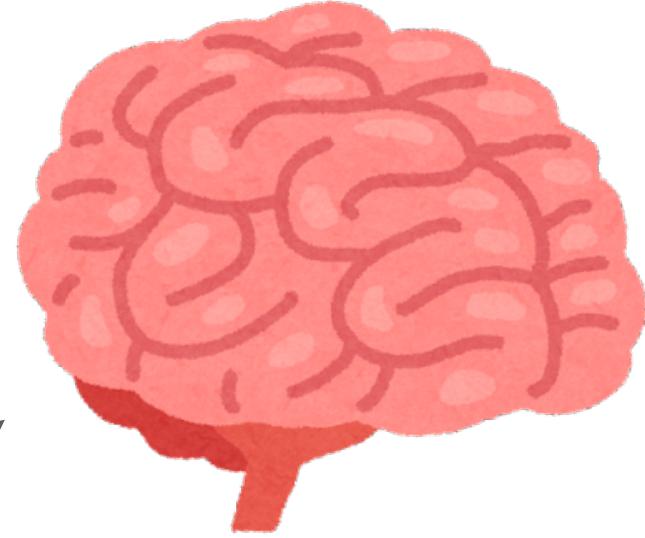
X_1



Topic 2 & 3: Predictive modeling

Training set

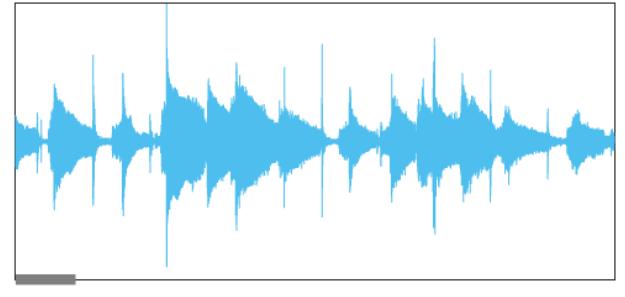
Neural responses



Music #1



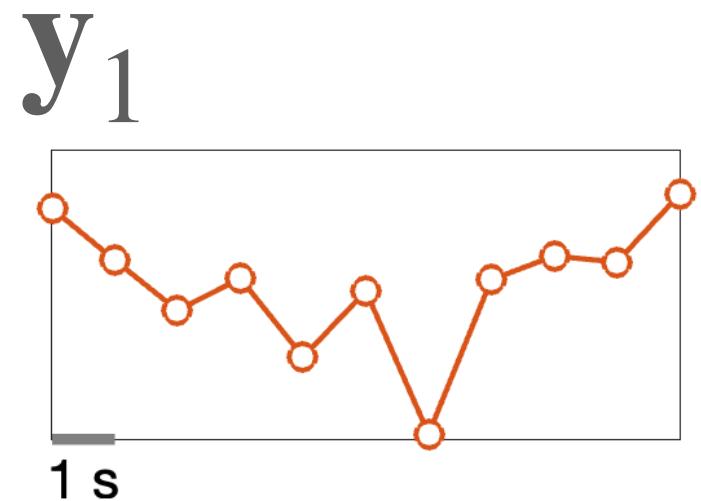
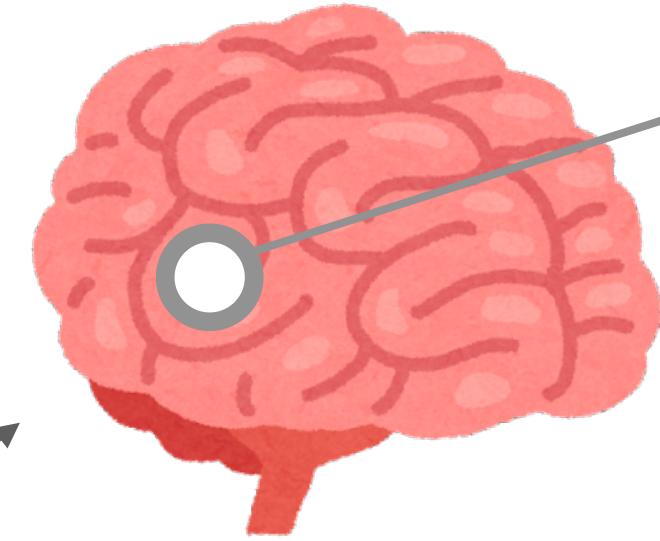
X_1



Topic 2 & 3: Predictive modeling

Training set

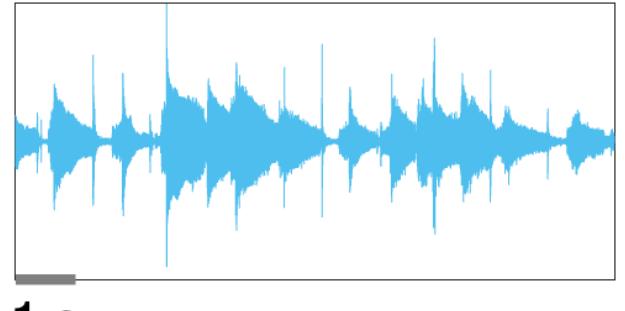
Neural responses



Music #1

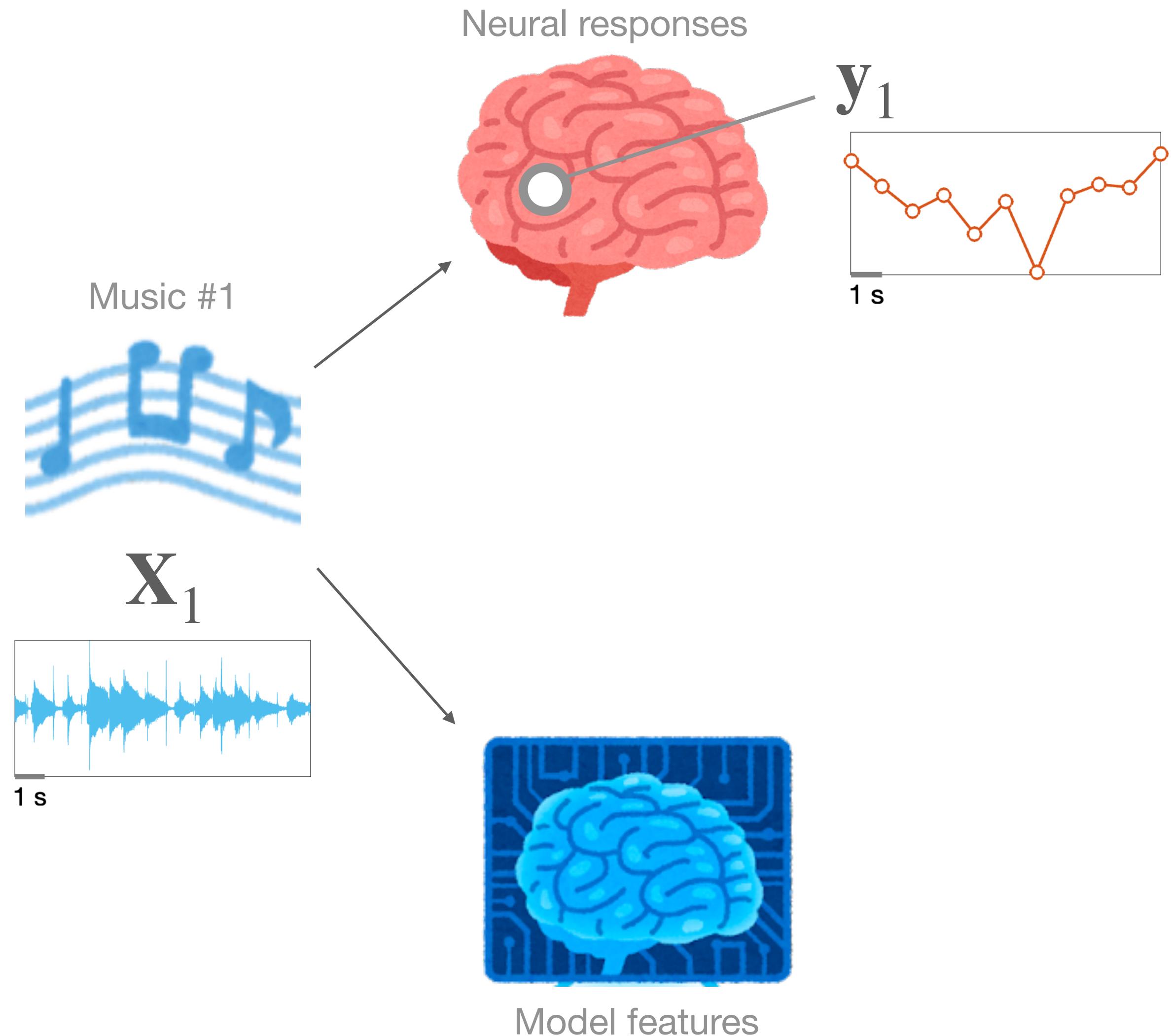


X_1



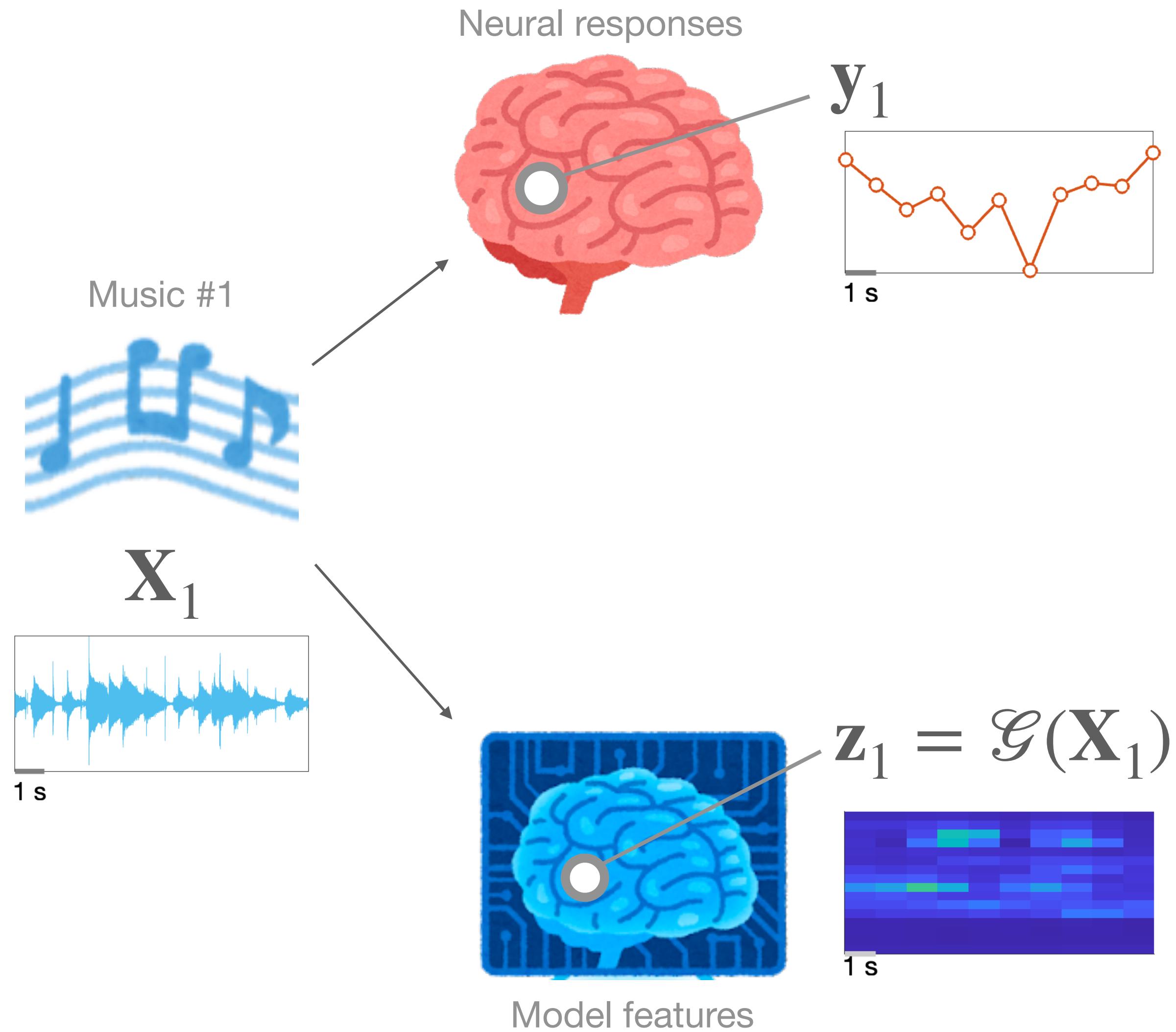
Topic 2 & 3: Predictive modeling

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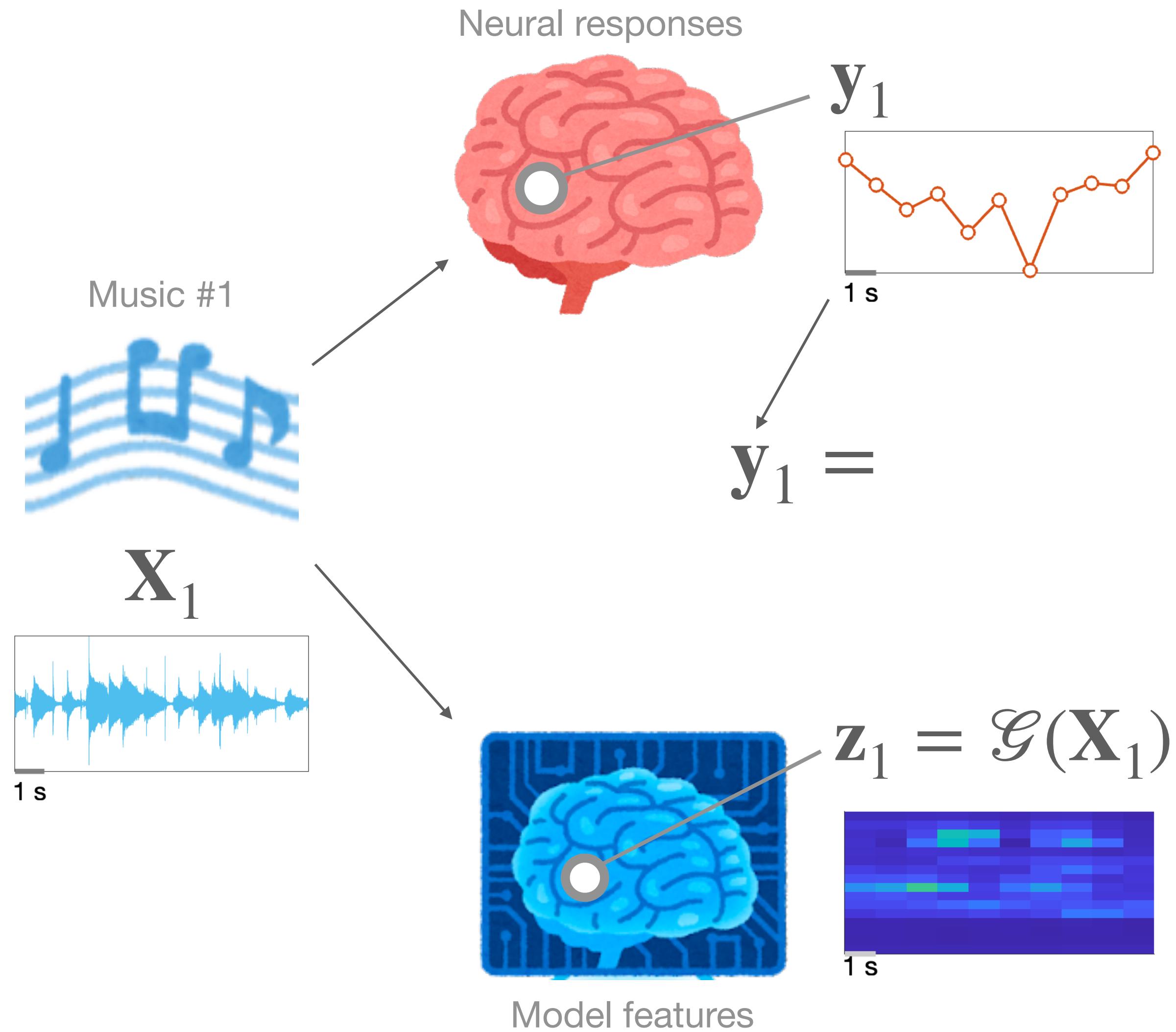
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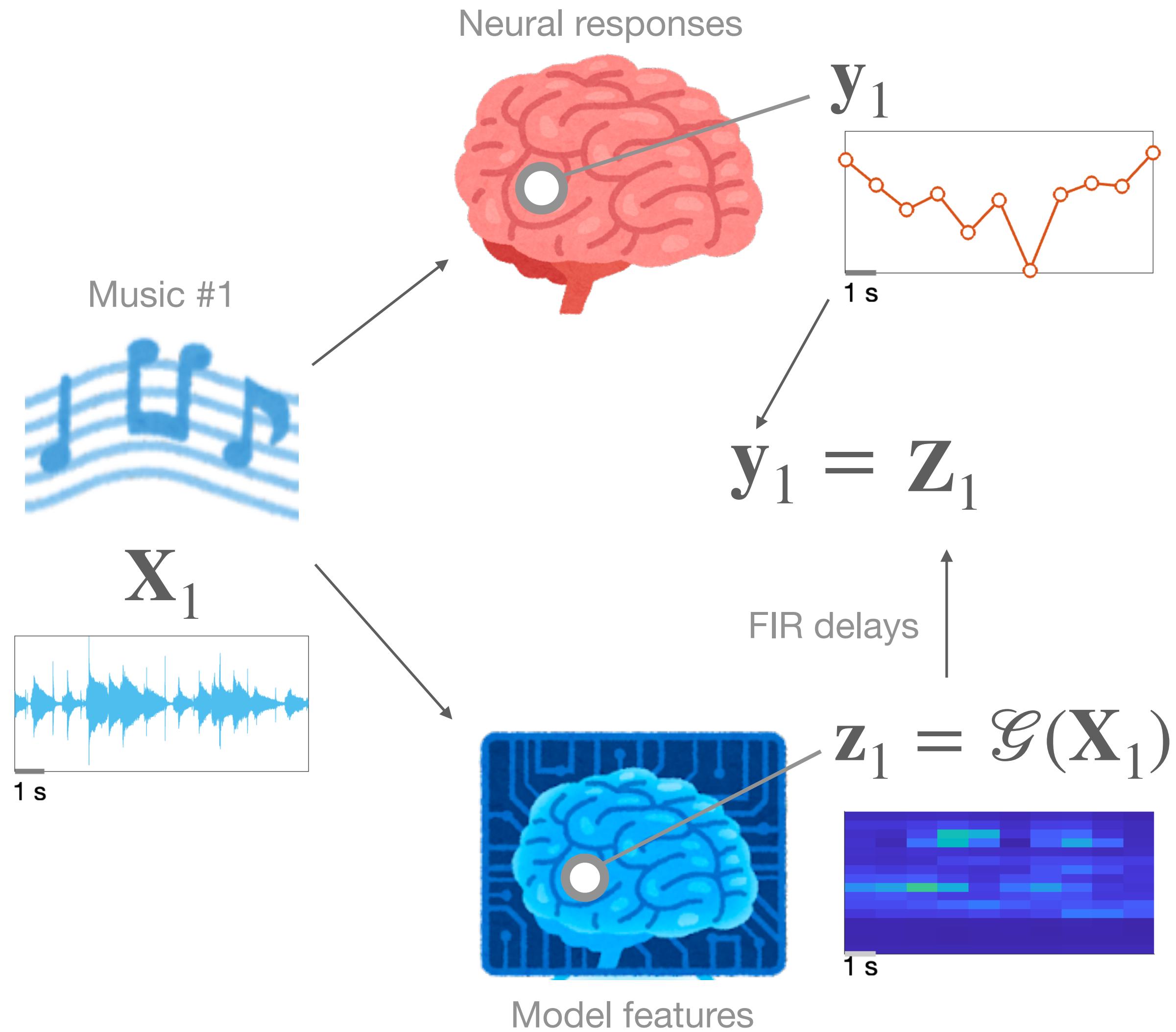
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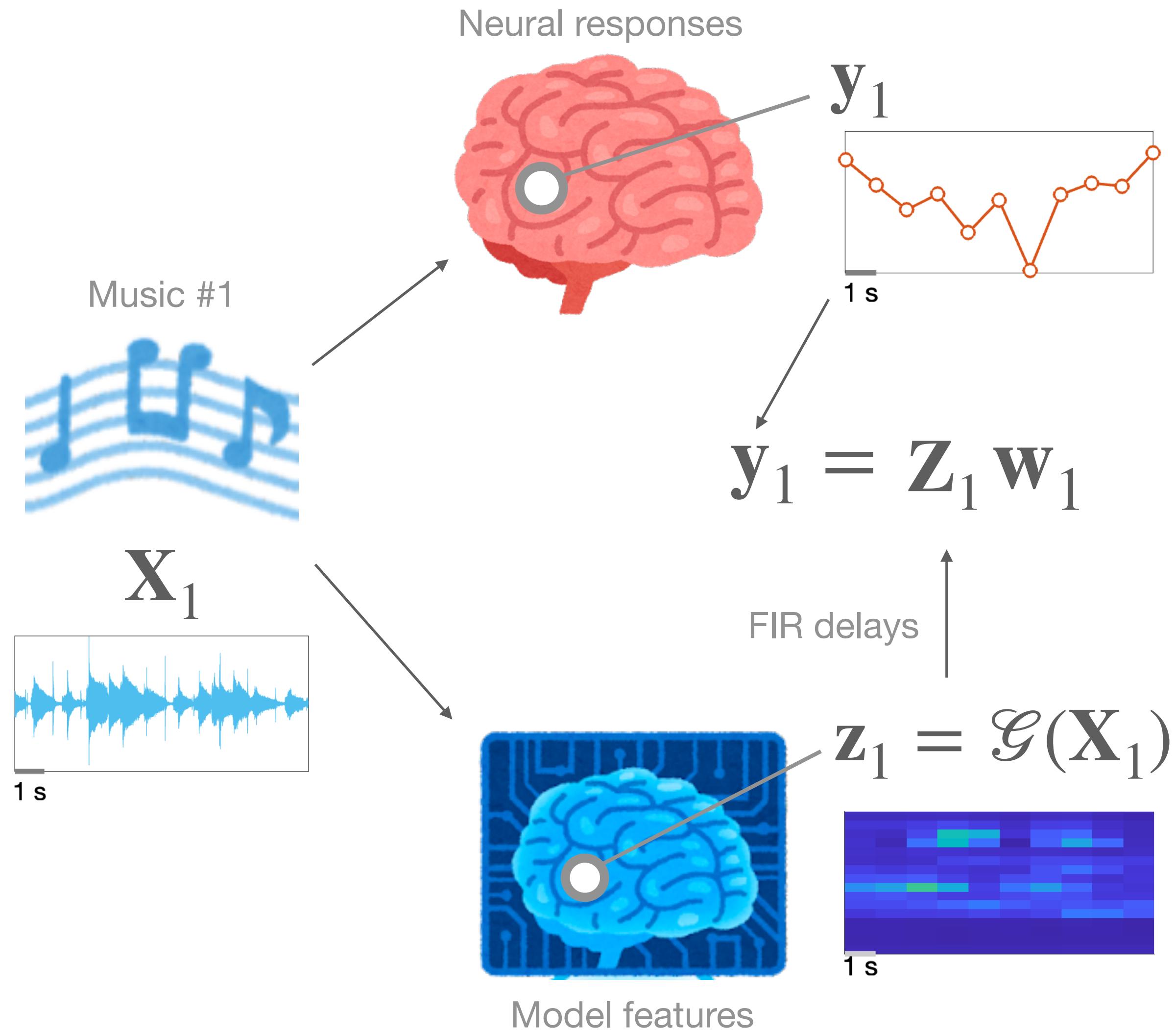
Topic 2 & 3: Predictive modeling

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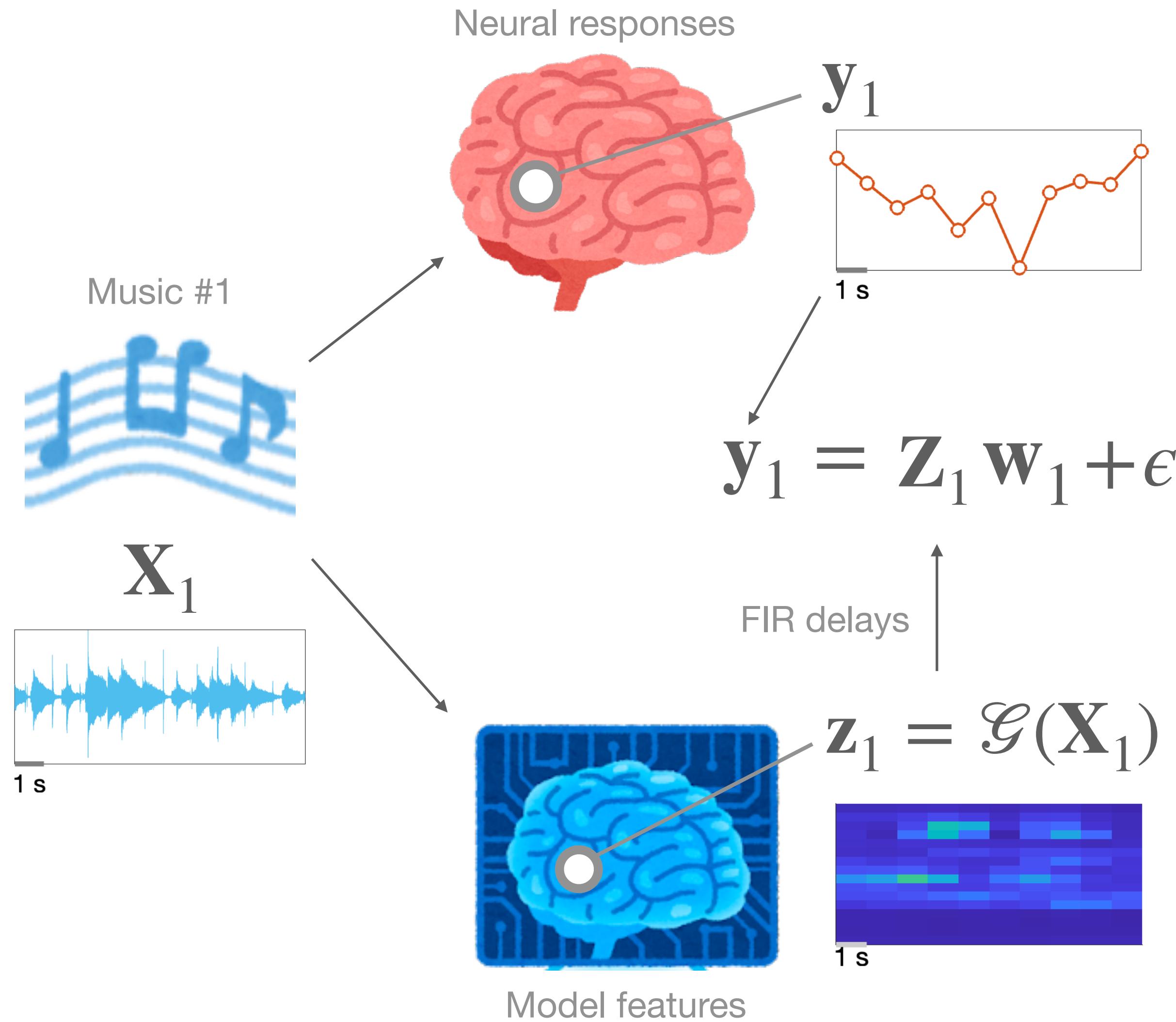
Topic 2 & 3: Predictive modeling

Training set



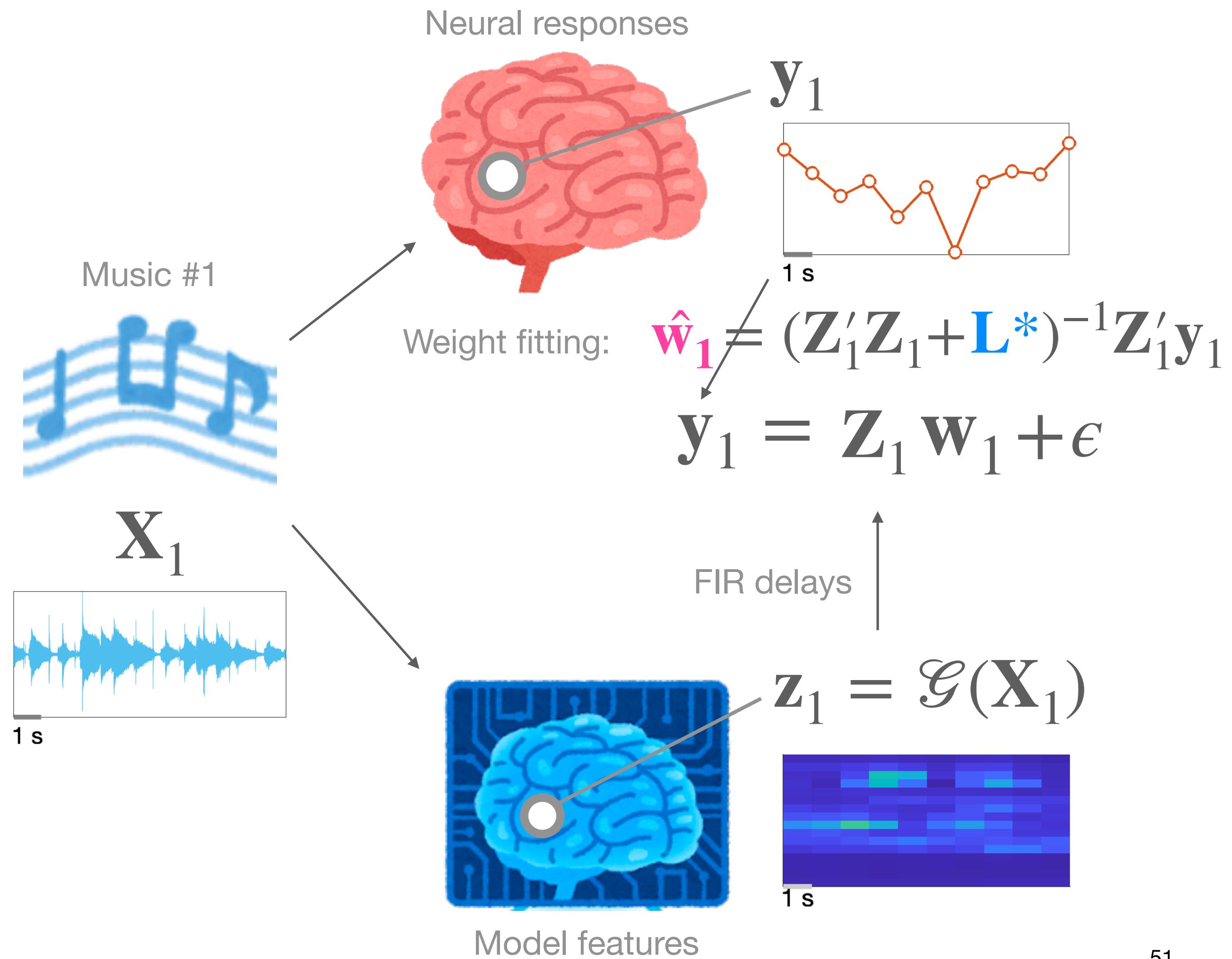
Topic 2 & 3: Predictive modeling

Training set



Topic 2 & 3: Predictive modeling

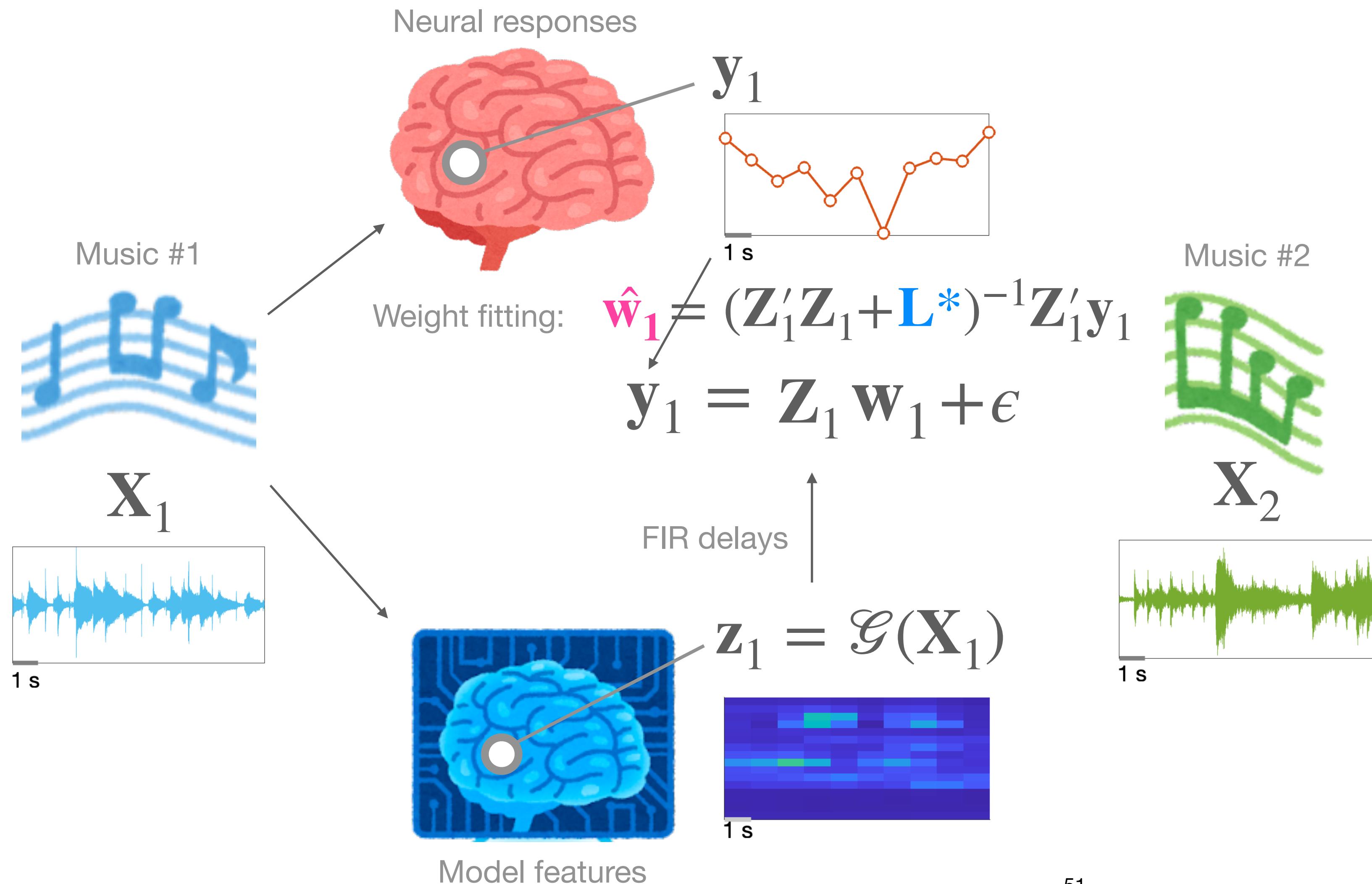
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Topic 2 & 3: Predictive modeling

Training set

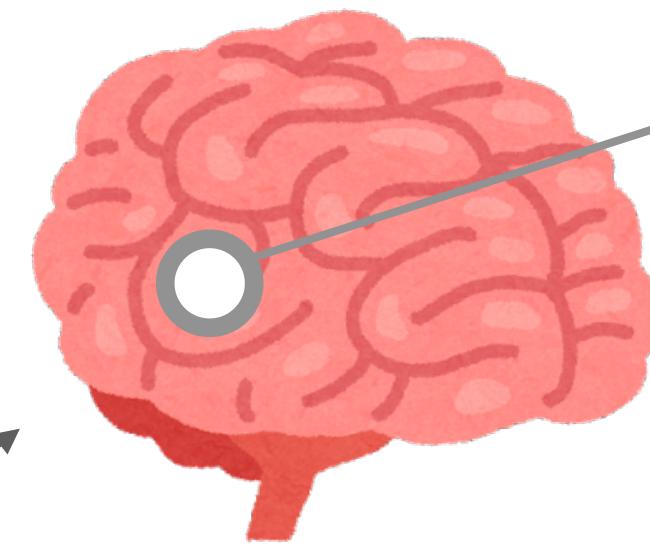
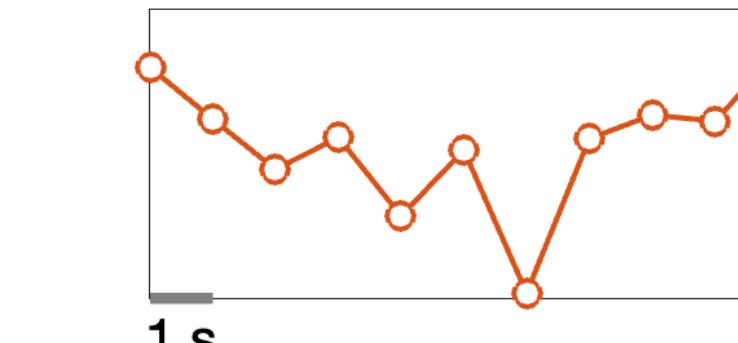
Test set



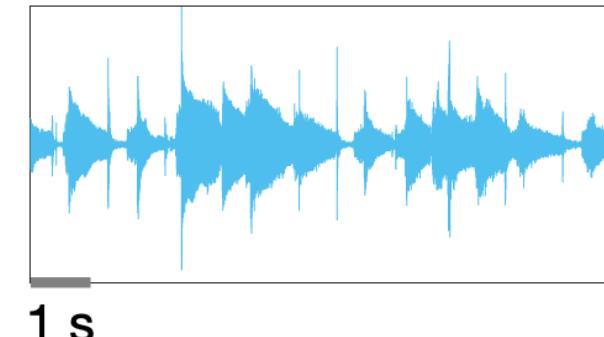
Topic 2 & 3: Predictive modeling

Training set

Neural responses

 y_1 

Music #1

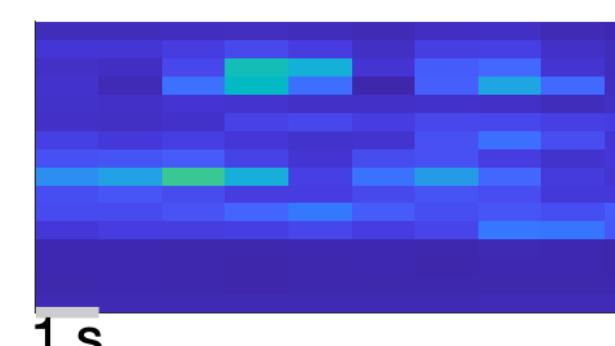
 X_1 

Weight fitting:

$$\hat{w}_1 = (Z'_1 Z_1 + L^*)^{-1} Z'_1 y_1$$

FIR delays

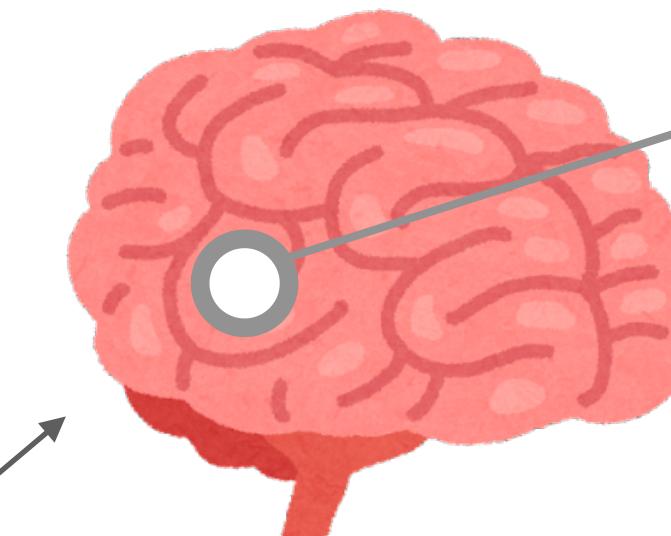
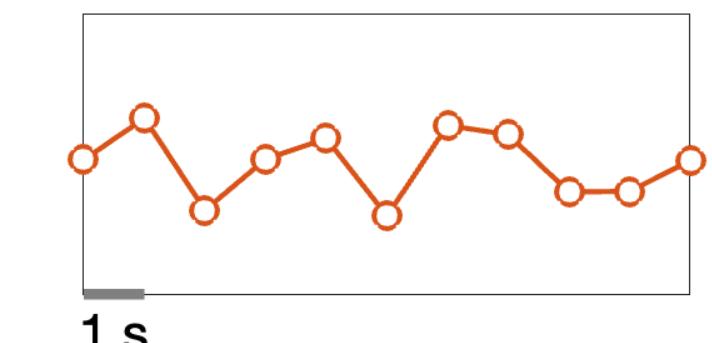
$$z_1 = \mathcal{G}(X_1)$$



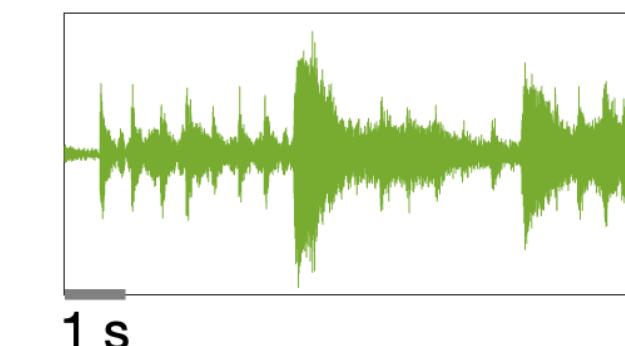
Model features

Test set

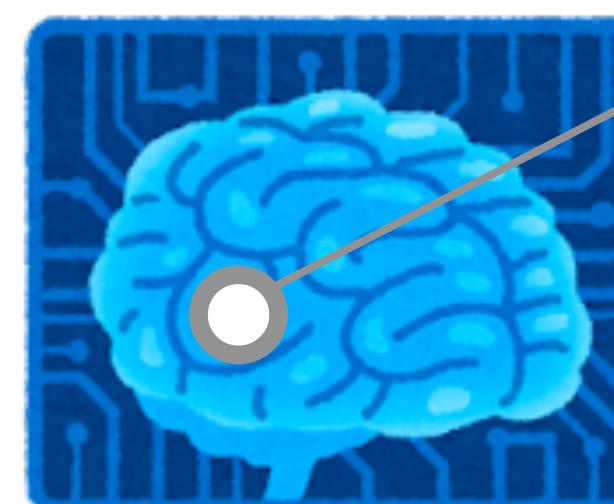
Neural responses

 y_2 

Music #2

 X_2 

$$z_2 = \mathcal{G}(X_2)$$

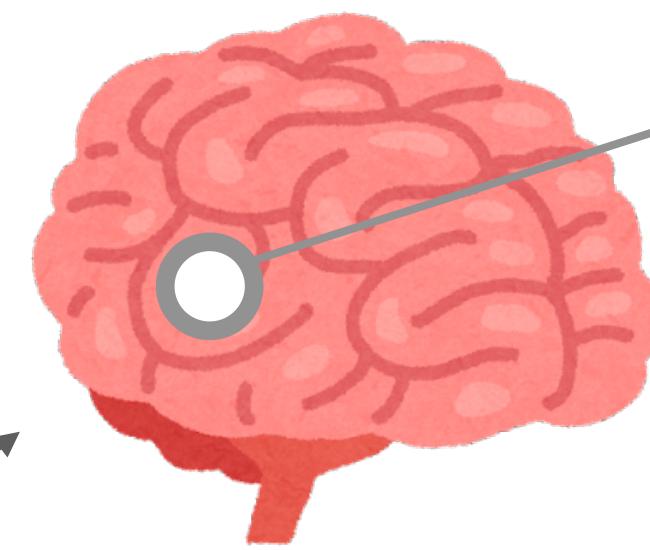
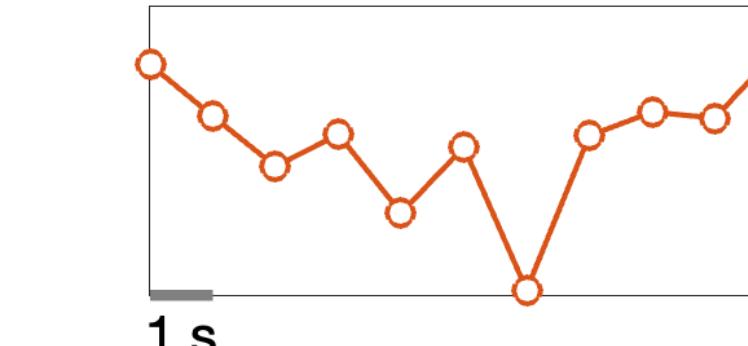


Model features

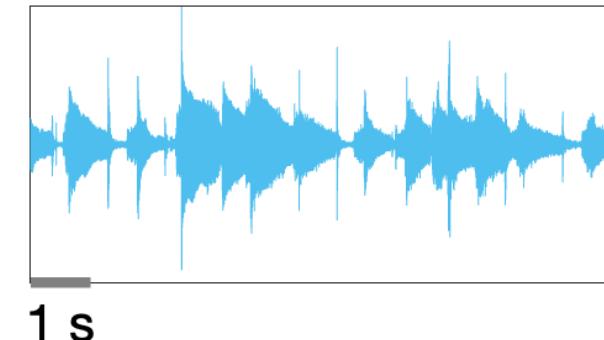
Topic 2 & 3: Predictive modeling

Training set

Neural responses

 y_1 

Music #1

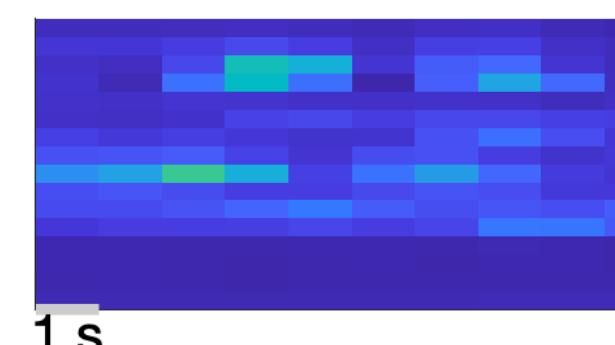
 X_1 

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$$\hat{w}_1 = (Z'_1 Z_1 + L^*)^{-1} Z'_1 y_1$$

FIR delays

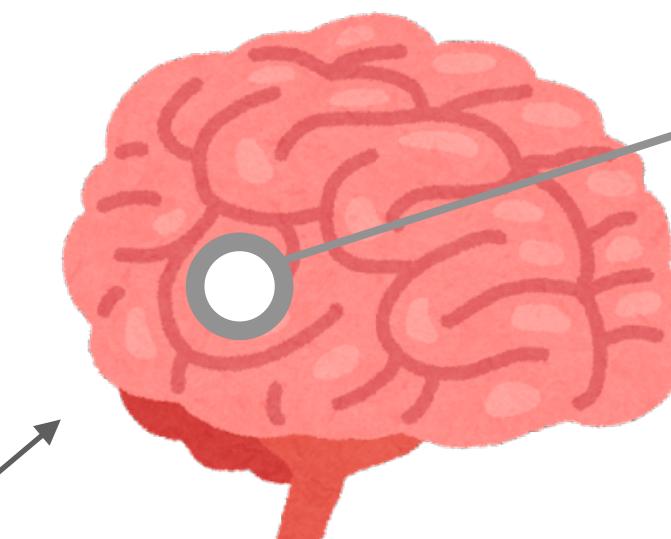
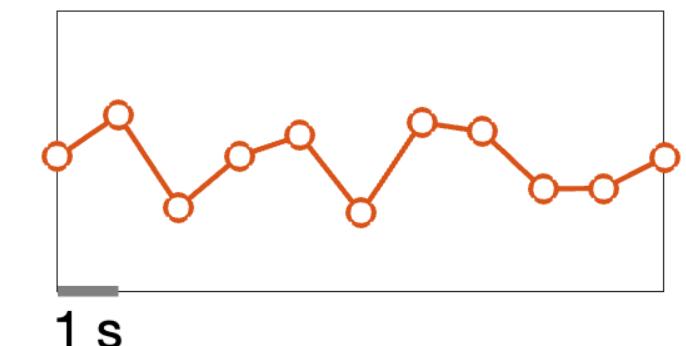
$$z_1 = \mathcal{G}(X_1)$$



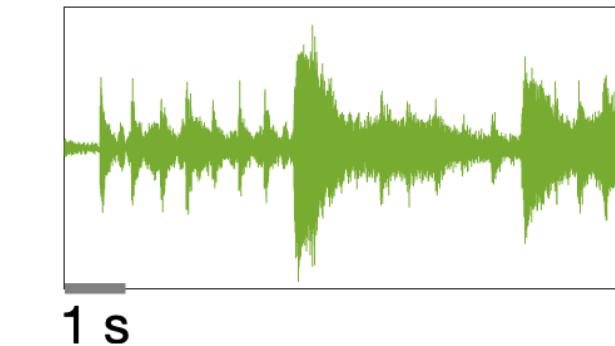
Model features

Test set

Neural responses

 y_2 

Music #2

 X_2 

Prediction:

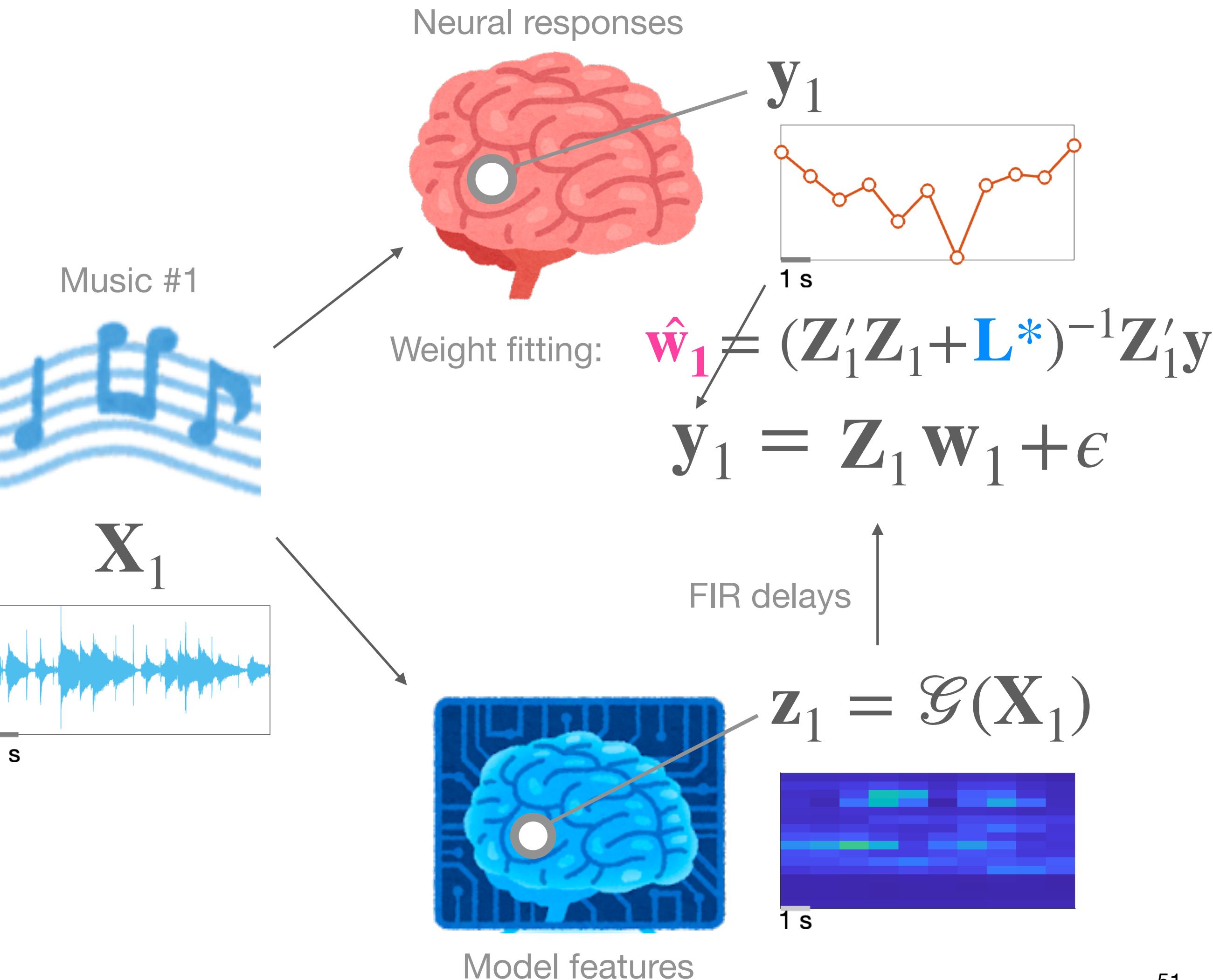
$$z_2 = \mathcal{G}(X_2)$$



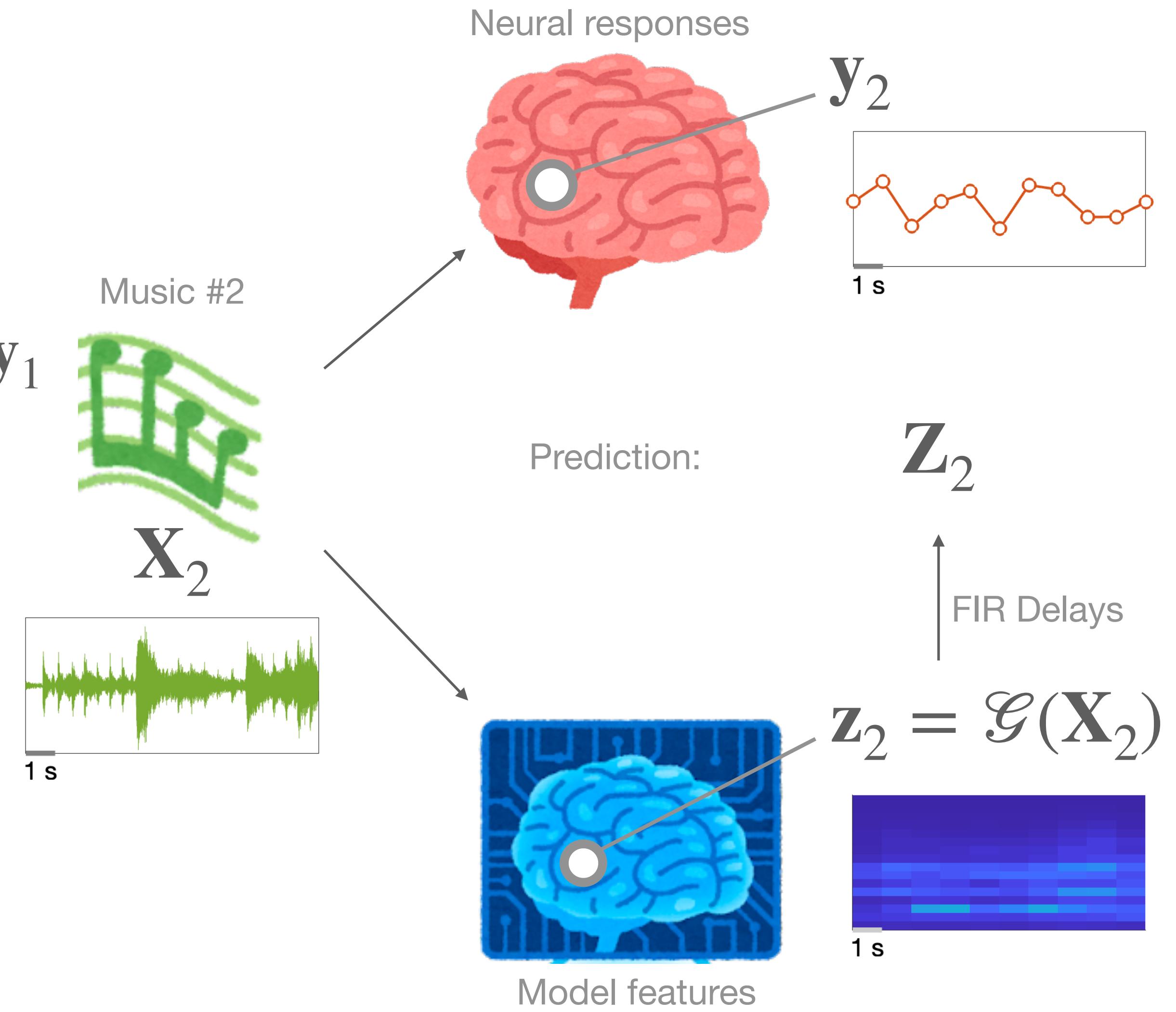
Model features

Topic 2 & 3: Predictive modeling

Training set



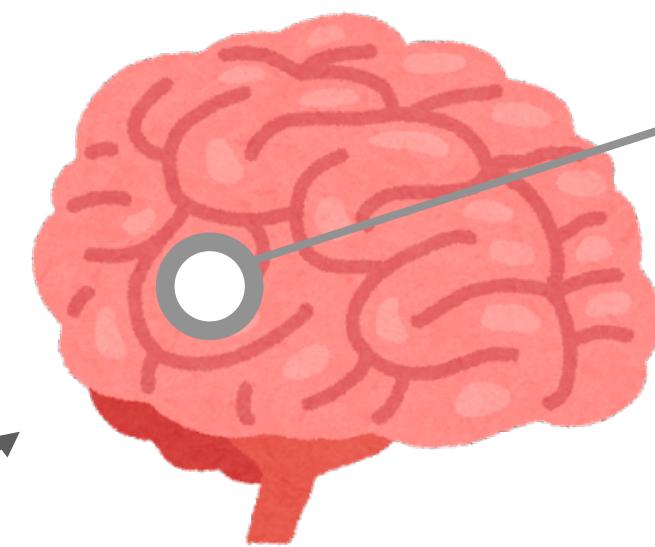
Test set



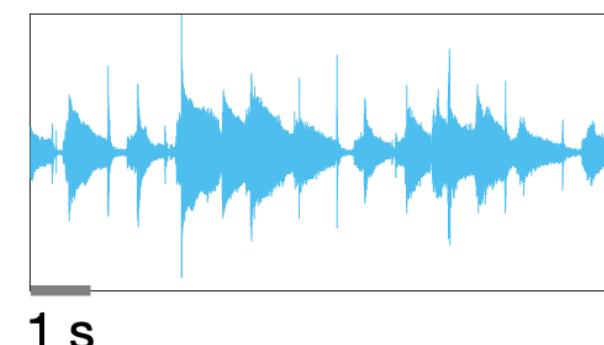
Topic 2 & 3: Predictive modeling

Training set

Neural responses



Music #1

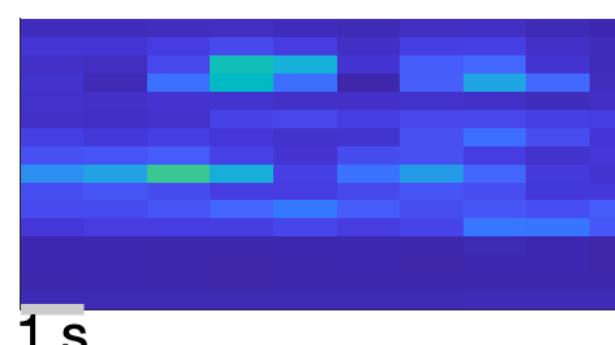
 X_1 

Weight fitting:

$$\hat{w}_1 = (Z'_1 Z_1 + L^*)^{-1} Z'_1 y_1$$
$$y_1 = Z_1 w_1 + \epsilon$$

FIR delays

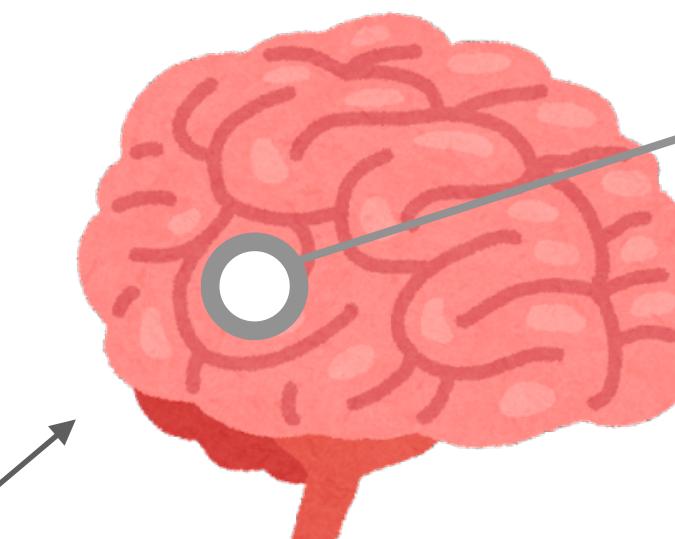
$$z_1 = \mathcal{G}(X_1)$$



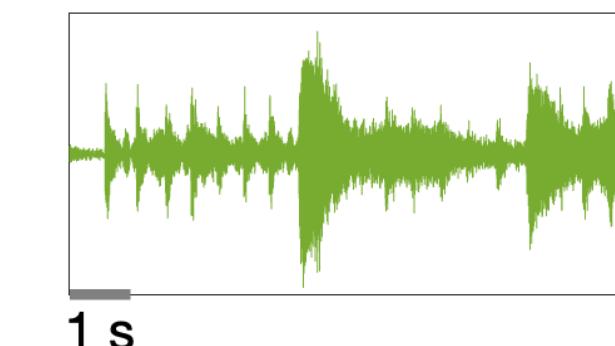
Model features

Test set

Neural responses



Music #2

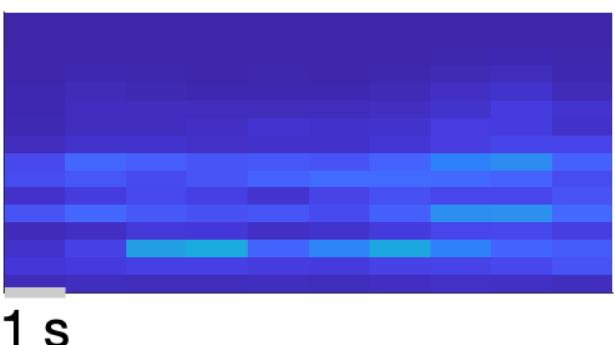
 X_2 

Prediction:

$$Z_2 \hat{w}_1$$

FIR Delays

$$z_2 = \mathcal{G}(X_2)$$

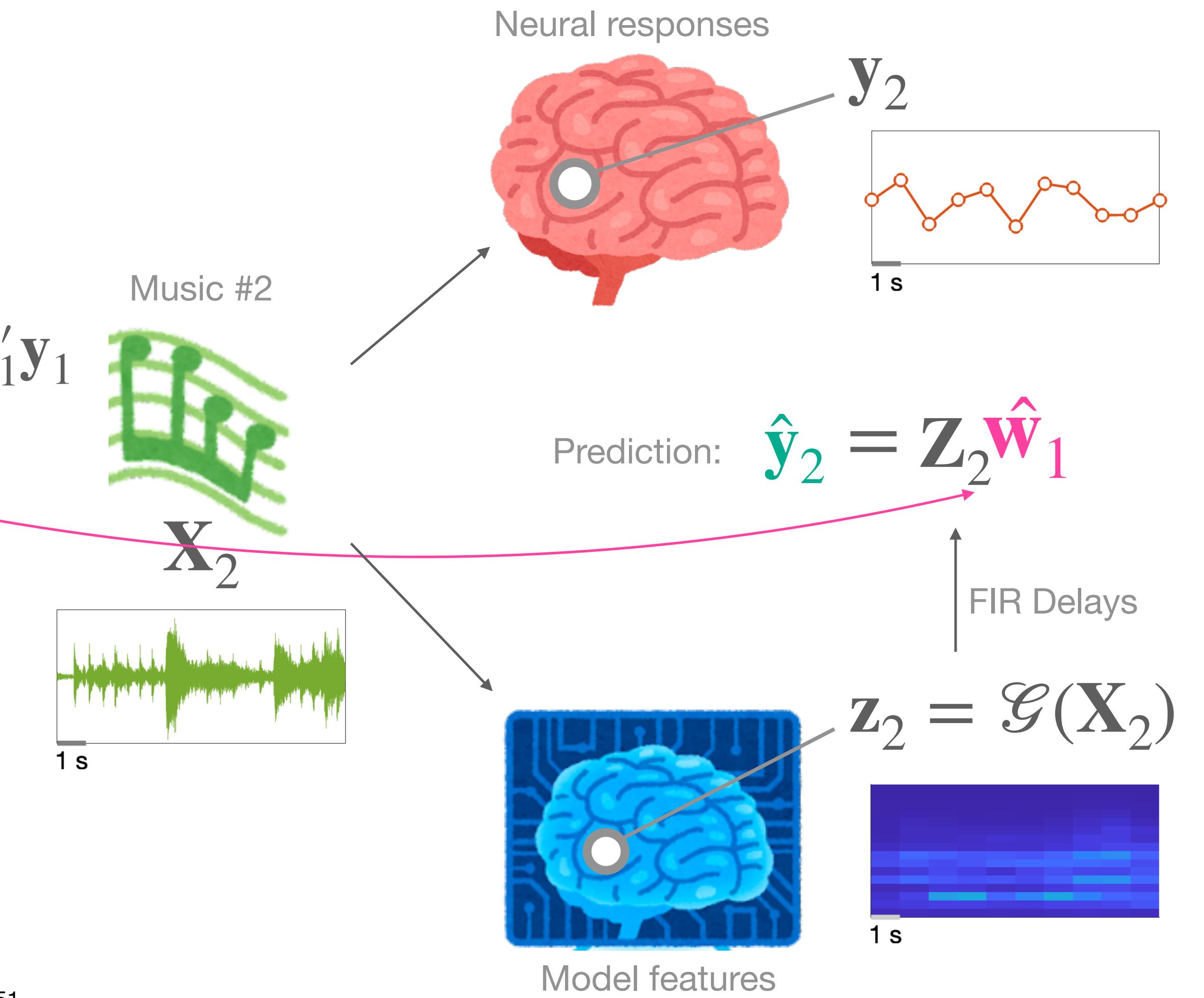
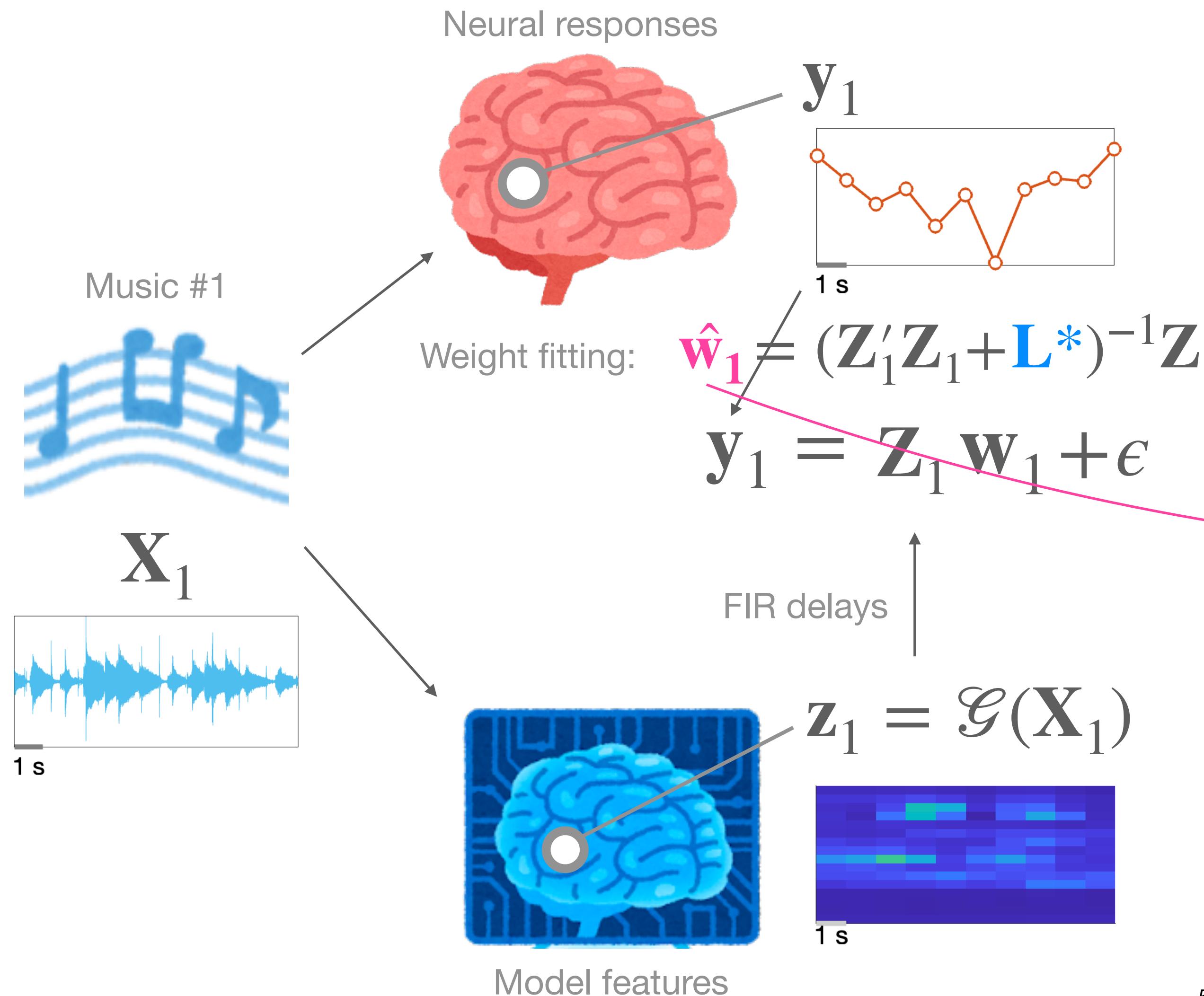


Model features

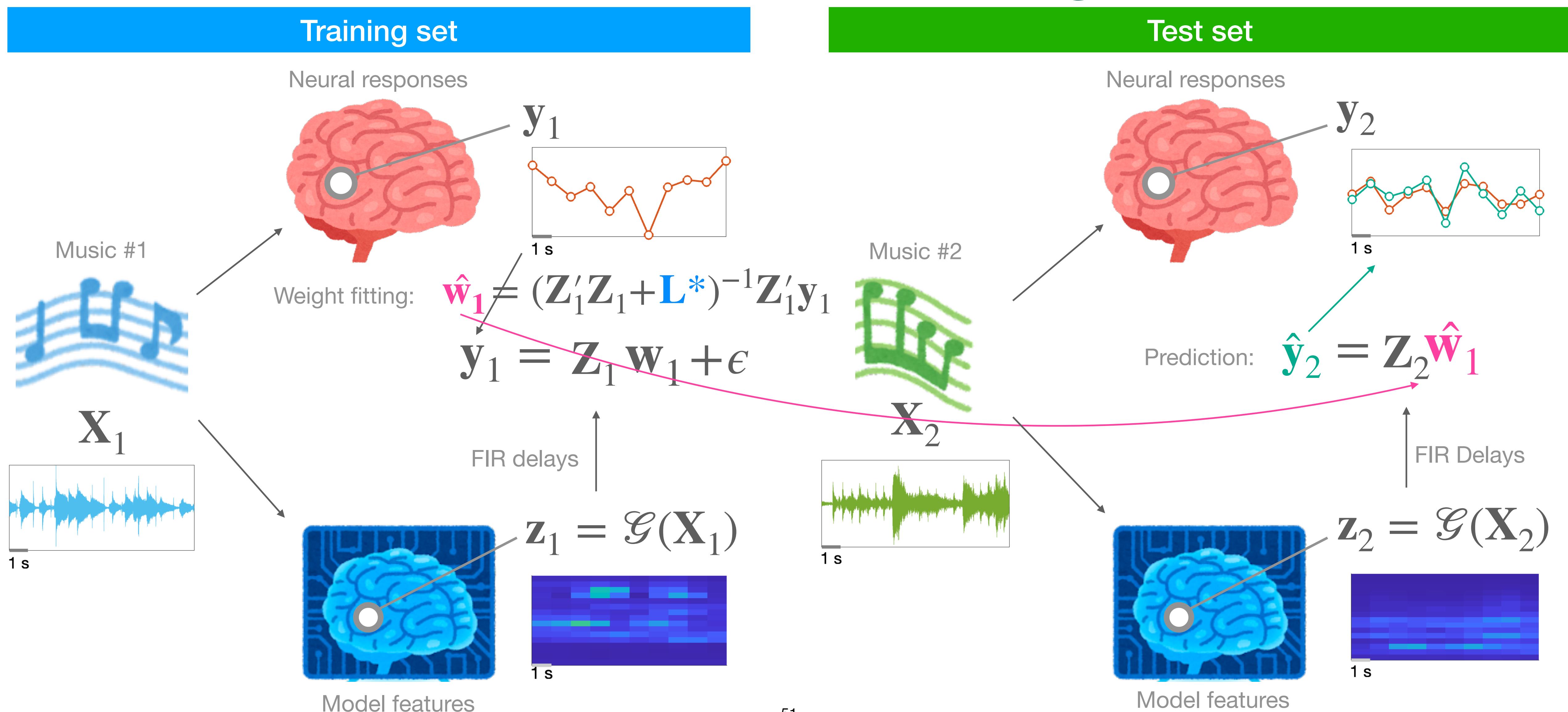
Topic 2 & 3: Predictive modeling

Training set

Test set



Topic 2 & 3: Predictive modeling



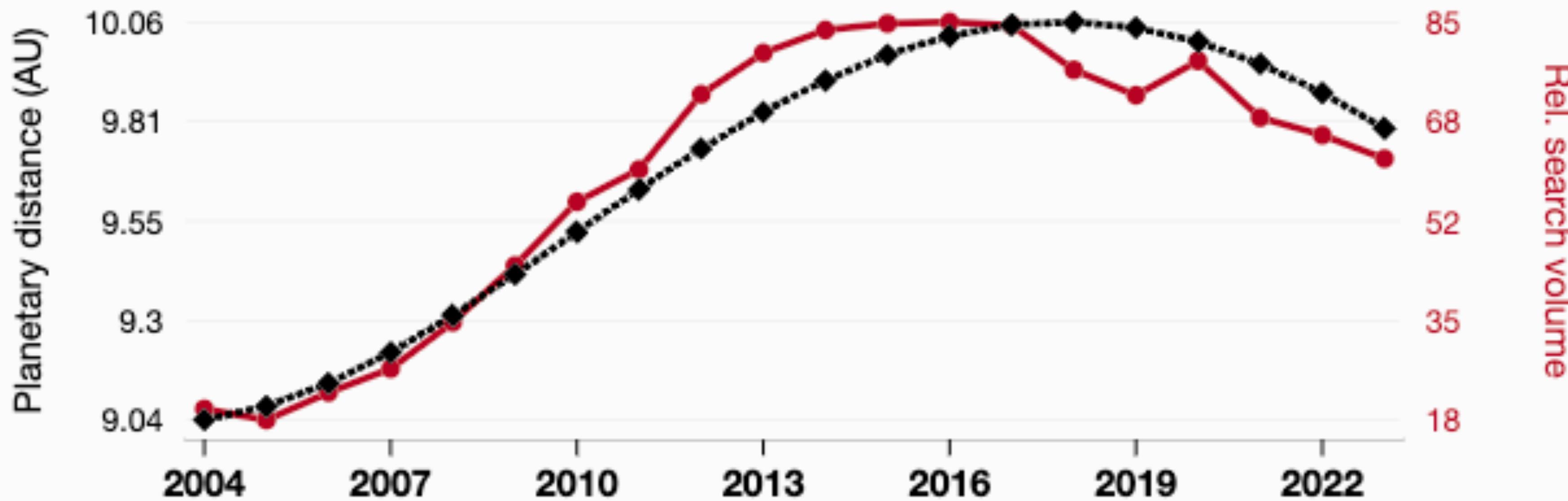
: Still, how do we know if this is not due to the random noise in the data?



The distance between Saturn and the Sun

correlates with

Google searches for 'how to make baby'



◆ The average distance between Saturn and the Sun as measured on the first day of each month · Source: Calculated using Astropy

● Relative volume of Google searches for 'how to make baby' (Worldwide), with quotes) · Source: Google Trends

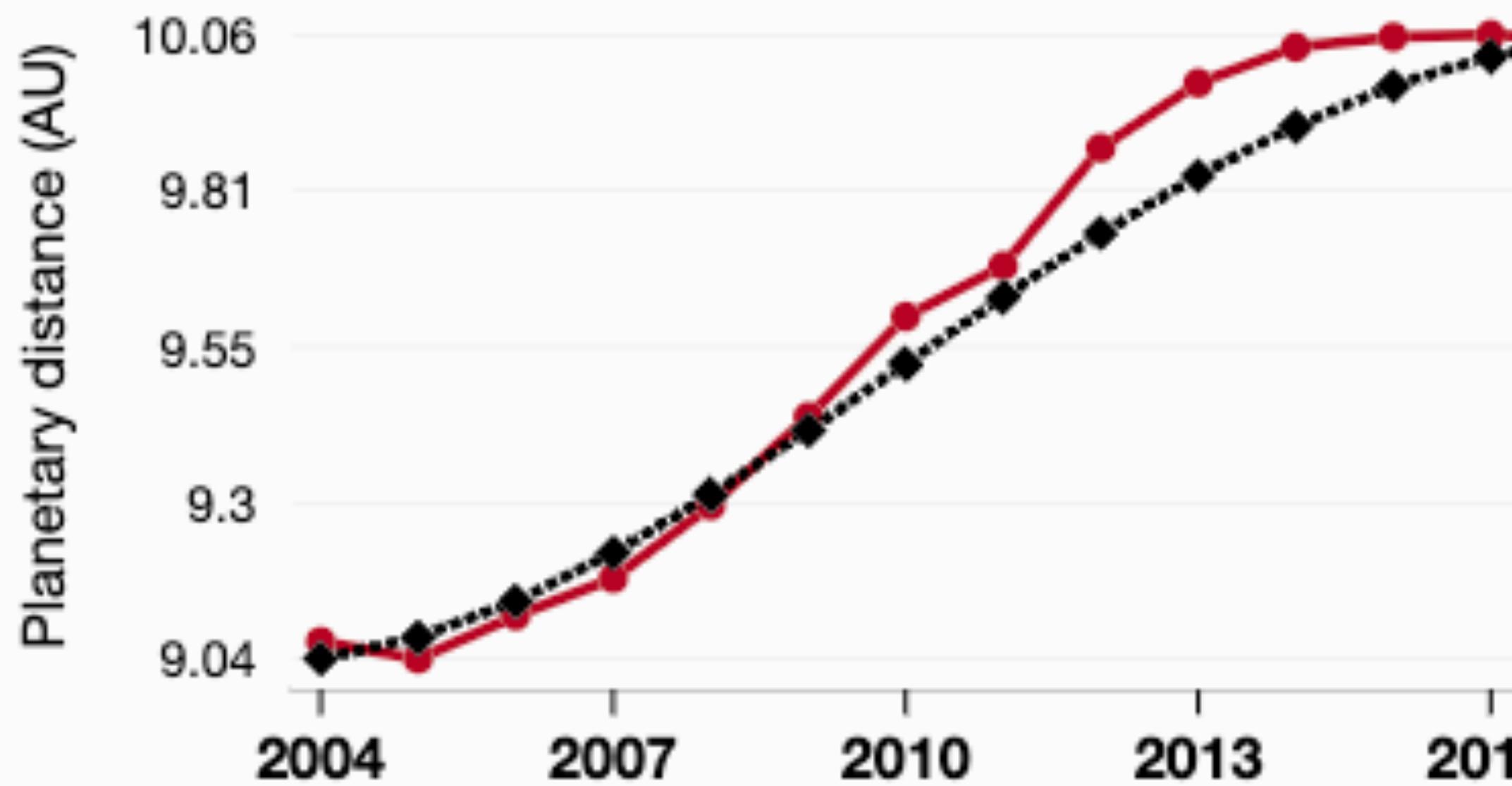
2004-2023, $r=0.967$, $r^2=0.935$, $p<0.01$ · tylervigen.com/spurious/correlation/1522



The distance between Saturn and the Sun

correlates with

Google searches for 'how to make baby'



◆ The average distance between Saturn and the Sun as recorded each month · Source: Calculated using Astropy

● Relative volume of Google searches for 'how to make baby' (0-100, with quotes) · Source: Google Trends

2004-2023, $r=0.967$, $r^2=0.935$, $p<0.01$ · 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

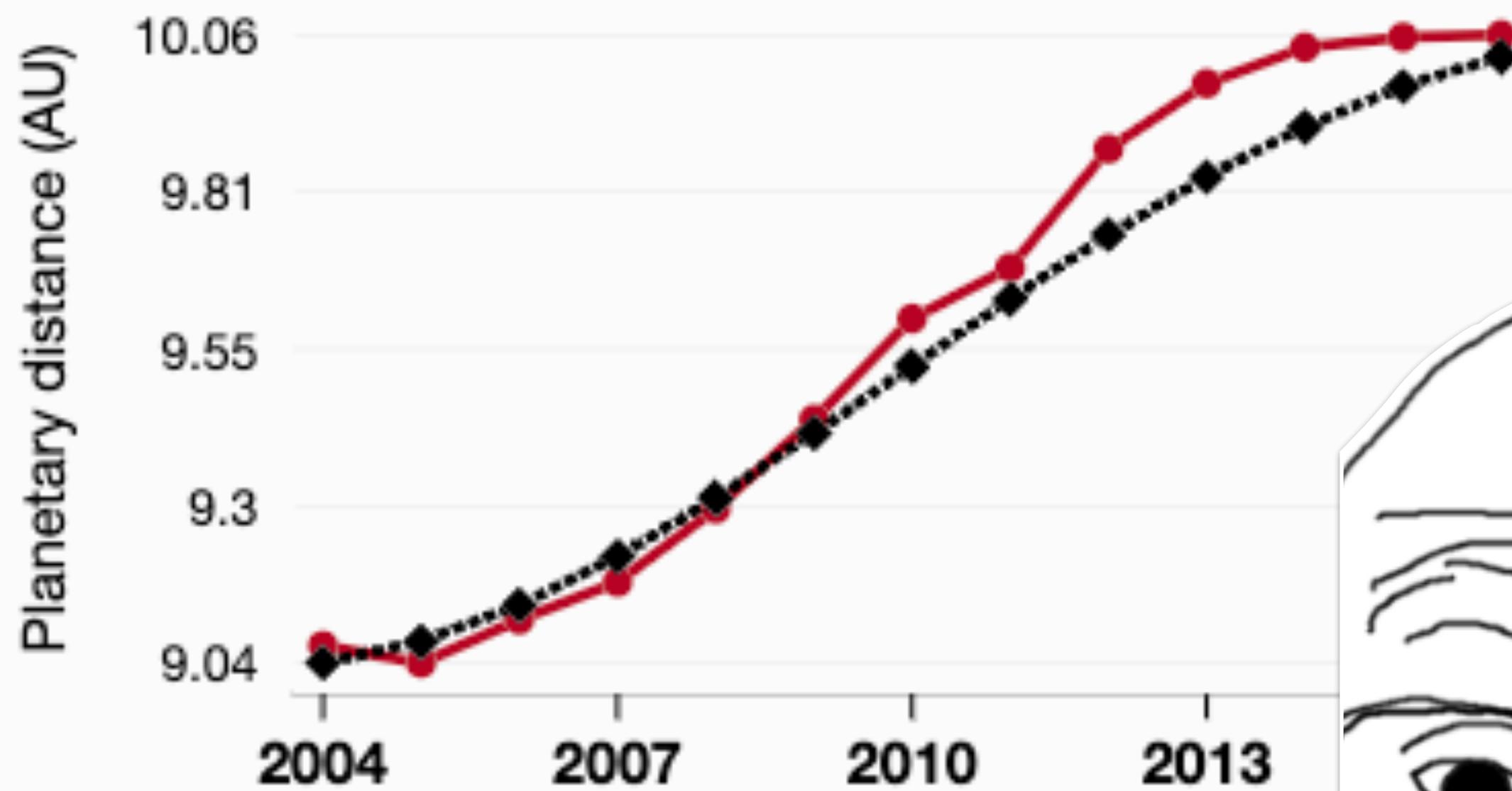




The distance between Saturn and the Sun

correlates with

Google searches for 'how to'



◆ The average distance between Saturn and the Sun (black diamonds) · Source: Calculated using Astropy's solar system module · Data updated monthly · Each point represents the average distance for each month.

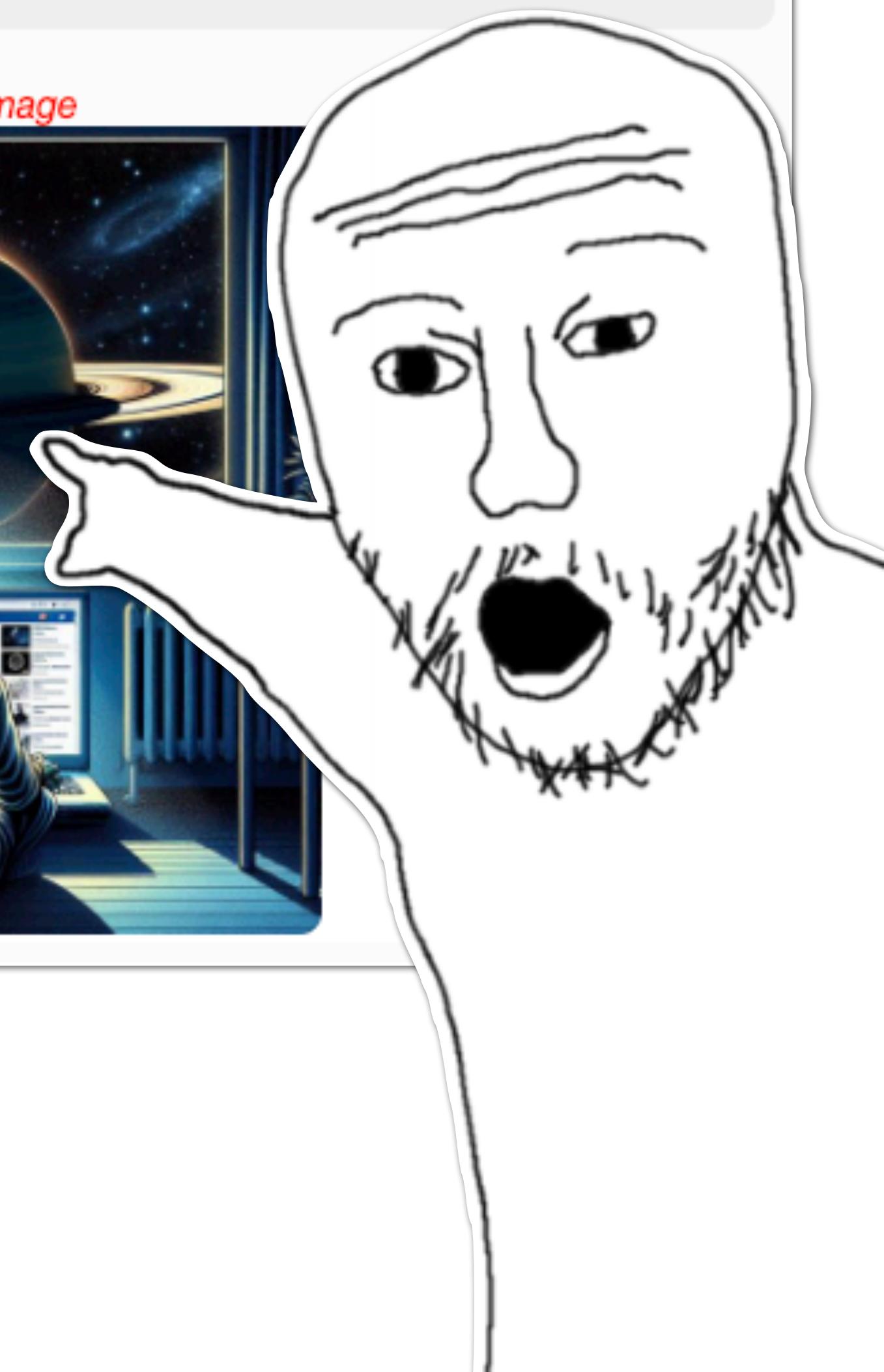
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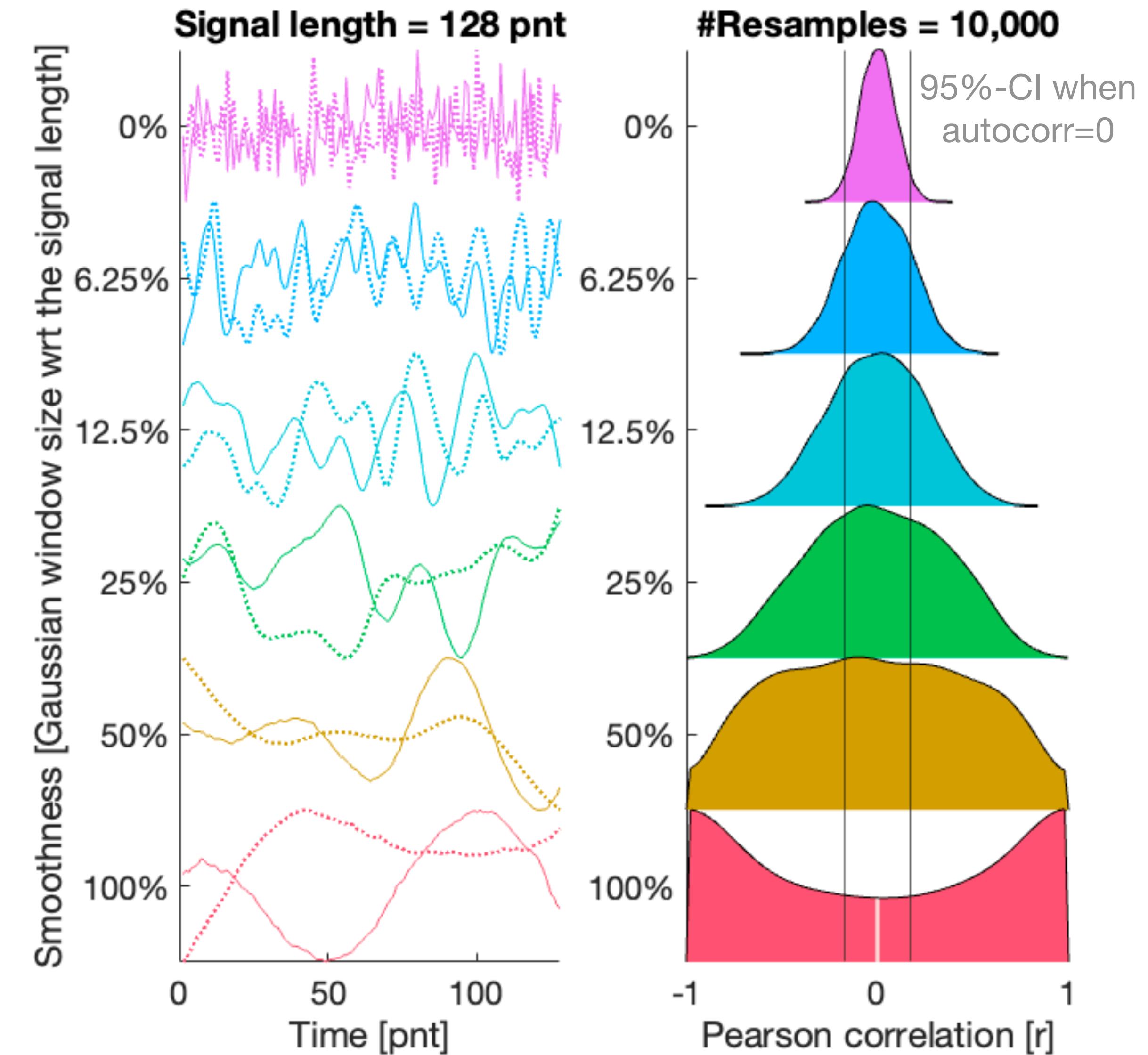
[Show GenAI image](#)



Topic 4: Statistical inference

Tests for time series

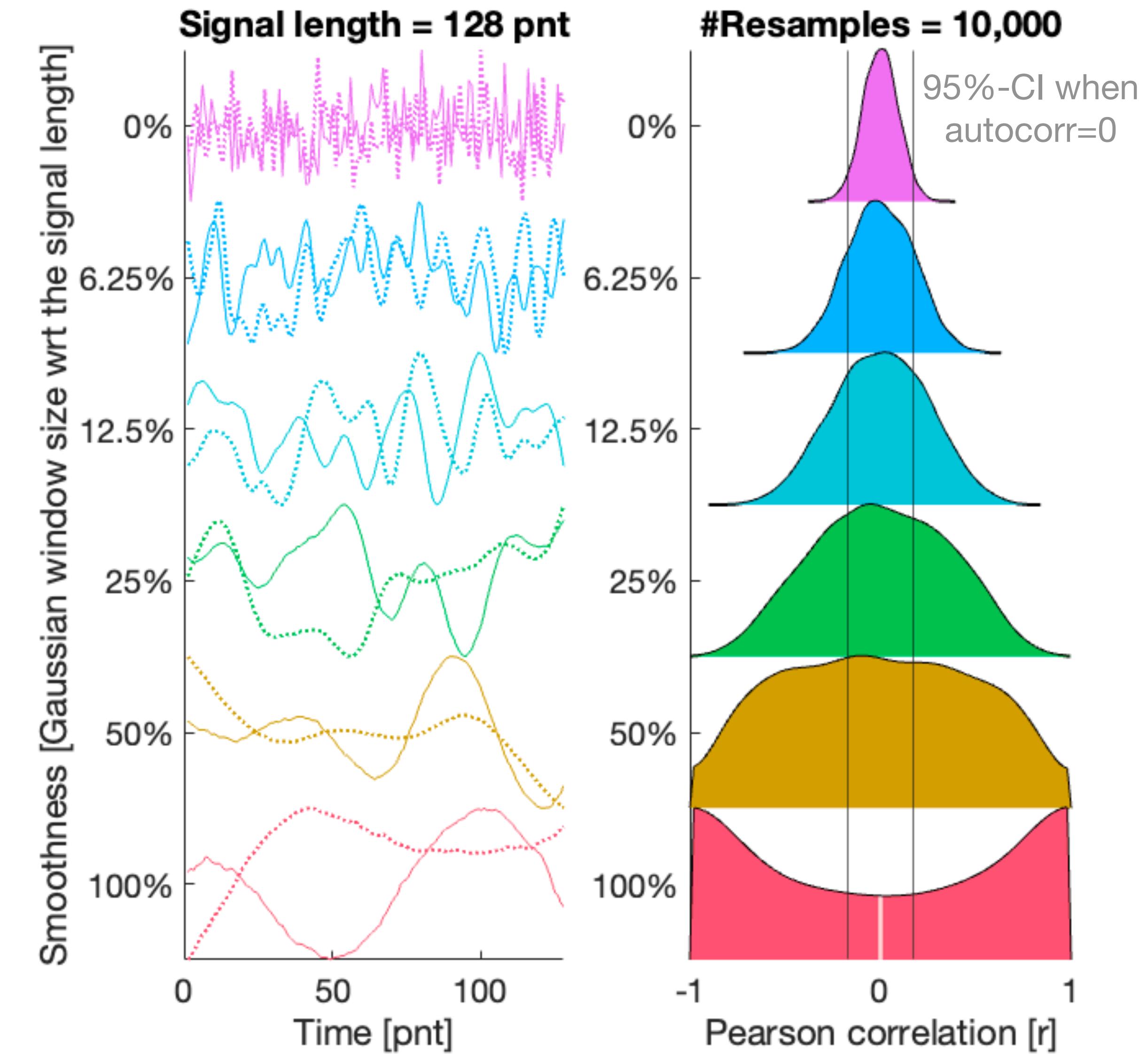
- Many **time series** look alike (i.e., spurious correlation) due to auto/serial-correlation.



Topic 4: Statistical inference

Tests for time series

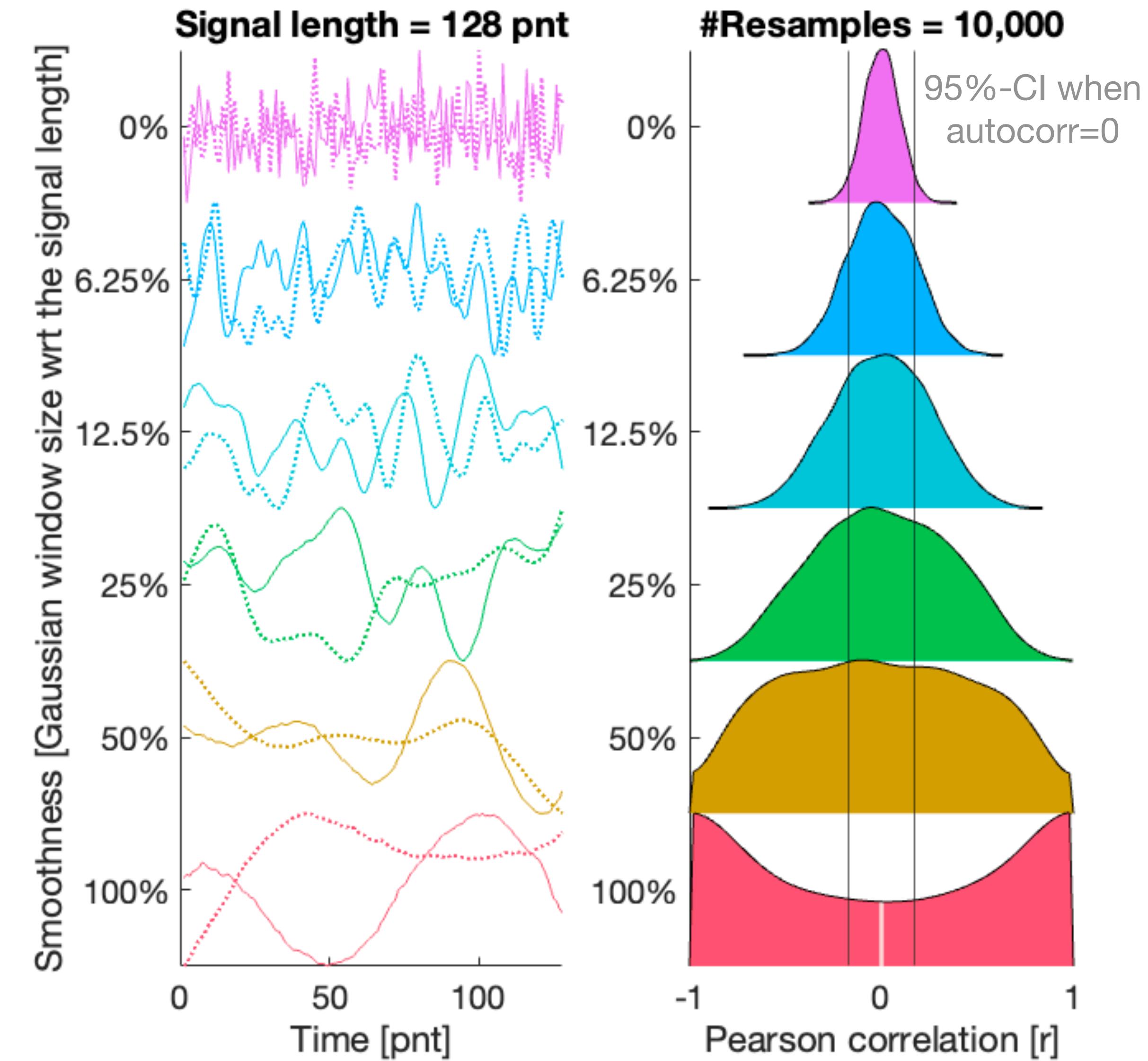
- Many **time series** look alike (i.e., spurious correlation) due to auto/serial-correlation.
- **Non-parametric statistical tests are feasible for any arbitrary noise distribution** with "proper" null (surrogate) data.



Topic 4: Statistical inference

Tests for time series

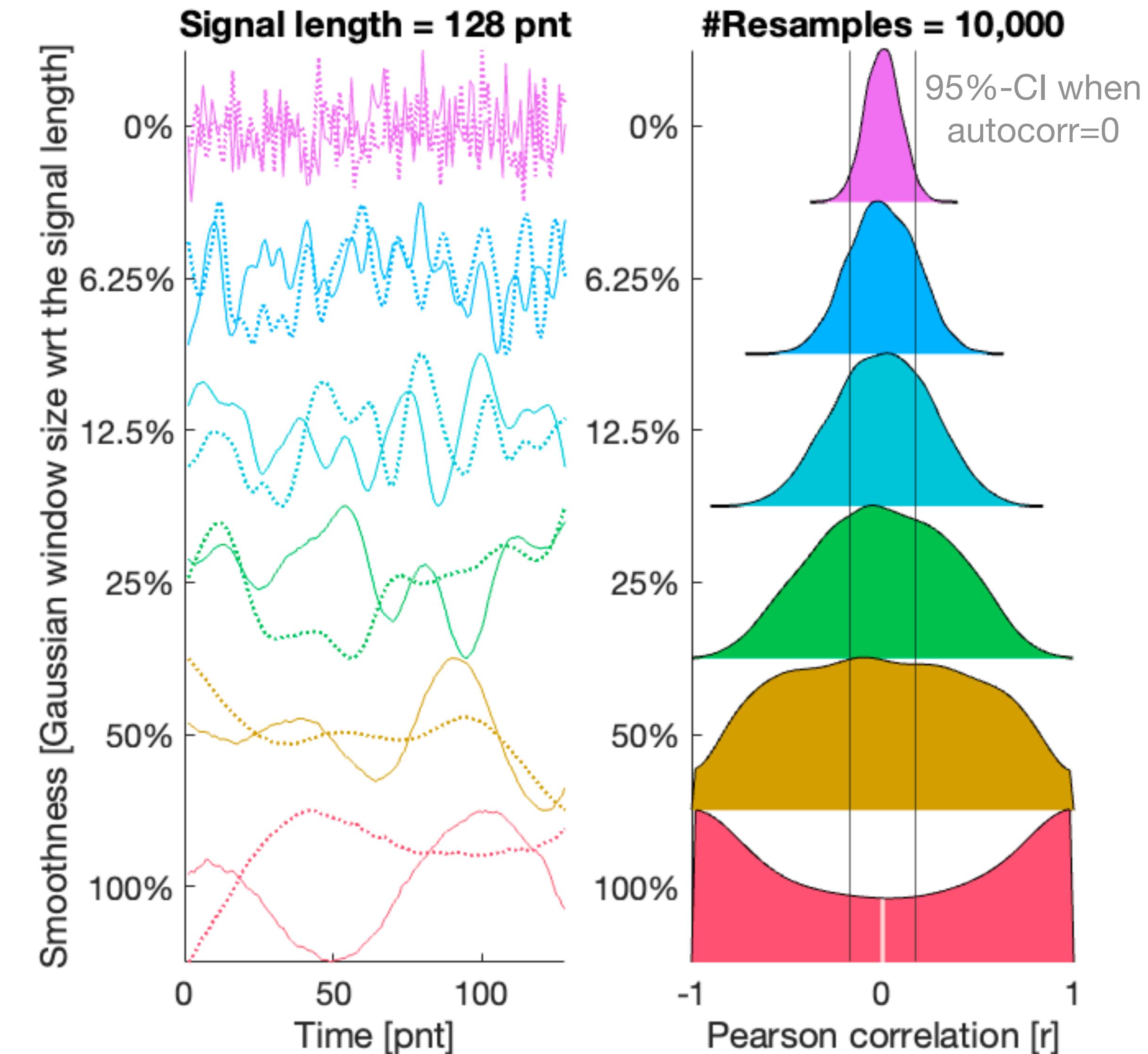
- Many **time series** look alike (i.e., spurious correlation) due to auto/serial-correlation.
- **Non-parametric statistical tests are feasible for any arbitrary noise distribution** with "proper" null (surrogate) data.
- Explicitly estimation autocorrelation from finite (non-infinite) data is hard.



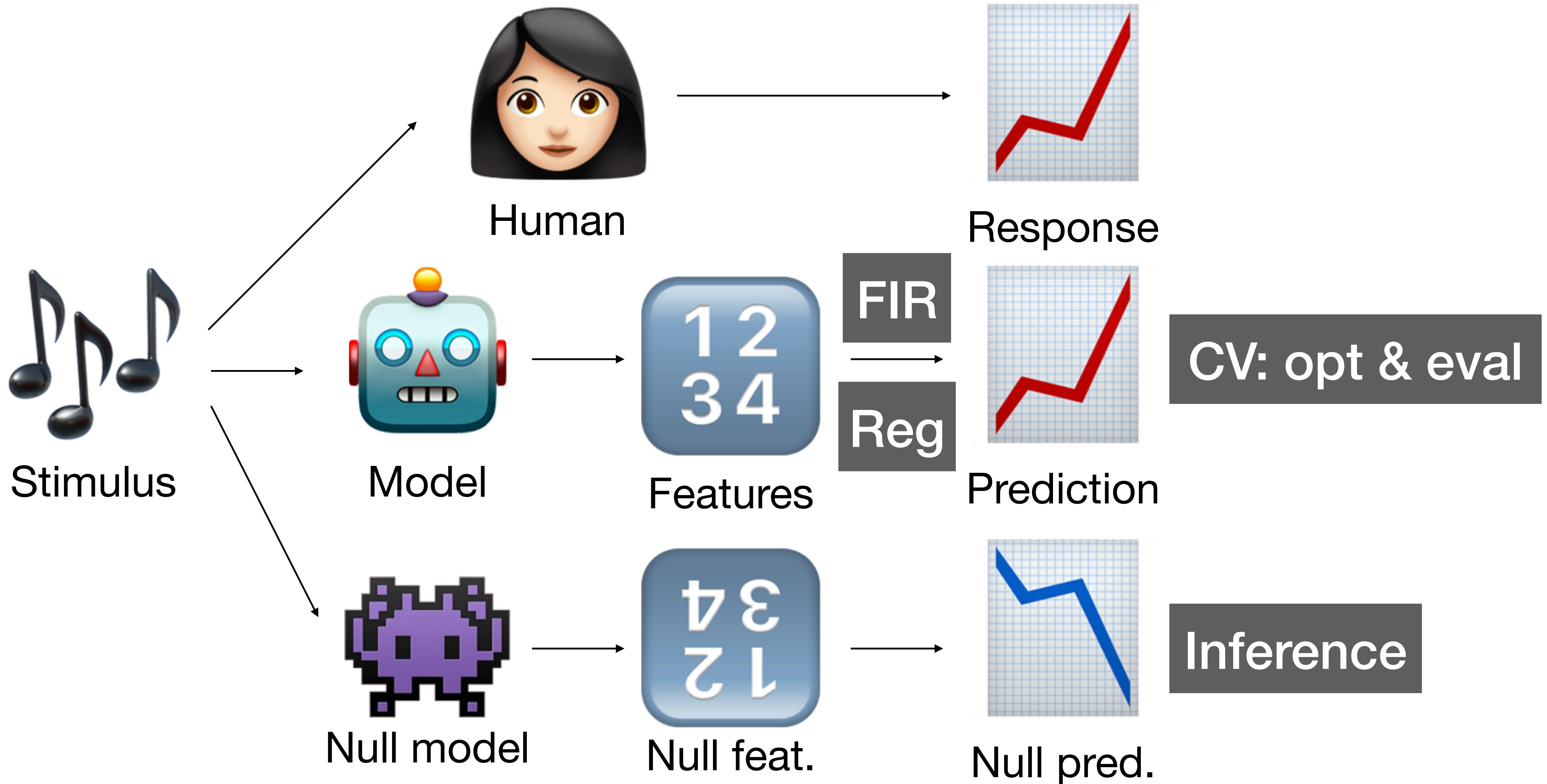
Topic 4: Statistical inference

Tests for time series

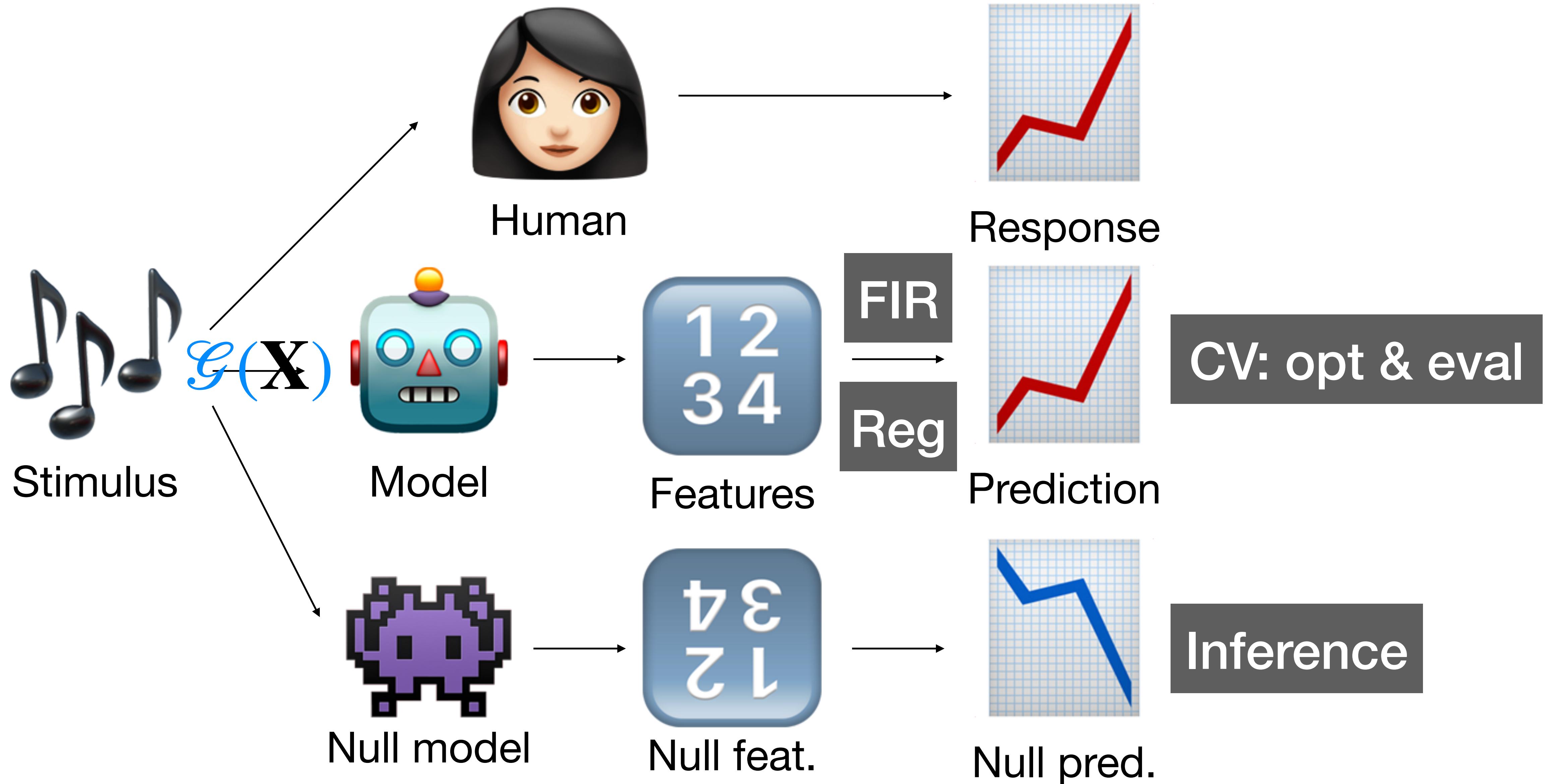
- Many **time series** look alike (i.e., spurious correlation) due to auto/serial-correlation.
- **Non-parametric statistical tests are feasible for any arbitrary noise distribution** with "proper" null (surrogate) data.
- Explicitly estimation autocorrelation from finite (non-infinite) data is hard.
- Preserving the dependency structure (e.g., serial/spatial, ...) is rather easy.



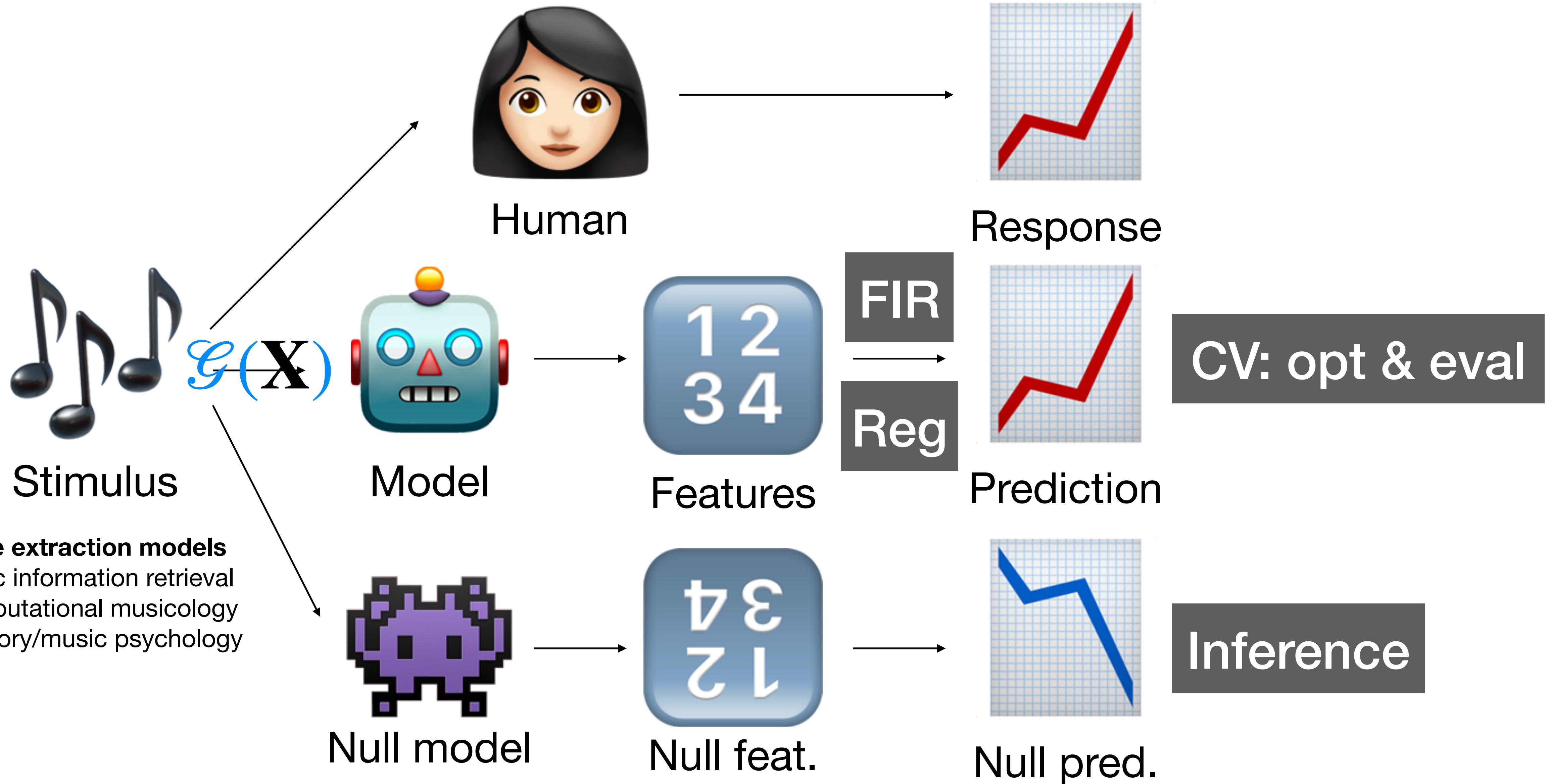
Summary: linearized encoding analysis



Summary: linearized encoding analysis



Summary: linearized encoding analysis



Any questions so far?

(Or I'll ask one 😈)

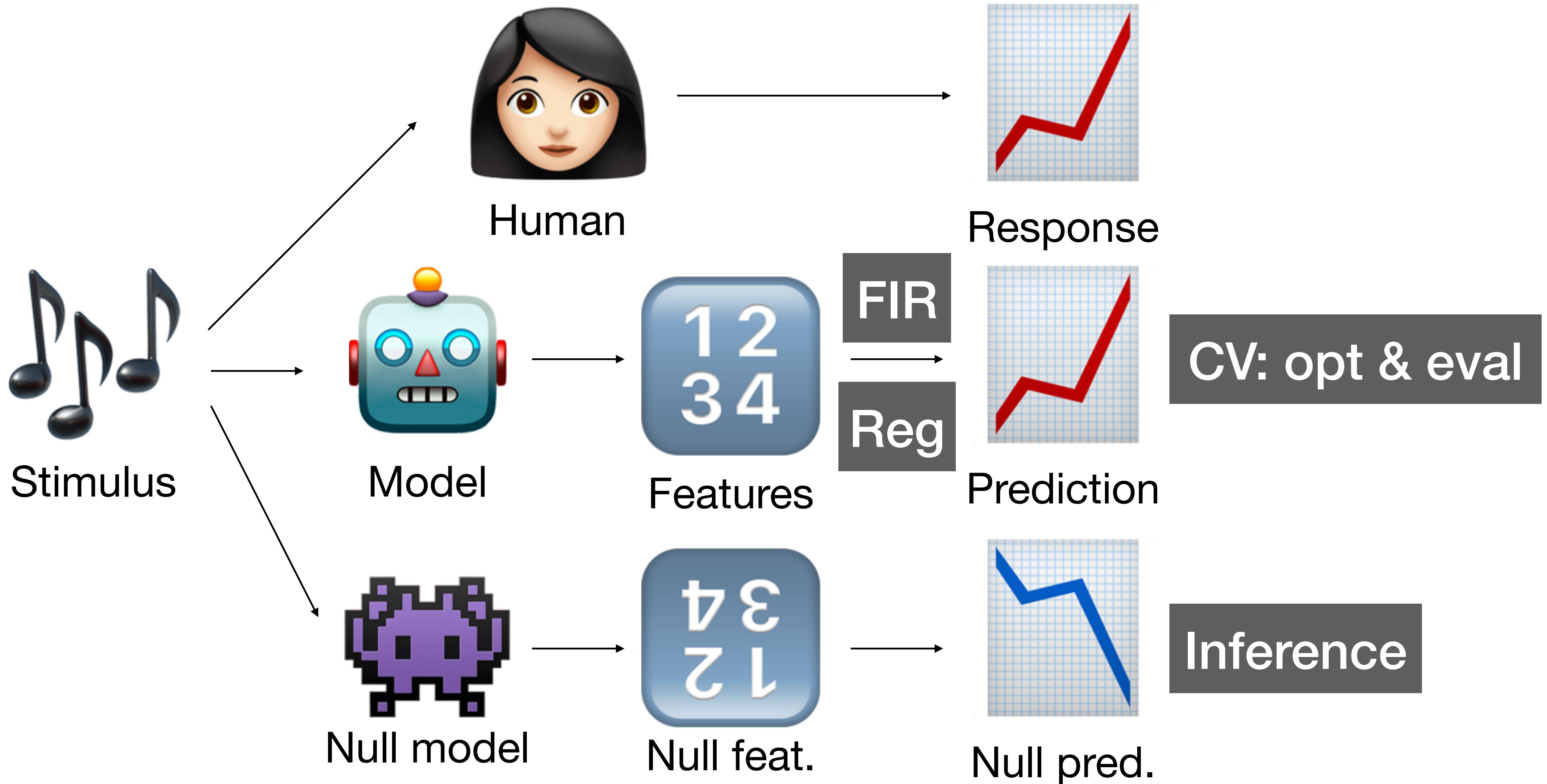


[Go back to SESSION PLAN](#)

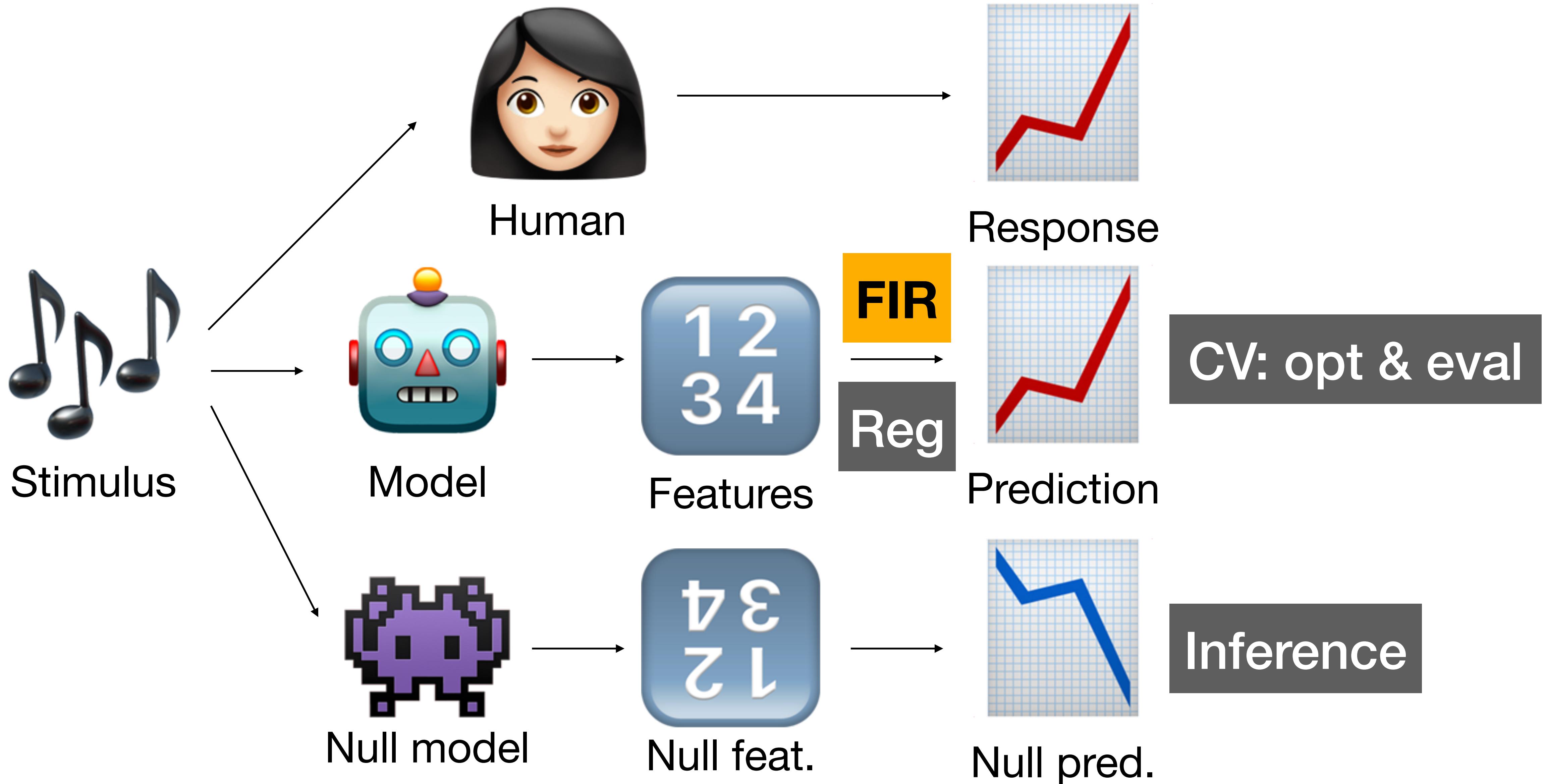


Methods (Hows): Linearized Encoding Analysis

Linearized encoding analysis overview (HOWs)

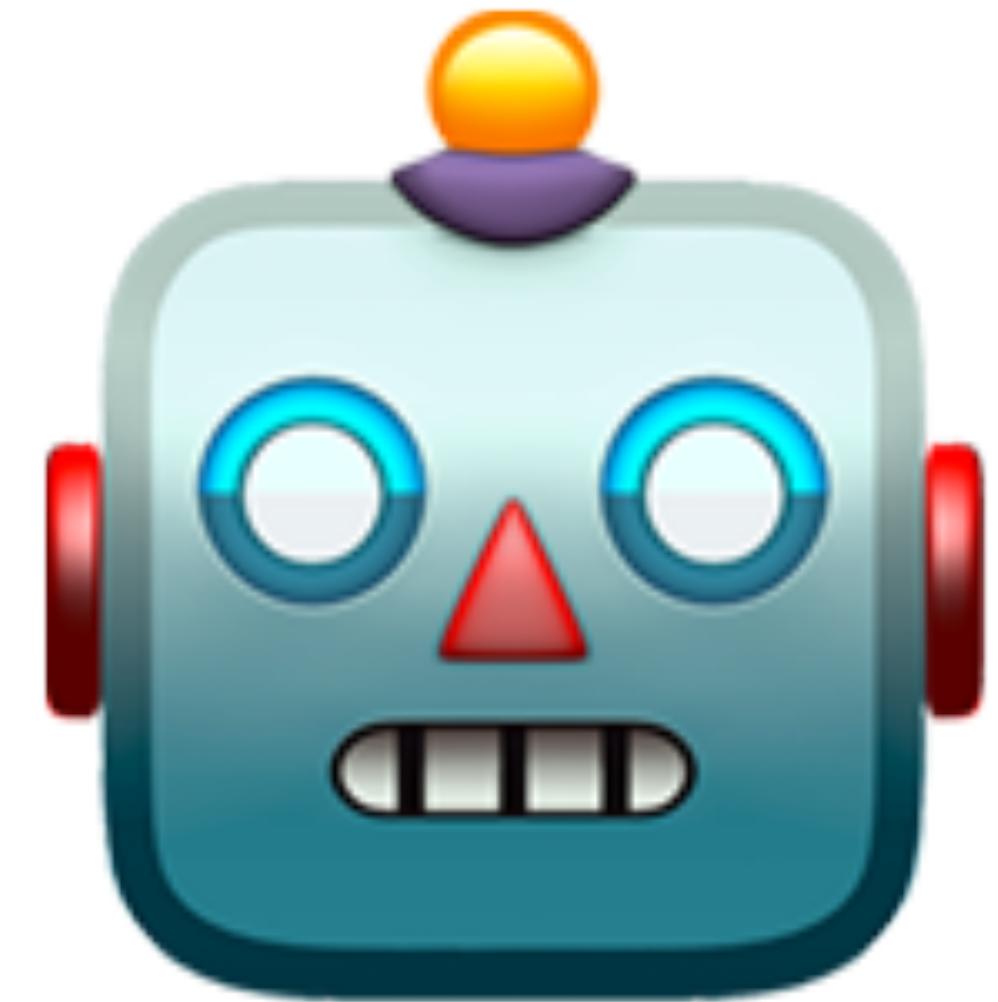


Linearized encoding analysis overview (HOWs)



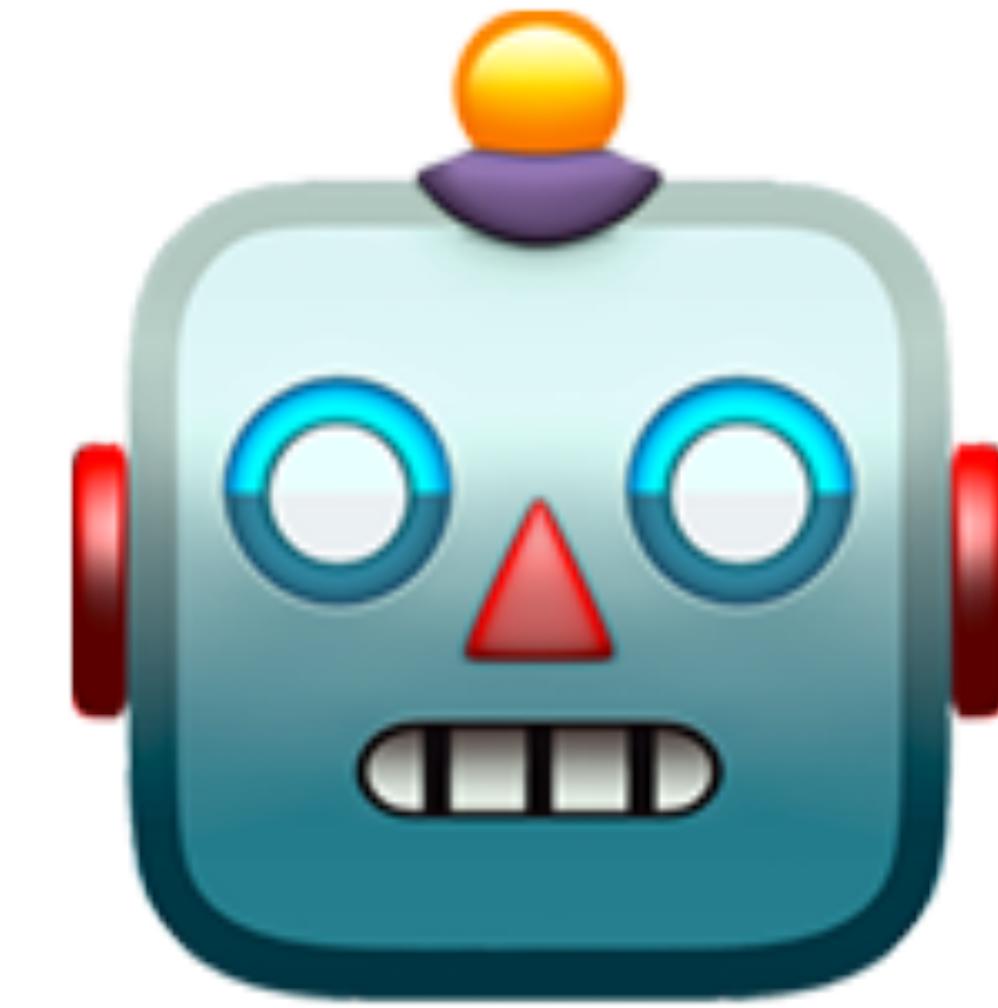
Finite impulse response modeling in time

A single-pixel time series



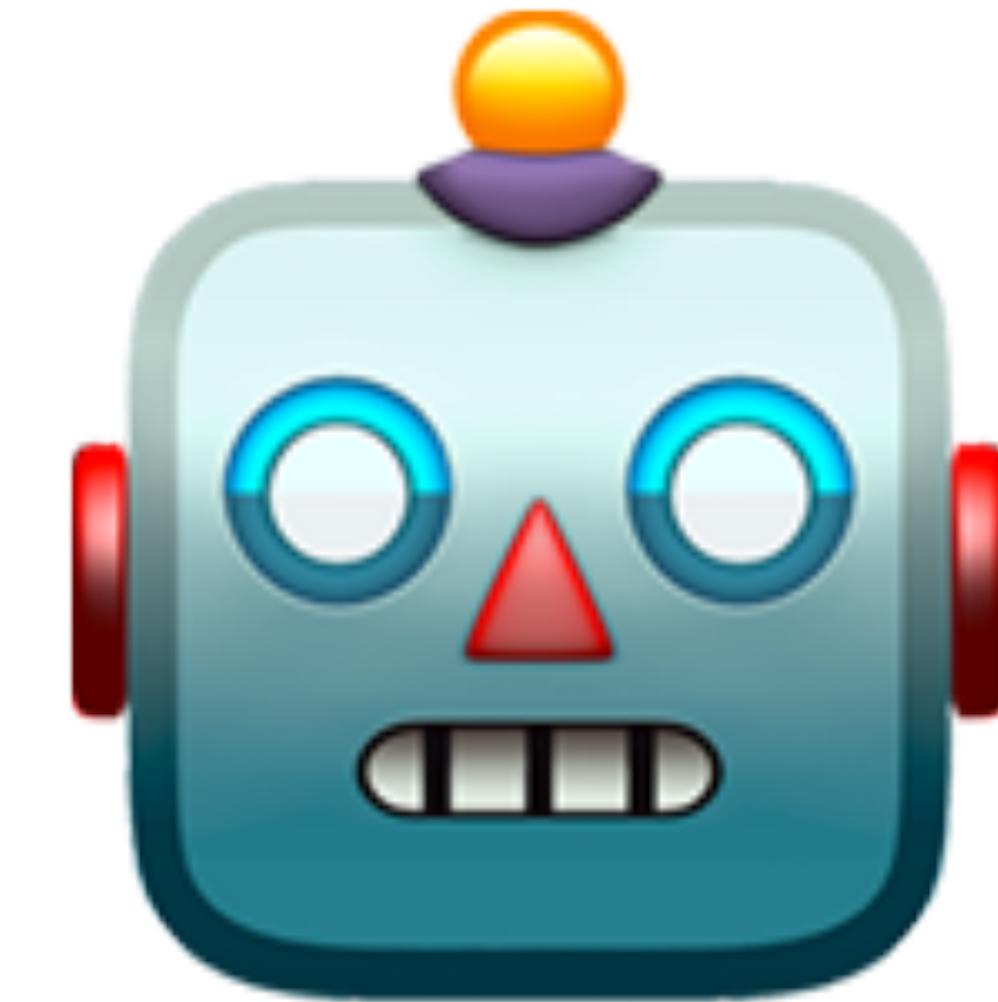
Finite impulse response modeling in time

A single-pixel time series



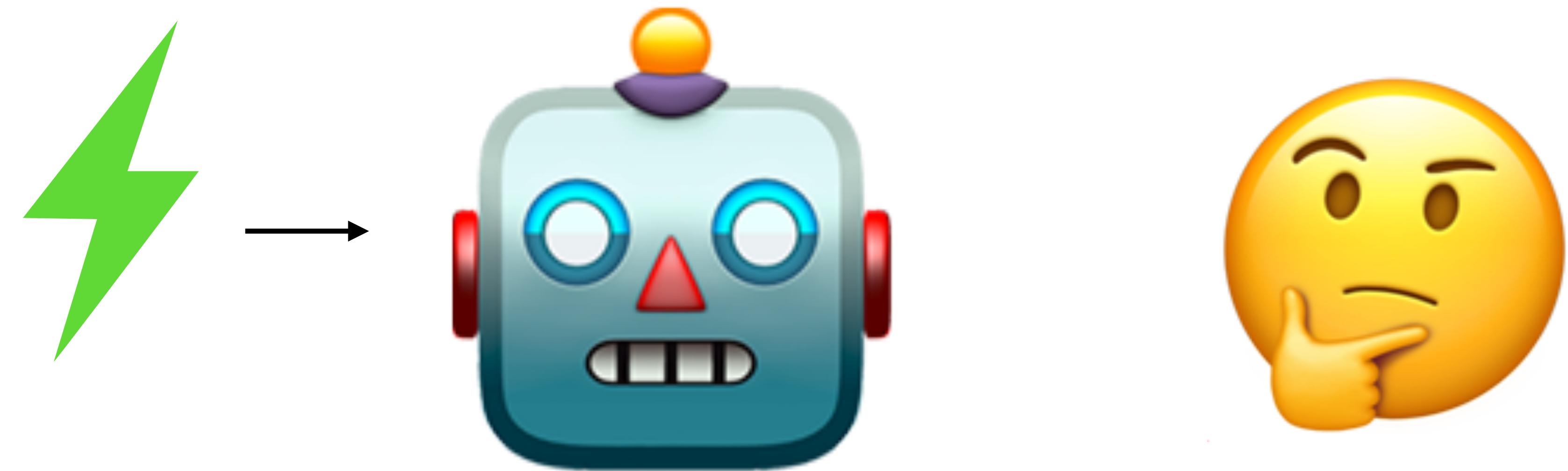
Finite impulse response modeling in time

A single-pixel time series



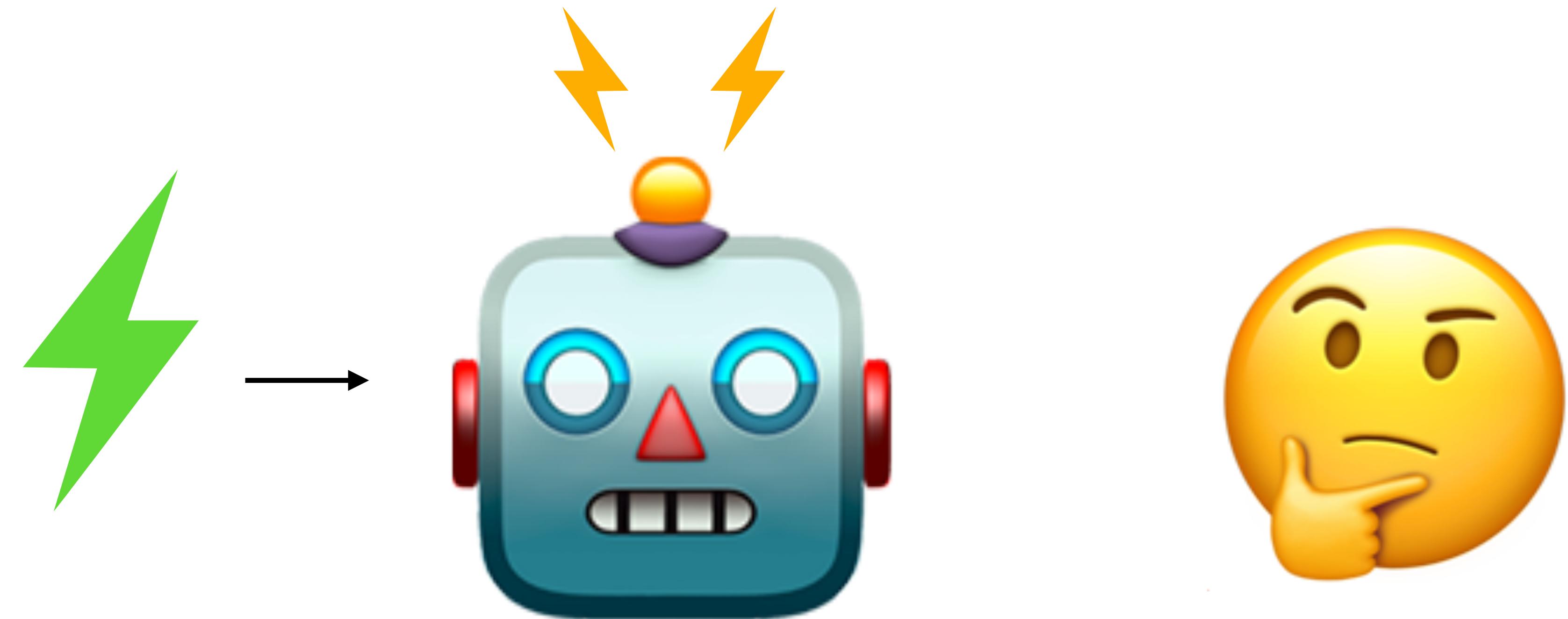
Finite impulse response modeling in time

A single-pixel time series



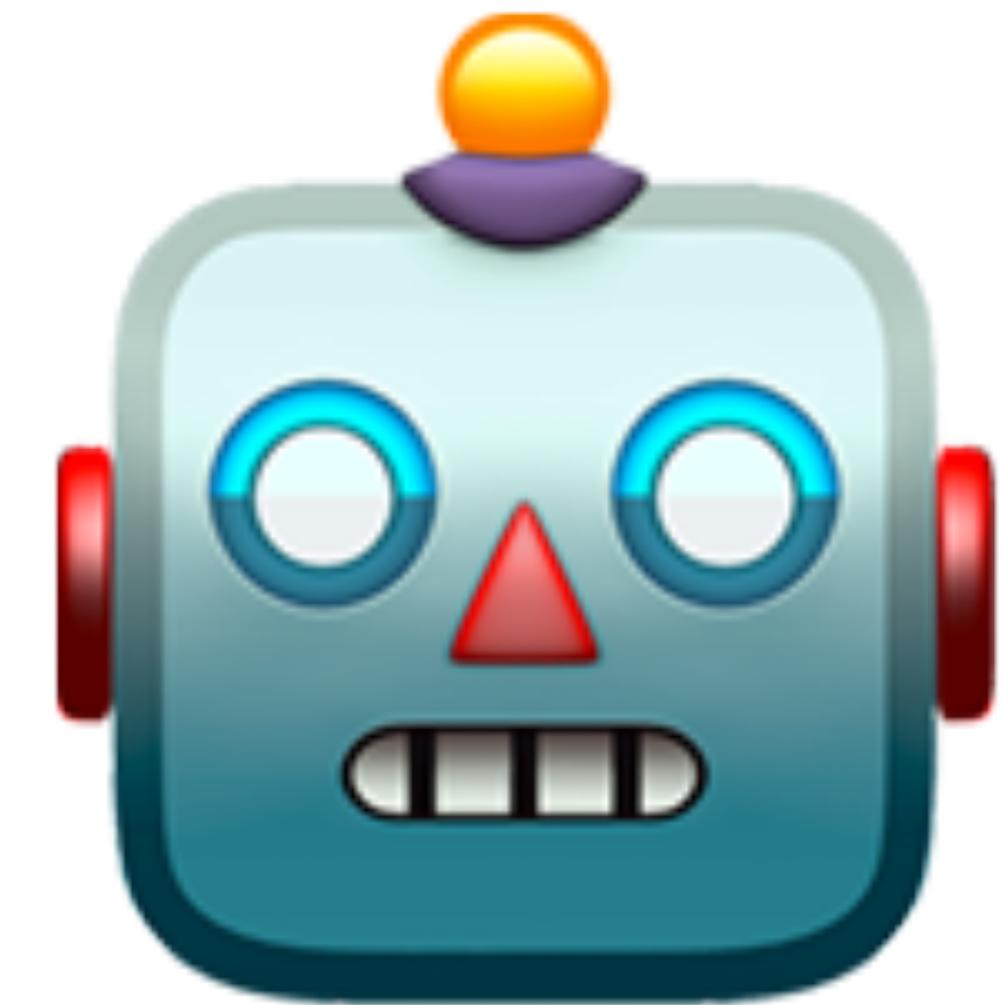
Finite impulse response modeling in time

A single-pixel time series



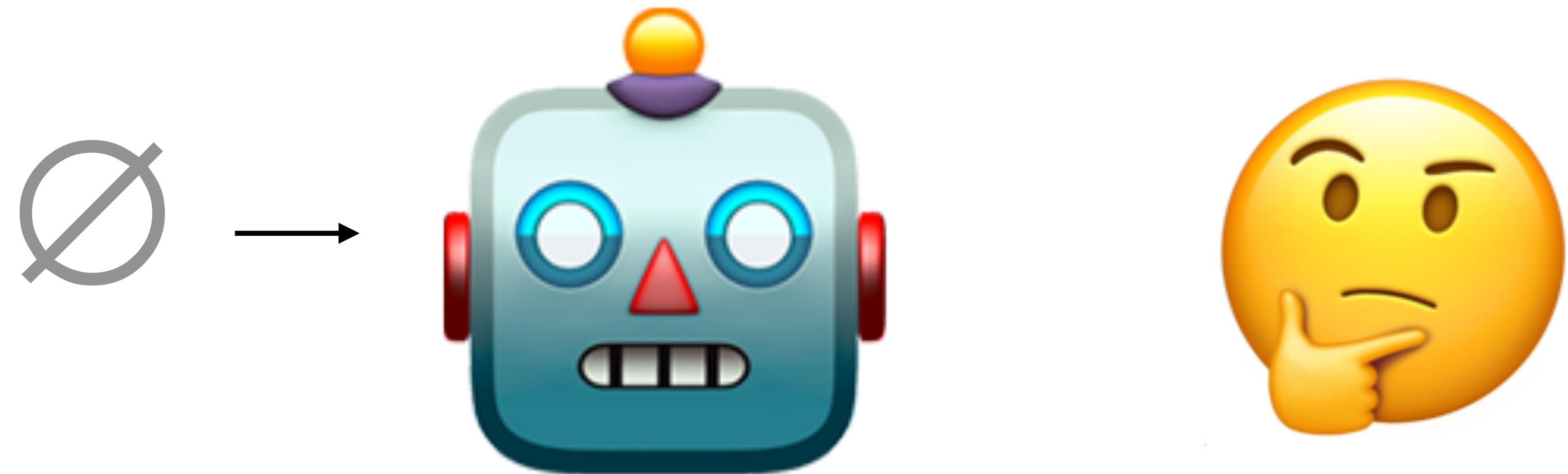
Finite impulse response modeling in time

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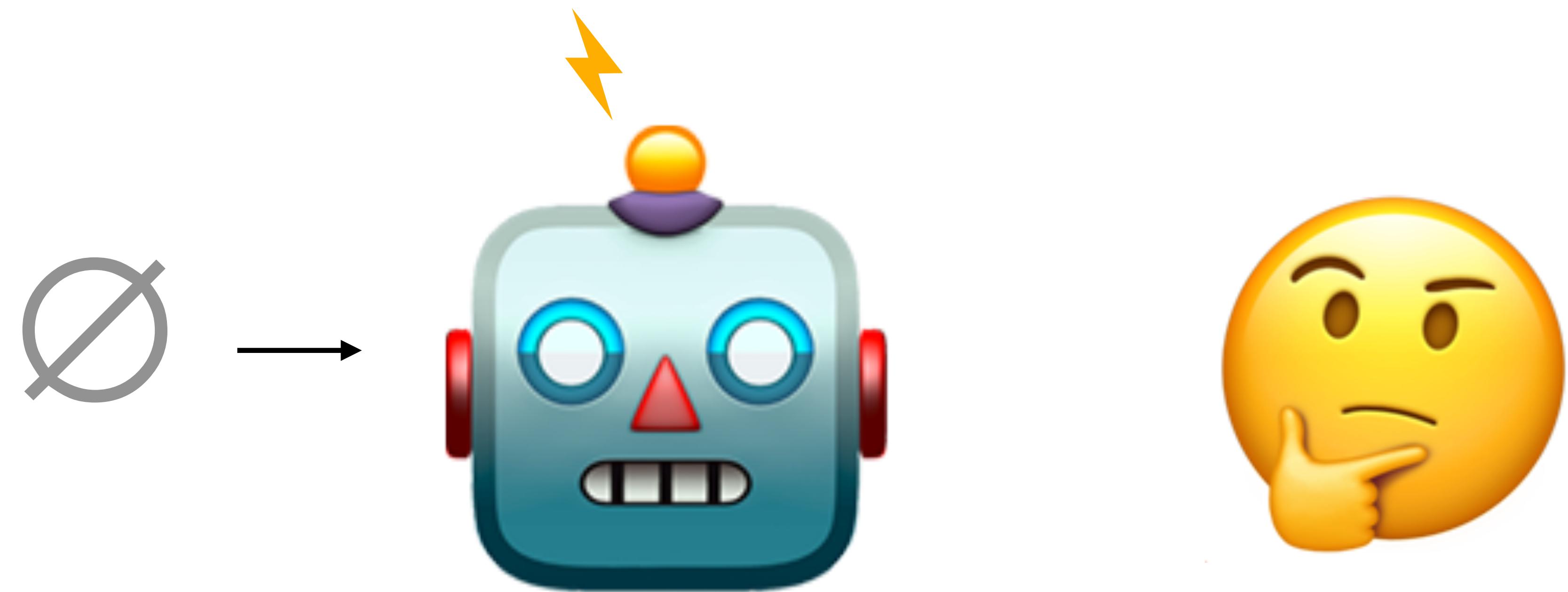
Finite impulse response modeling in time

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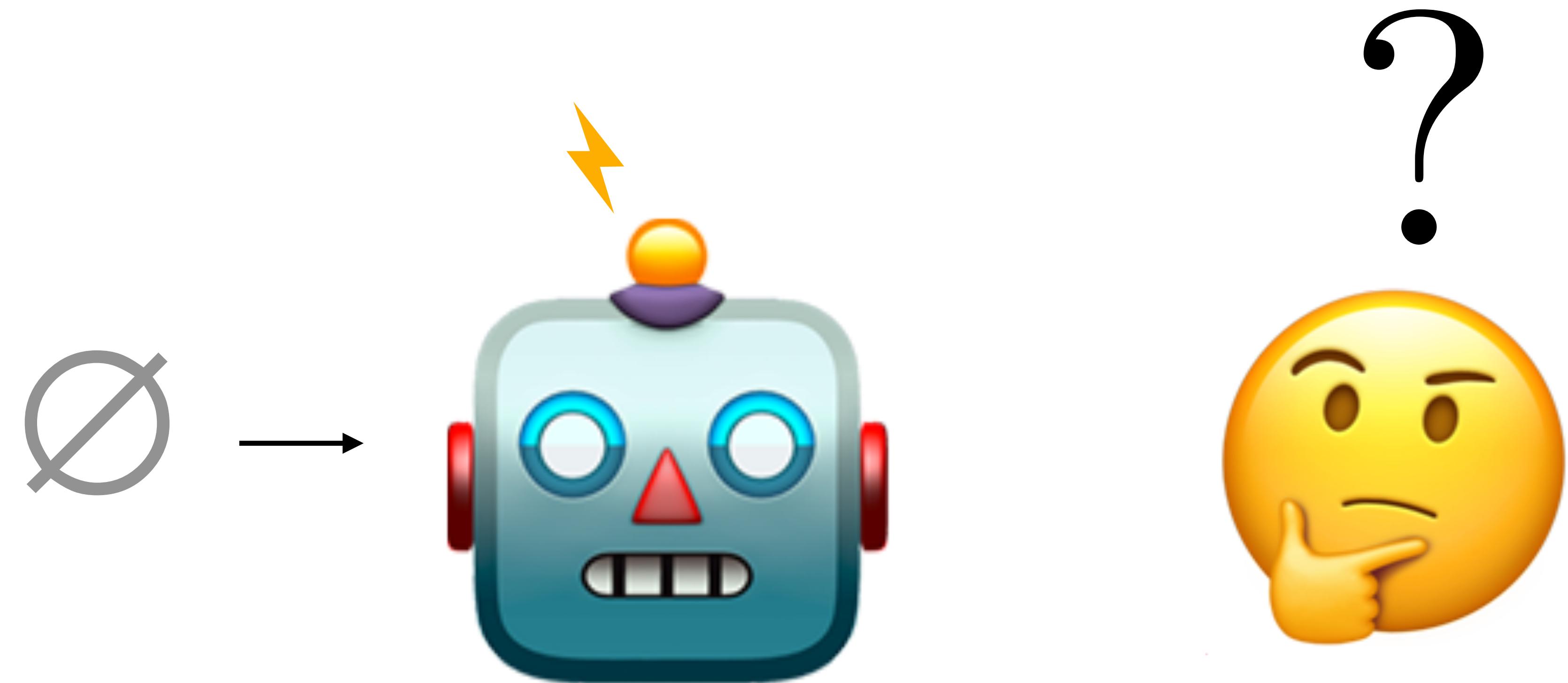
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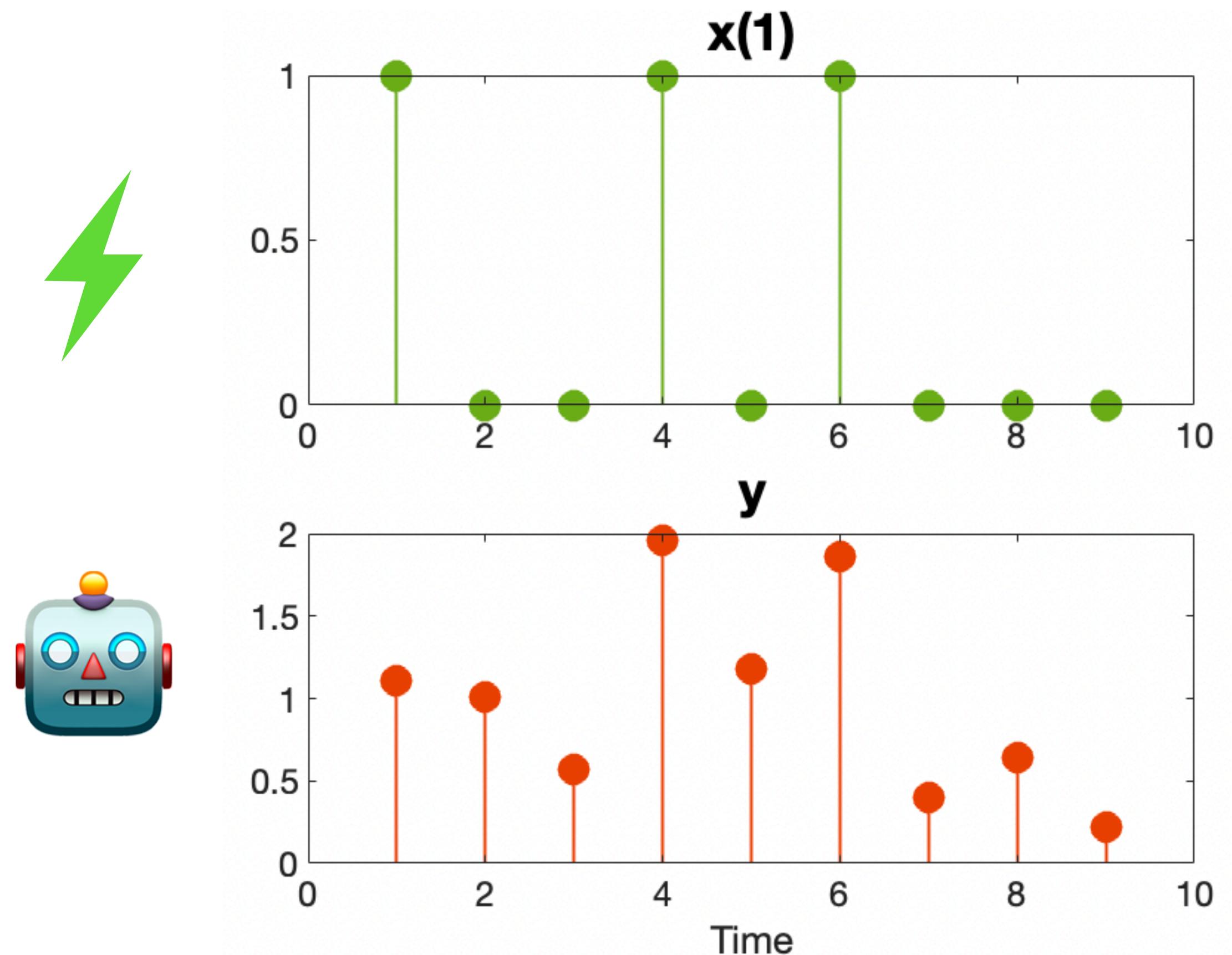
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Finite impulse response modeling in time

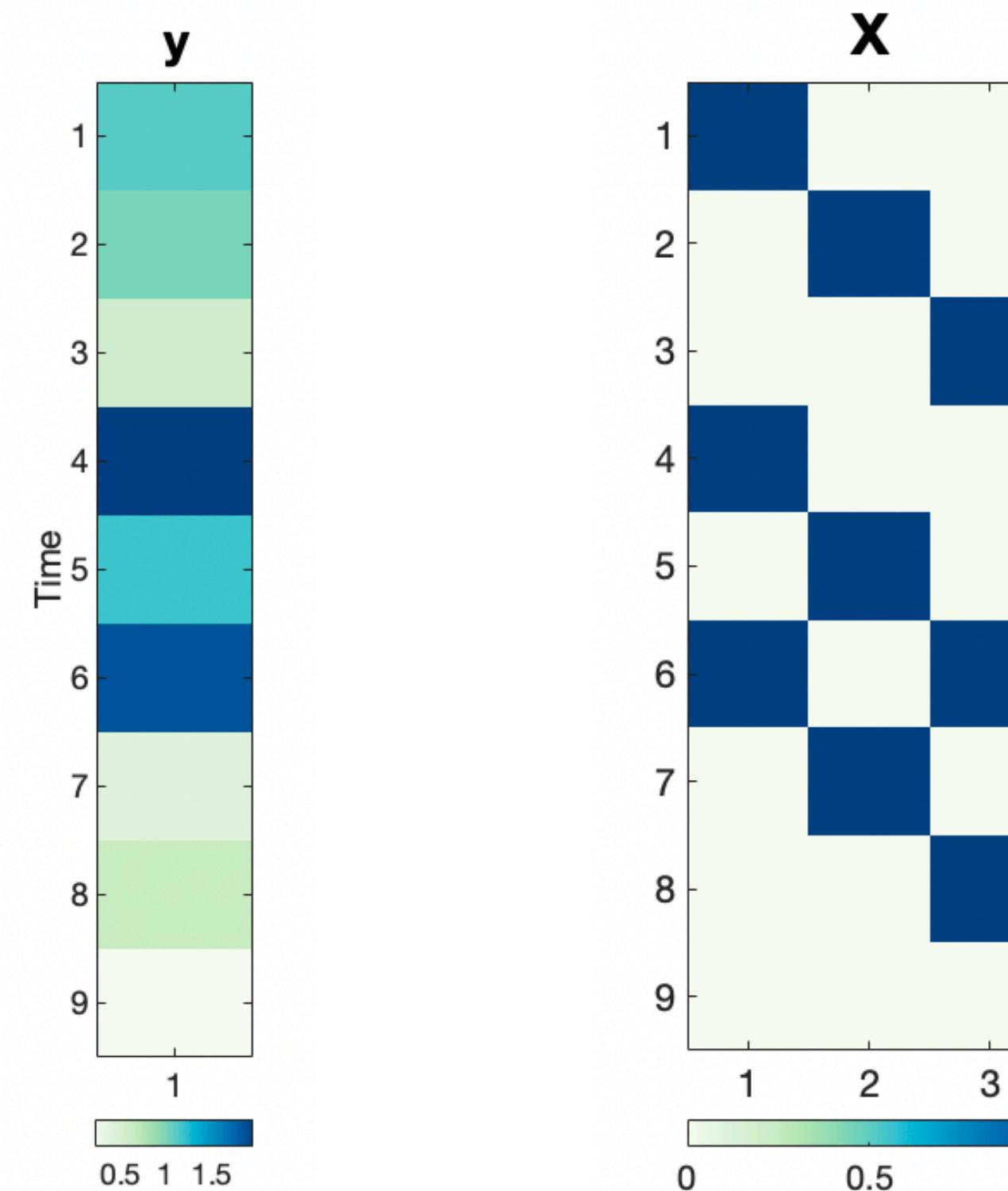
A single-pixel time series



FIR as a linear regression

$$\mathbf{y} = \mathbf{X} \mathbf{b} + \mathbf{e}$$

$(t \times 1) \quad (t \times d) \quad (d \times 1) \quad (t \times 1)$



Ordinary least squares (OLS):

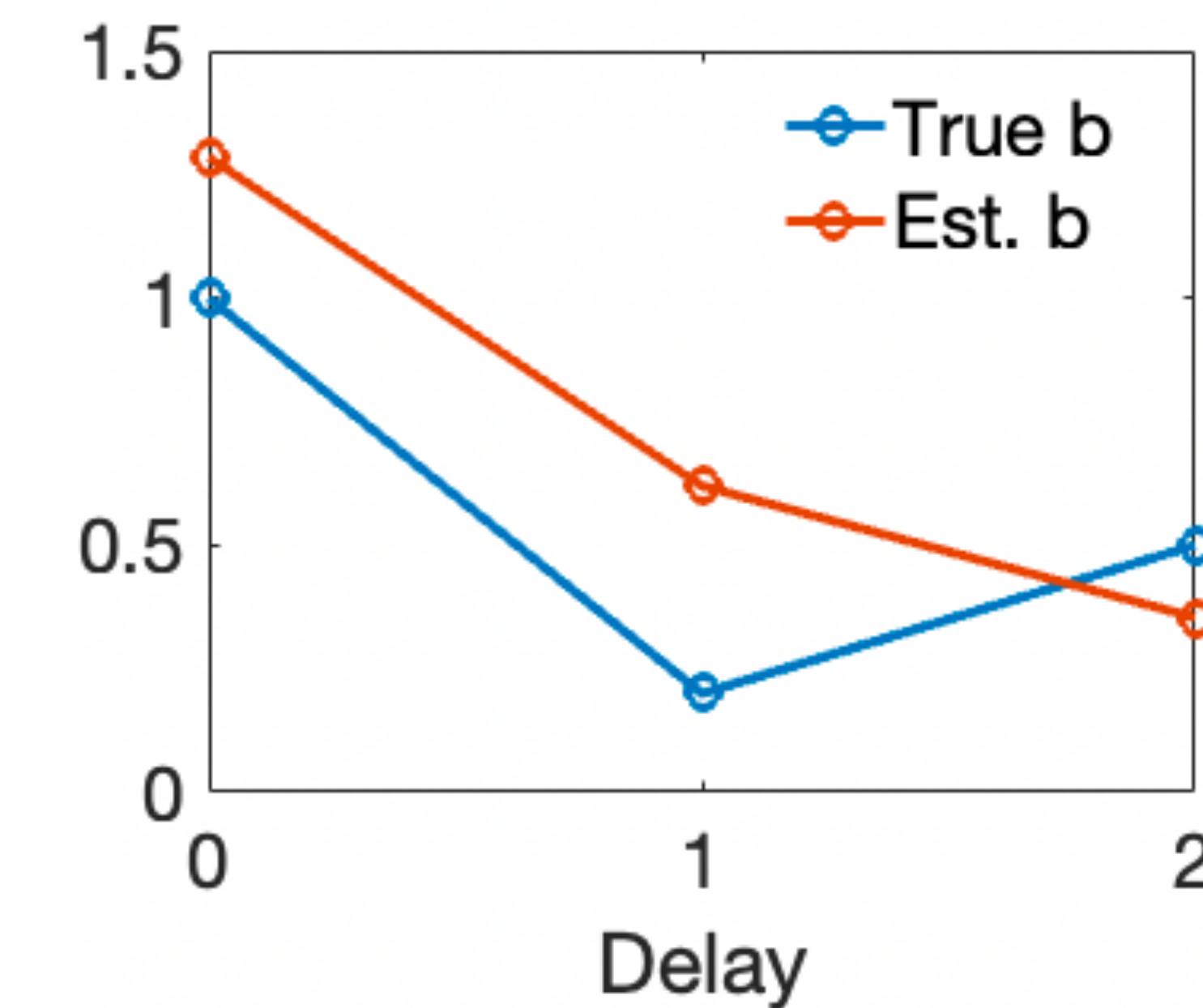
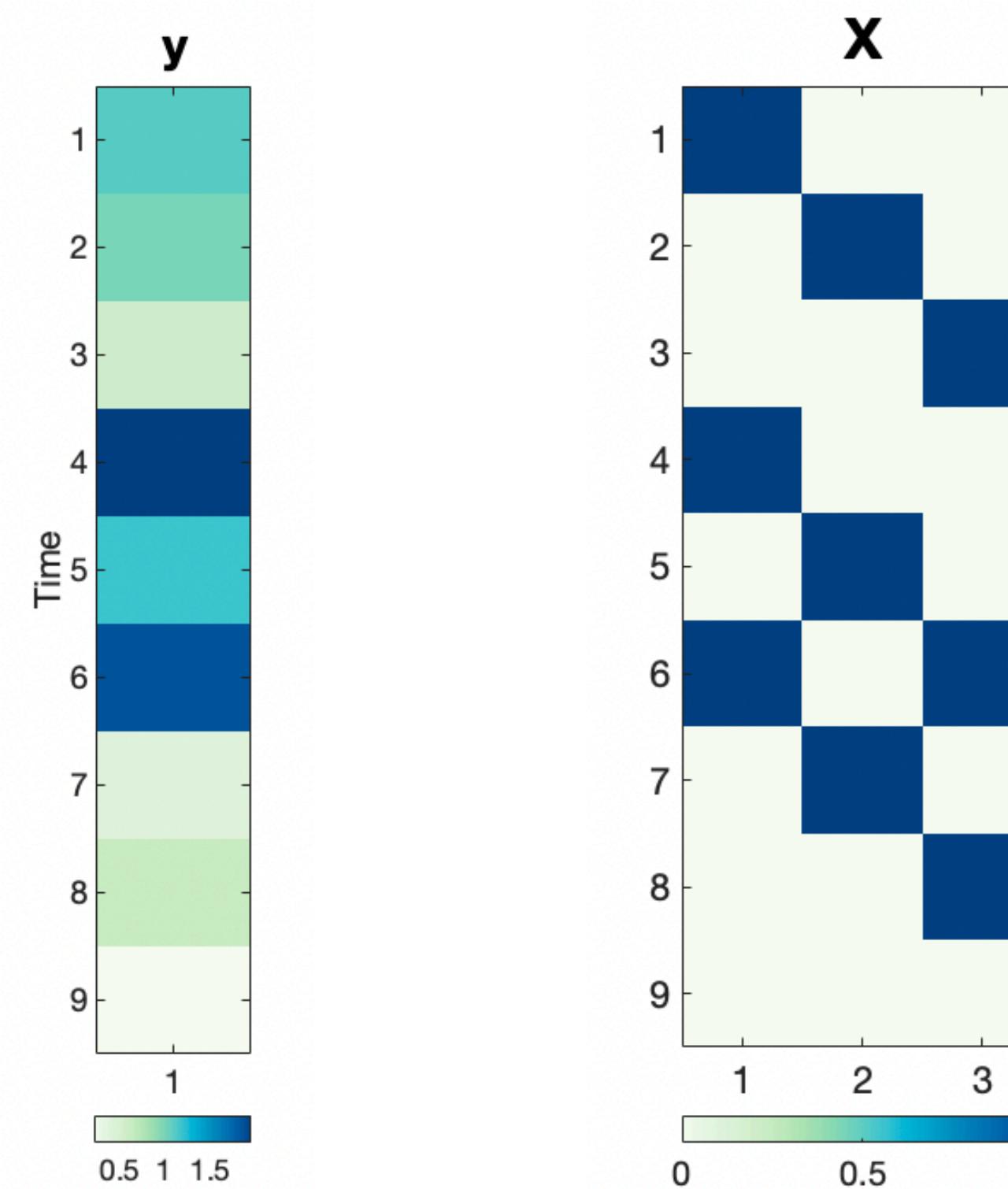
$$\hat{\mathbf{b}} = \mathbf{X}^+ \mathbf{y}$$

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

FIR as a linear regression

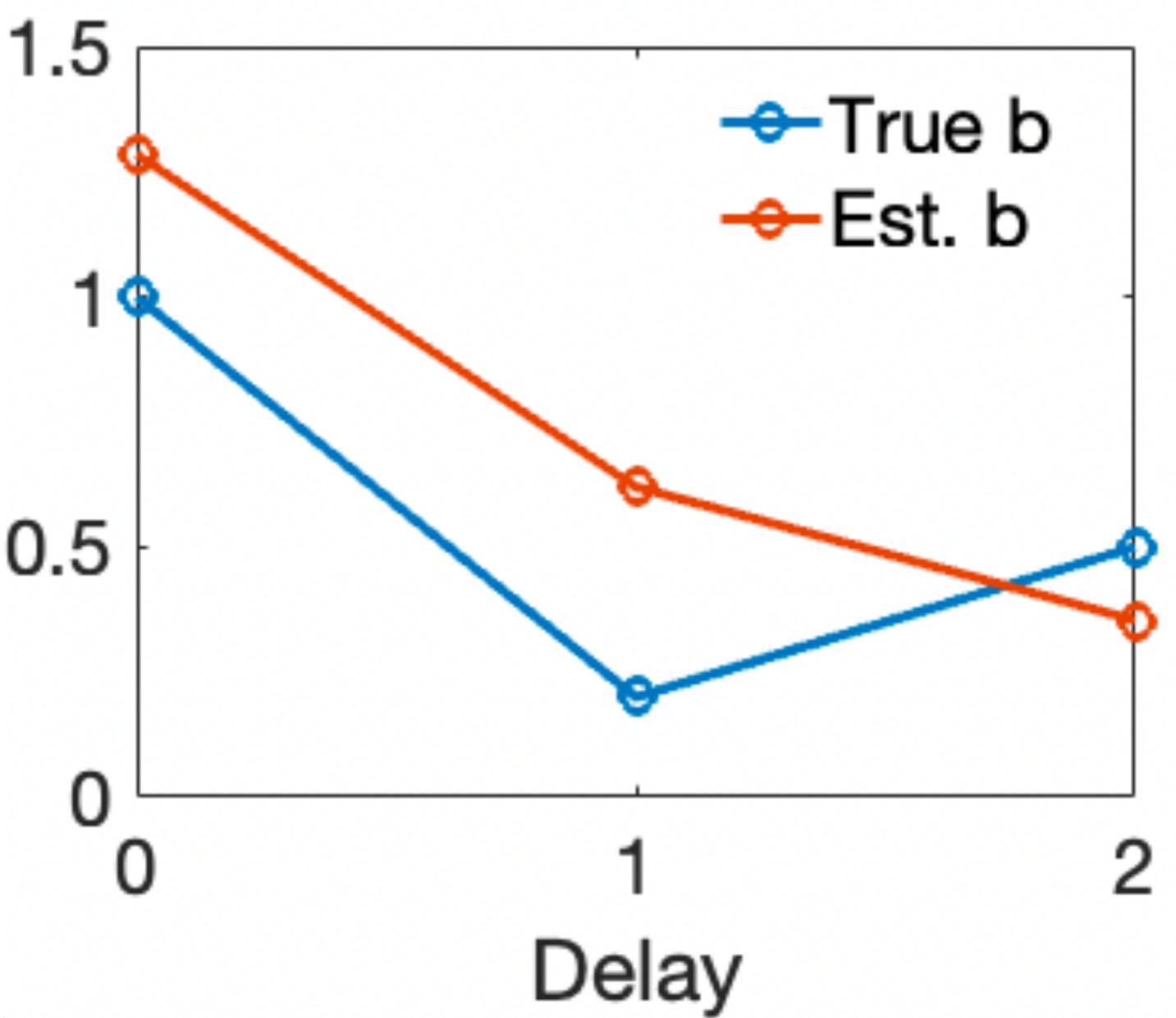
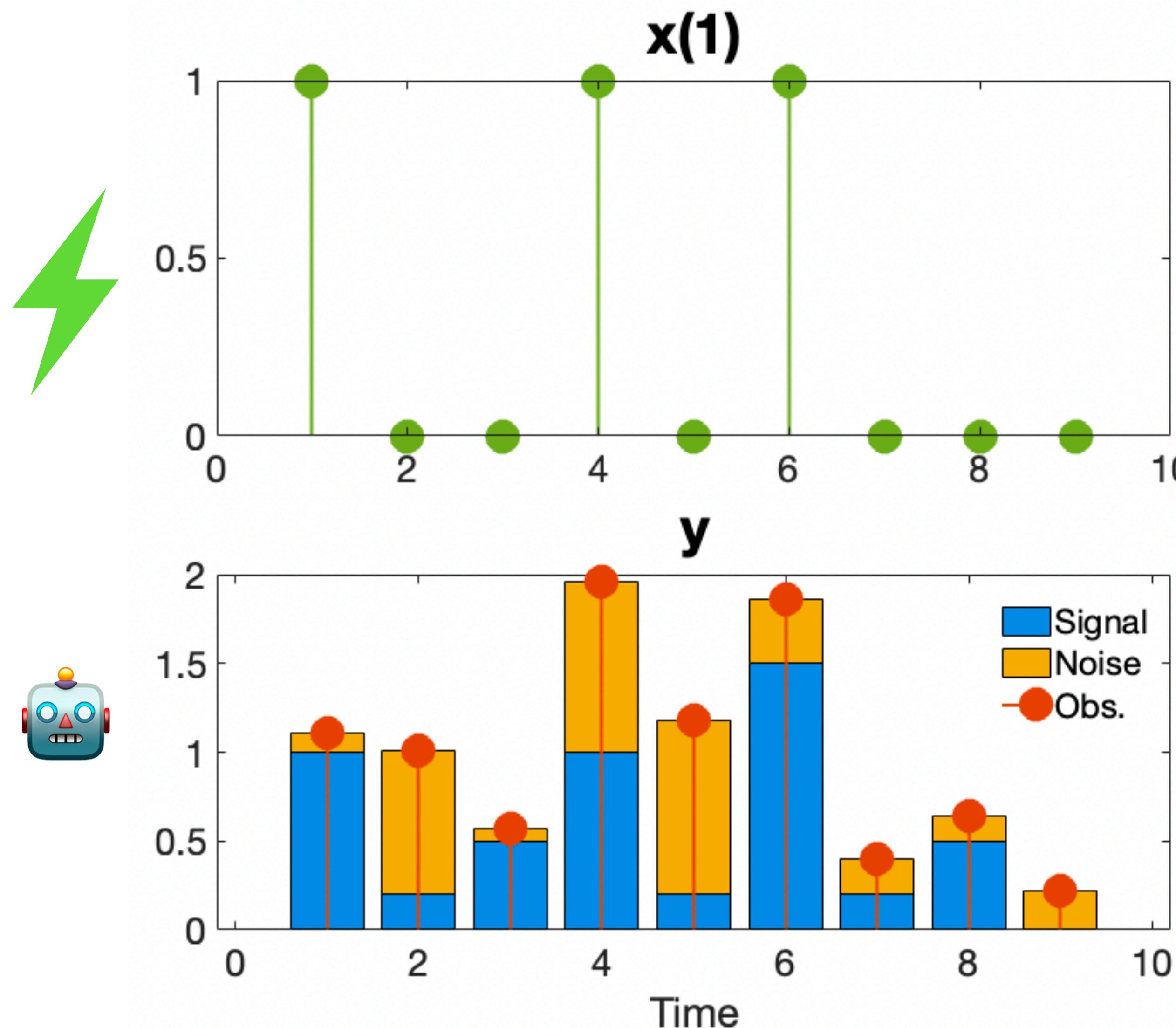
$$\mathbf{y} = \mathbf{X} \mathbf{b} + \mathbf{e}$$

$(t \times 1) \quad (t \times d) \quad (d \times 1) \quad (t \times 1)$



: But why not identical?

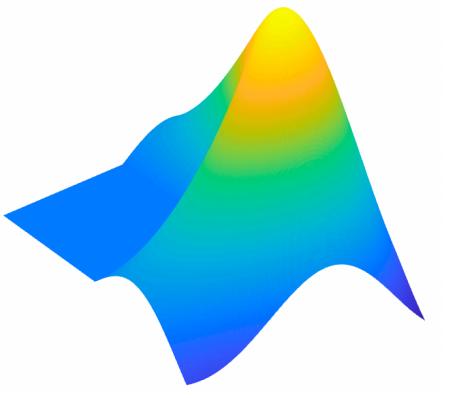
Because there is no sample without noise!



Estimation is
overfitting to **noise** 😞



Interactive demo



Summary [1/4]: Finite impulse response

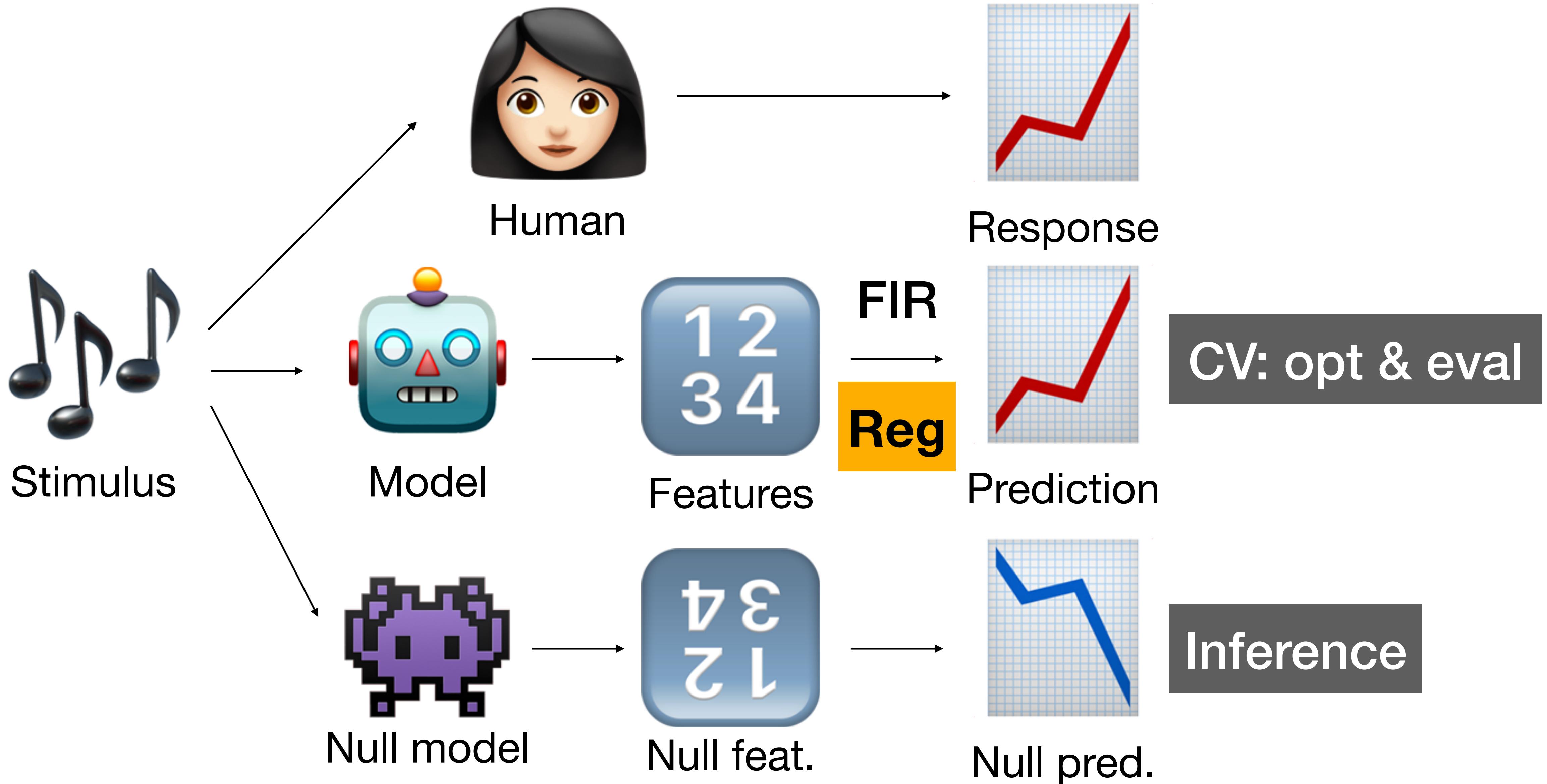
FIR modeling in the time domain

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?

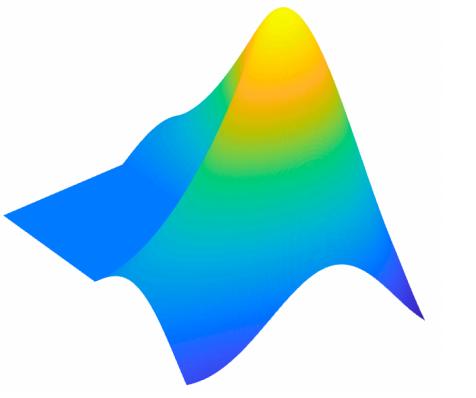
Ridge regression

Regularized linear regression

- LSE: $b^* = \arg \min_b \|y - Xb\|_2^2 = (X'X)^{-1}X'y = X^+y$
- Ridge: $b^* = \arg \min_b \|y - Xb\|_2^2 + \lambda \|b\|_2^2 = (X'X + \lambda^2 I)^{-1}X'y$
 - $\lambda = 0$: LSE
 - $\lambda \gg 0$: it makes $b^* \approx 0$
 - 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

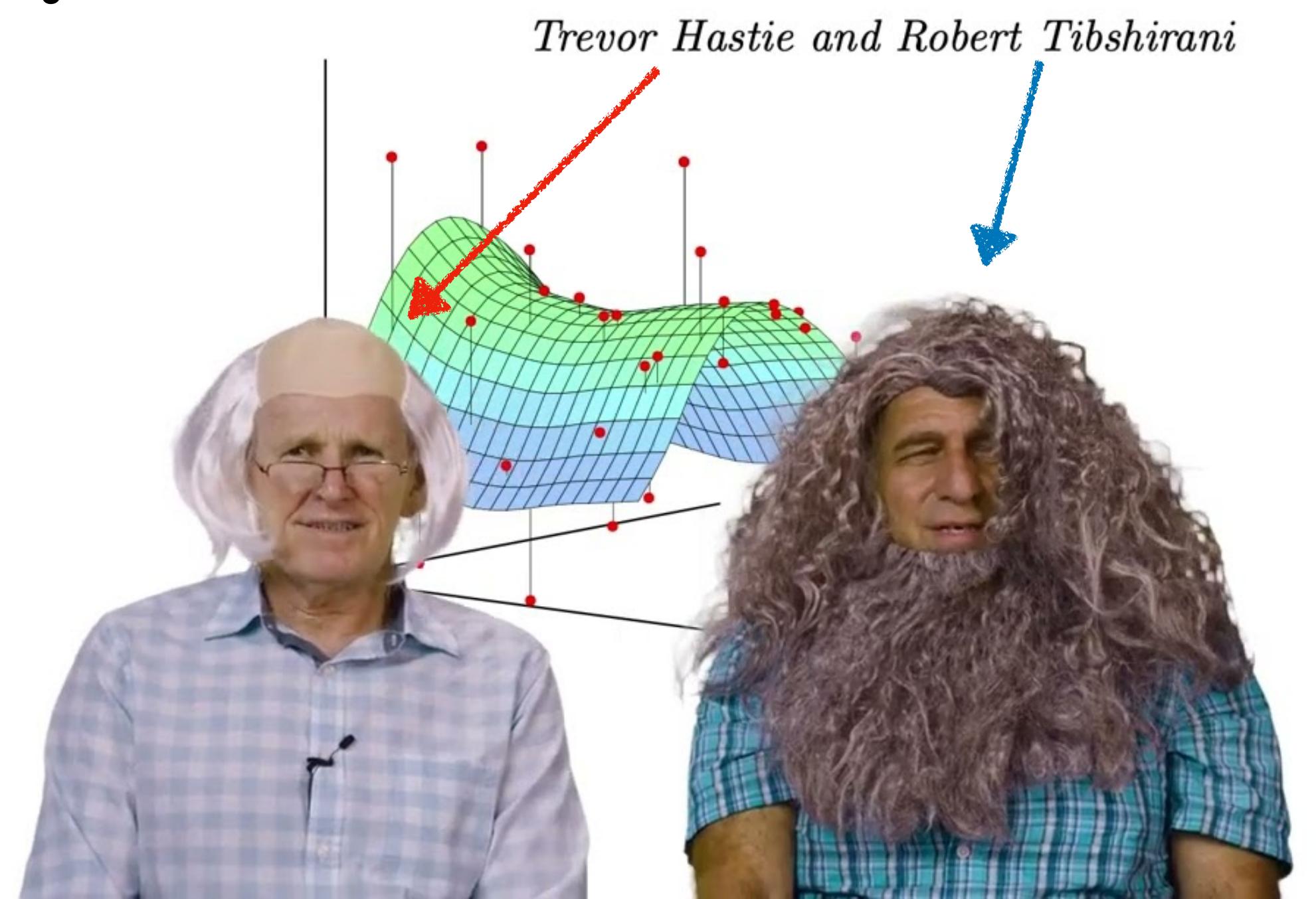
- LSE:

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

- Ridge (Diagonal matrix; Hoerl & Kennard, 1970):

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

Statistical Learning



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

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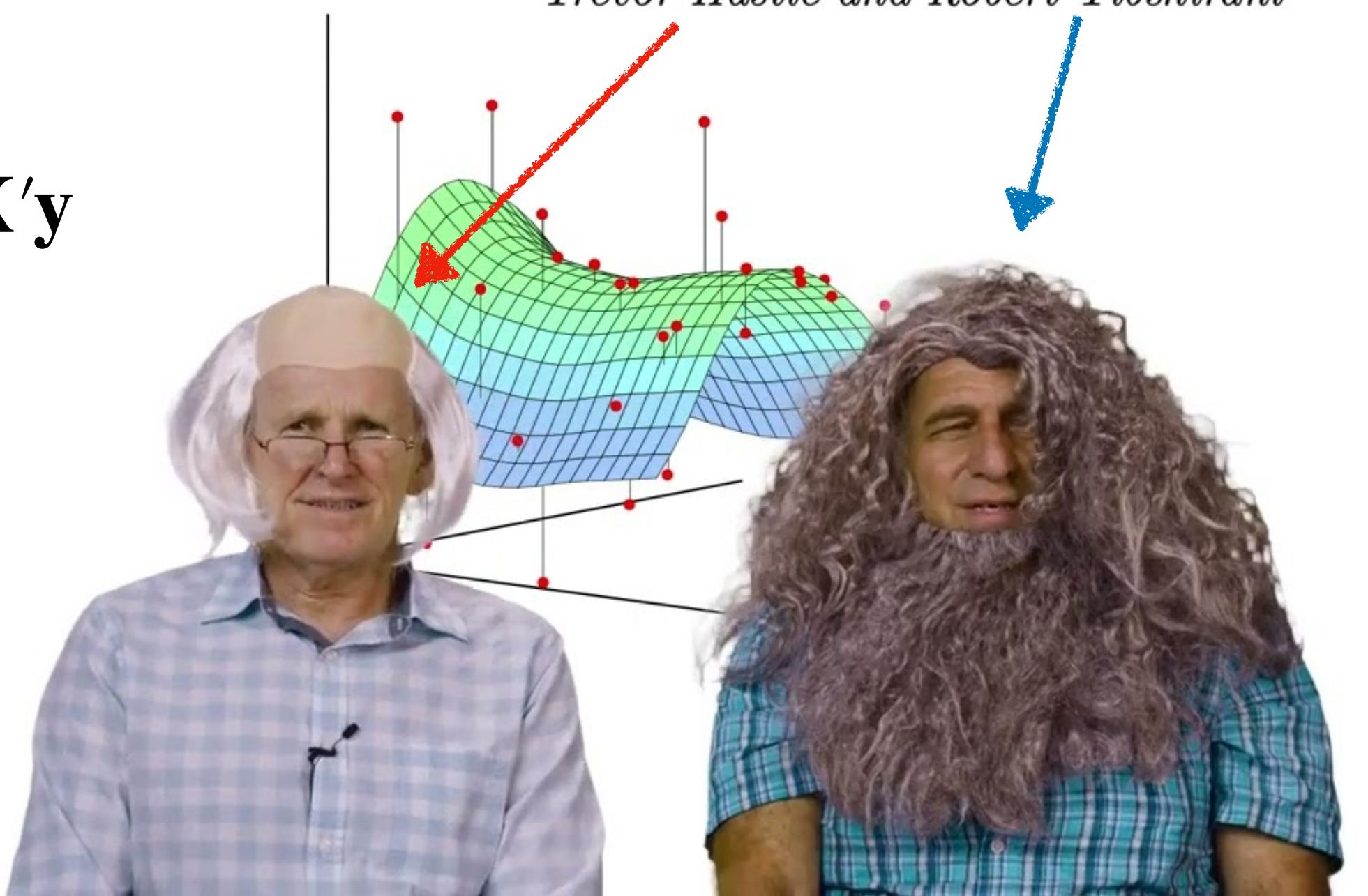
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- Tikhonov (Symmetric matrix; Tikhonov, 1943):

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Statistical Learning

Trevor Hastie and Robert Tibshirani



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

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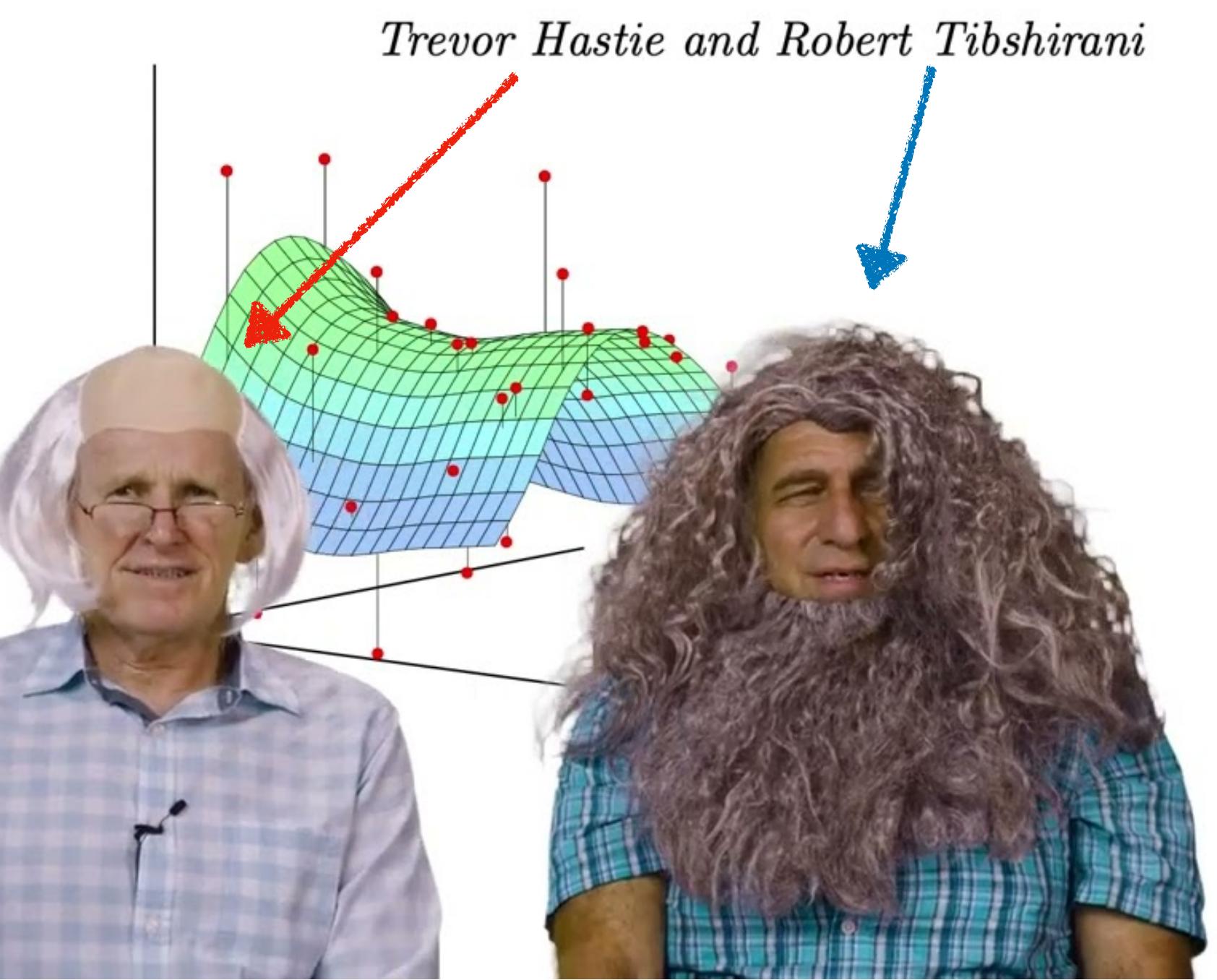
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- Lasso (L1-norm; Santosa et al., 1986; **Tibshirani**, 1996):

$$\mathbf{b}_{\text{lasso}} = \arg \min_{\mathbf{b}} \|\mathbf{y} - \mathbf{X}\mathbf{b}\|_2^2 + \|\lambda\mathbf{b}\|_1$$

Statistical Learning



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

Other types of regularization for regression

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

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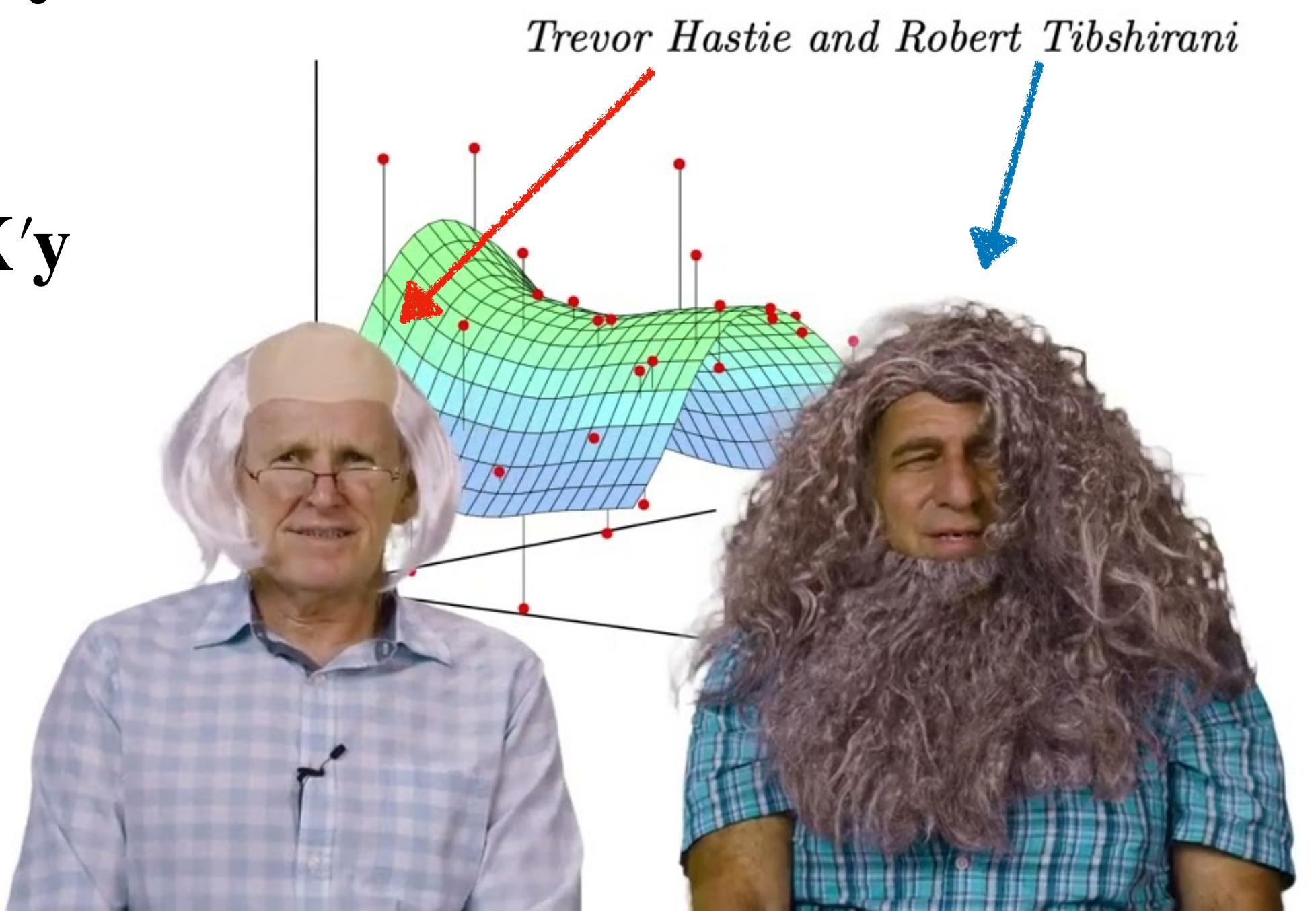
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- Elastic net (L1-norm + L2-norm; Zou & **Hastie**, 2005):

$$\mathbf{b}_{\text{elastic}} = \arg \min_{\mathbf{b}} \|\mathbf{y} - \mathbf{X}\mathbf{b}\|_2^2 + \|\lambda\mathbf{b}\|_1 + \lambda \|\mathbf{b}\|_2^2$$

Statistical Learning

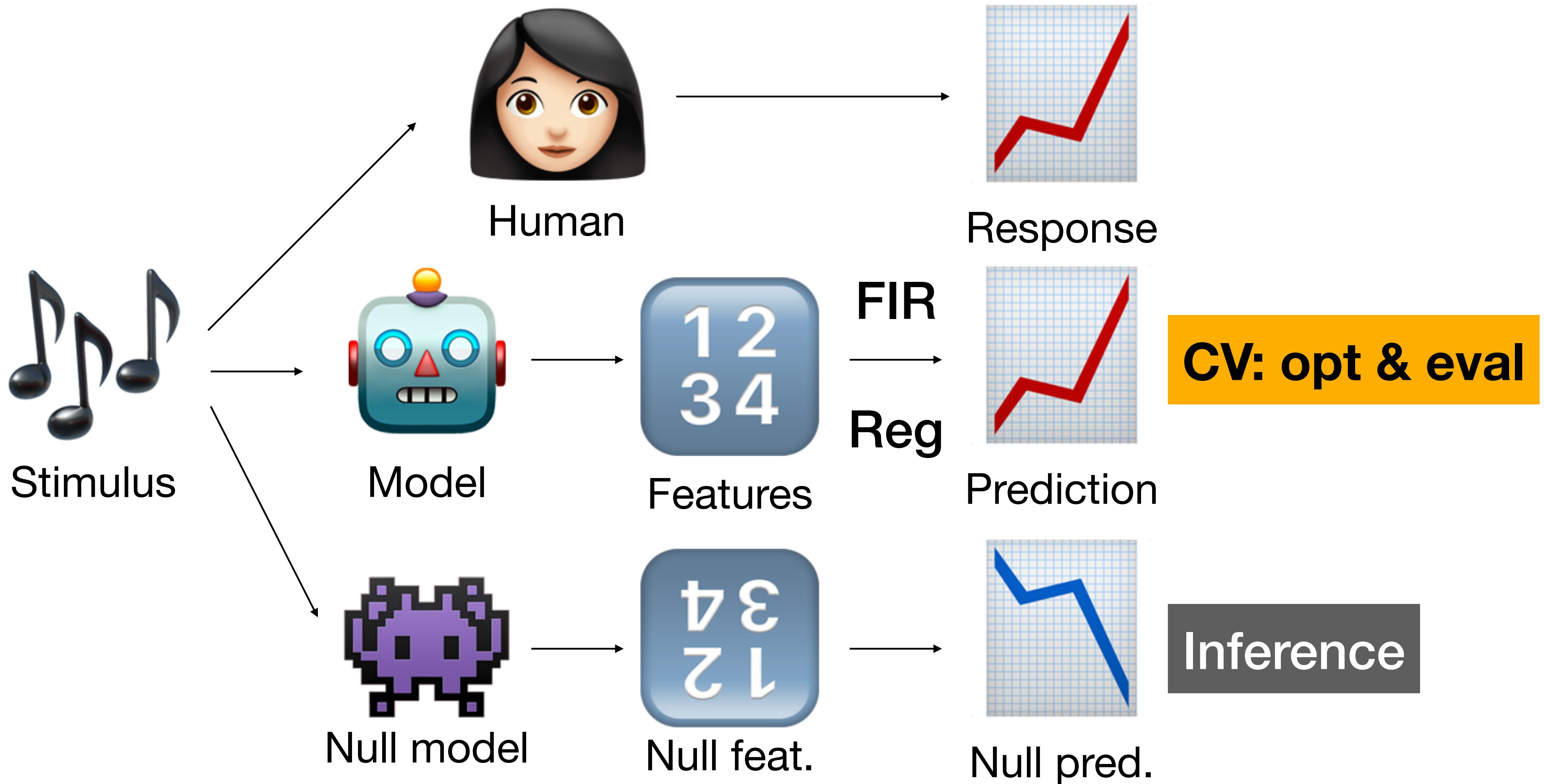


<https://www.youtube.com/watch?v=9vIDVxG4uIA>

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



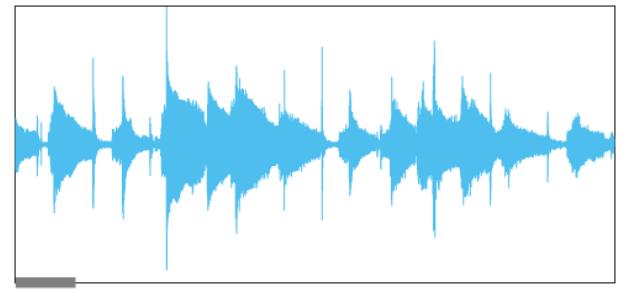
Validation (out-sample prediction)

Training set

Music #1



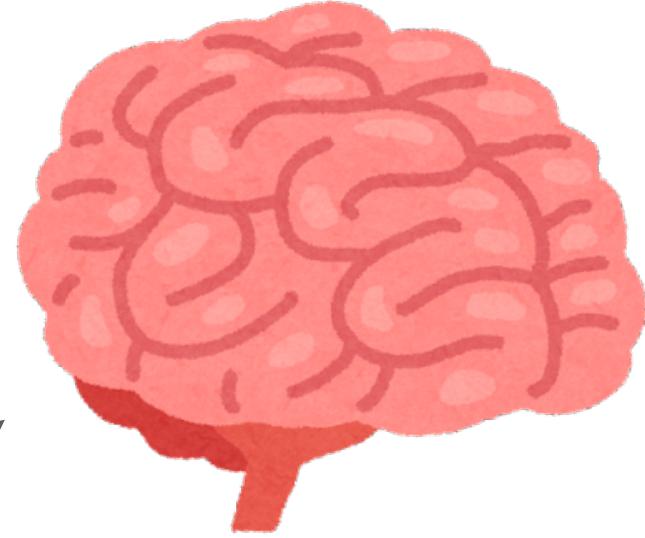
X_1



Validation (out-sample prediction)

Training set

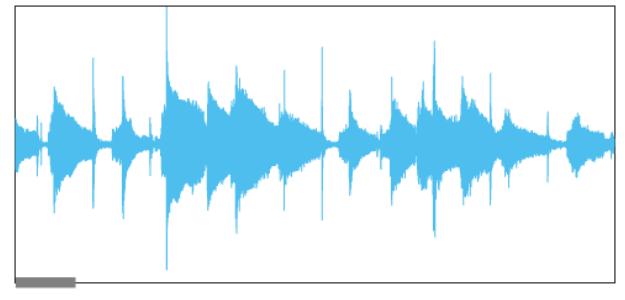
Neural responses



Music #1



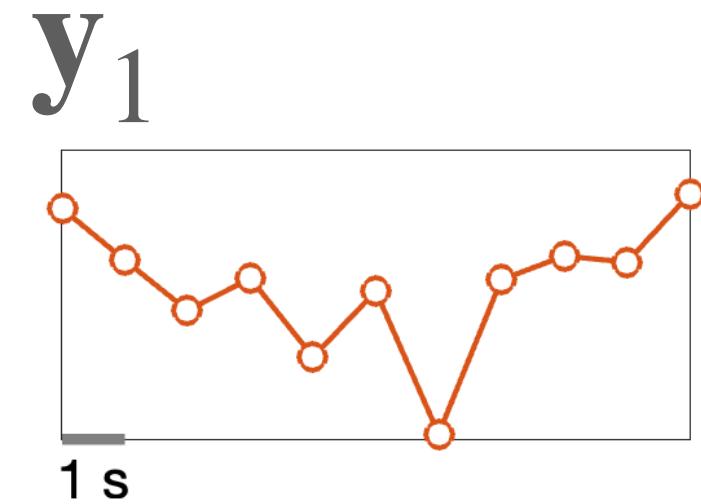
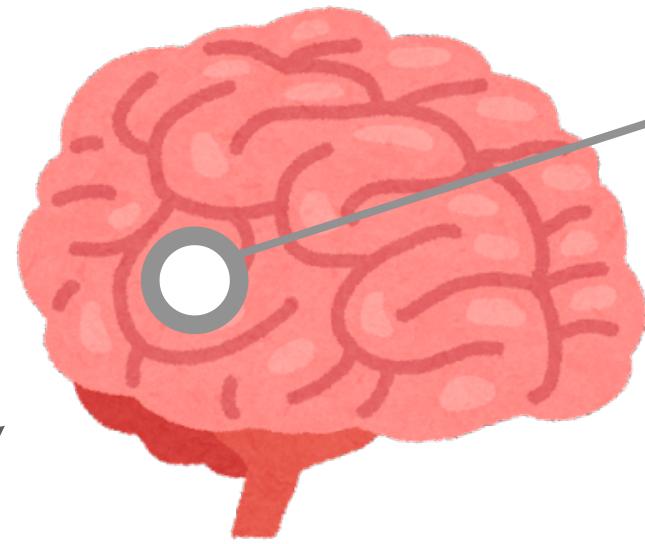
X_1



Validation (out-sample prediction)

Training set

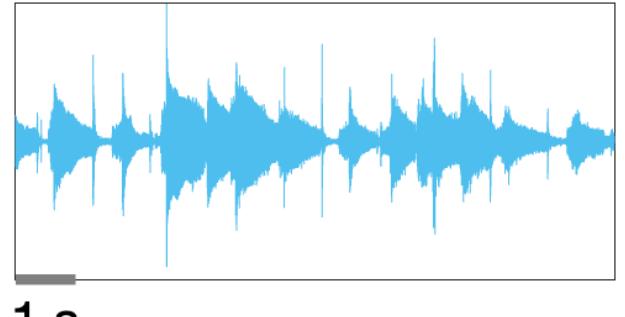
Neural responses



Music #1



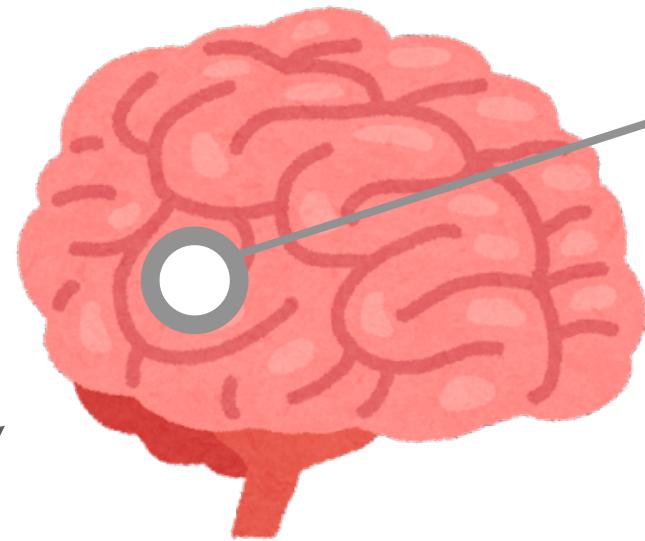
X_1



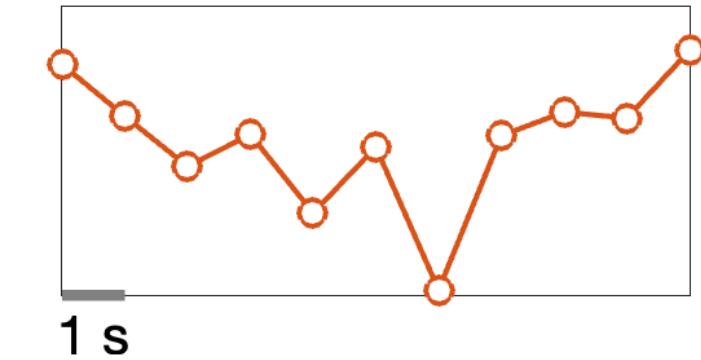
Validation (out-sample prediction)

Training set

Neural responses



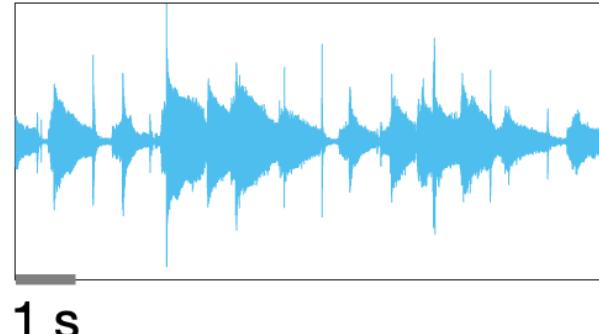
y_1



Music #1



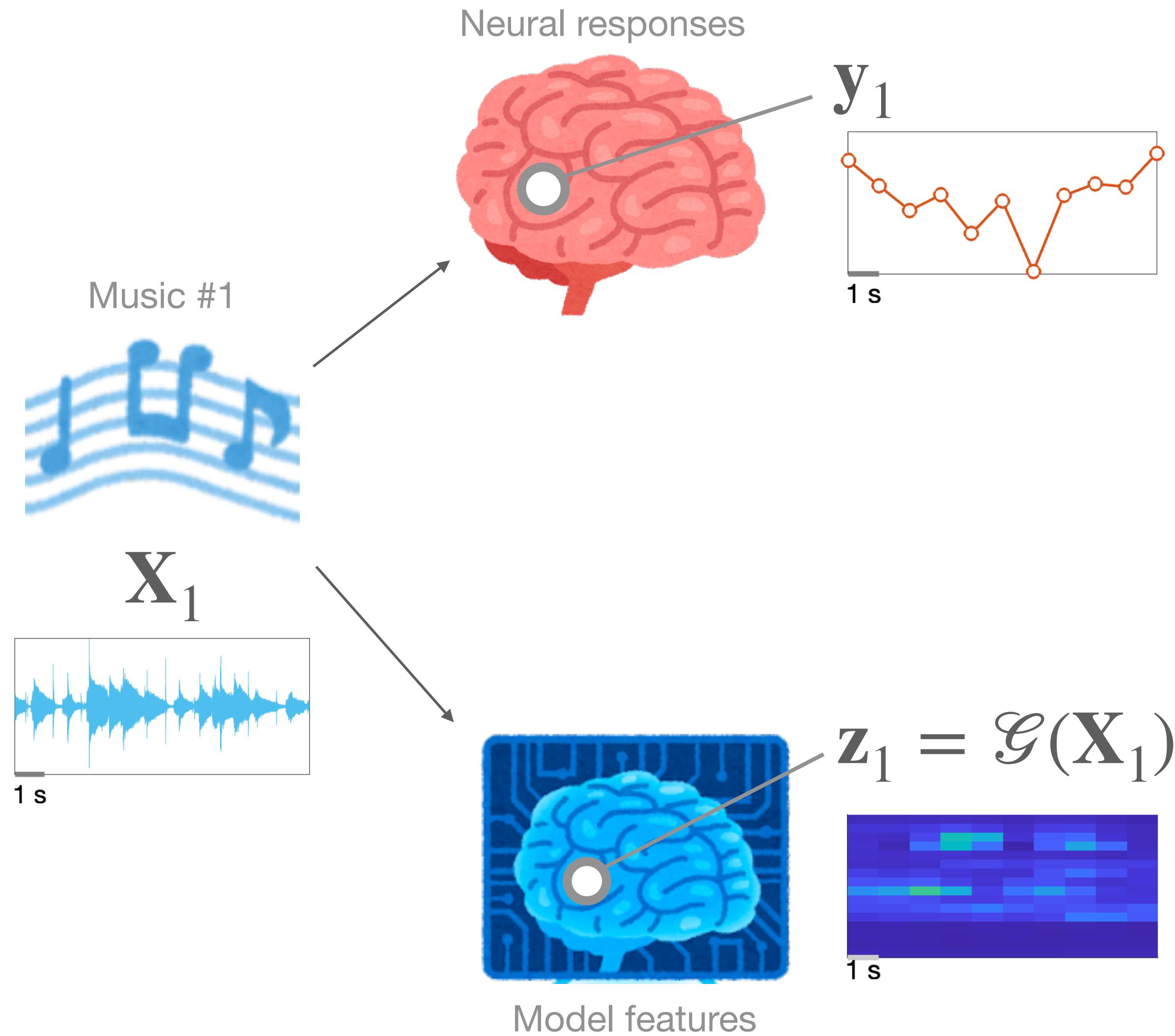
X_1



Model features

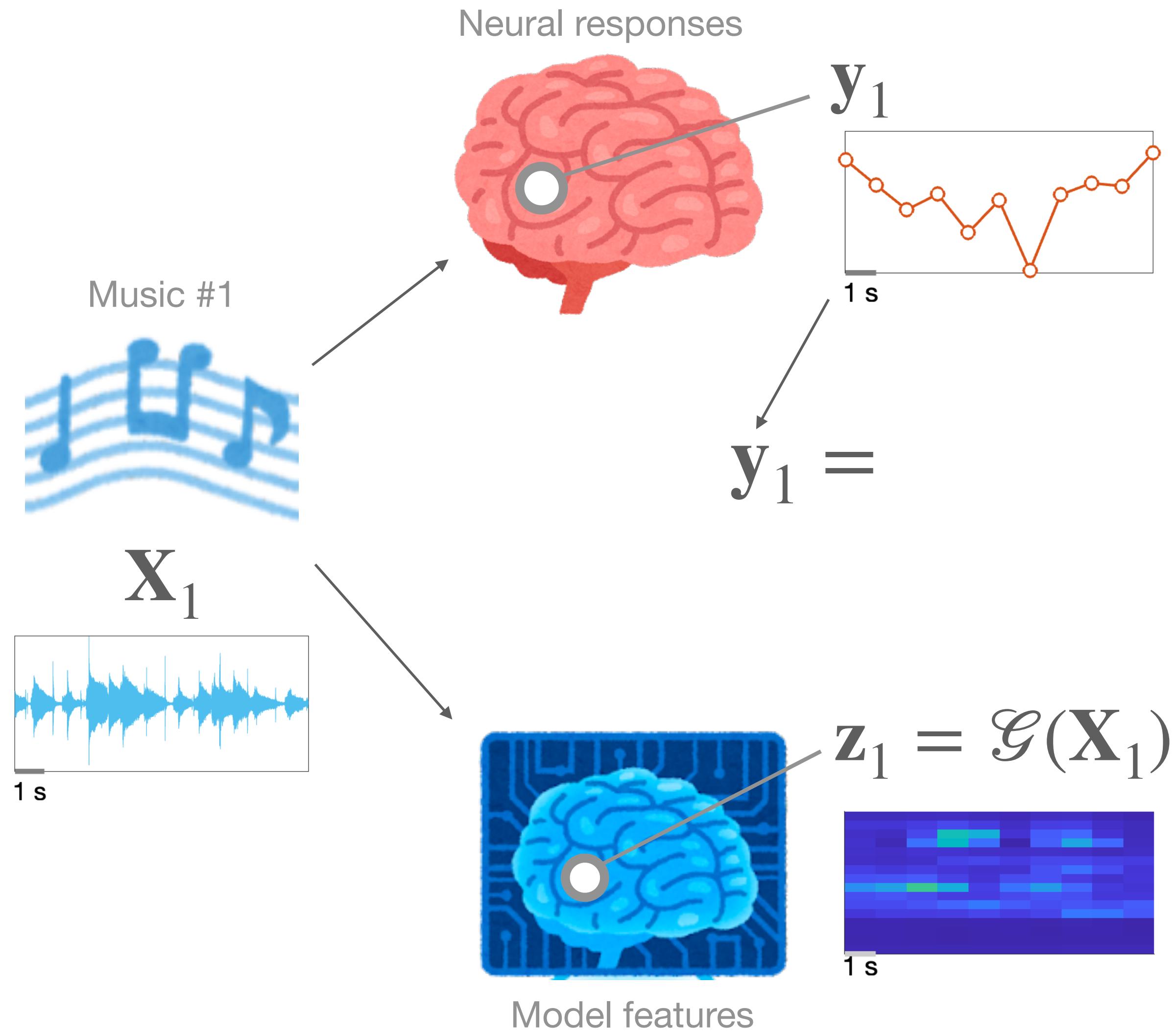
Validation (out-sample prediction)

Training set



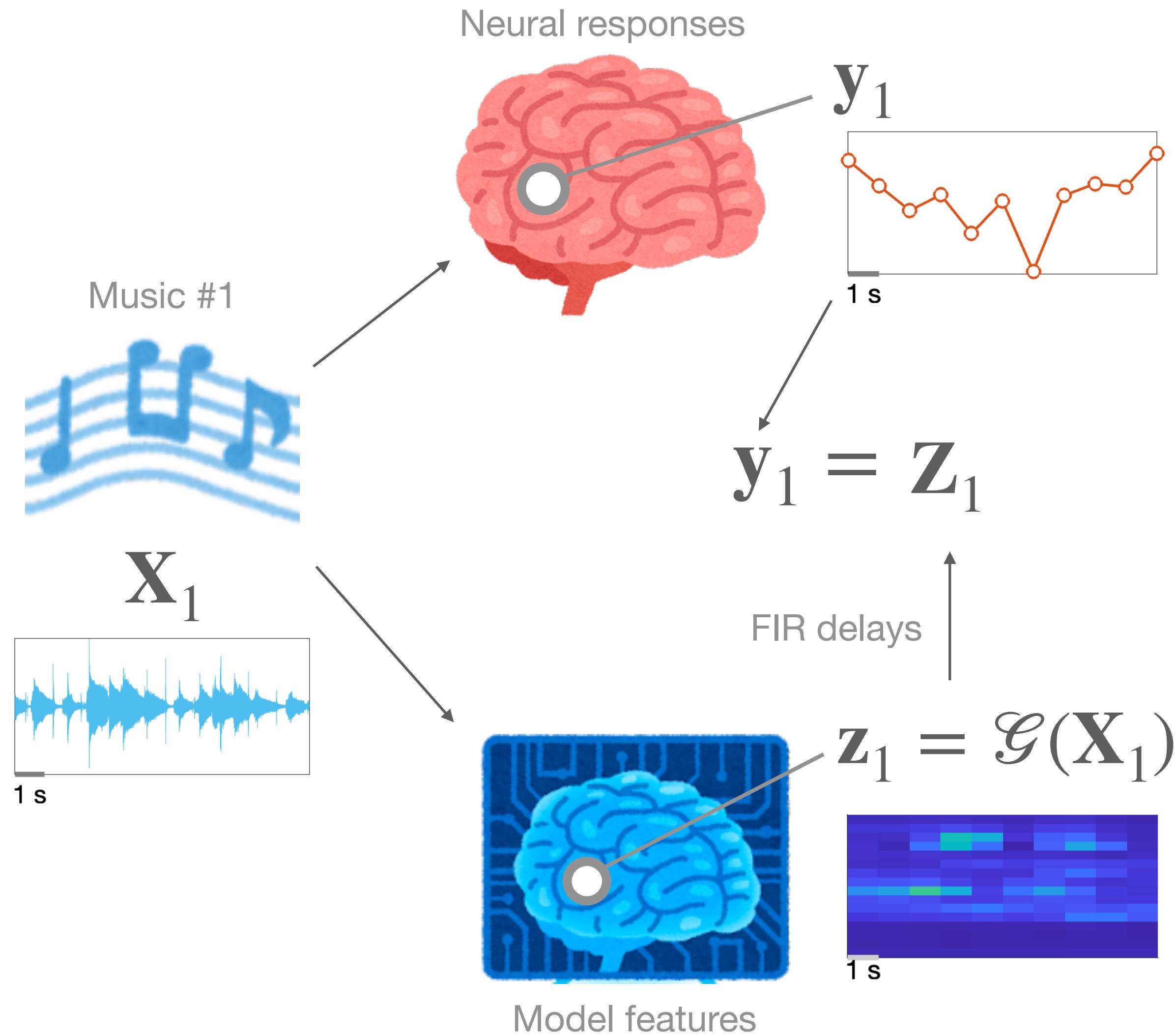
Validation (out-sample prediction)

Training set



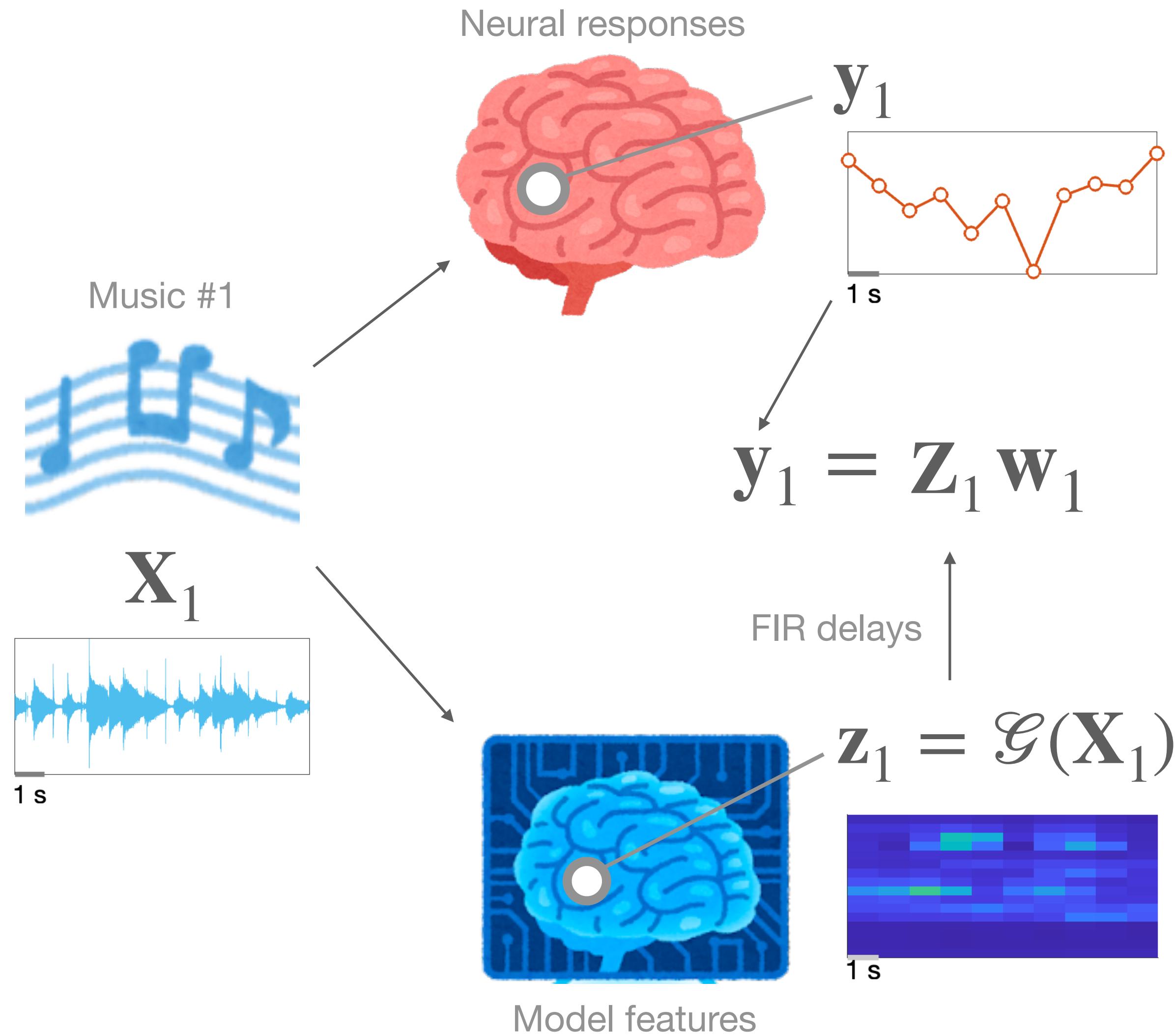
Validation (out-sample prediction)

Training set



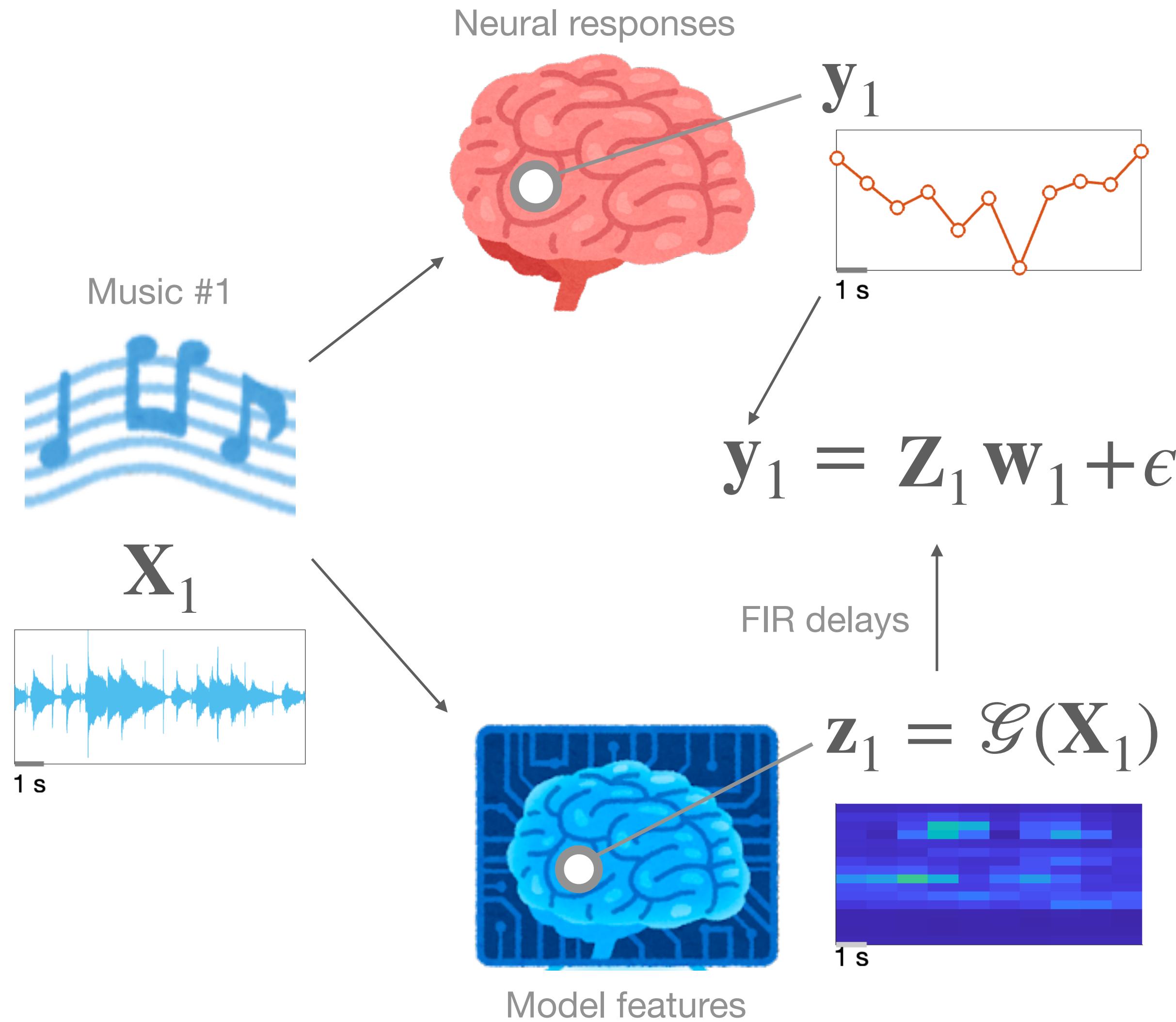
Validation (out-sample prediction)

Training set



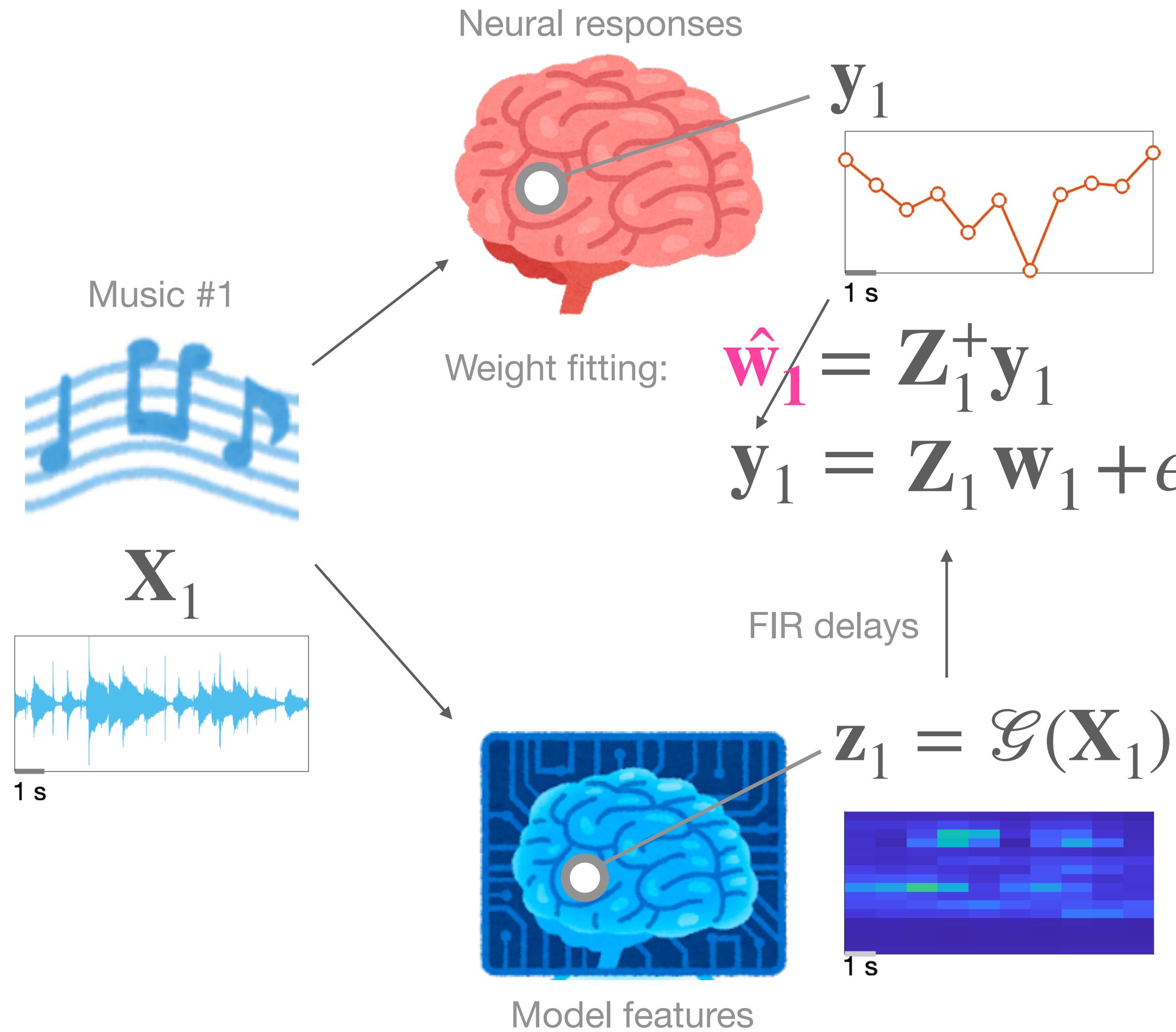
Validation (out-sample prediction)

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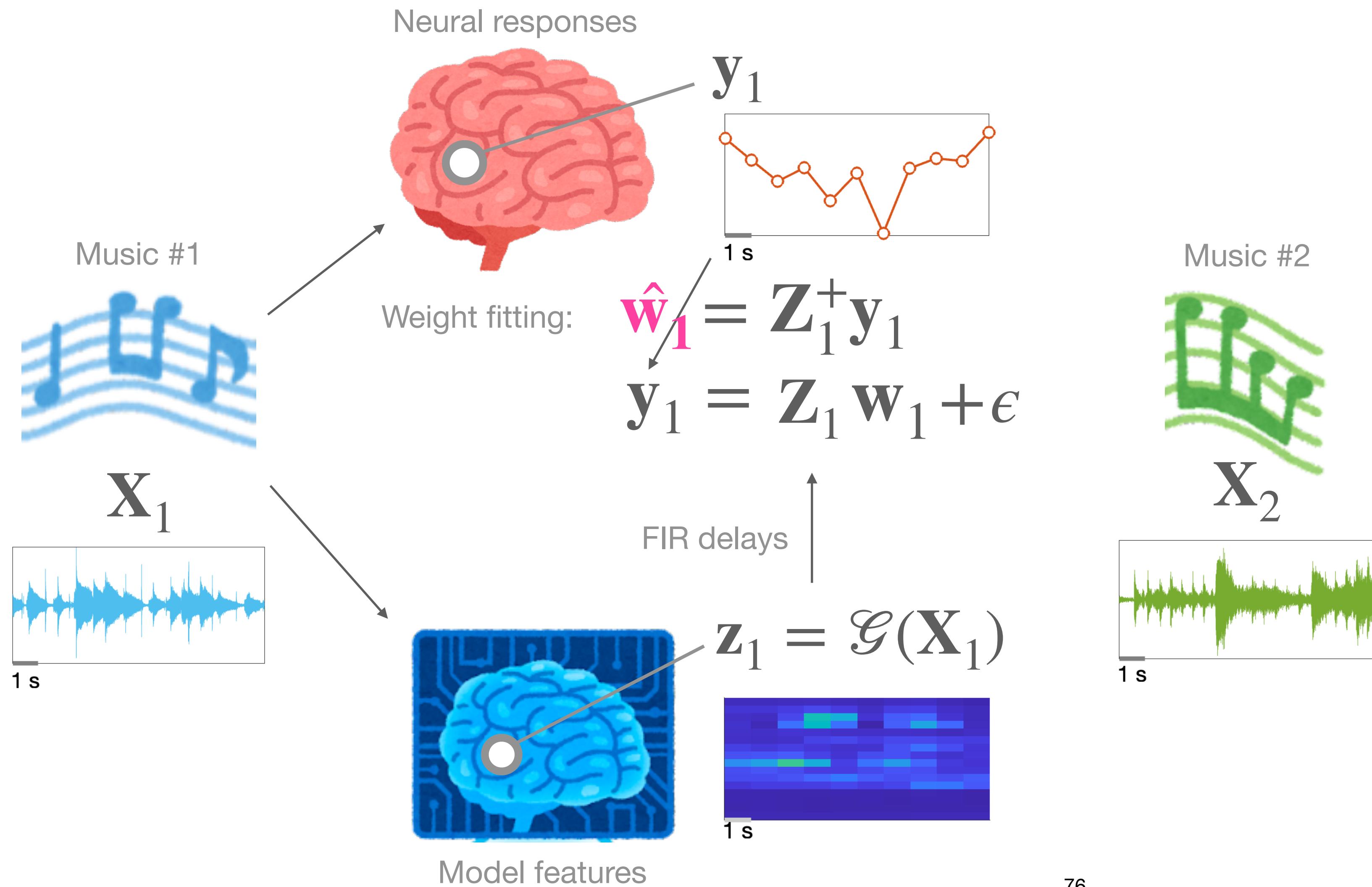
Training set



Validation (out-sample prediction)

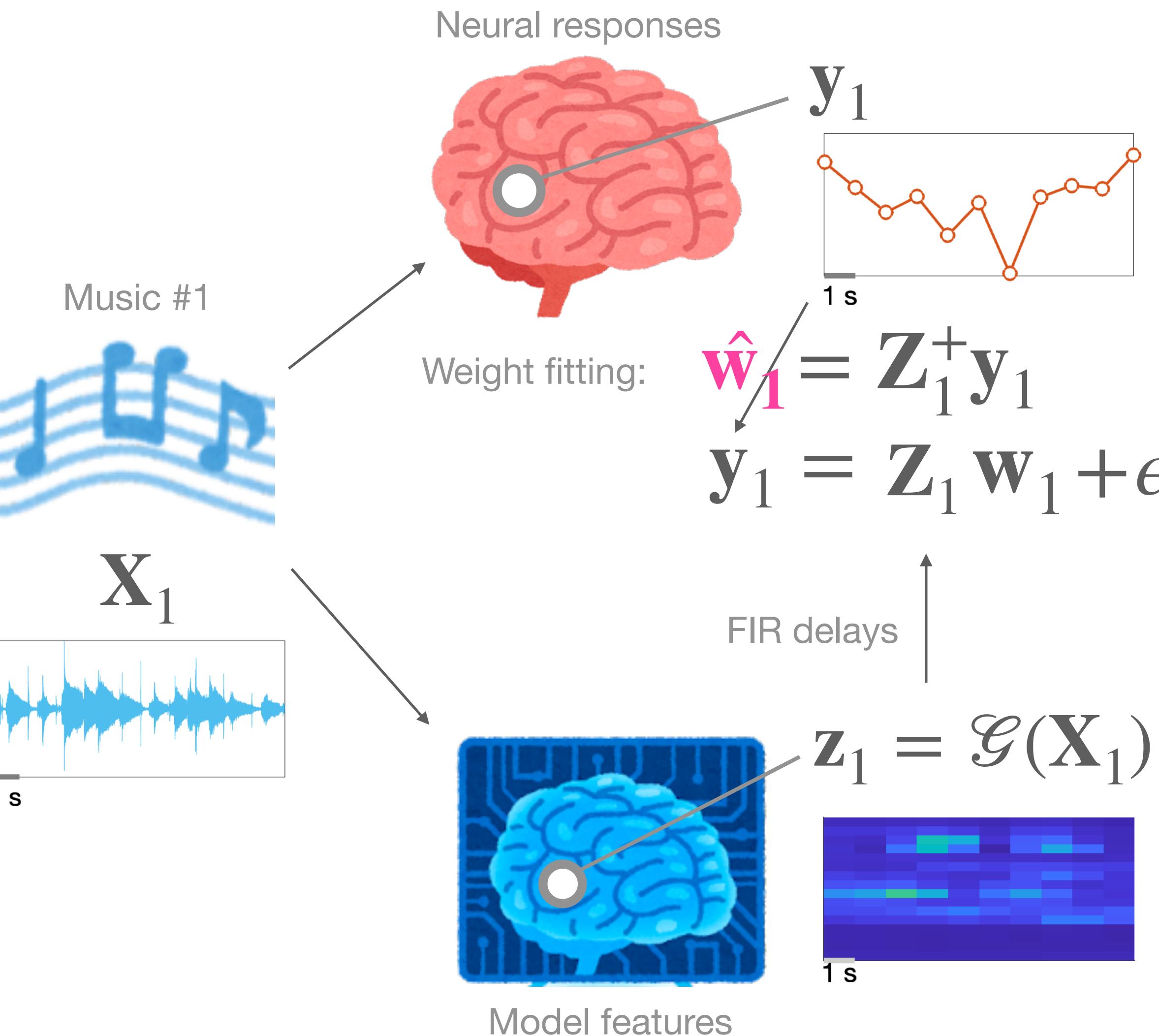
Training set

Test set

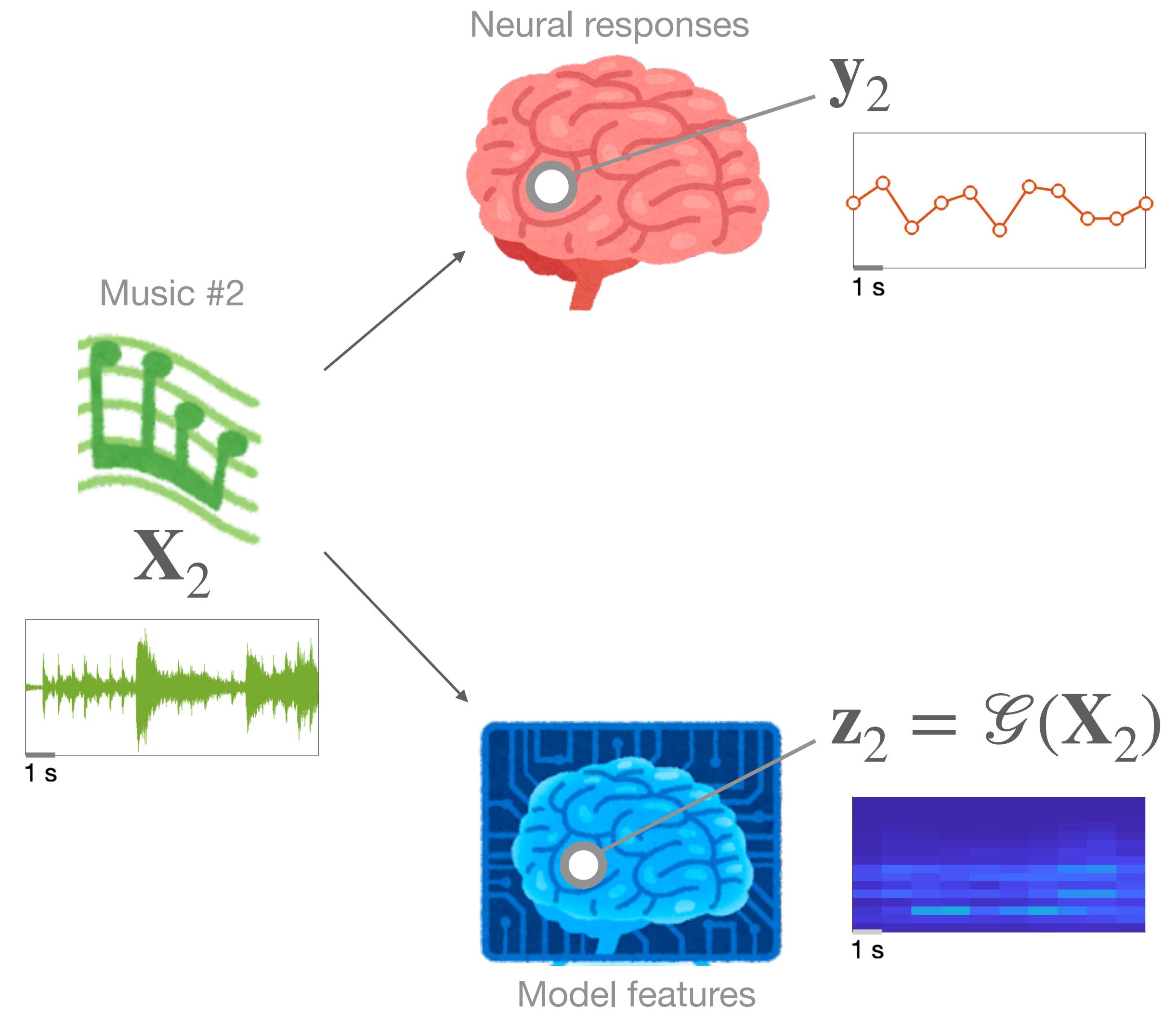


Validation (out-sample prediction)

Training set

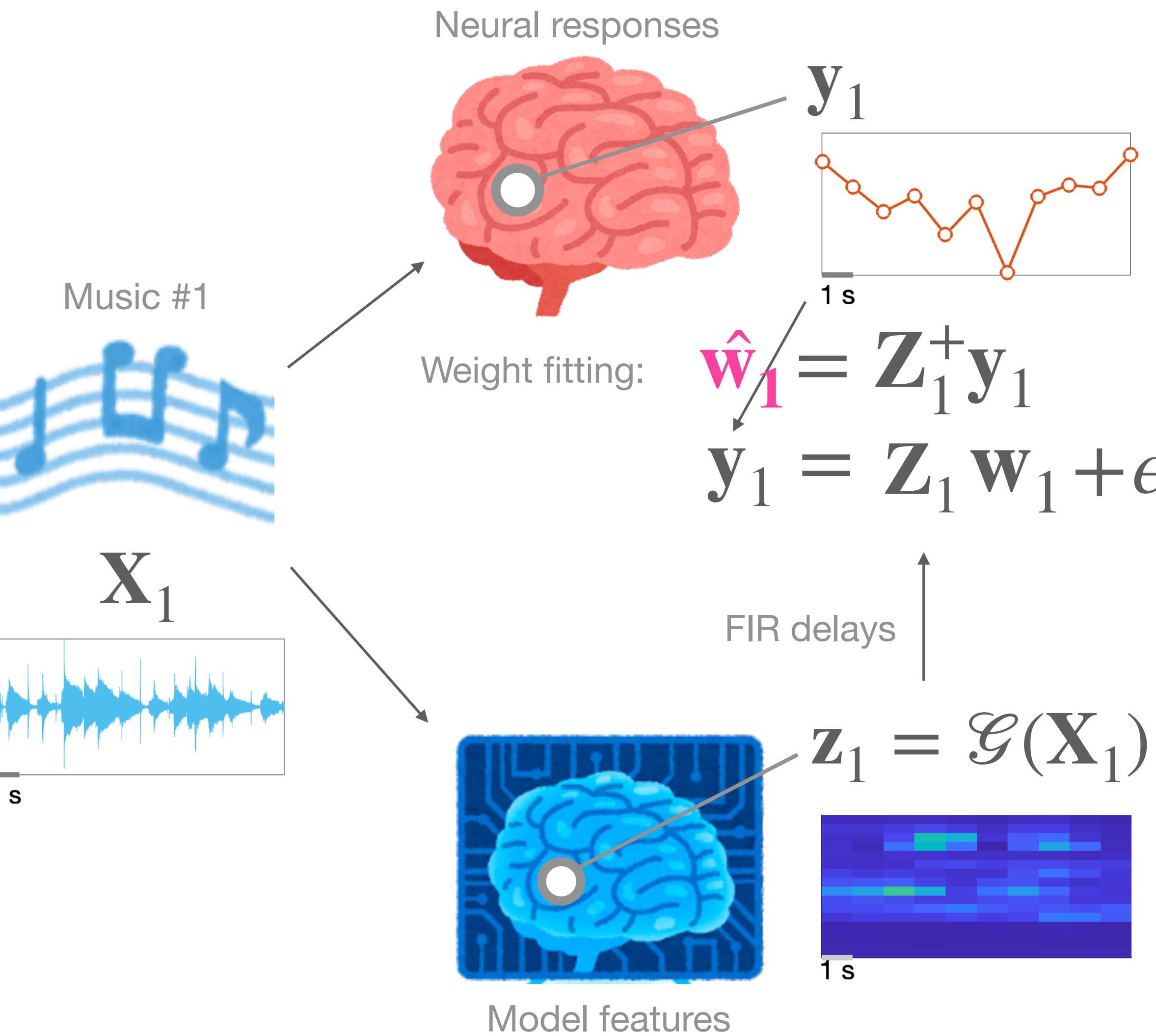


Test set

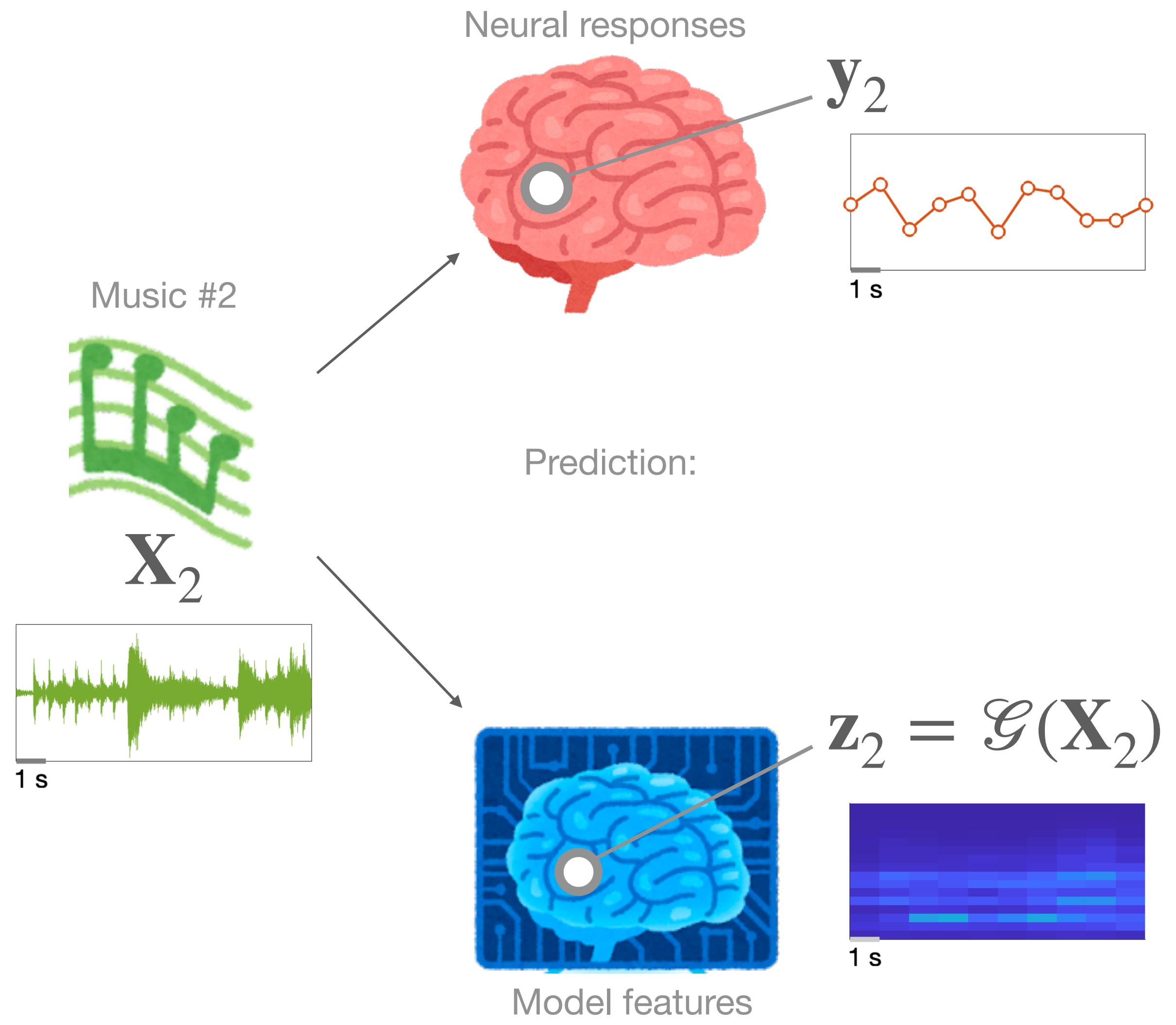


Validation (out-sample prediction)

Training set

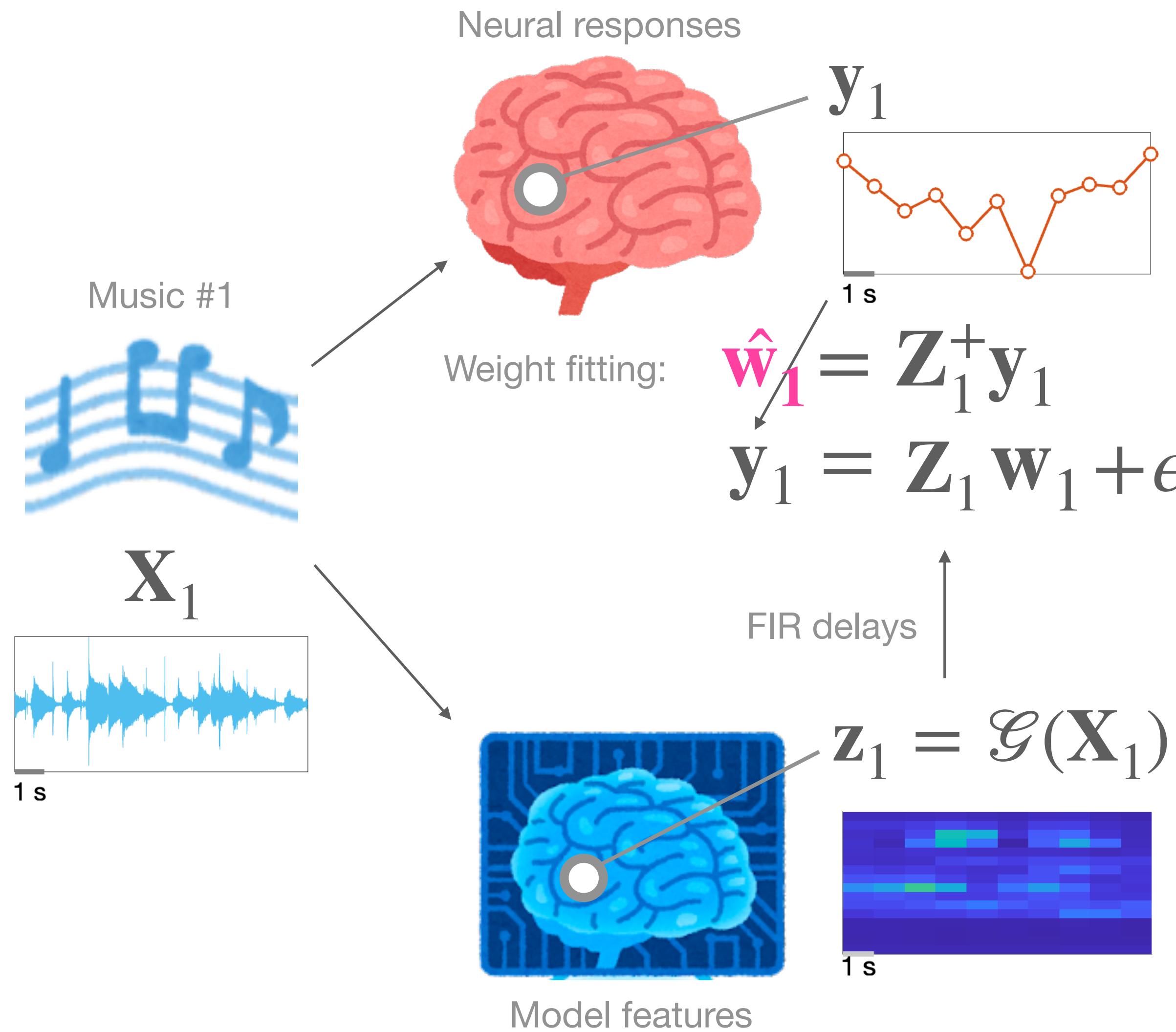


Test set

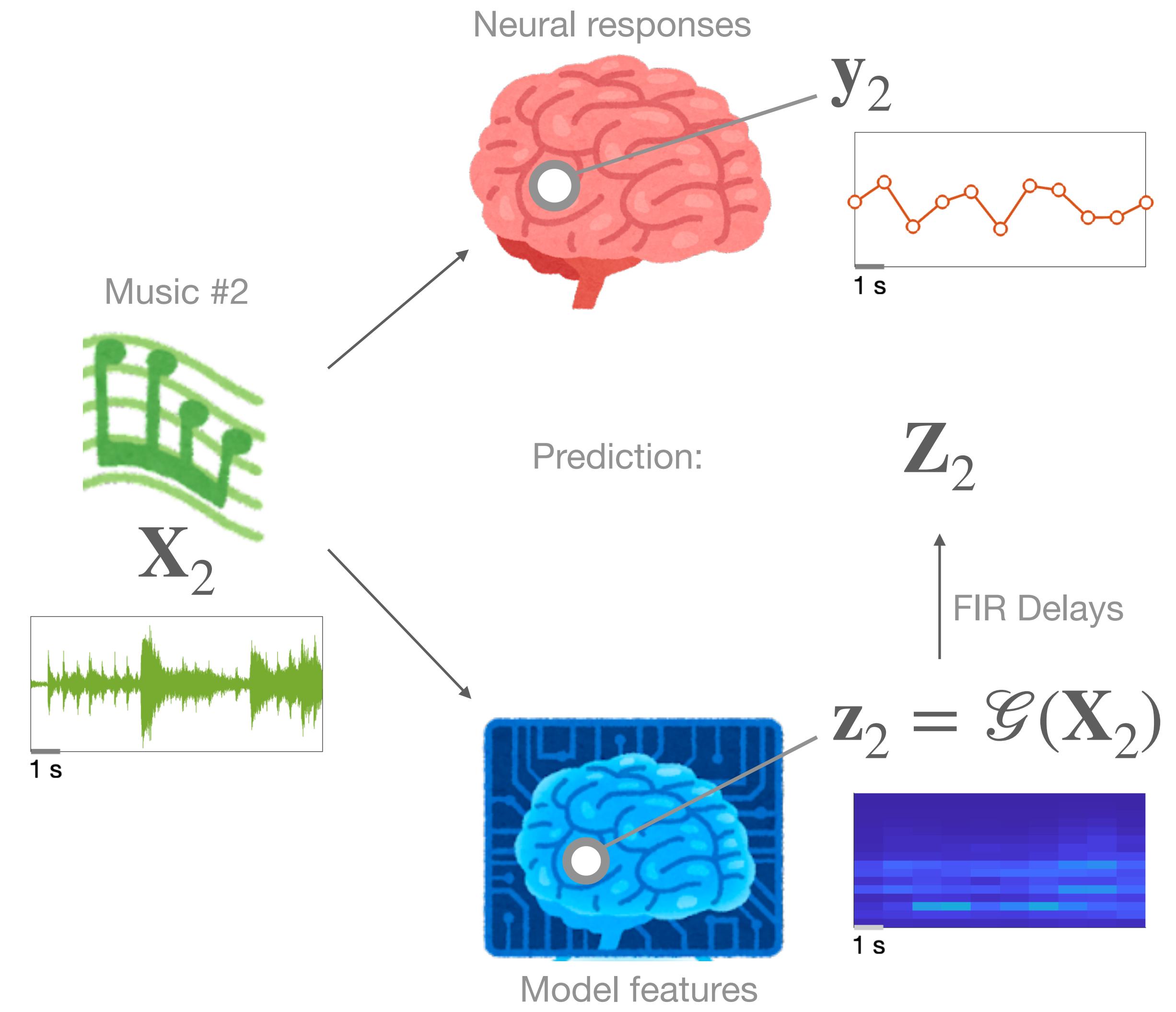


Validation (out-sample prediction)

Training set

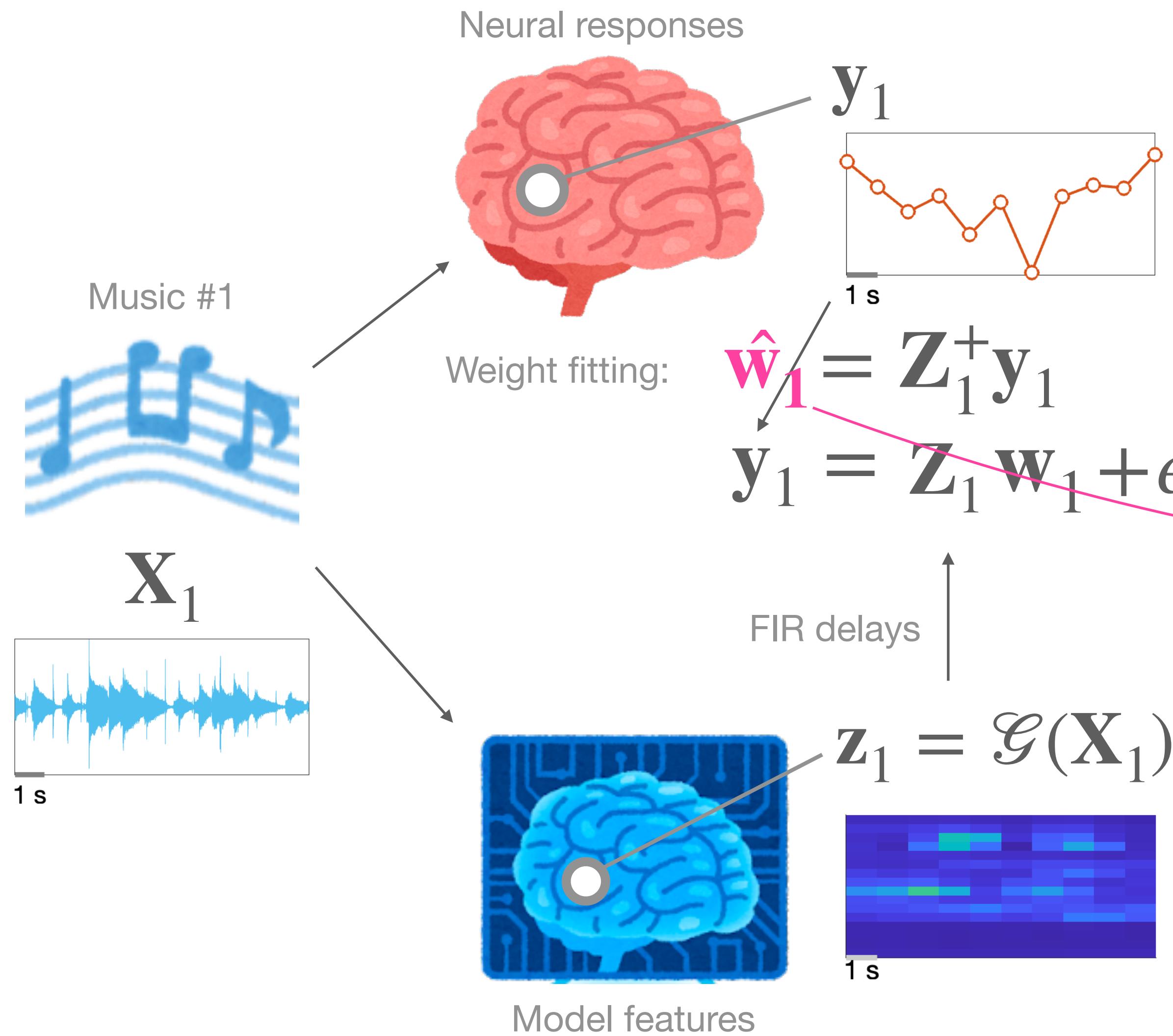


Test set

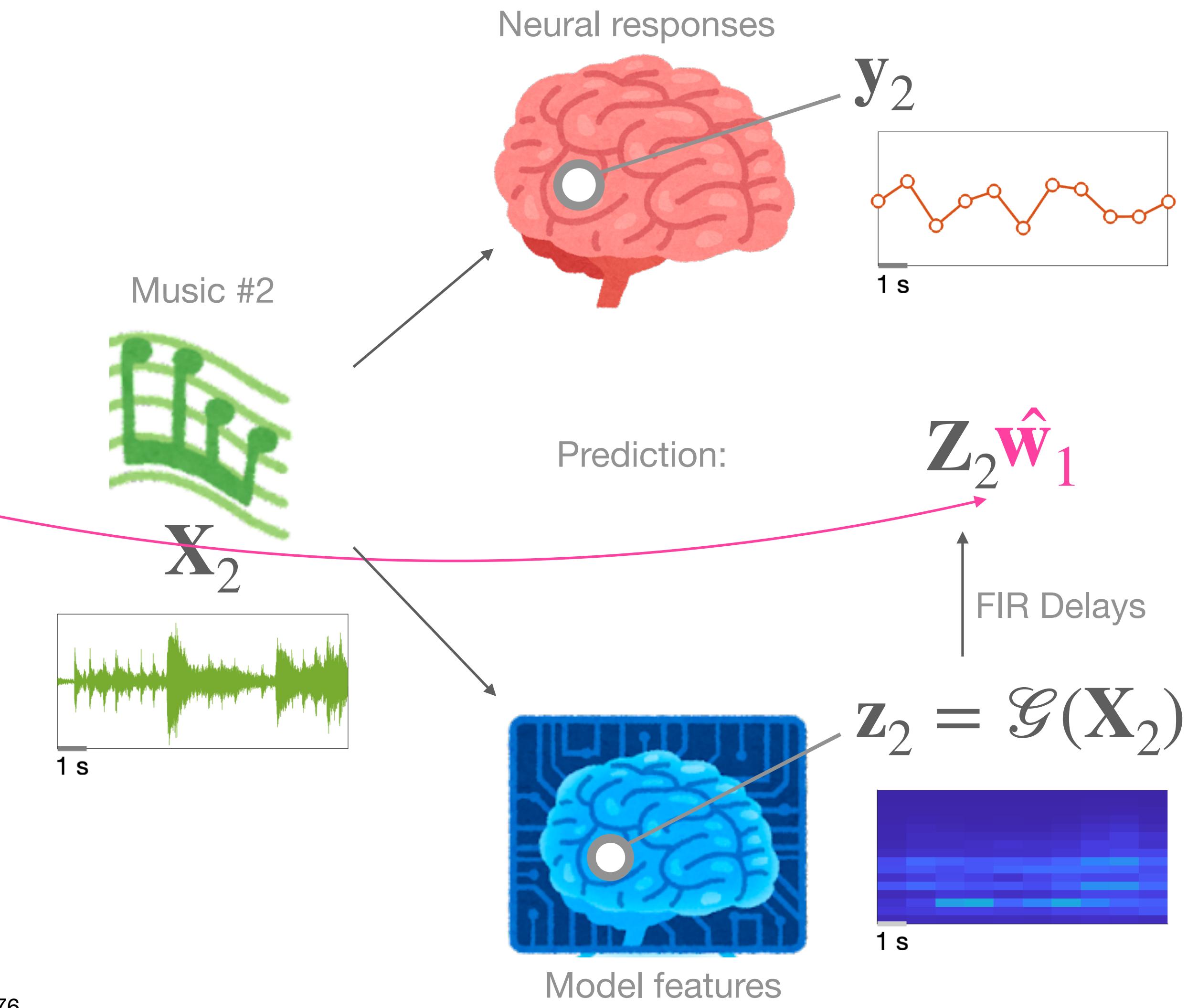


Validation (out-sample prediction)

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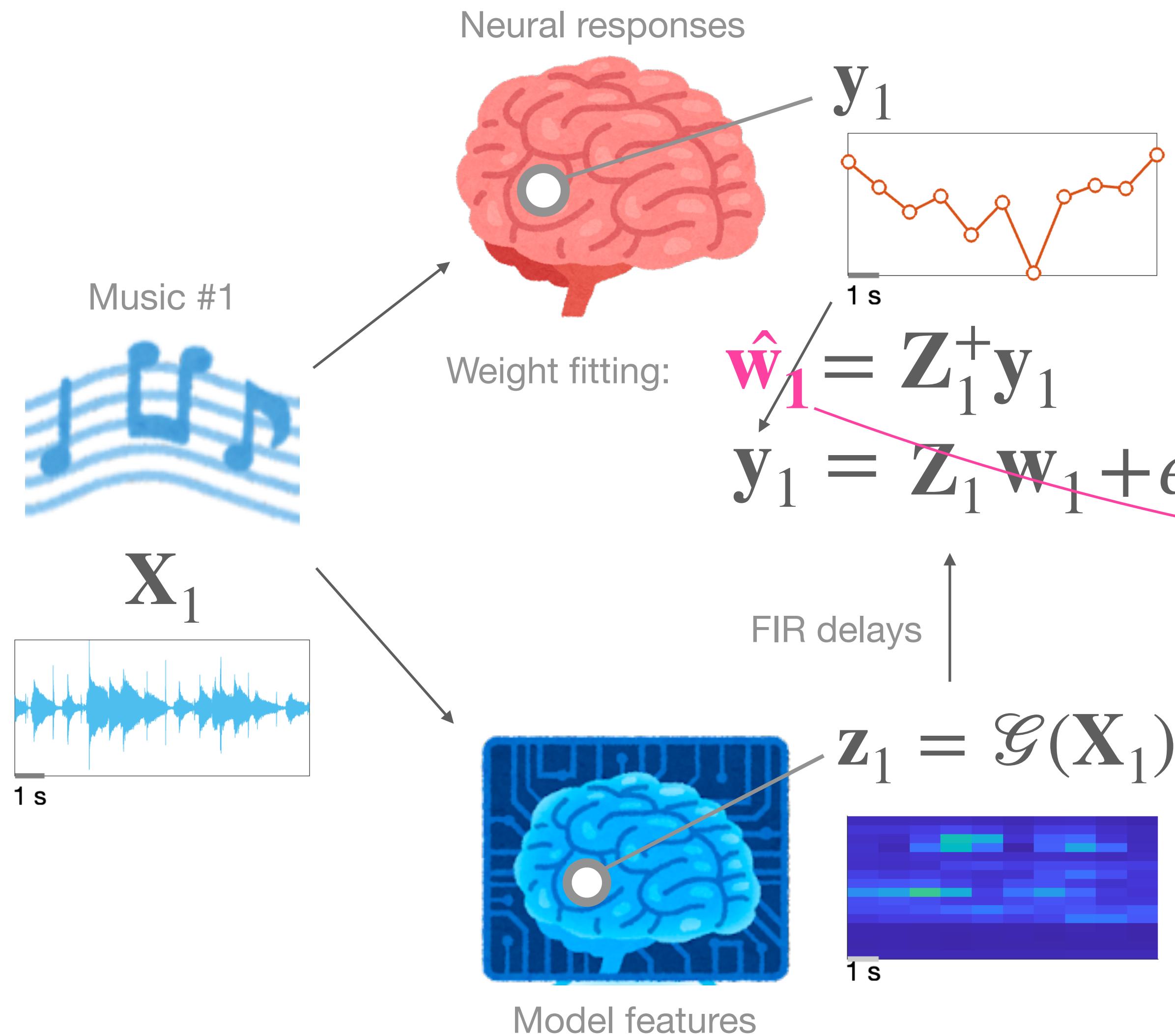


Test set

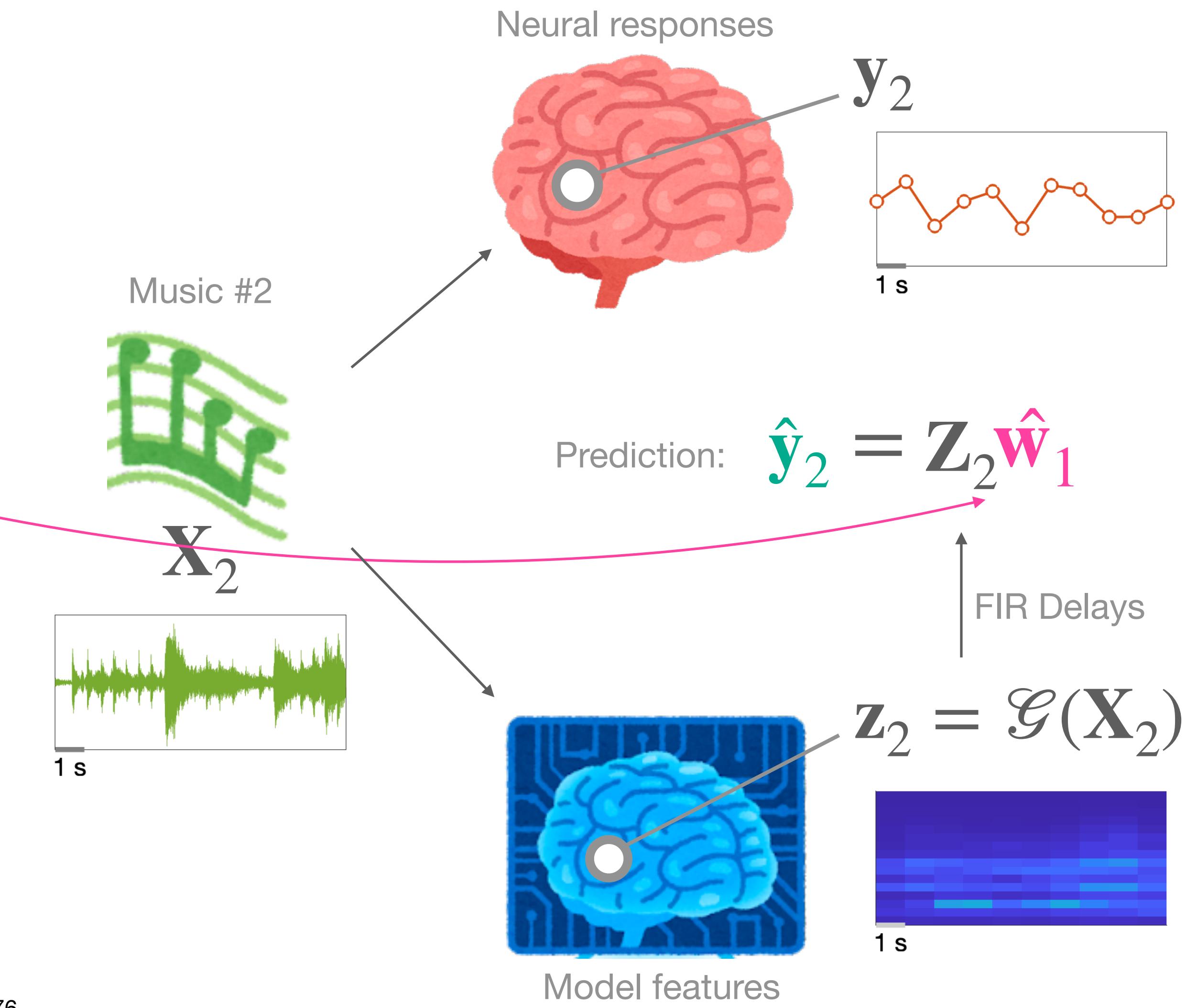


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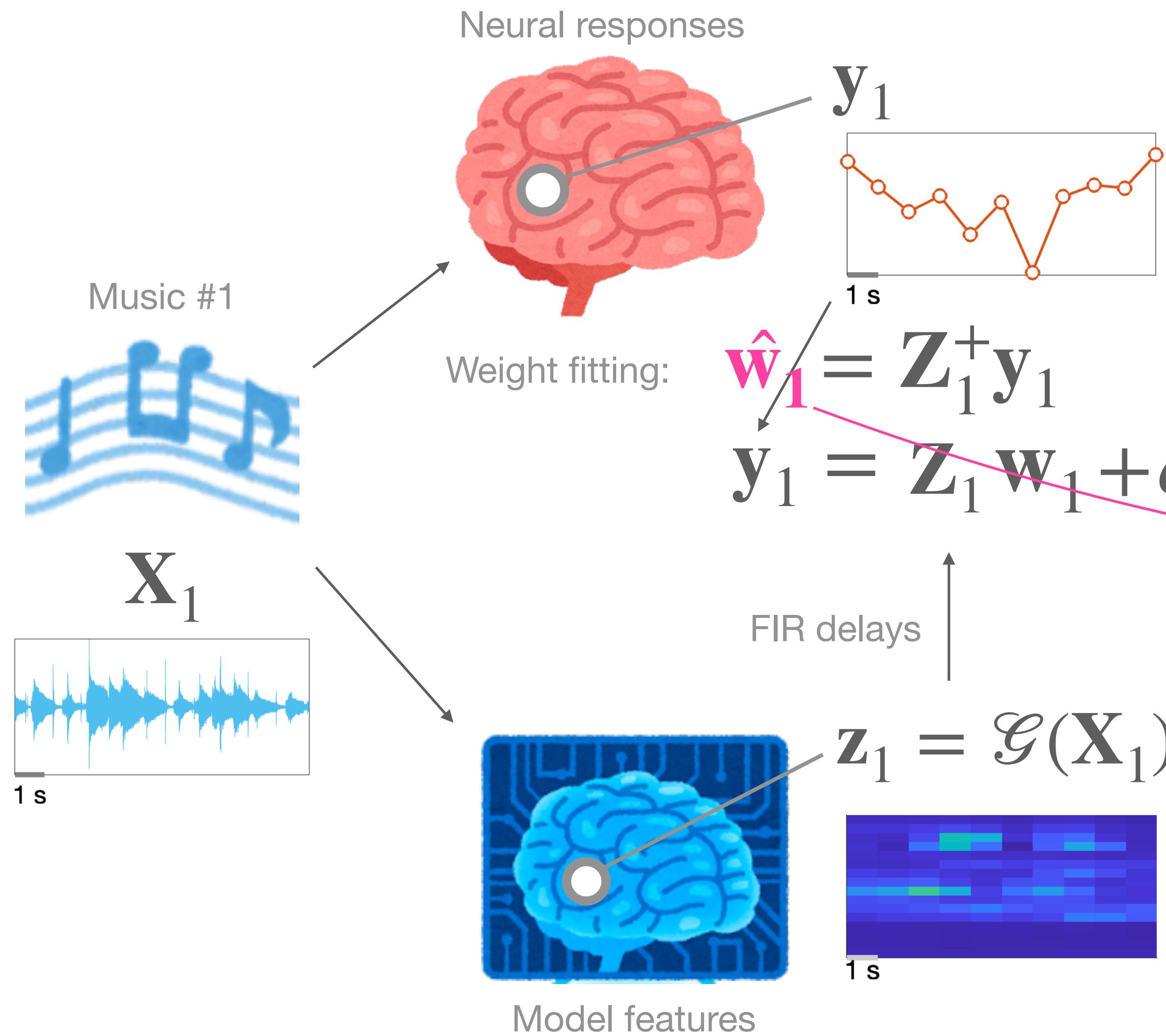


Test set

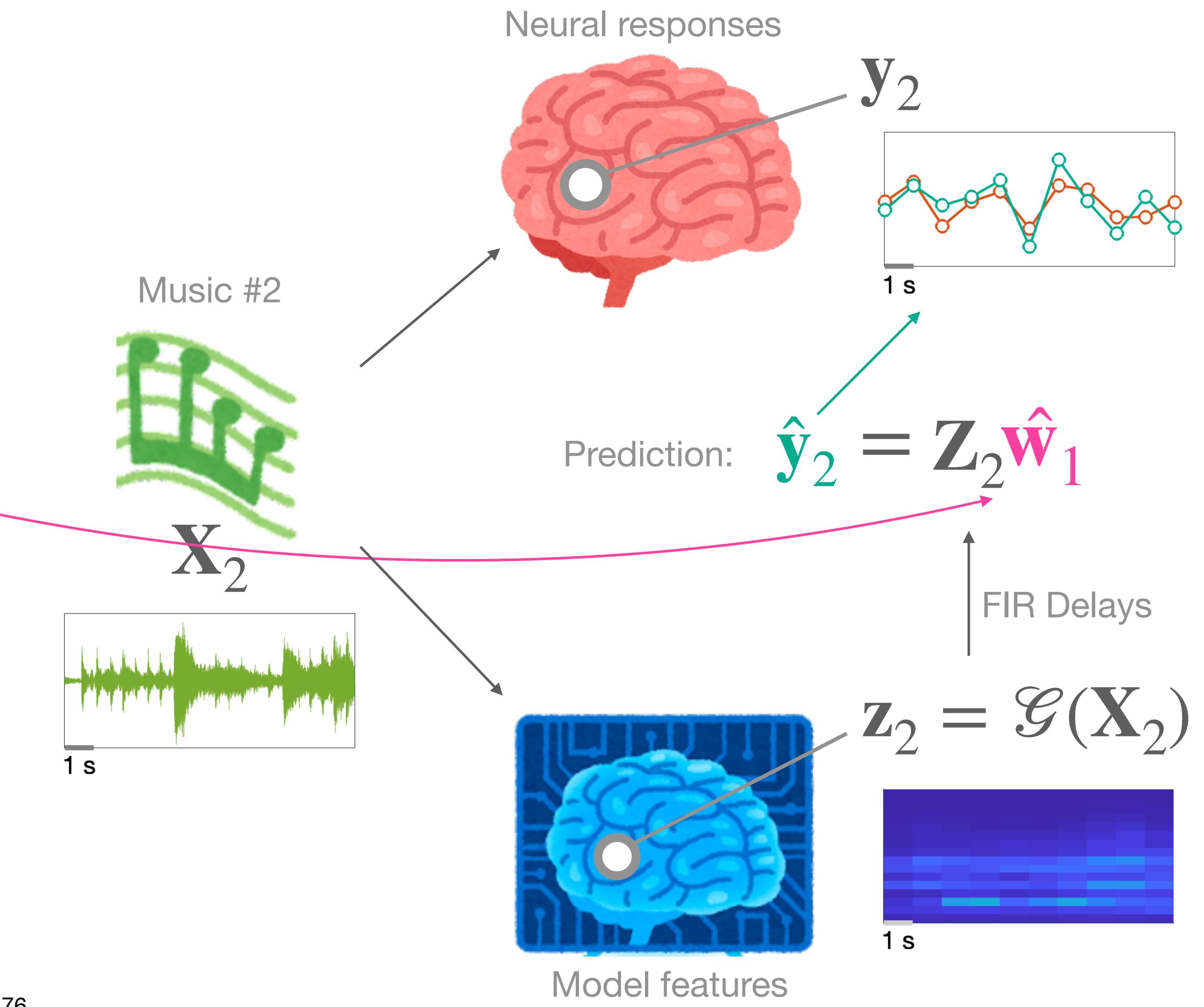


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Training set



Test set

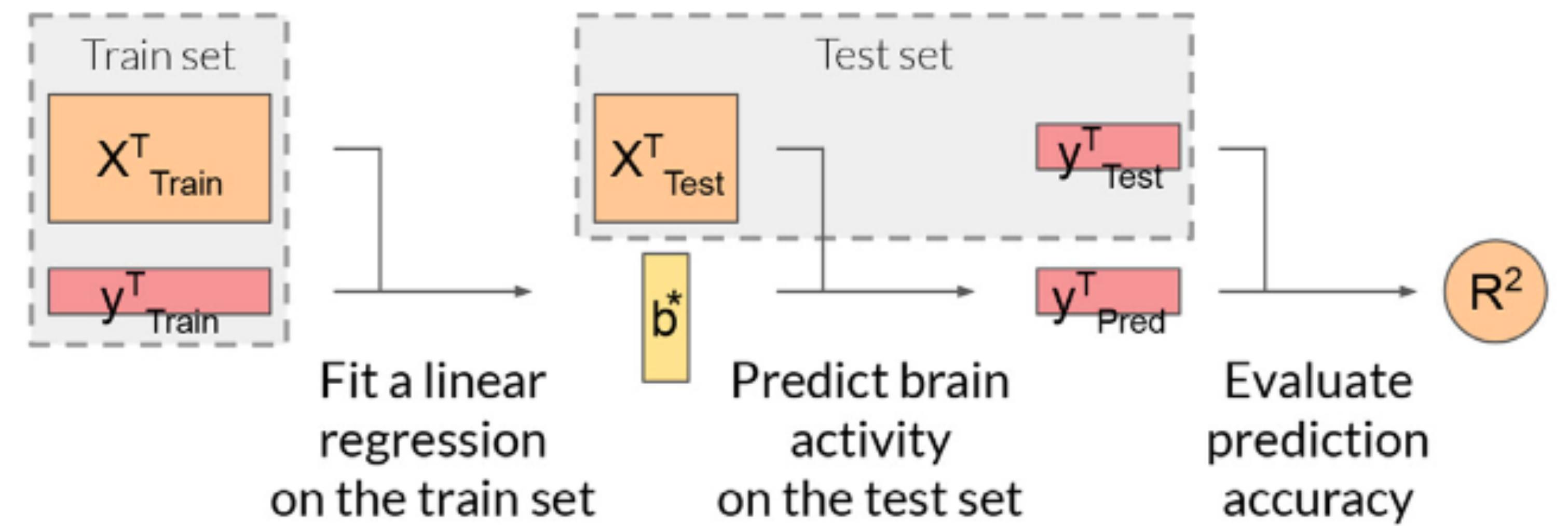


Prediction accuracy measure

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”



Over-optimization

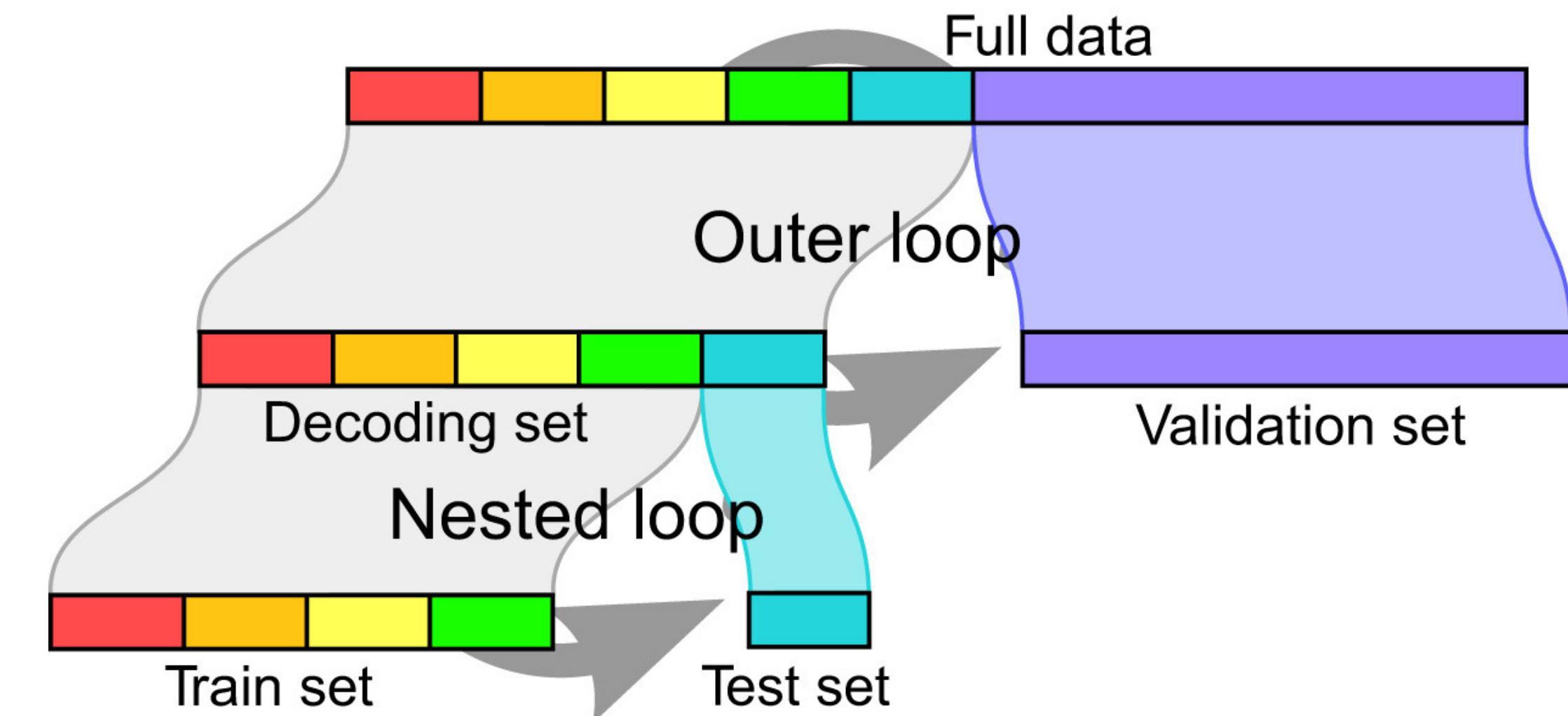
“Cross-validation failure”

- 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

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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*).

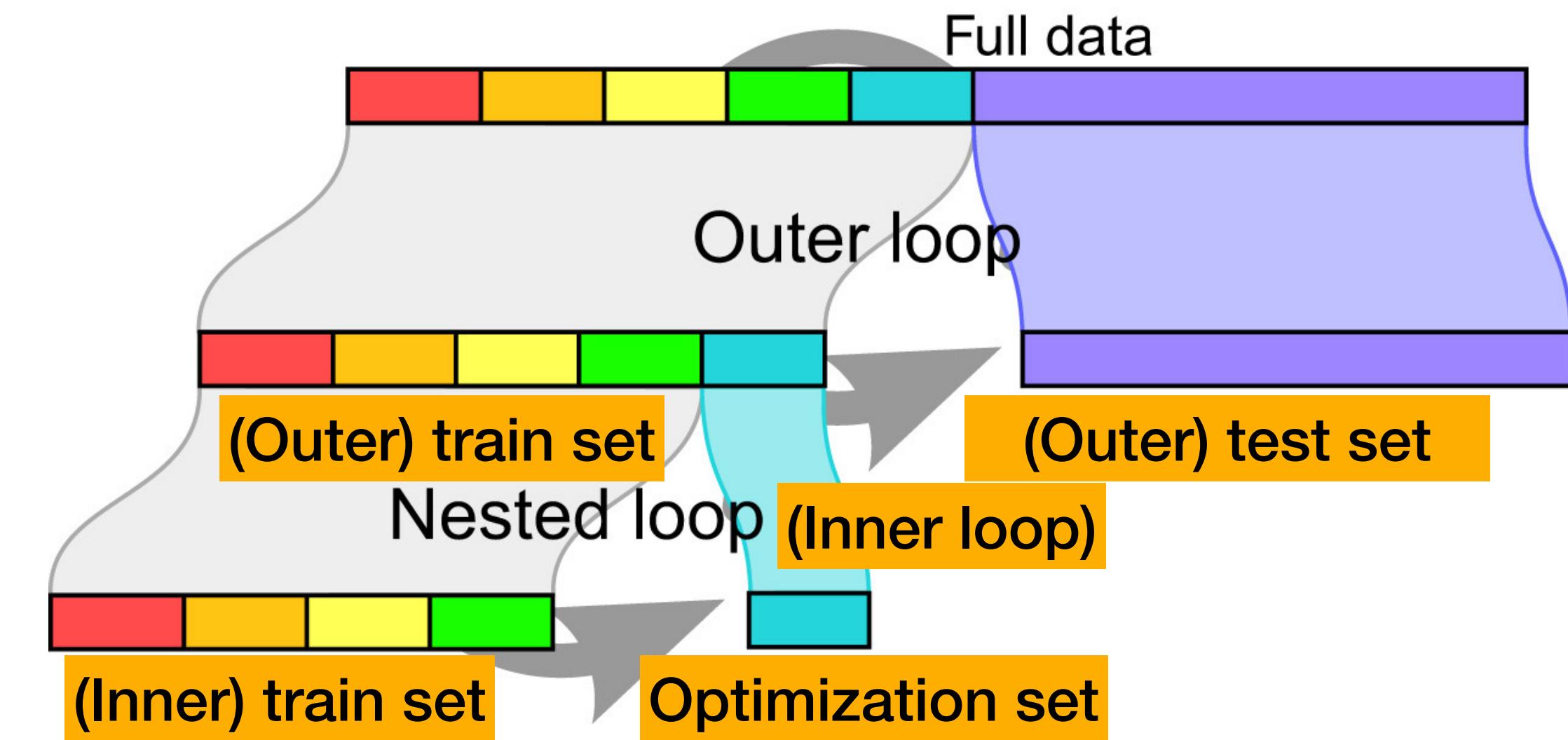


Varoquaux et al., 2017, *NeuroImage*.

Over-optimization

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

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- **Leakage by design decision** (e.g., variable selection based on the whole dataset [training and testing sets])
- **Leakage in training examples** (e.g., one of identical twins in the training and the other in the testing set)

Double-dipping

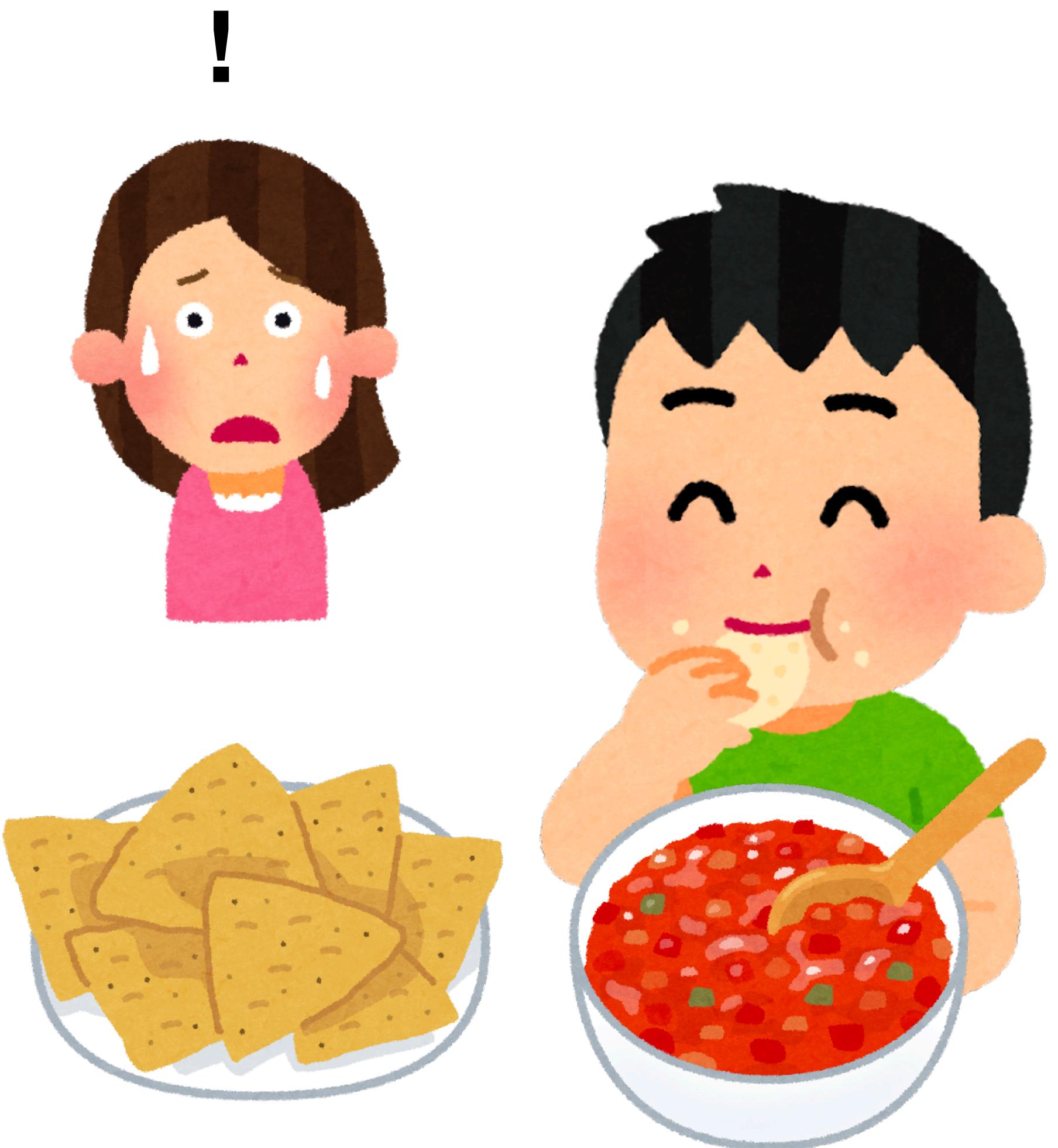
Kriegeskorte et al., 2009, *Nat Neuro*



Double-dipping

Kriegeskorte et al., 2009, *Nat Neuro*

- It's gross.



Double-dipping

Kriegeskorte et al., 2009, *Nat Neuro*

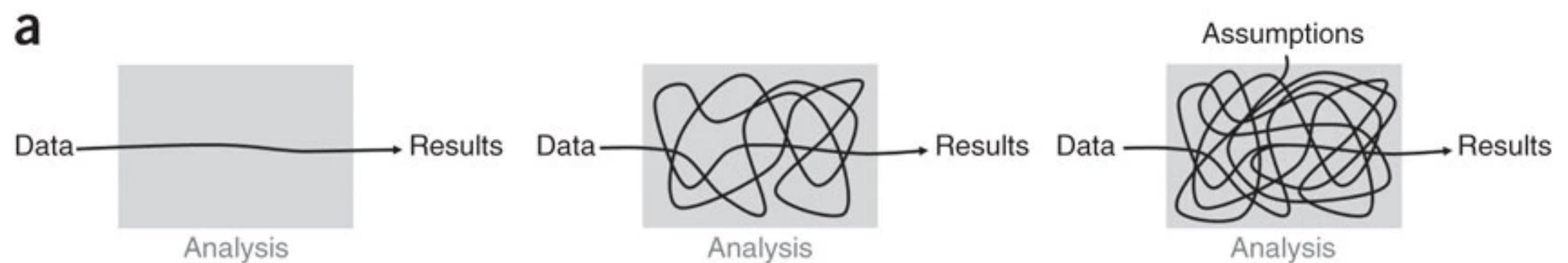
- It's gross.
- It's introduced by YOUR wrong design decision.



Double-dipping

Kriegeskorte et al., 2009, *Nat Neuro*

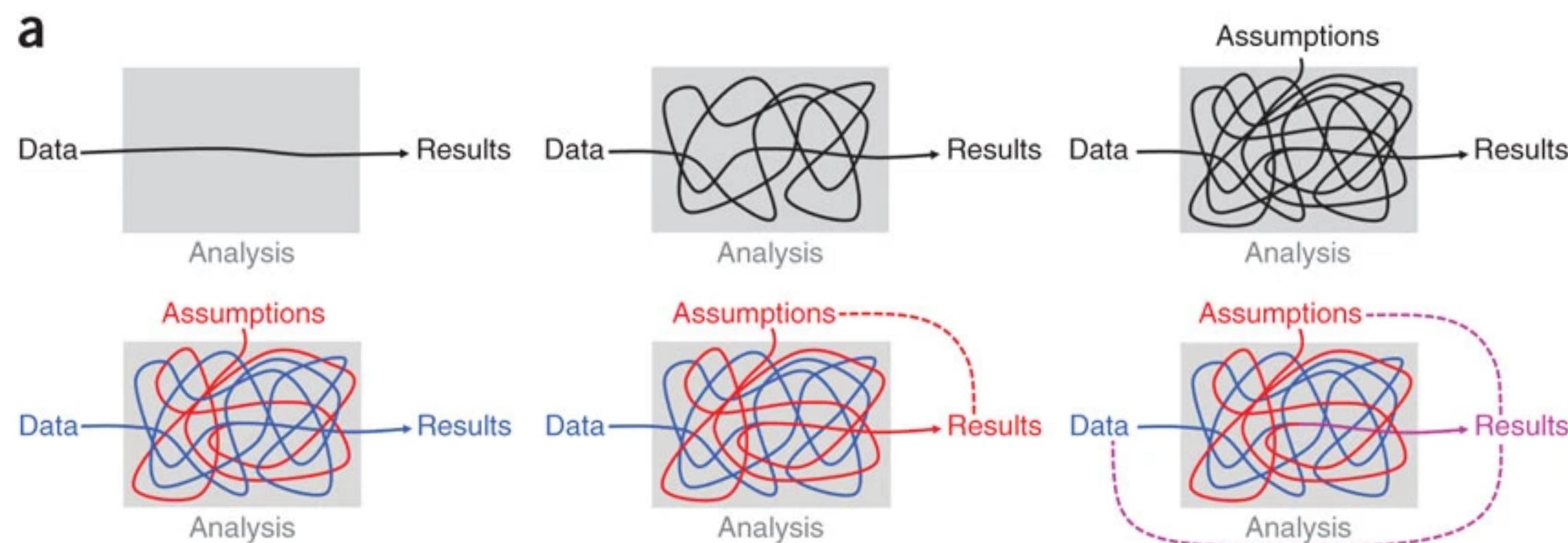
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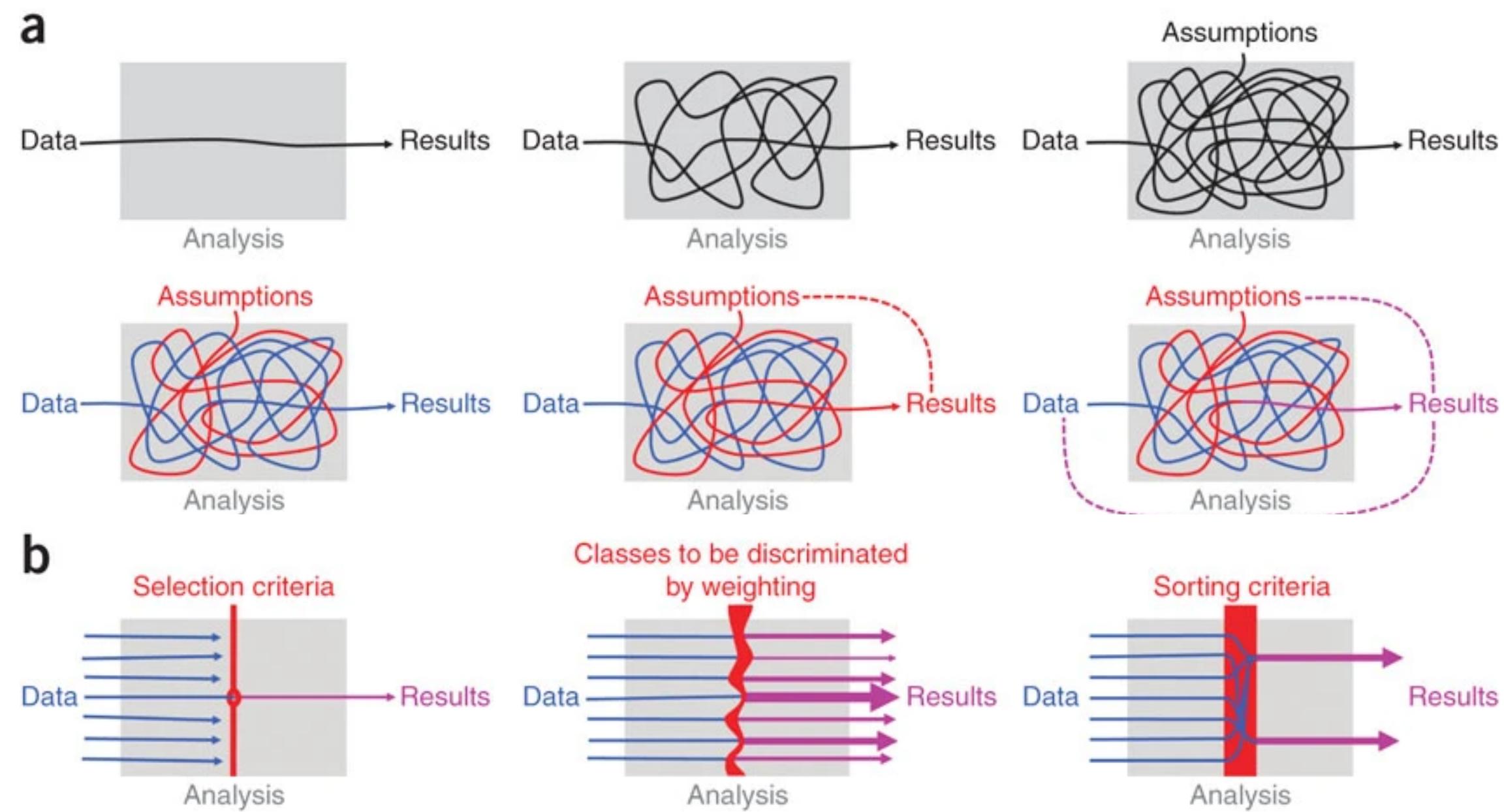


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Kriegeskorte et al., 2009, *Nat Neuro*

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!



Double-dipping

Example

Kriegeskorte et al., 2009, *Nature Neuroscience*.

Double-dipping

Example

a

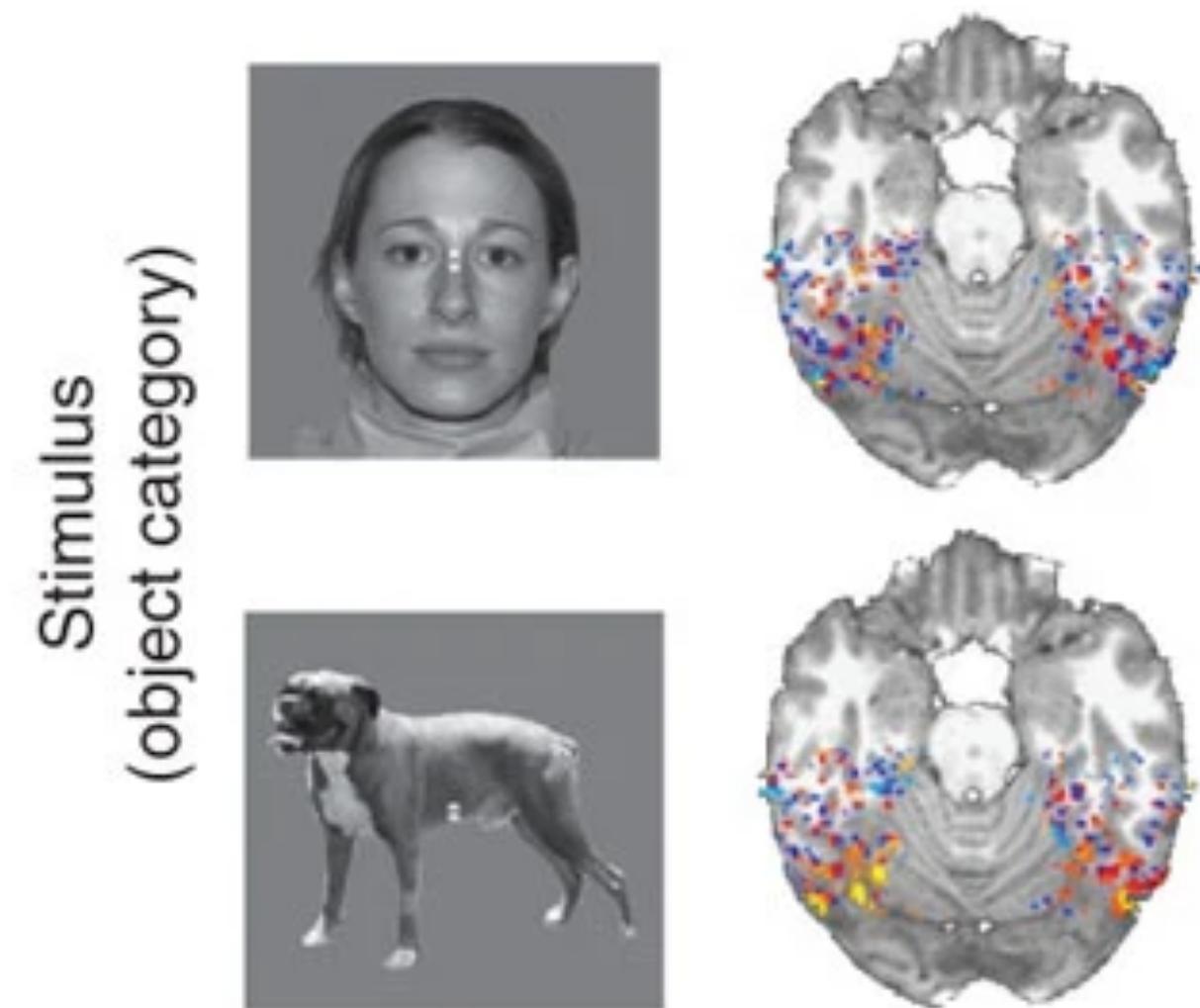


Kriegeskorte et al., 2009, *Nature Neuroscience*.

Double-dipping

Example

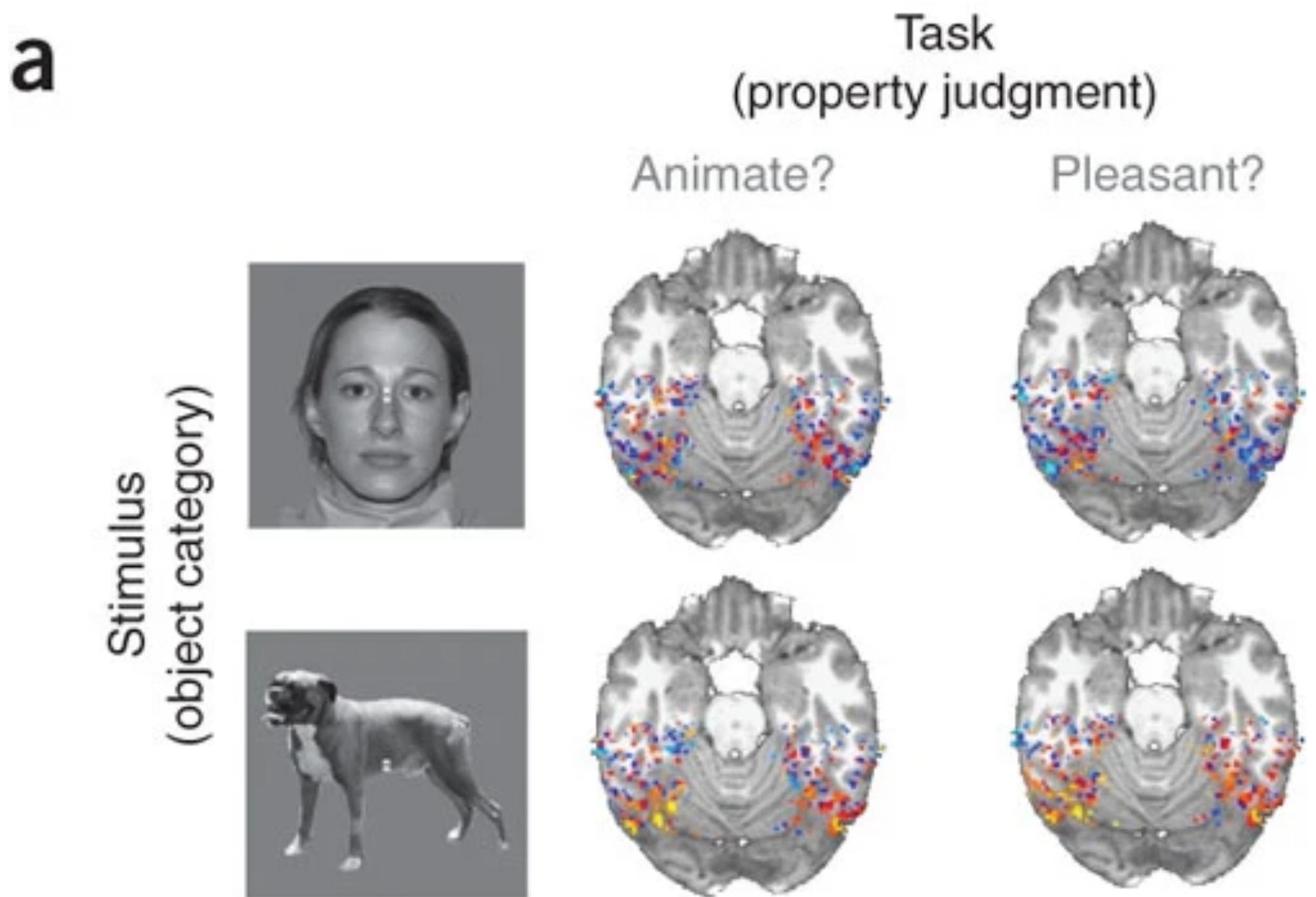
a



Kriegeskorte et al., 2009, *Nature Neuroscience*.

Double-dipping

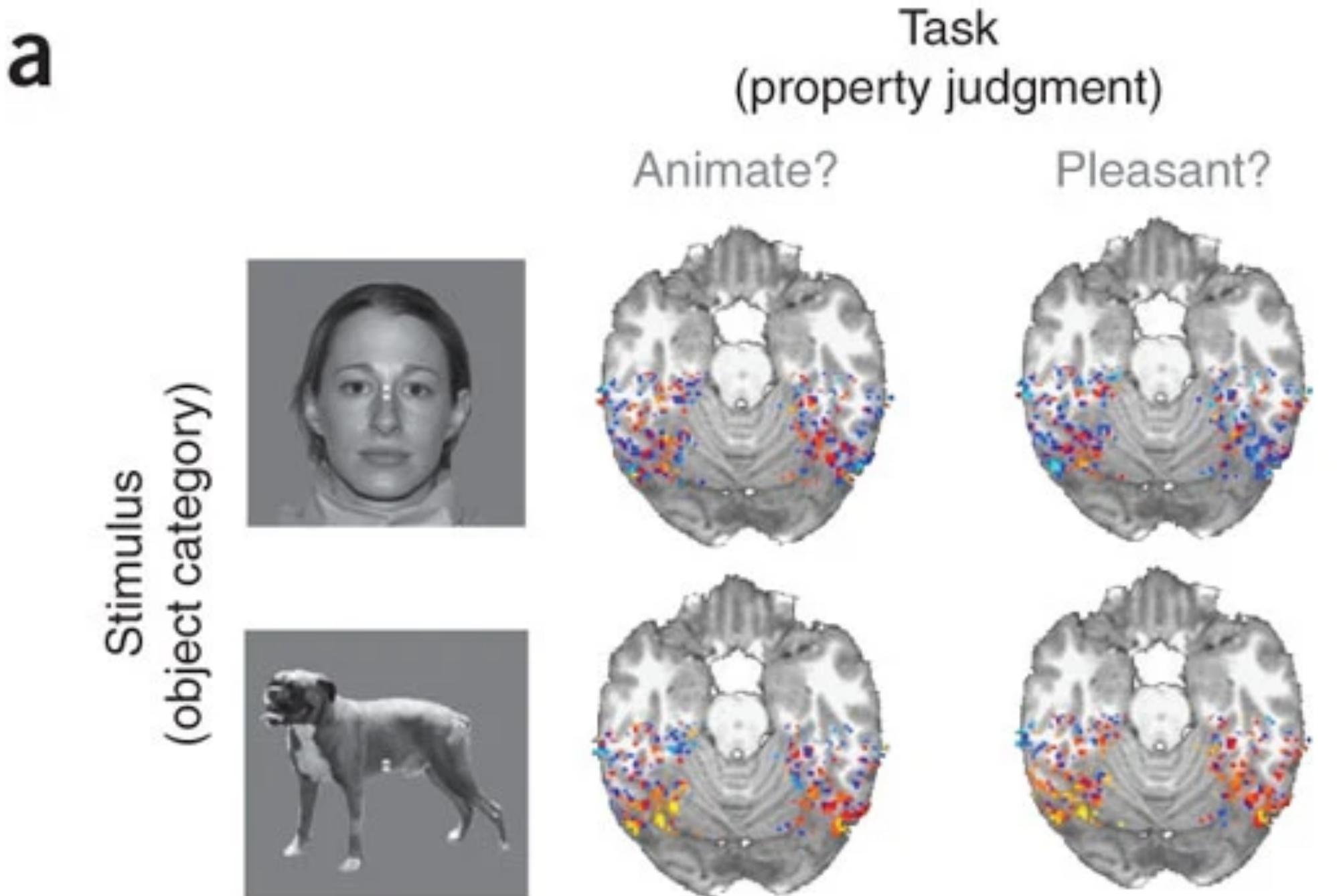
Example



Kriegeskorte et al., 2009, *Nature Neuroscience*.

Double-dipping

Example



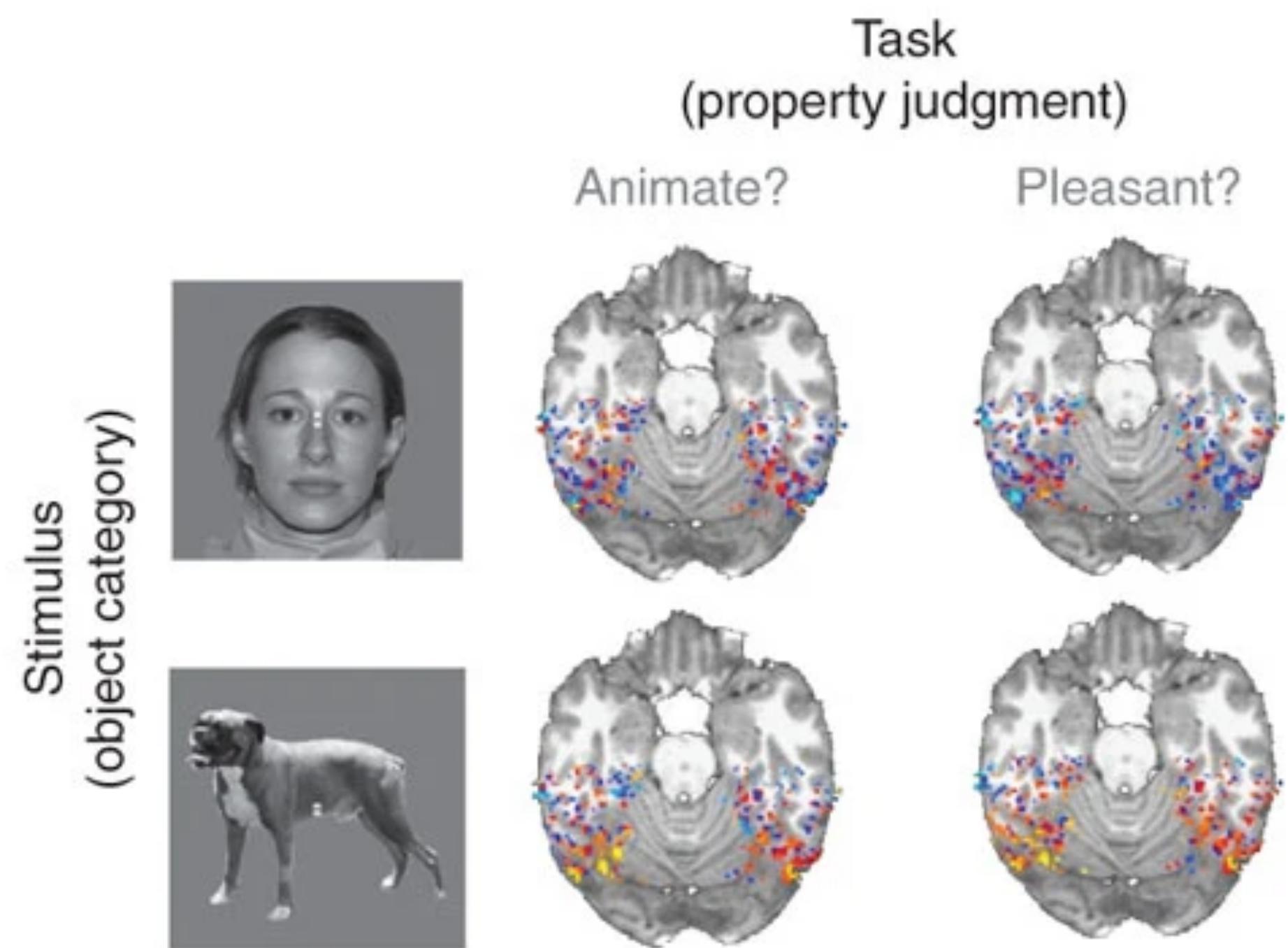
Kriegeskorte et al., 2009, *Nature Neuroscience*.

Training data
(Run 1, 3, 5)

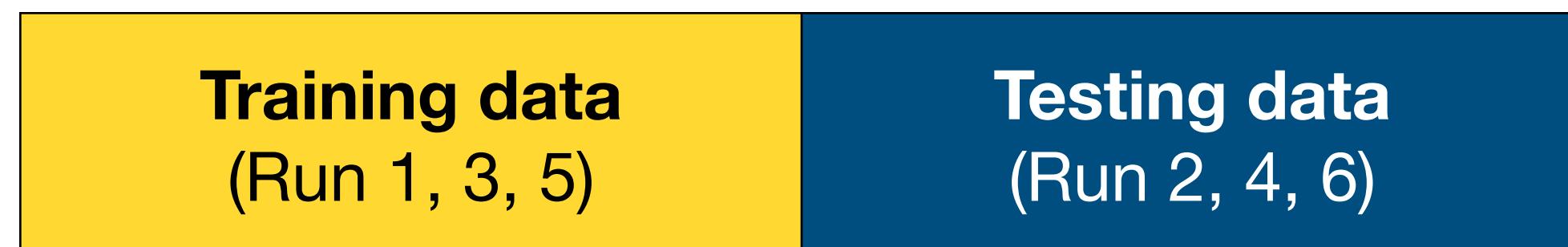
Testing data
(Run 2, 4, 6)

Double-dipping

Example

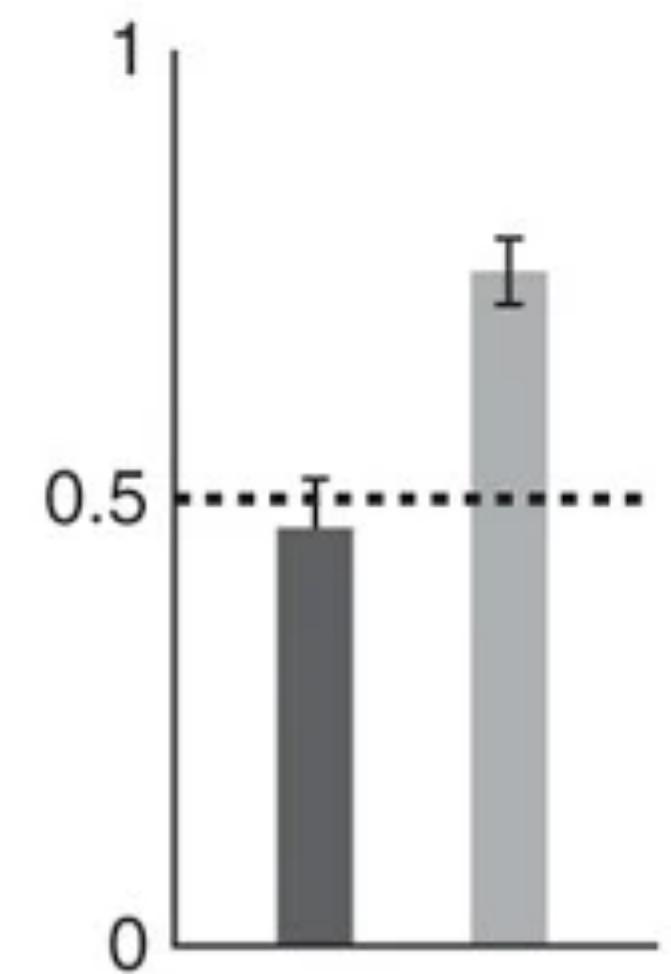
a

Kriegeskorte et al., 2009, *Nature Neuroscience*.

**b**

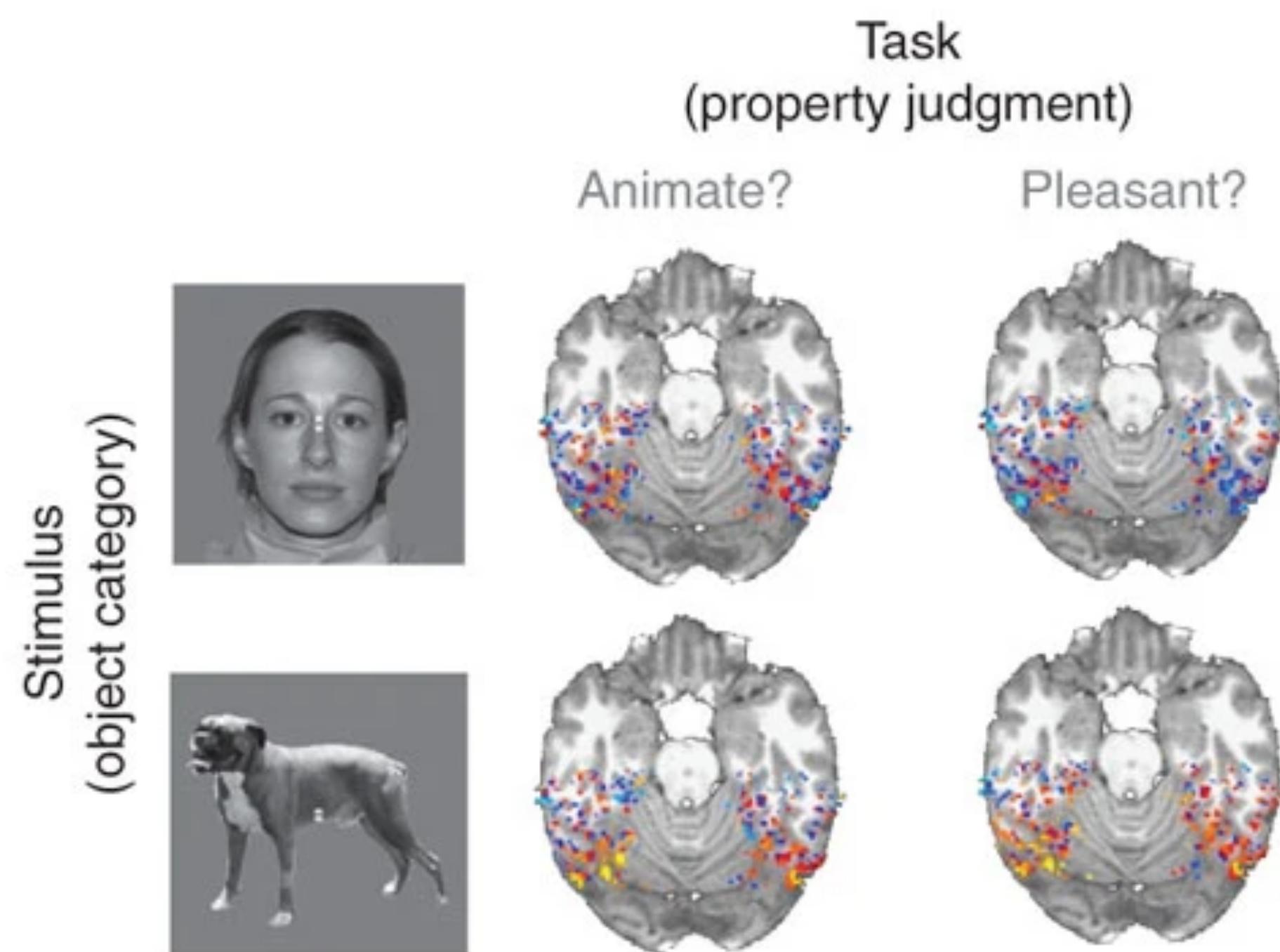
fMRI data

Voxel selection
Using only
training data

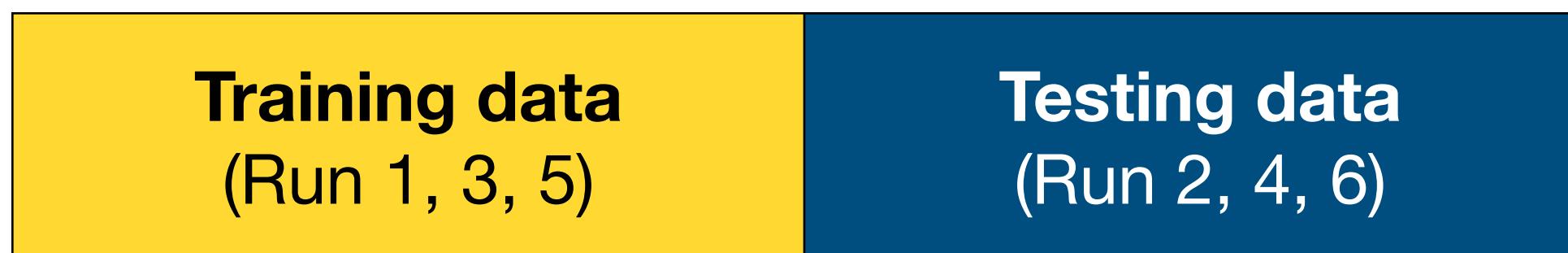
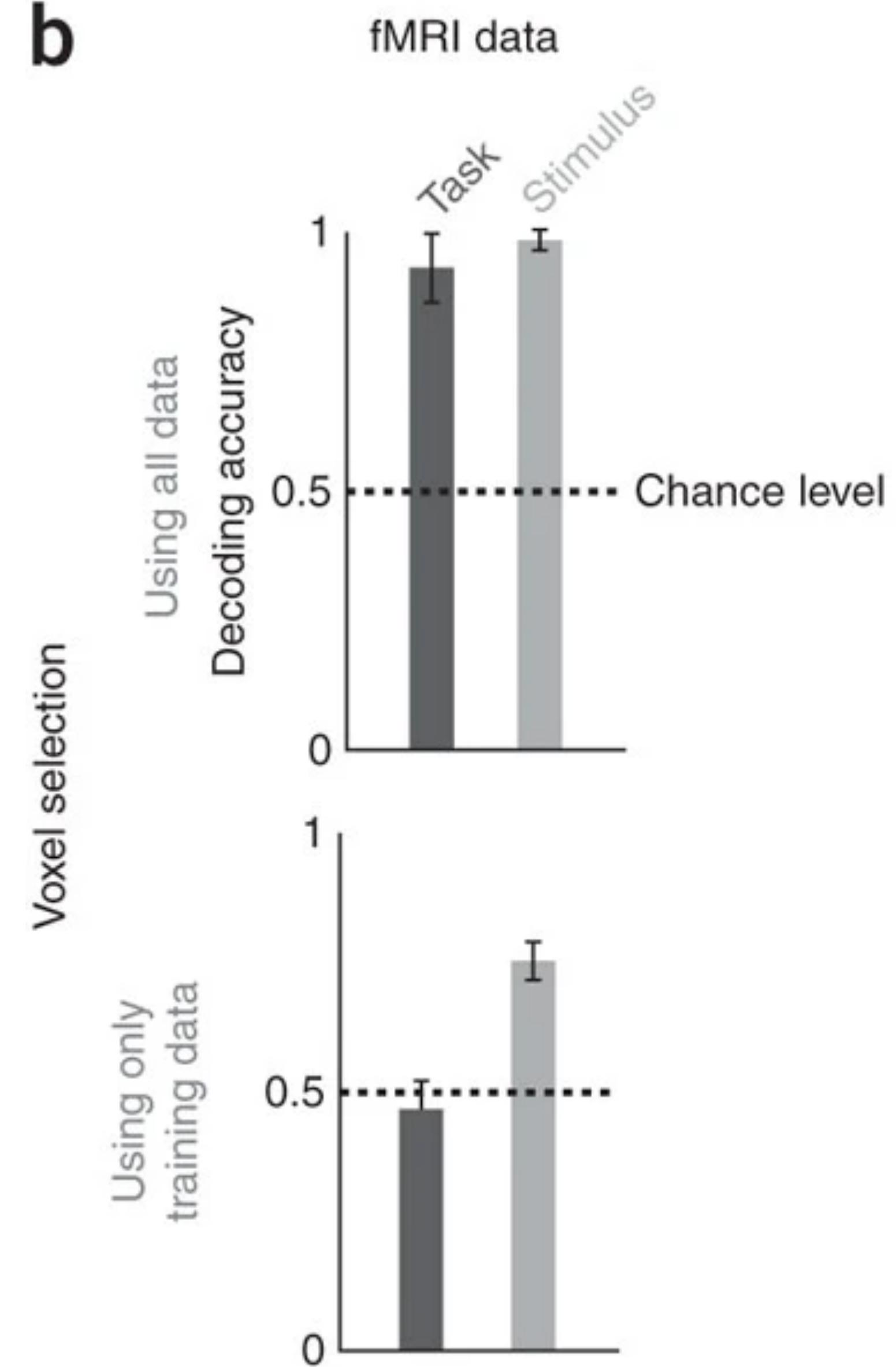


Double-dipping

Example

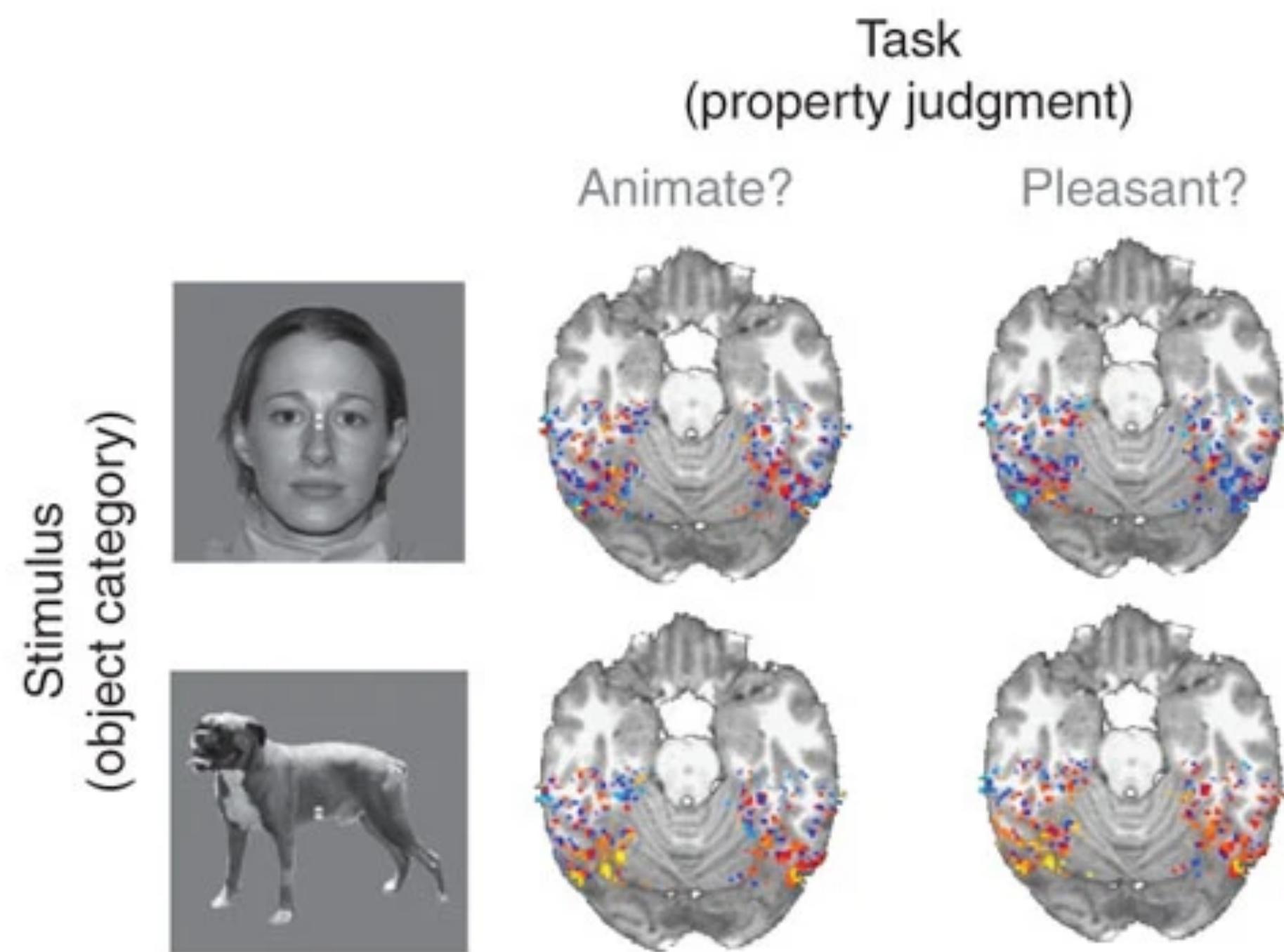
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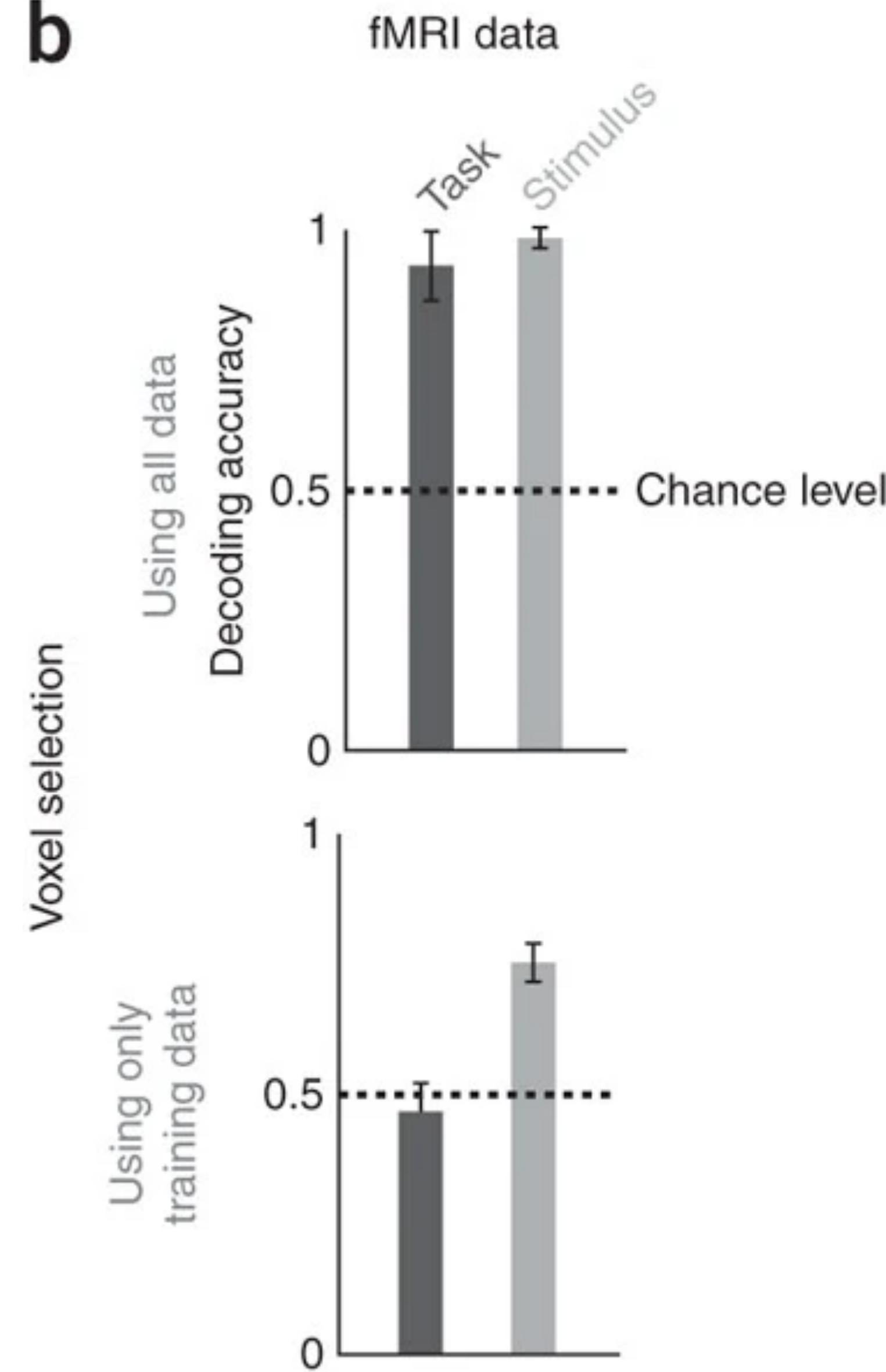
Double-dipping

Example

a

Training data
(Run 1, 3, 5)

Testing data
(Run 2, 4, 6)

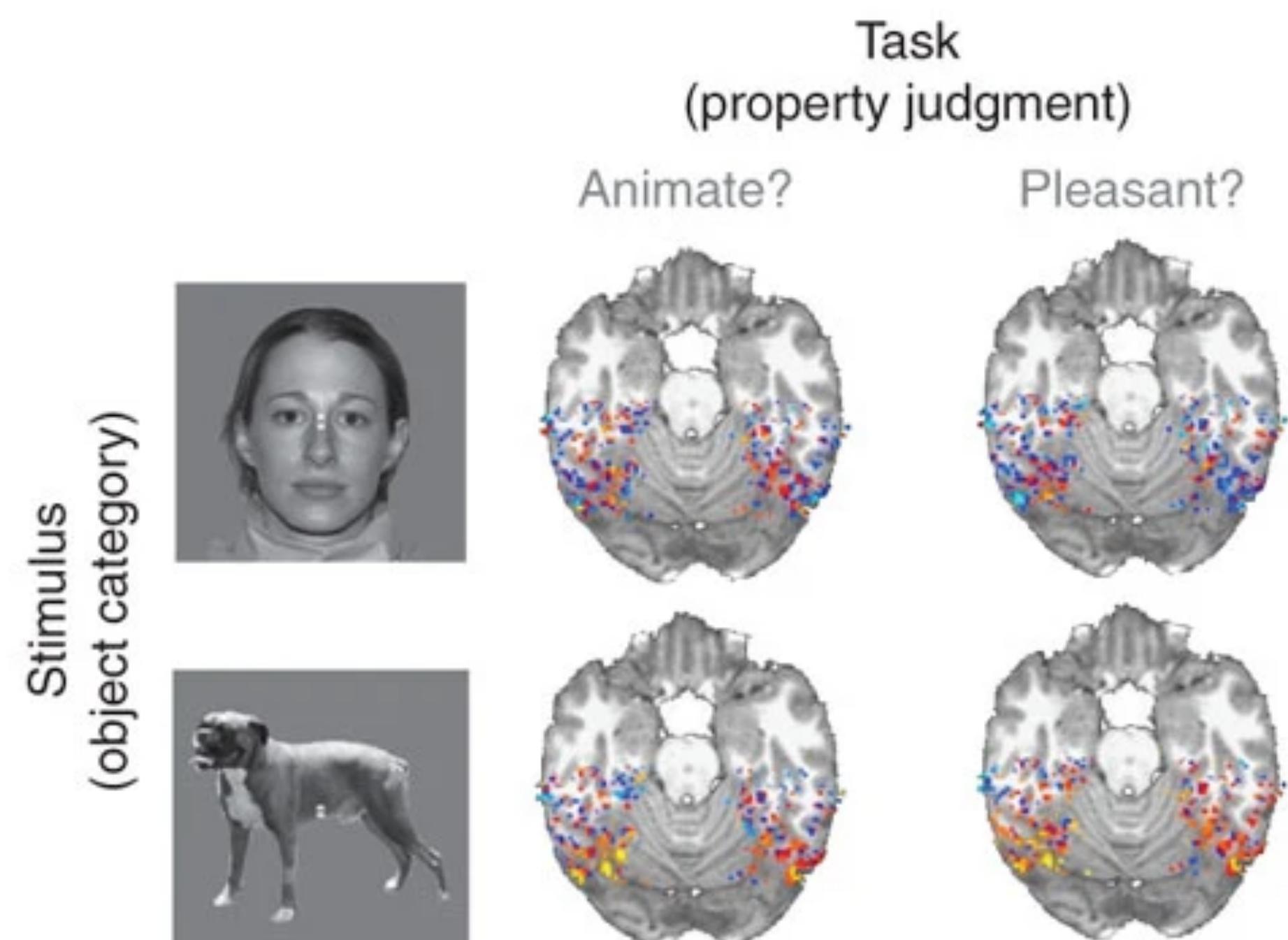
b

Data from
random generator



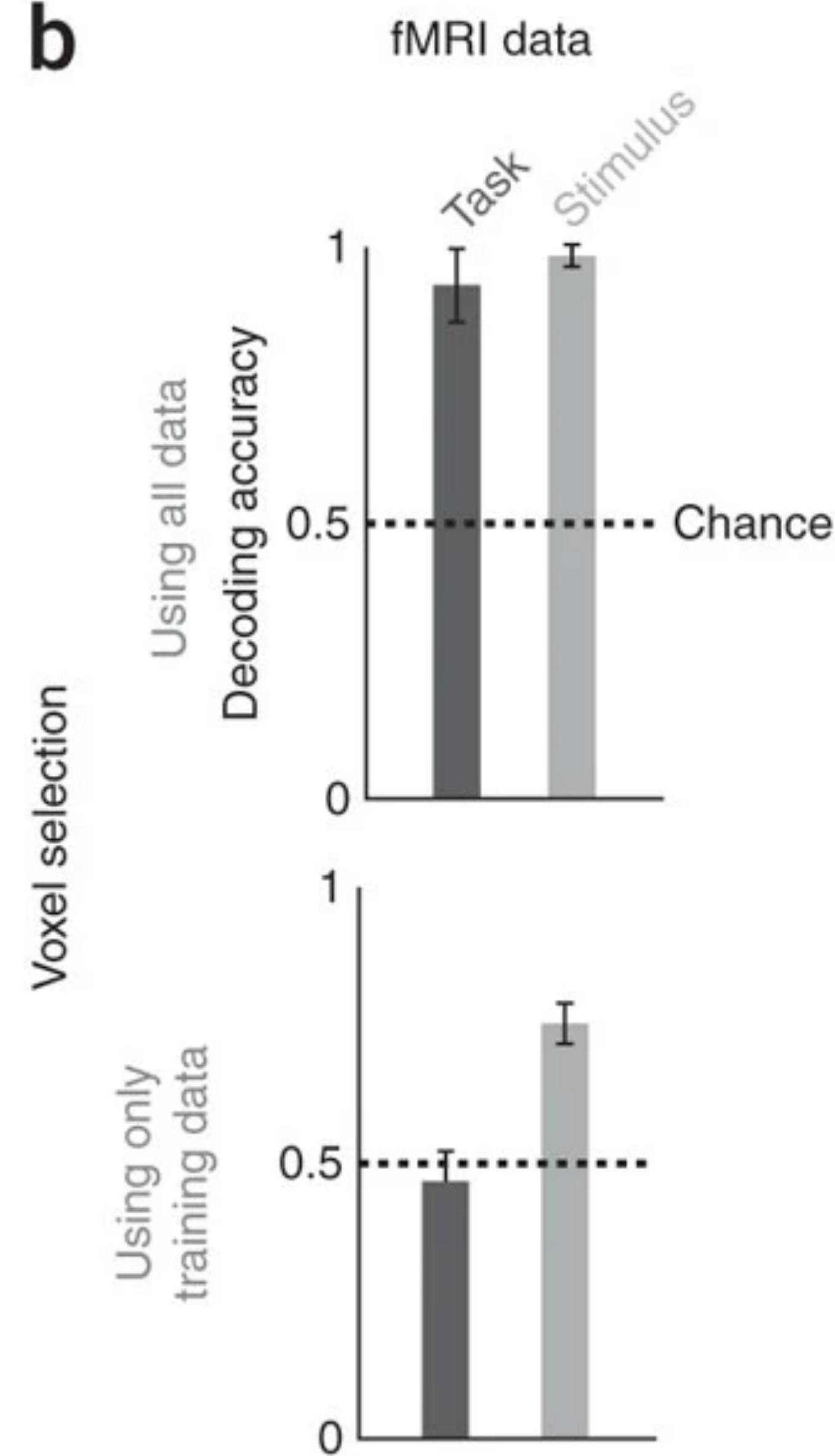
Double-dipping

Example

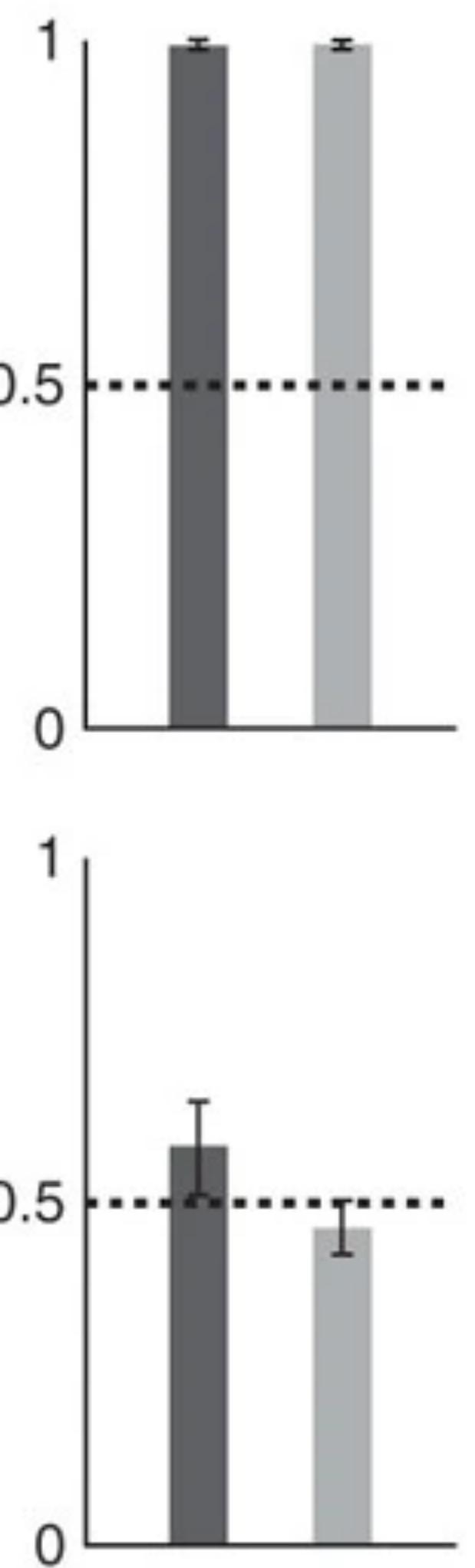
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Testing data
(Run 2, 4, 6)

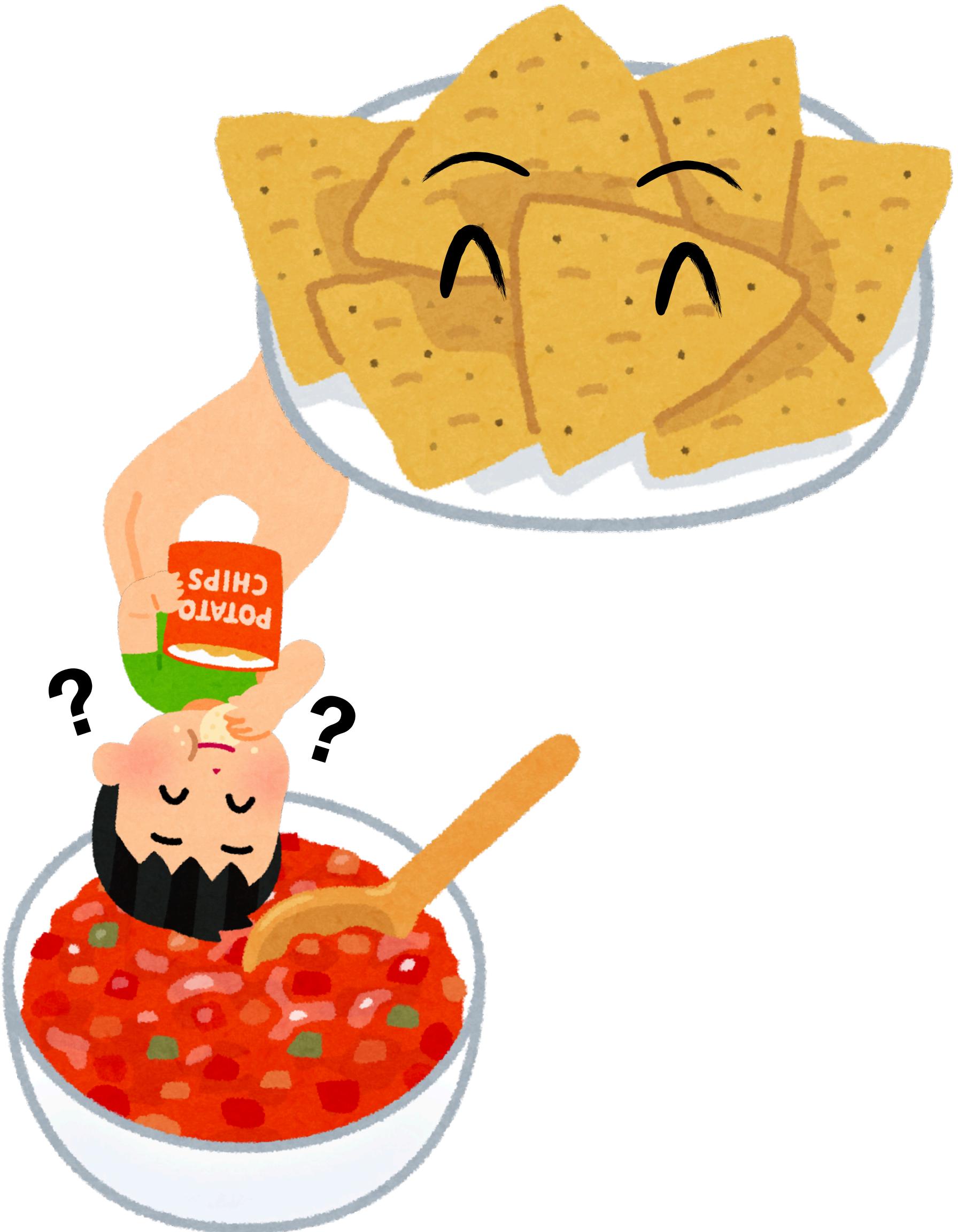
b

Data from
random generator



Reverse double-dipping

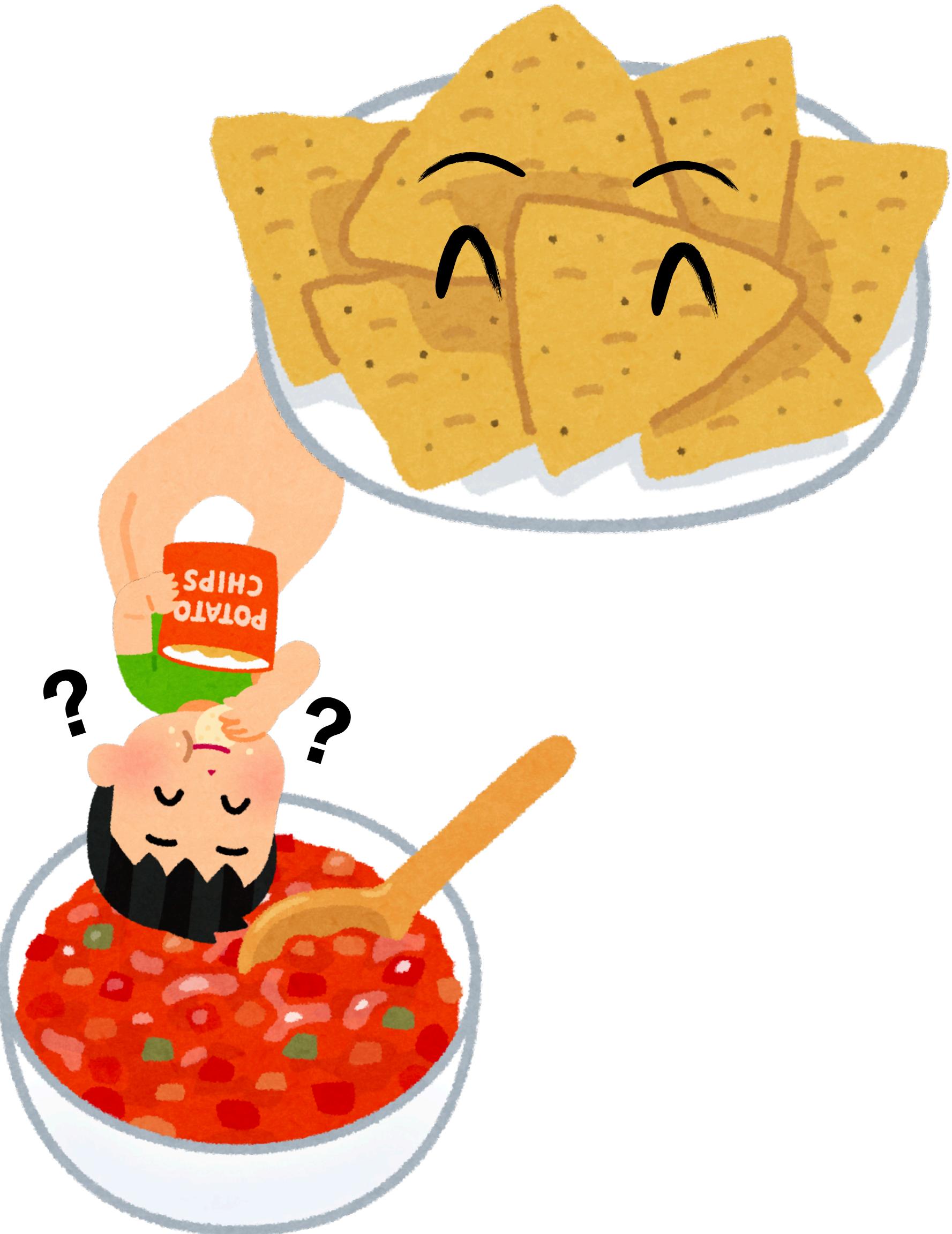
Kim, *in prep.*



Reverse double-dipping

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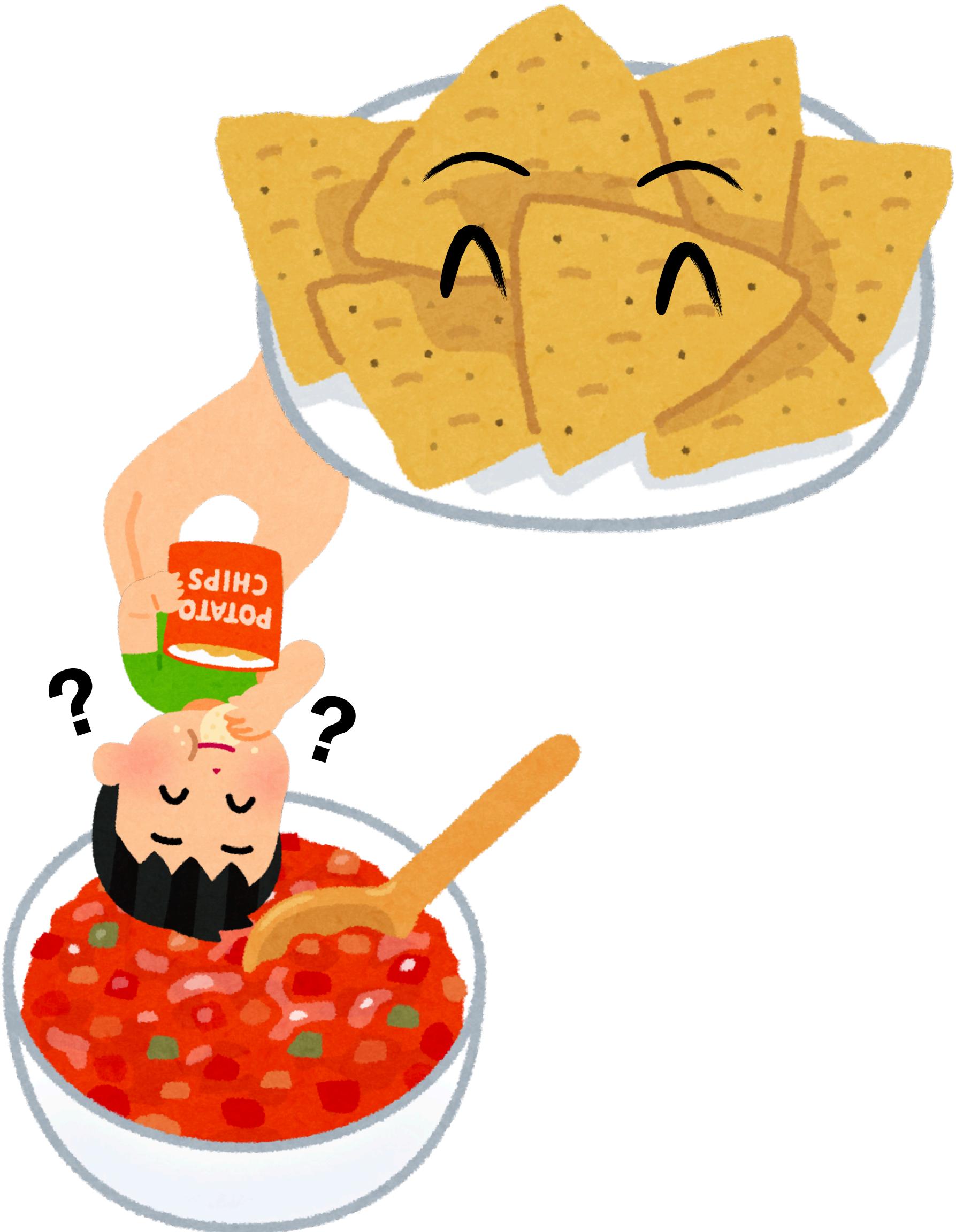
- You don't do particularly wrong.



Reverse double-dipping

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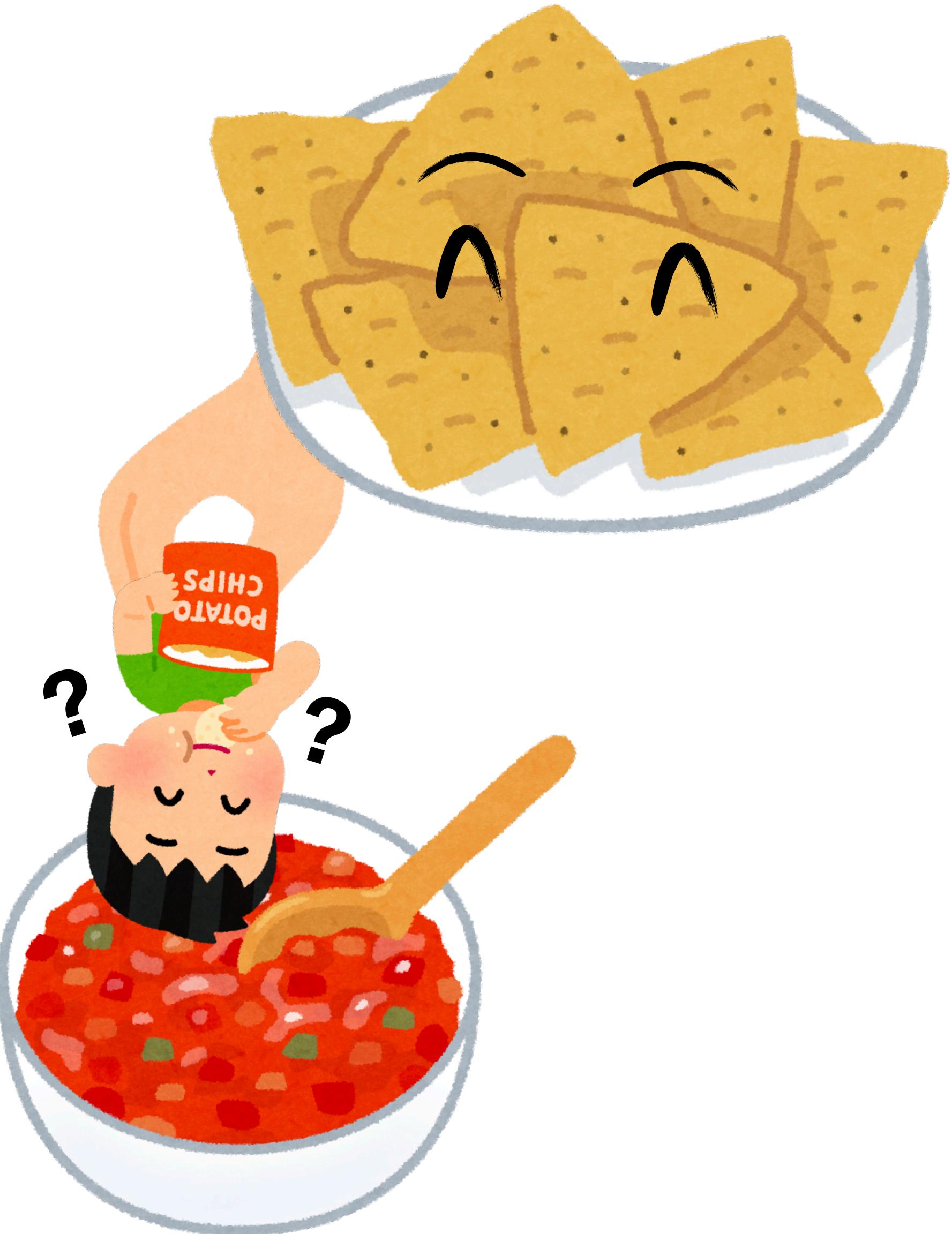
- You don't do particularly wrong.
- However, unbeknownst to the similarity between training and testing sets, you can fall victim to **Reverse Double-Dipping!**



Reverse double-dipping

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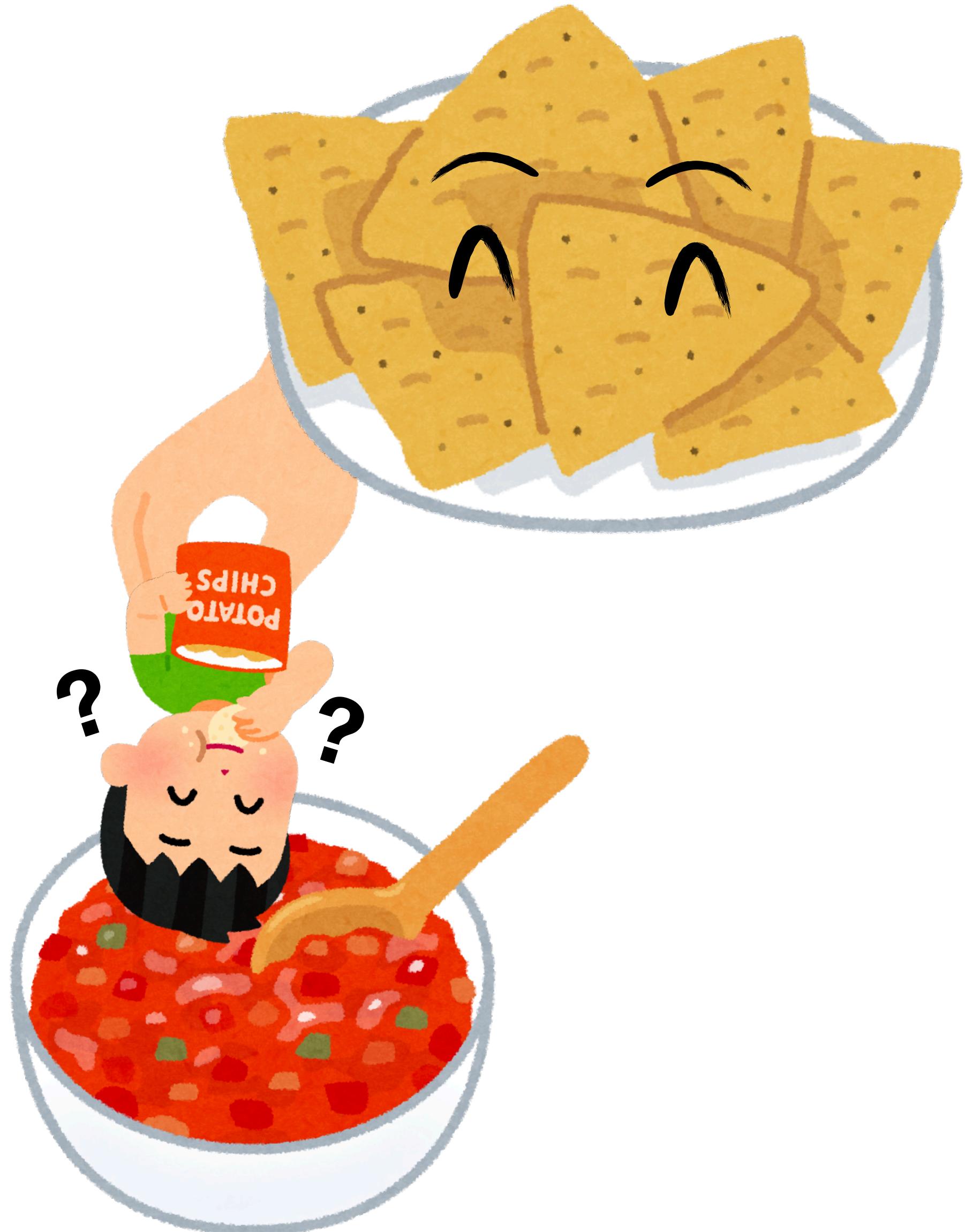
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- The data dips you in the training set and testing set (twice).



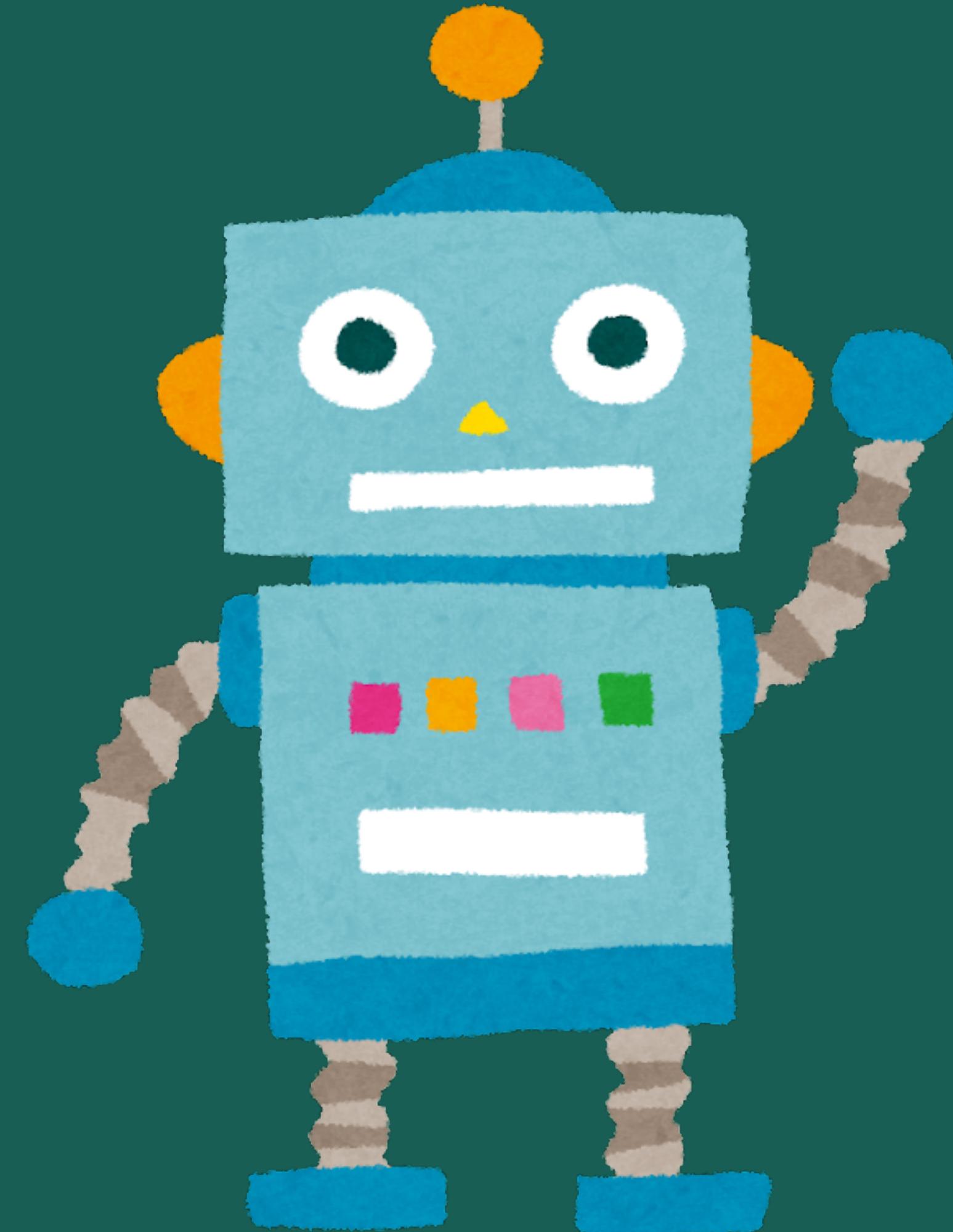
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- You don't do particularly wrong.
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- The data dips you in the training set and testing set (twice).
- This happens due to the **common stimulus-evoked responses** across trials/subjects/...



Toy example

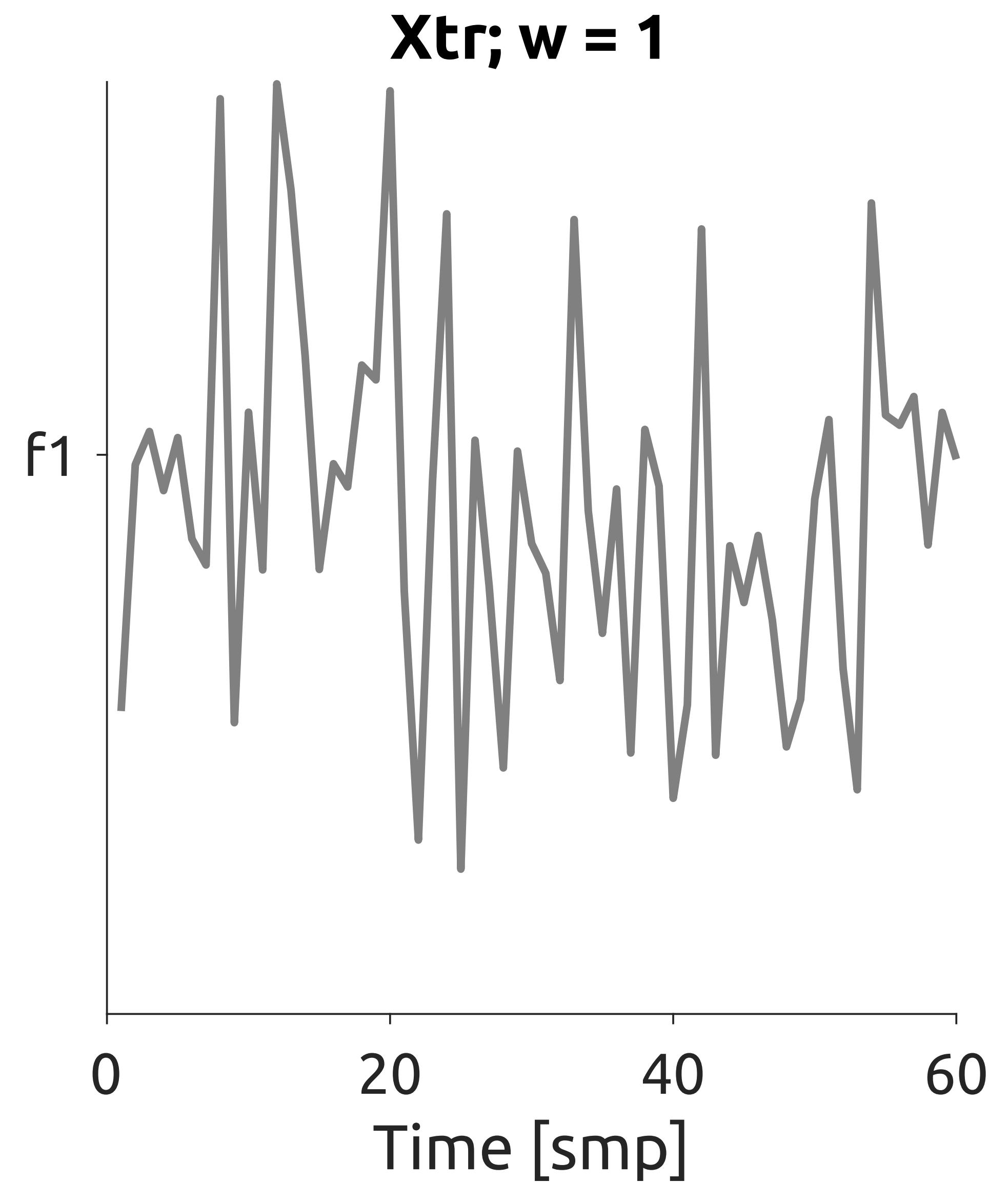


Toy specification

True features

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

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

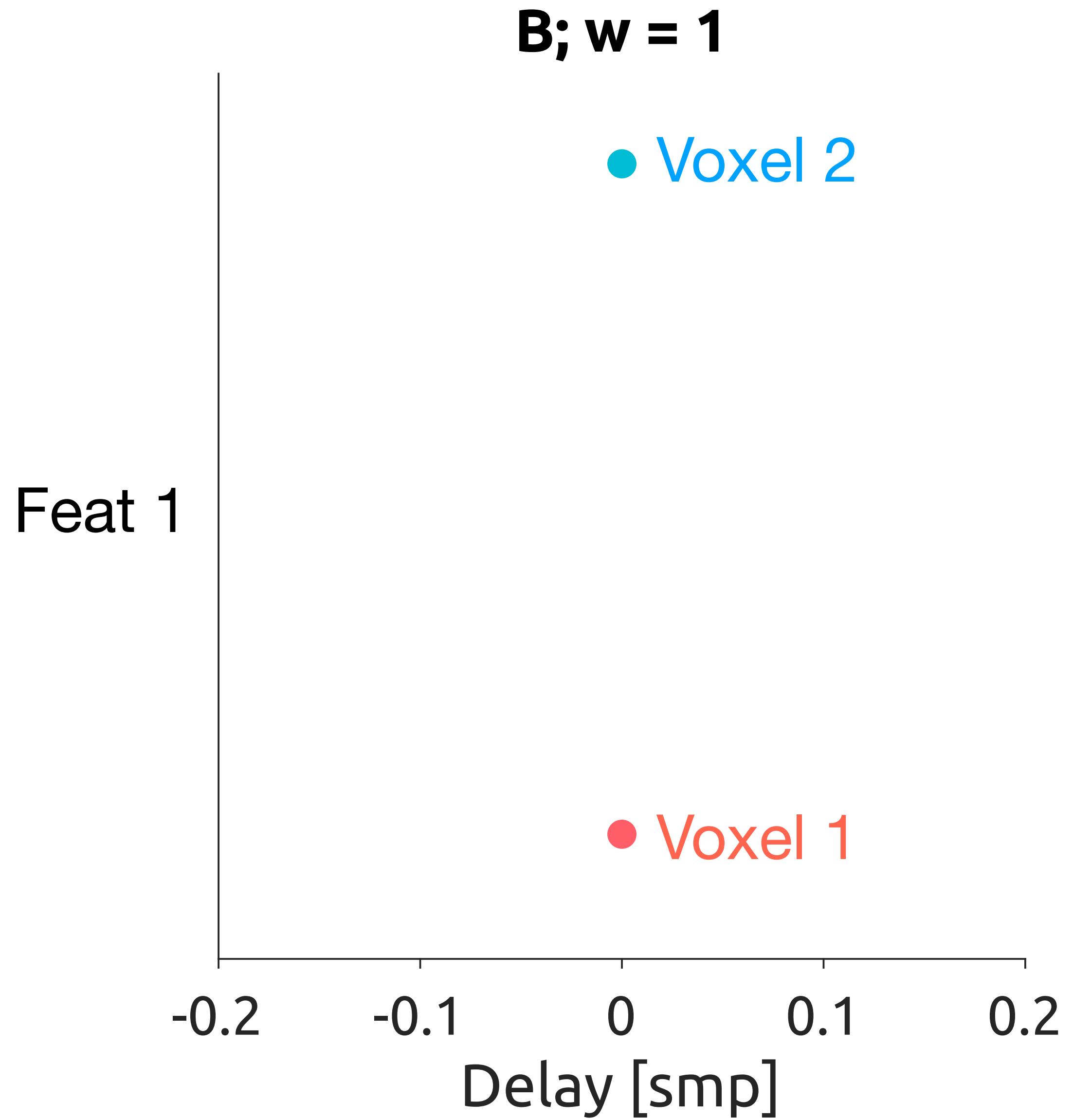


Toy specification

True weights

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

- \mathbf{B} : <#Delays.#Features x #Voxels>
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- #Features = 1
- #Voxels = 2
- Weight smoothness window = 1

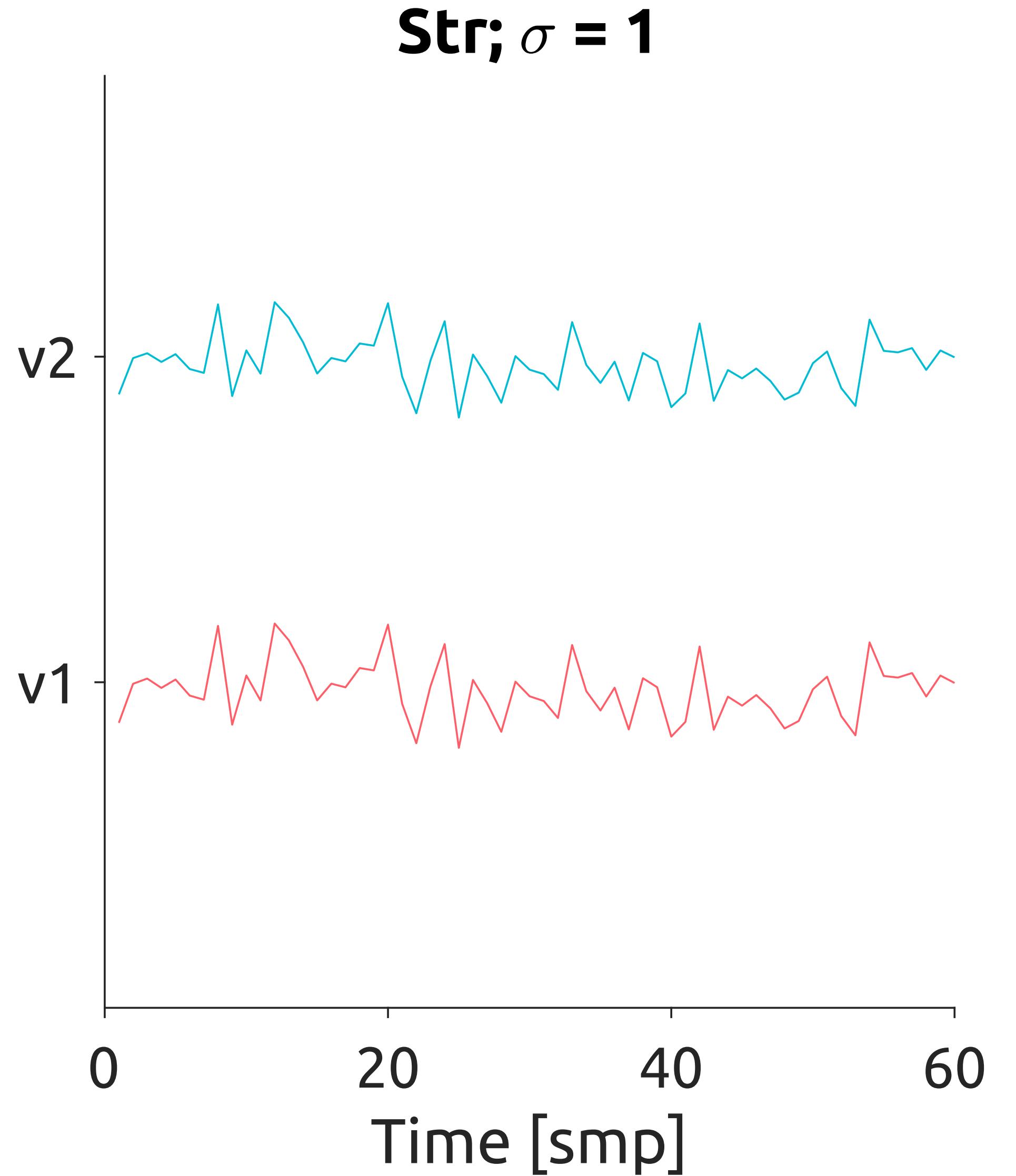


Toy specification

True signal (features x weights)

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

- **XB:** <#Timepoints x #Voxels>
- #Timepoints = 60
- #Voxels = 2
- Signal amplitude (standard deviation, $\sigma[\text{signal}]$) = 1

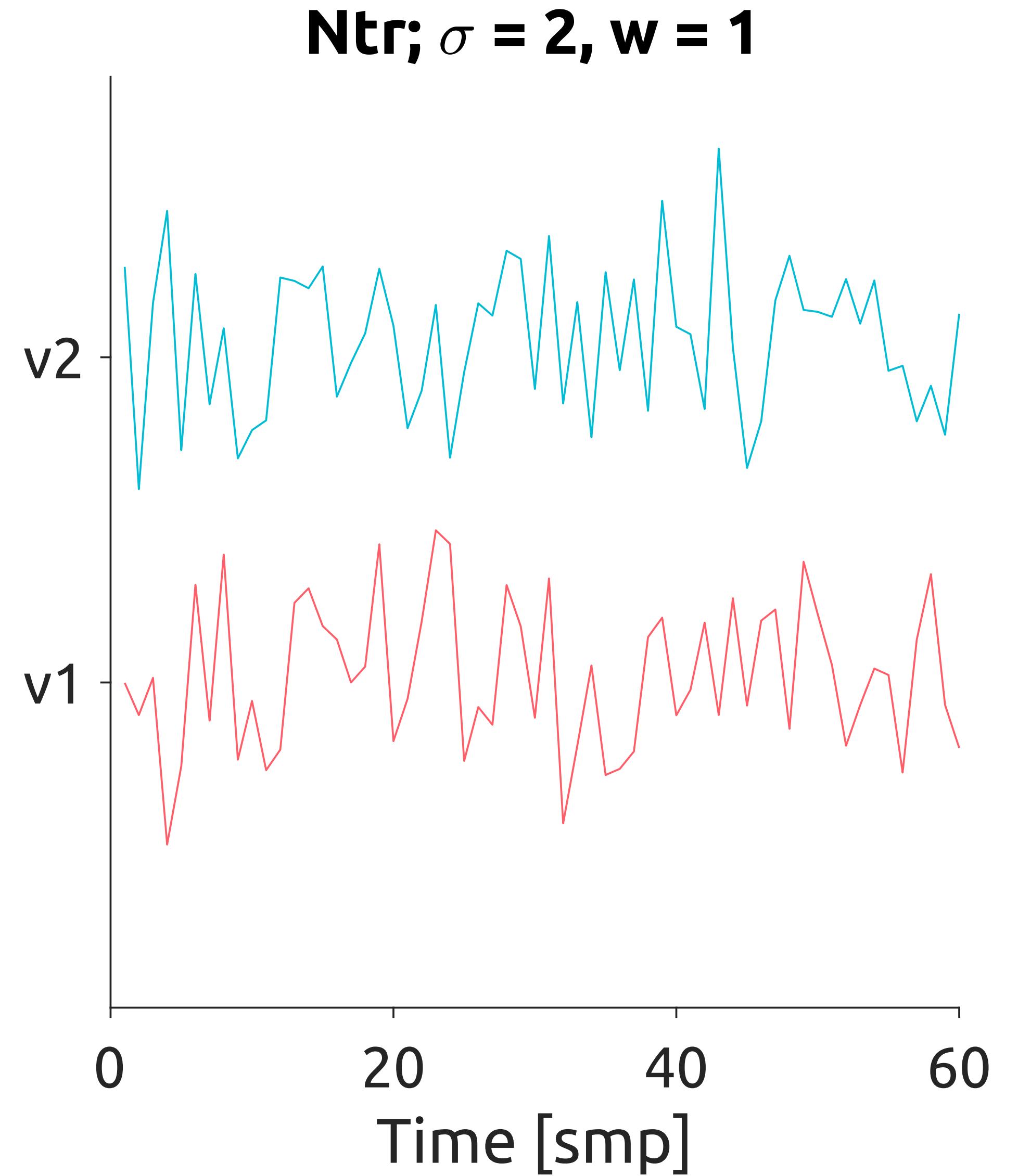


Toy specification

True noise

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

- \mathbf{E} : <#Timepoints x #Voxels>
- #Timepoints = 60
- #Voxels = 2
- Noise smoothness window = 1
- Noise amplitude ($\sigma[\text{noise}]$) = 2

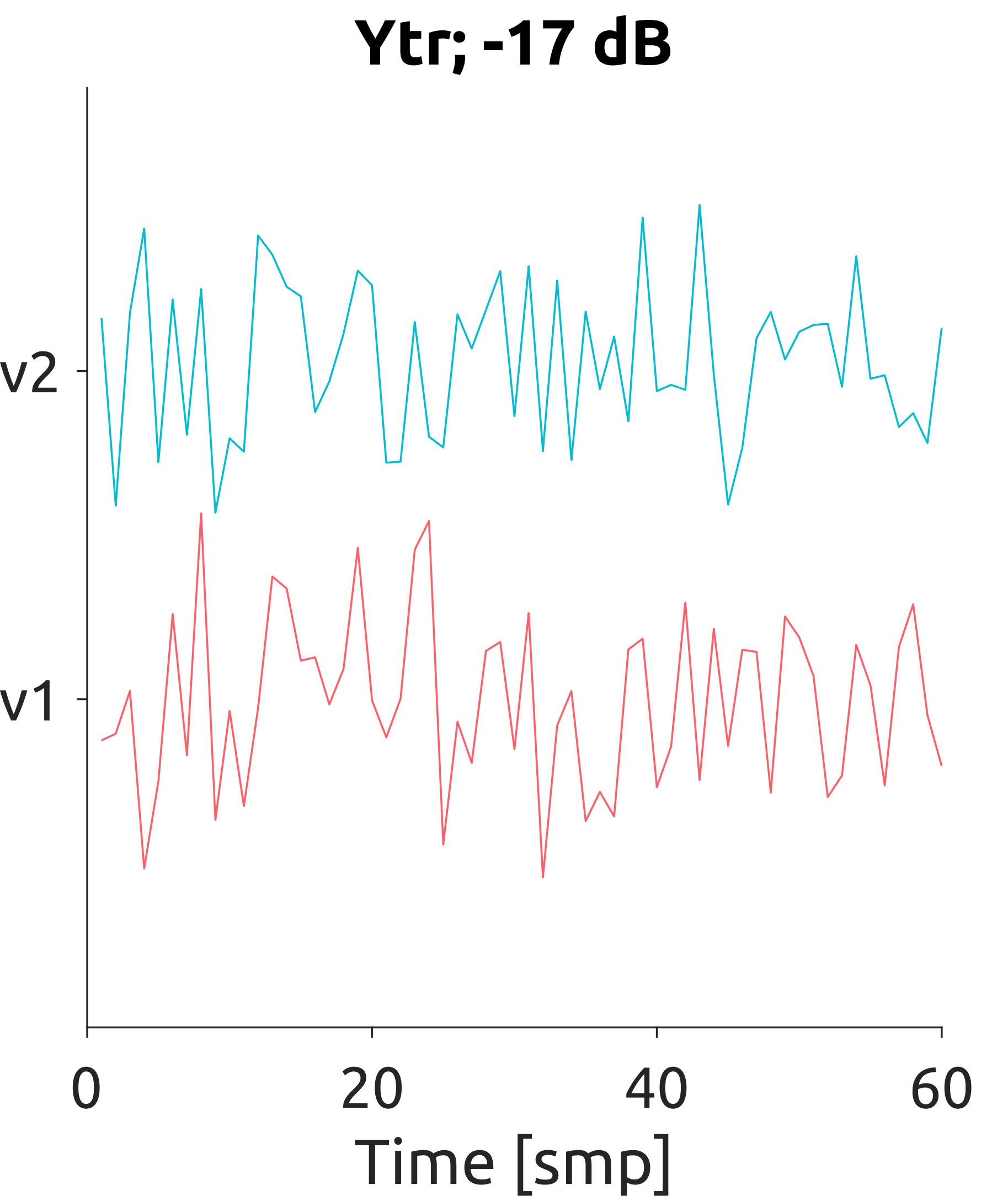


Toy specification

Training data = True signal + True noise

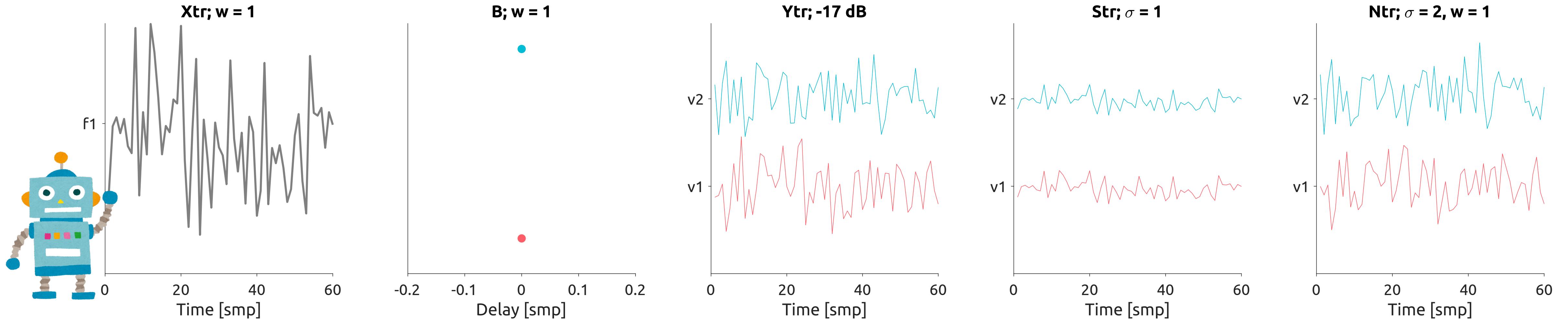
$$\mathbf{Y} = \mathbf{XB} + \mathbf{E}$$

- \mathbf{Y} : <#Timepoints x #Voxels>
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- #Voxels = 2
- SNR = dB($\sigma^2[\text{signal}] / \sigma^2[\text{noise}]$)



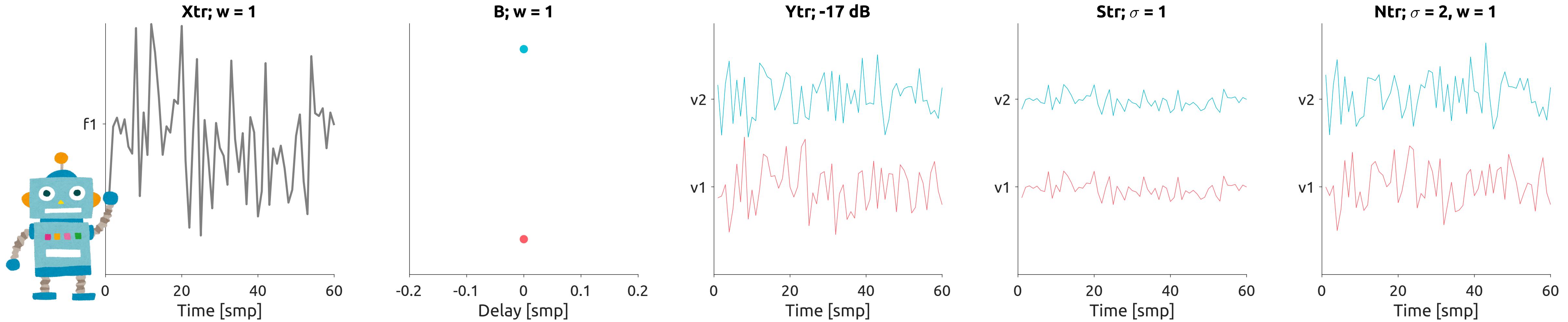
Training & testing datasets

Training set

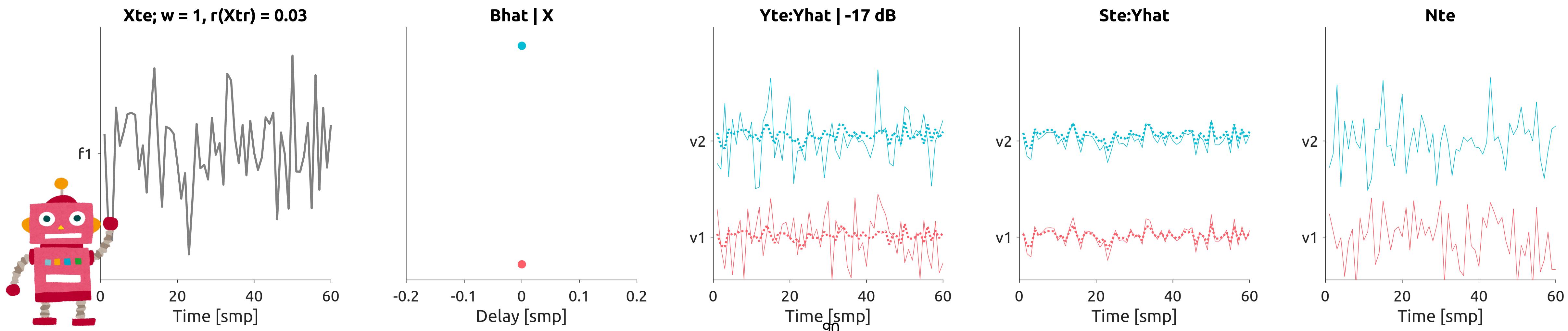


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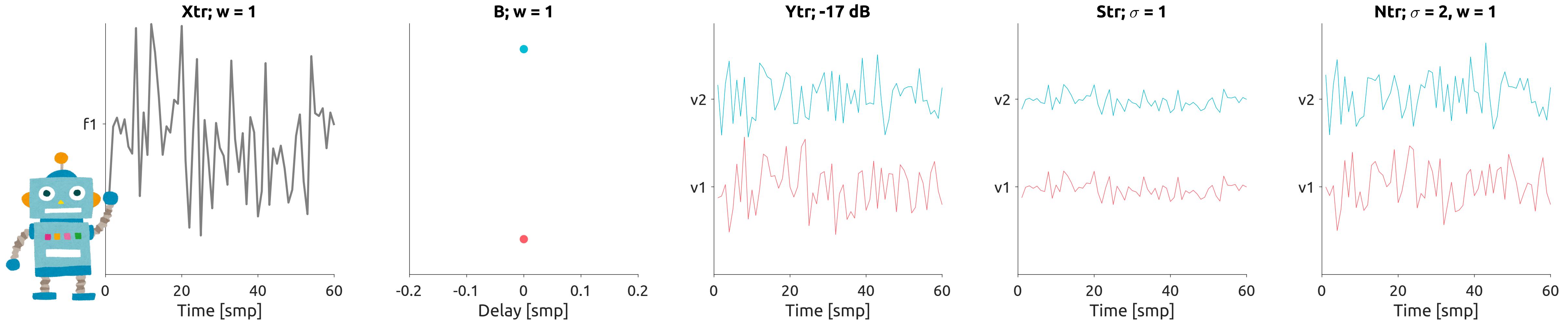


Testing set

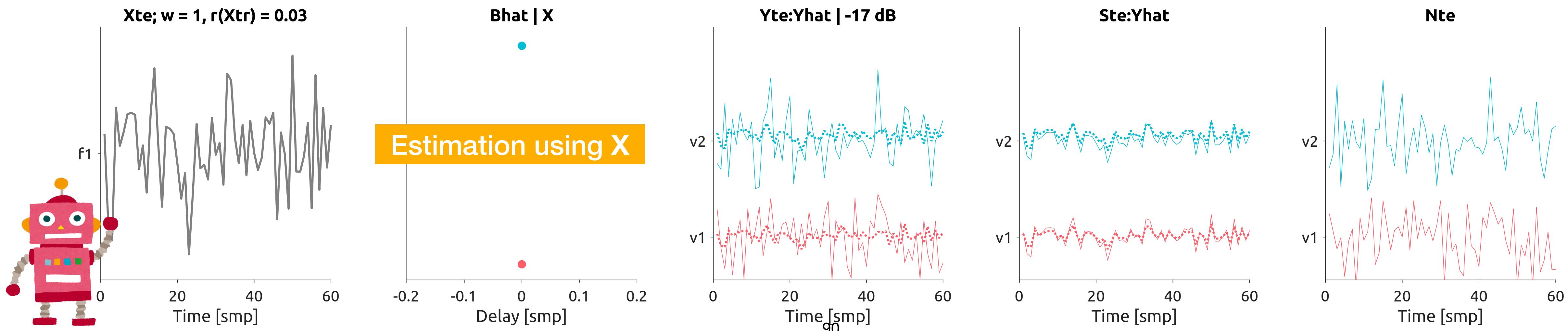


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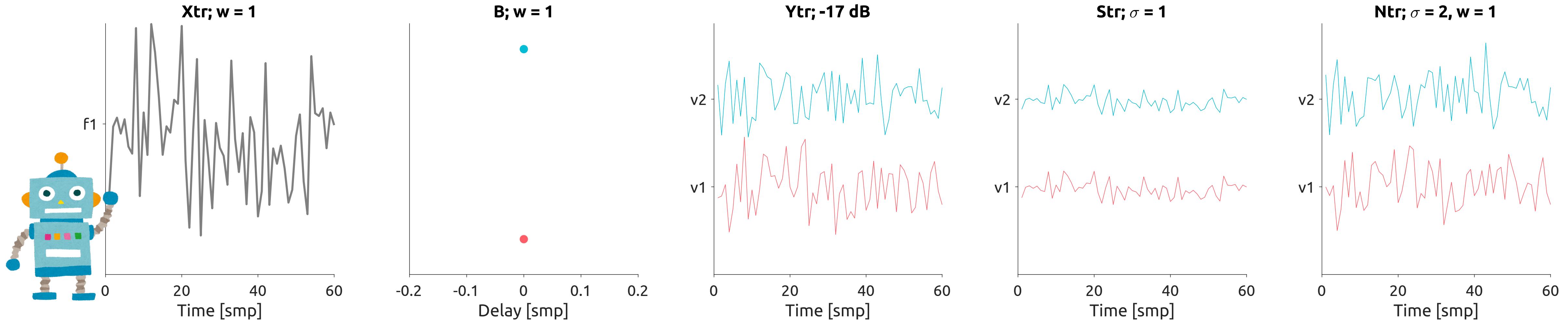


Testing set

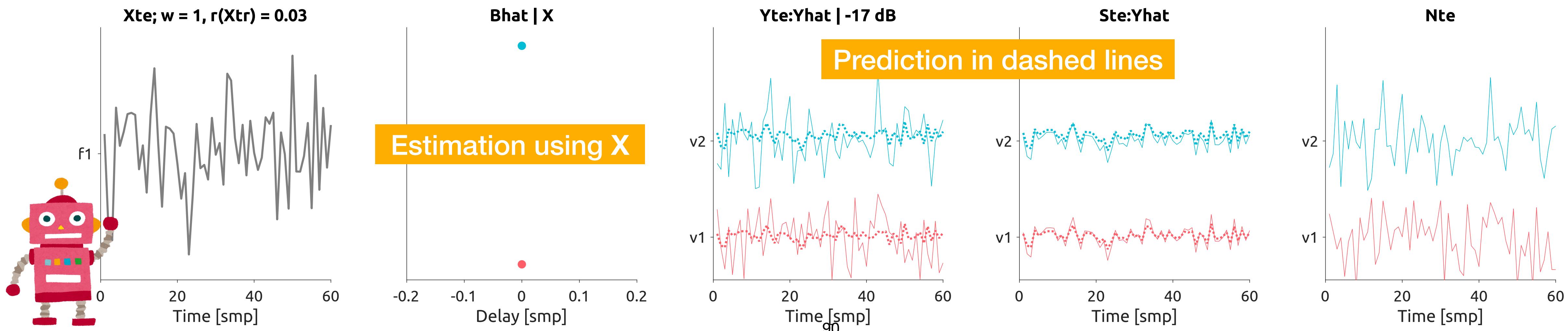


Training & testing datasets

Training set



Testing set

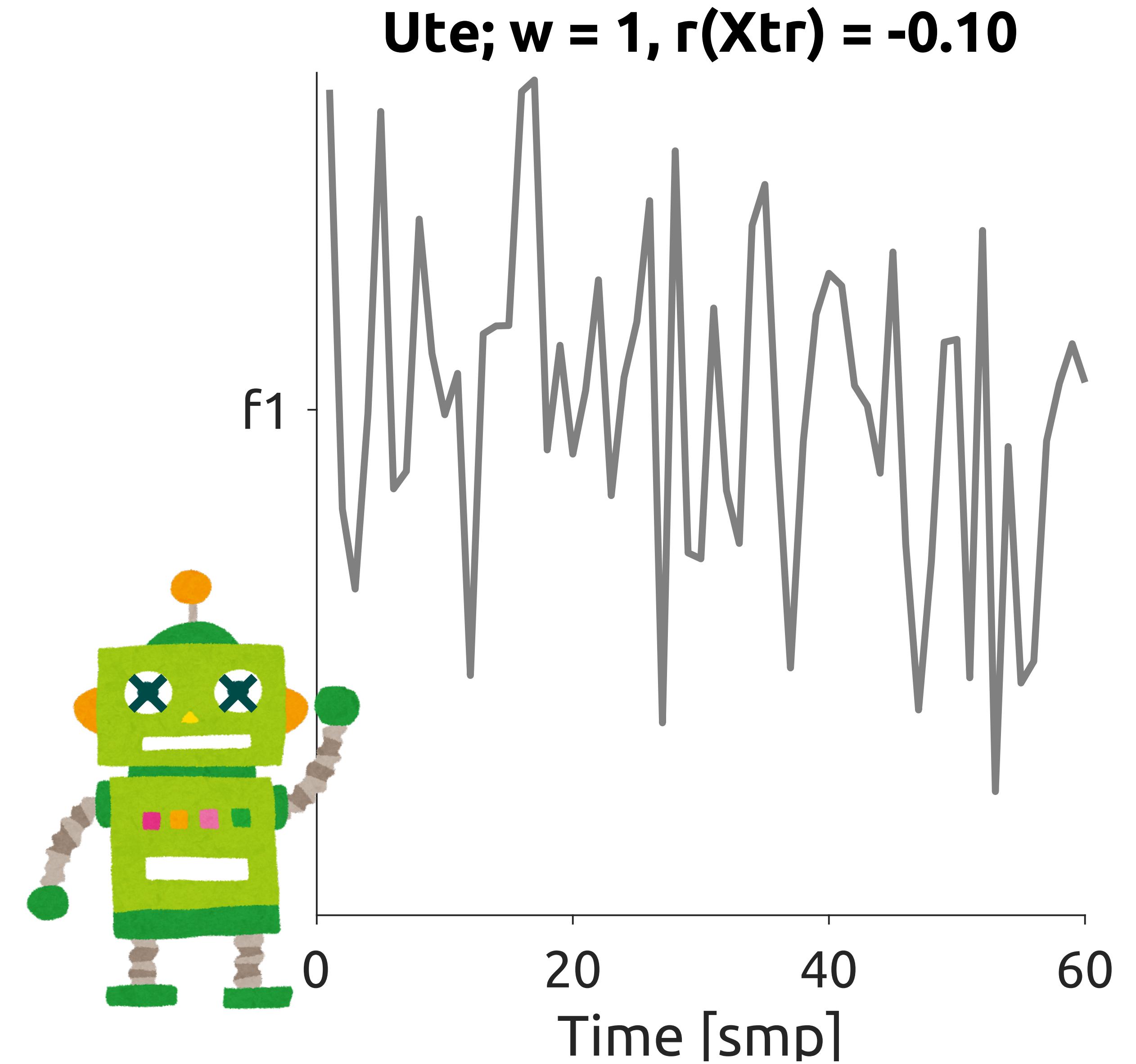


Toy specification

Null features

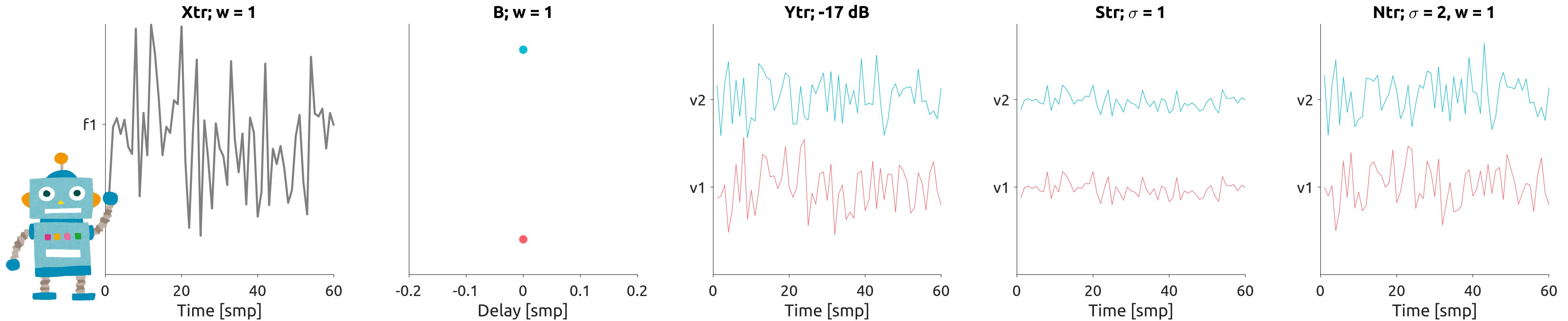
$$\hat{Y}_0 = \textcolor{magenta}{U} \hat{B}_0$$

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

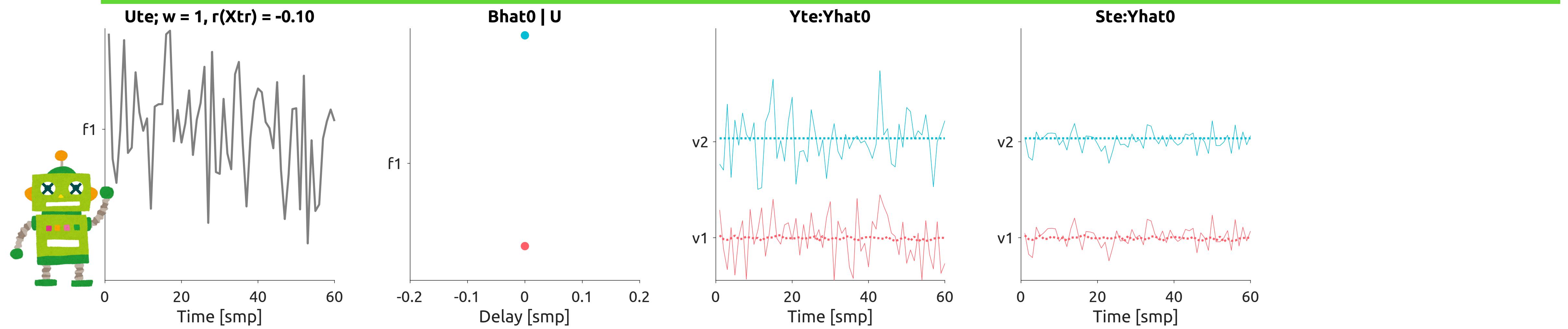


Training & testing datasets

Training set

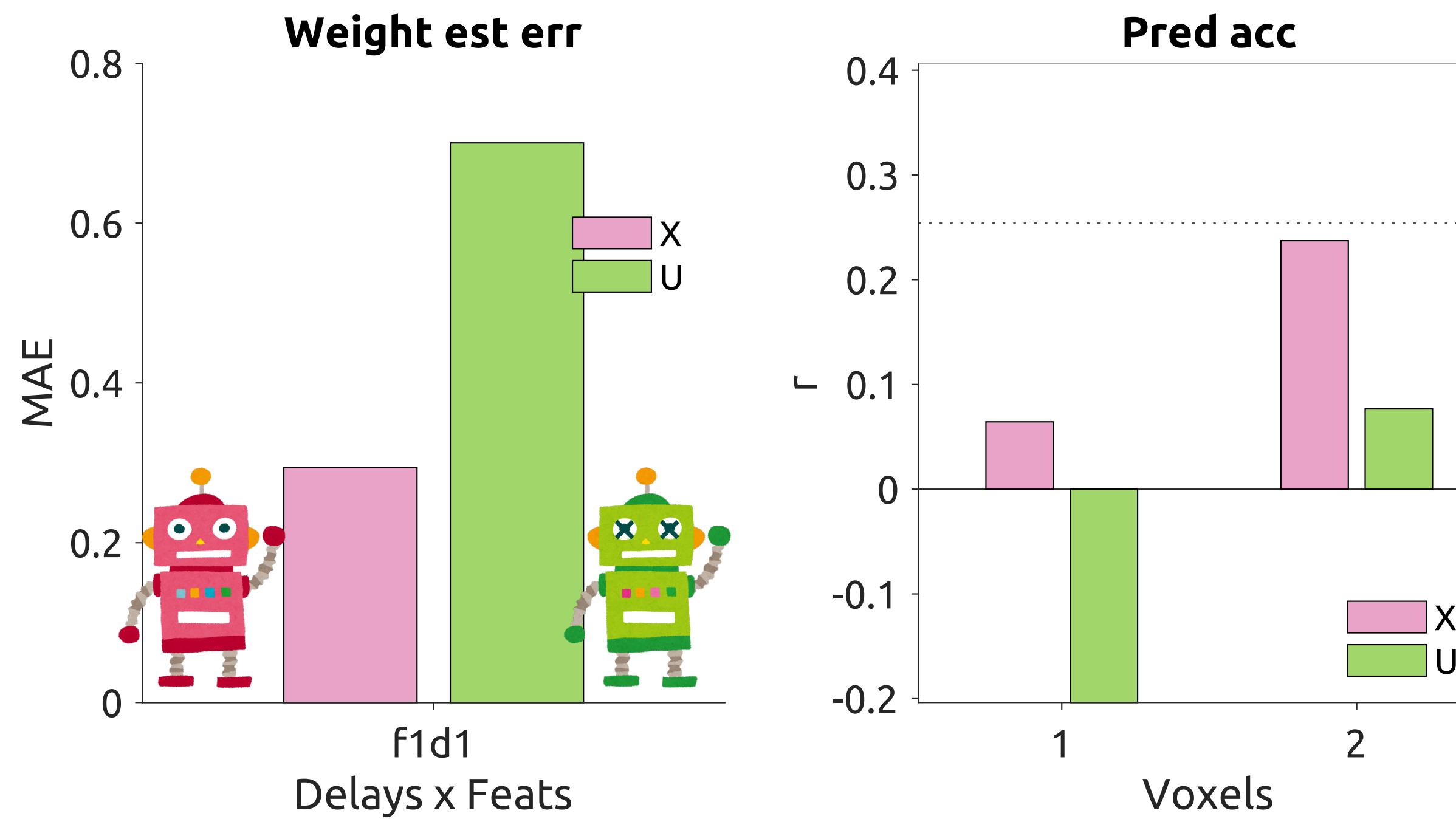


Null model



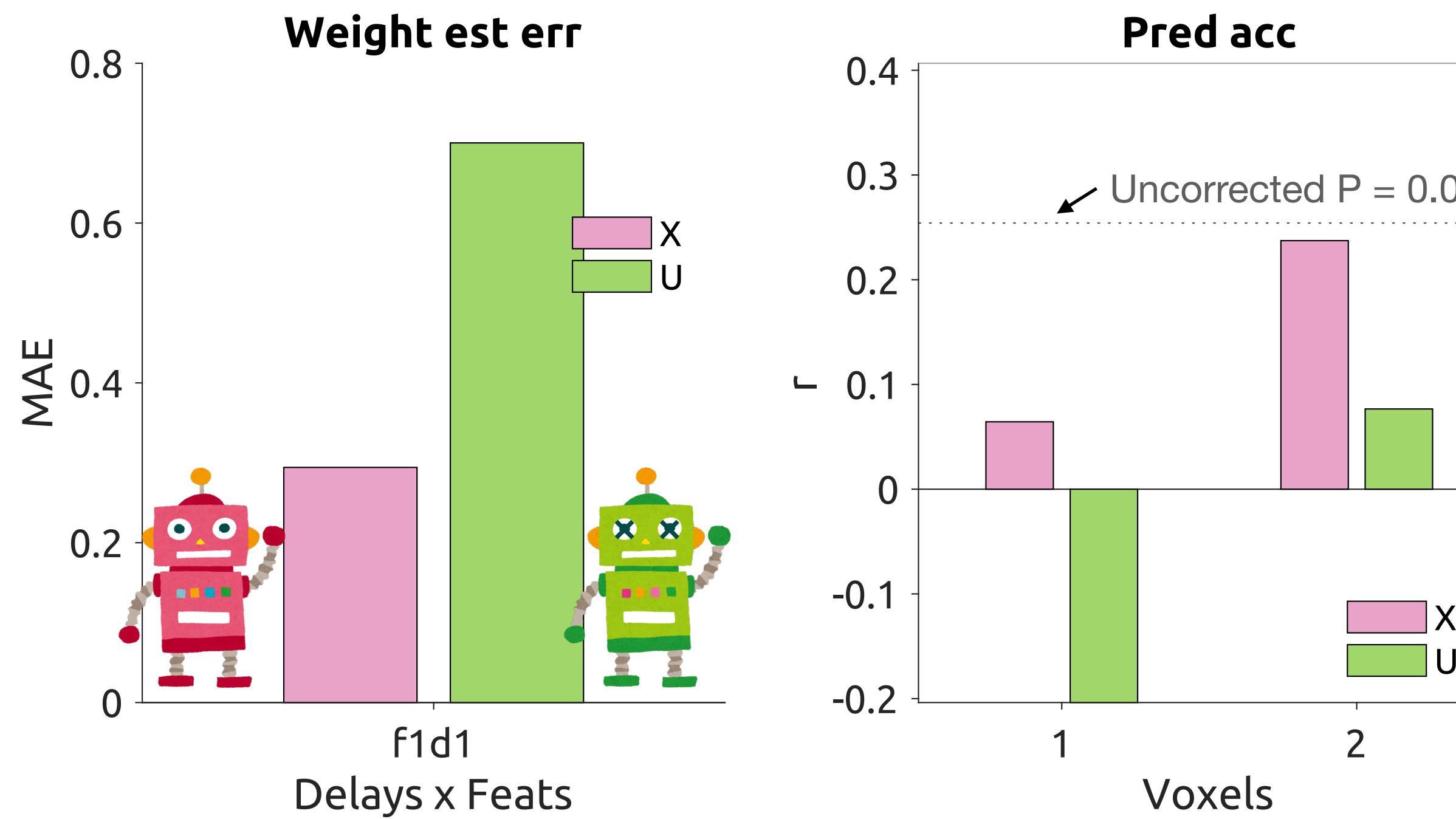
Prediction performances | #Sims = 100

MAE: mean absolute error; r: Pearson correlation



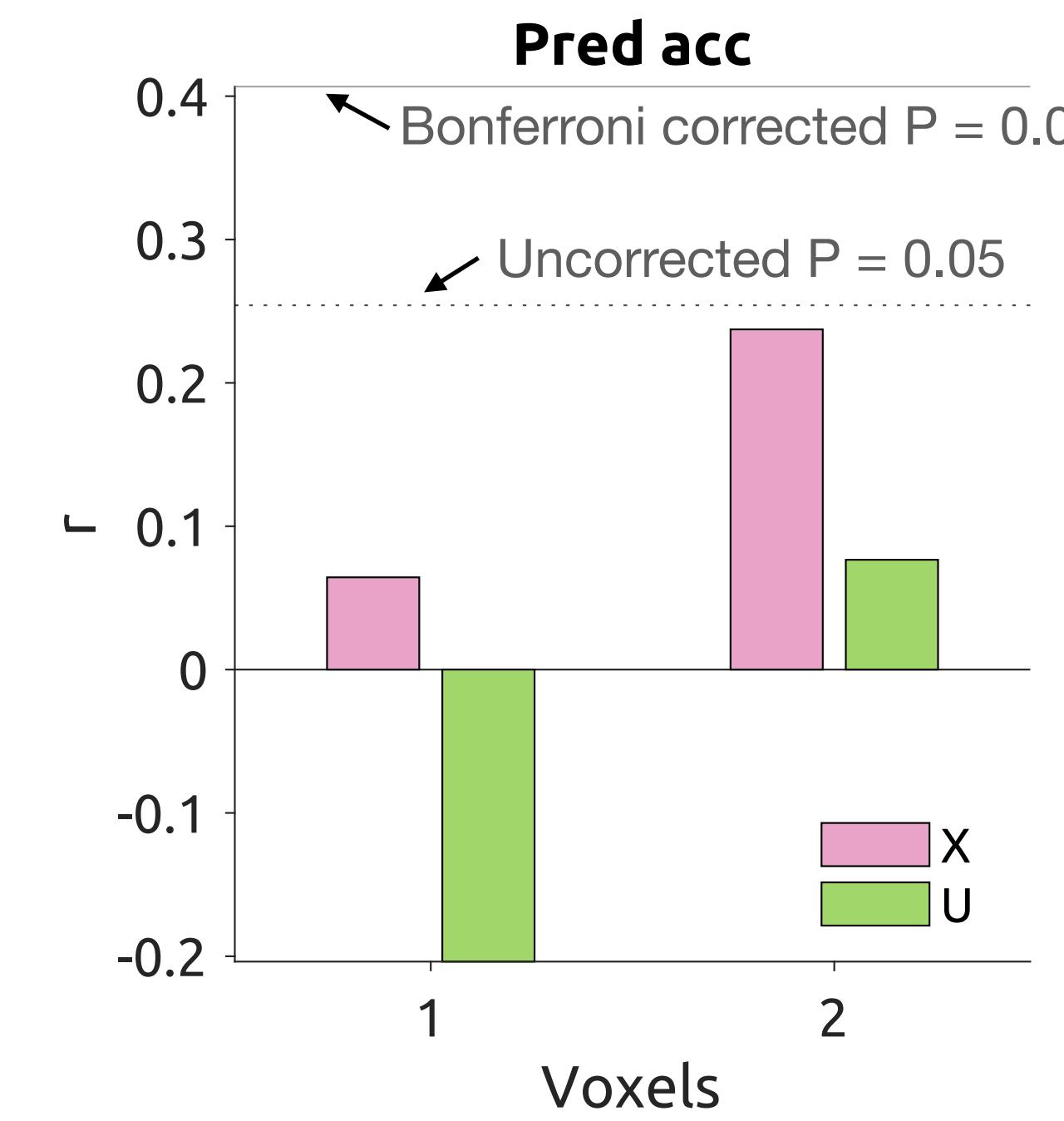
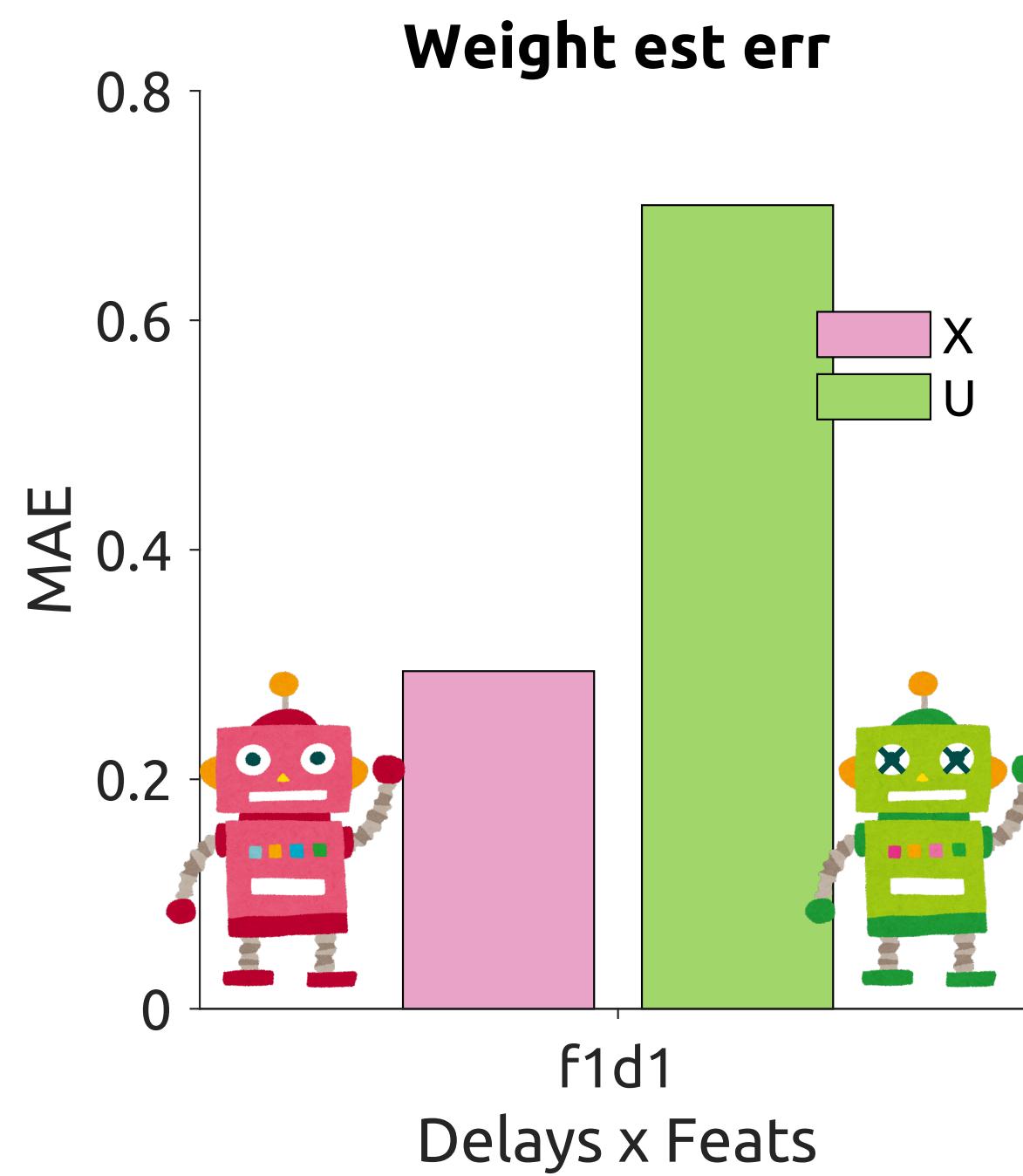
Prediction performances | #Sims = 100

MAE: mean absolute error; r: Pearson correlation



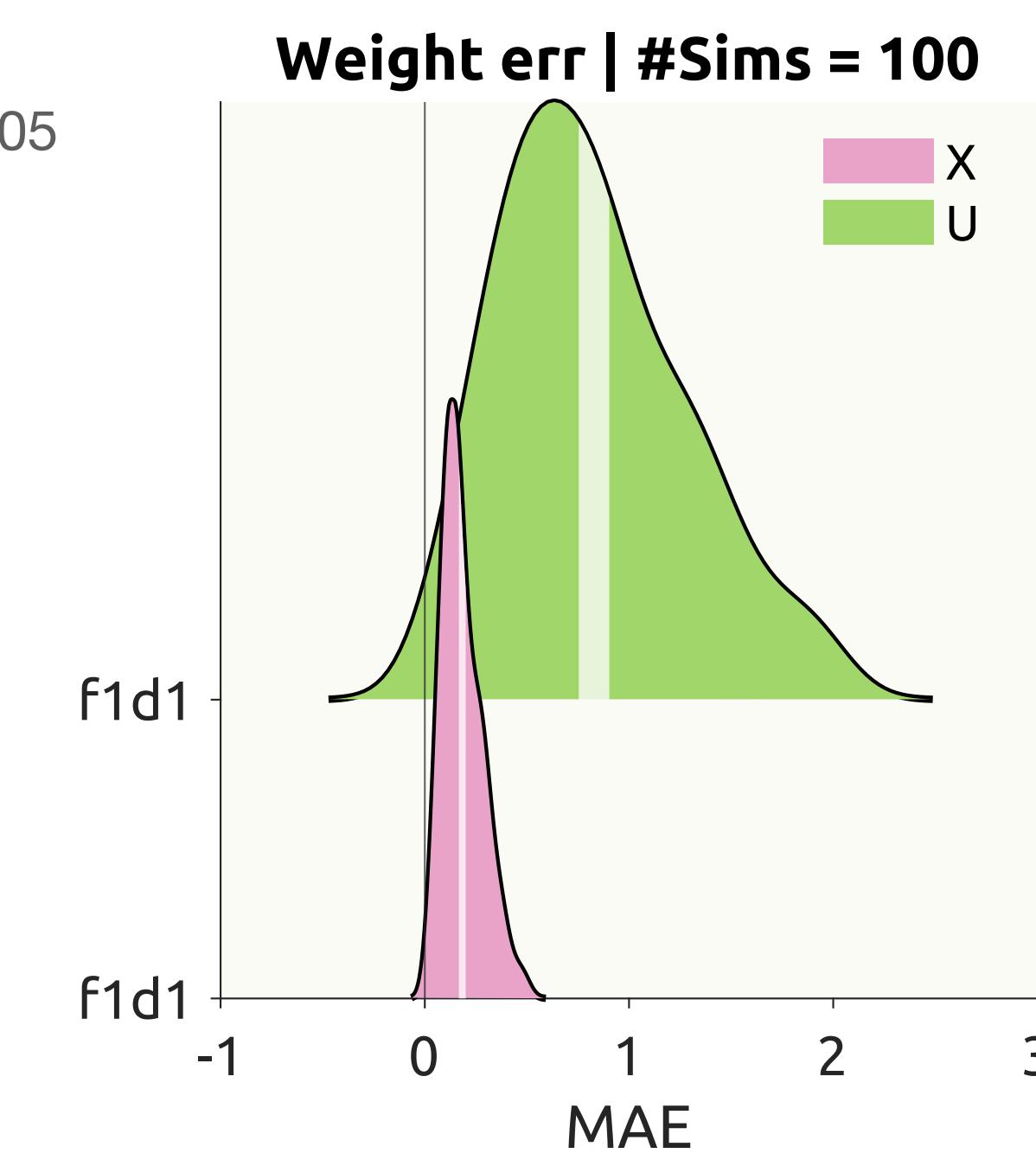
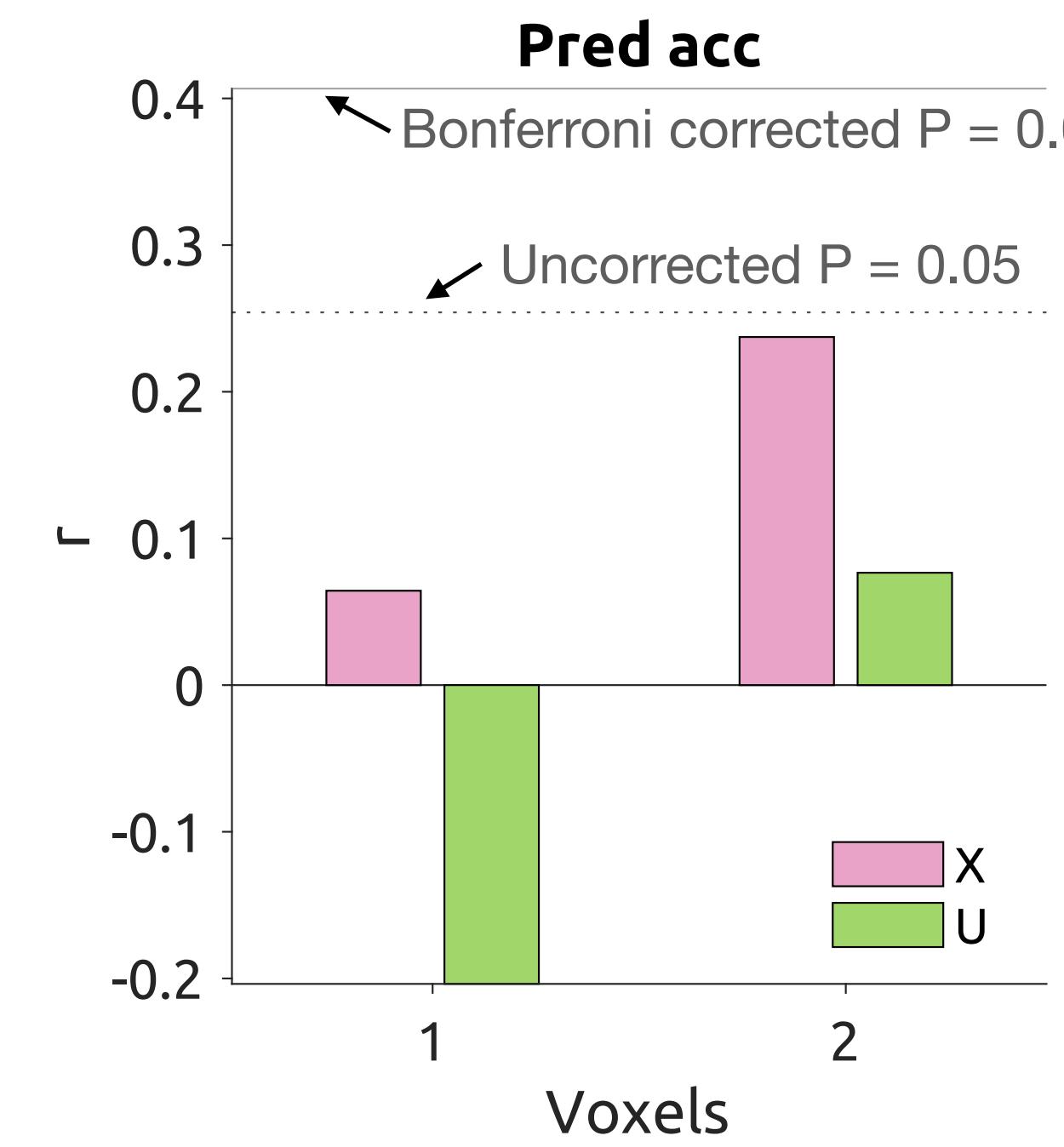
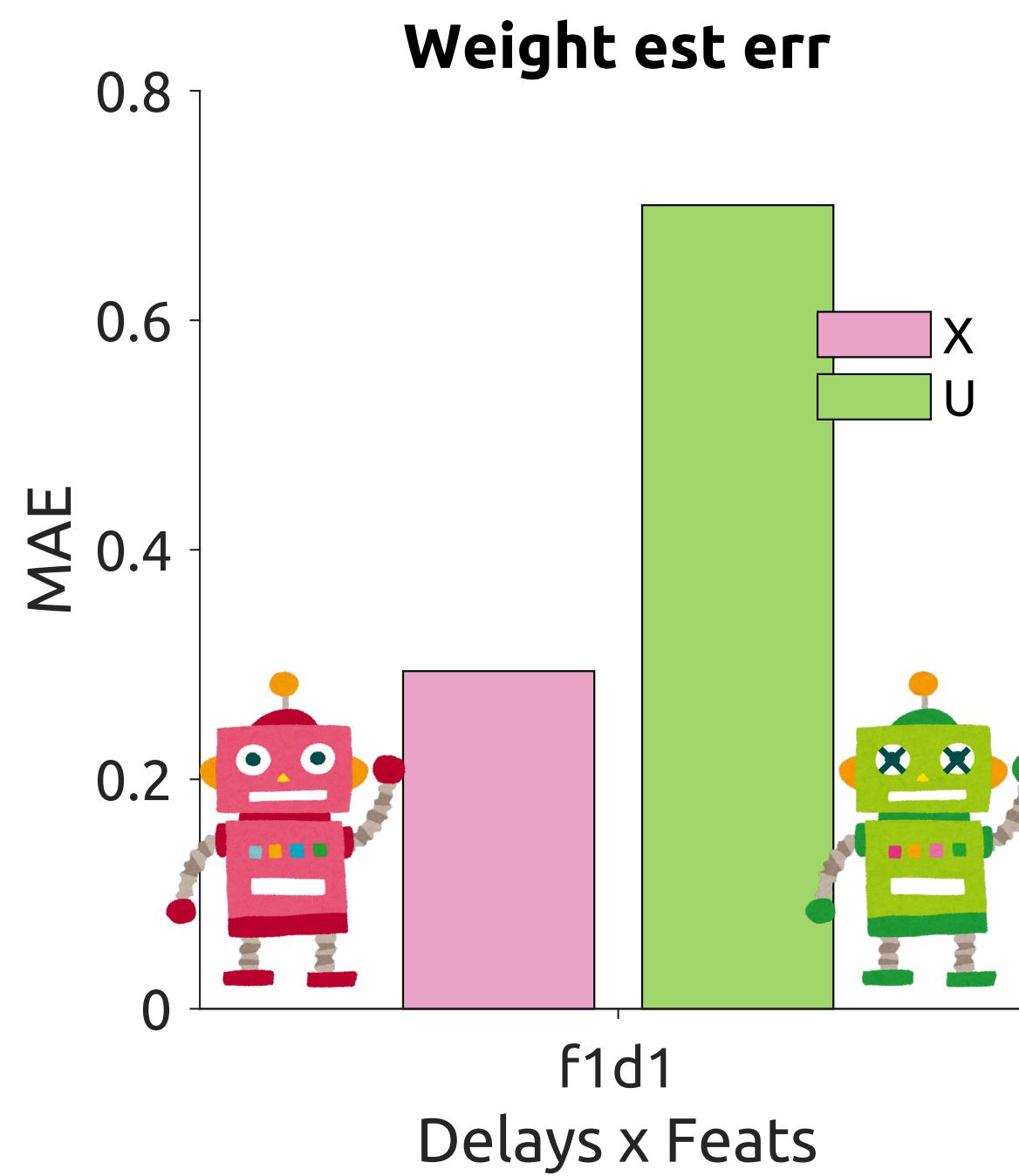
Prediction performances | #Sims = 100

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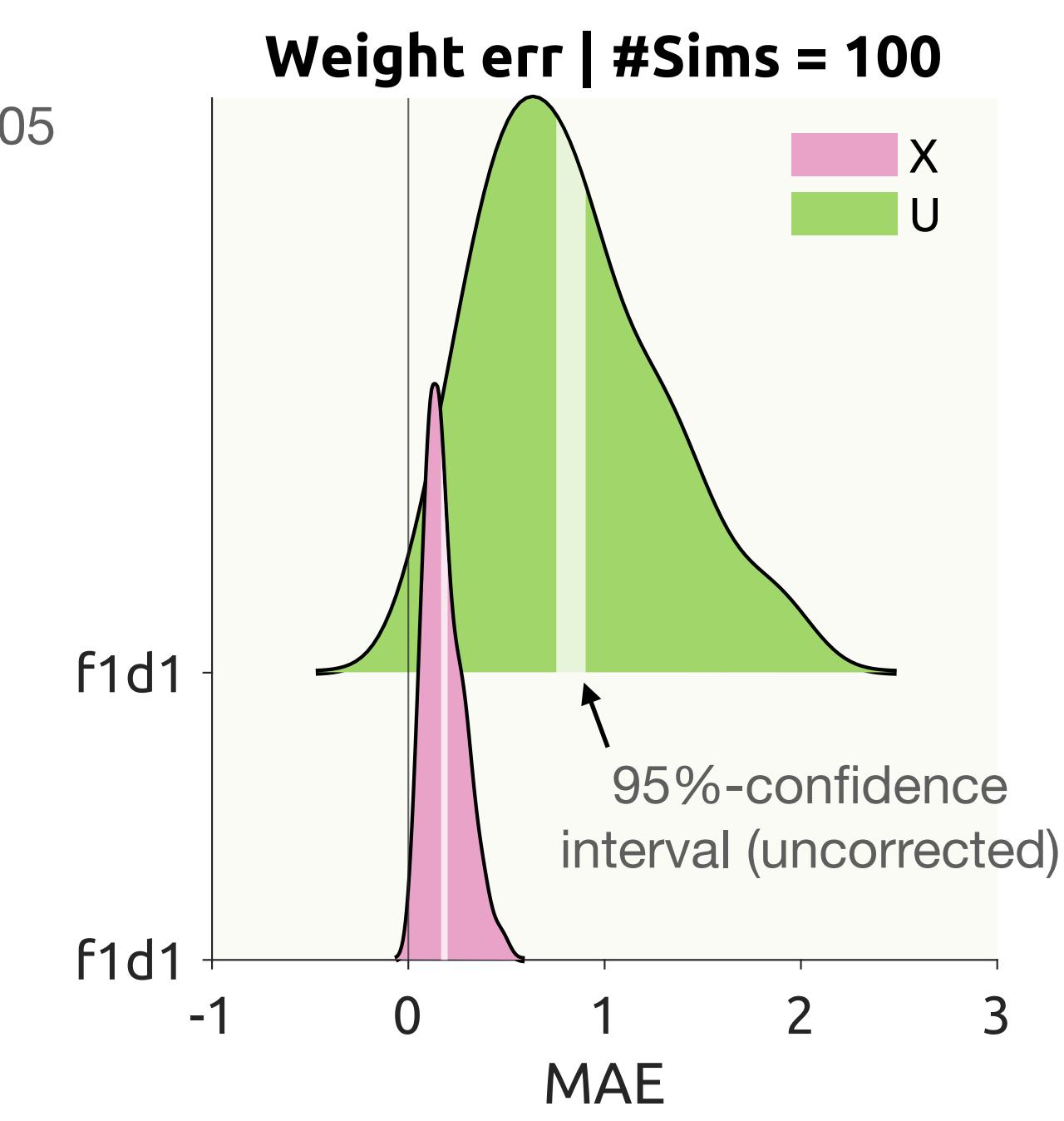
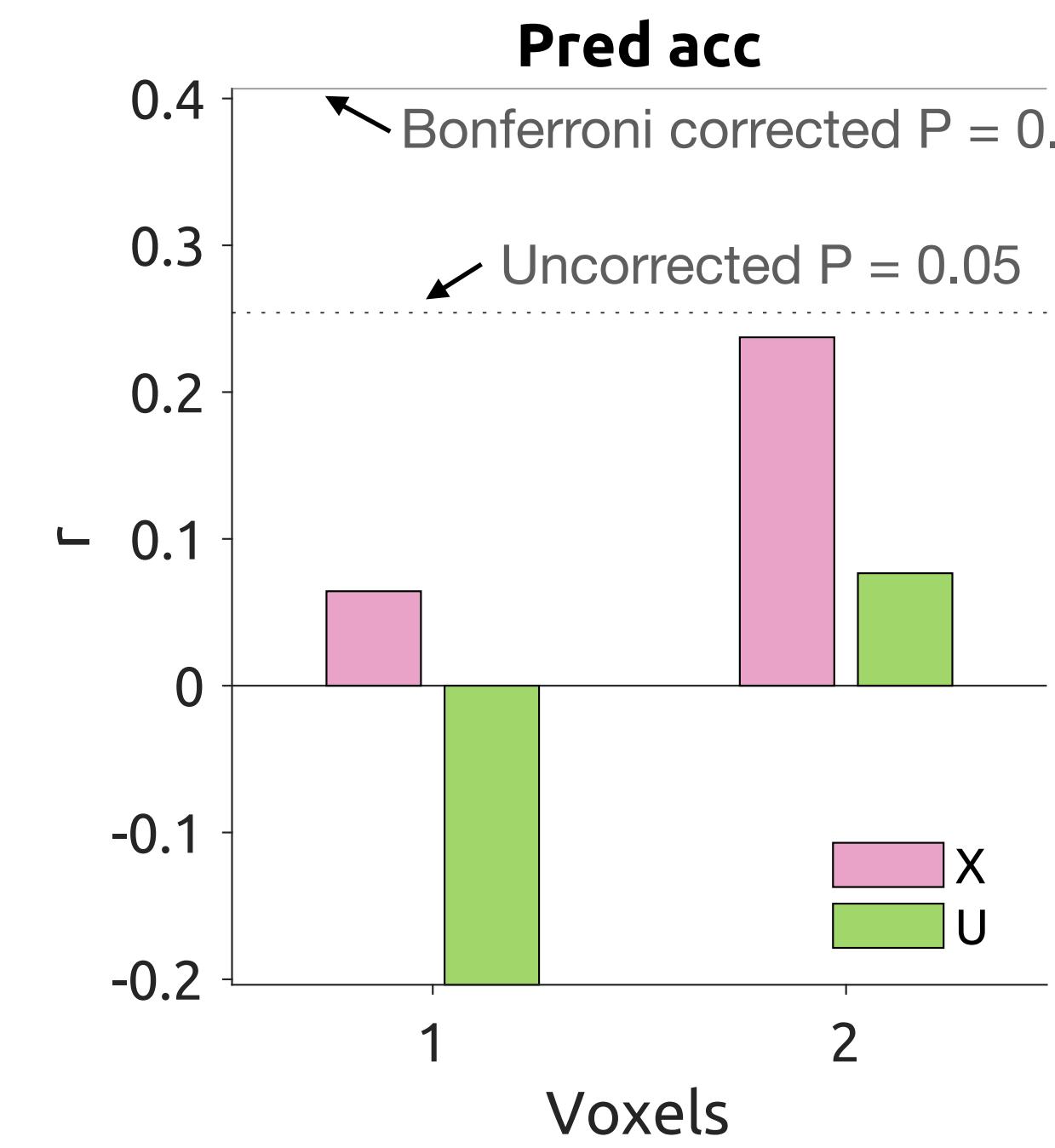
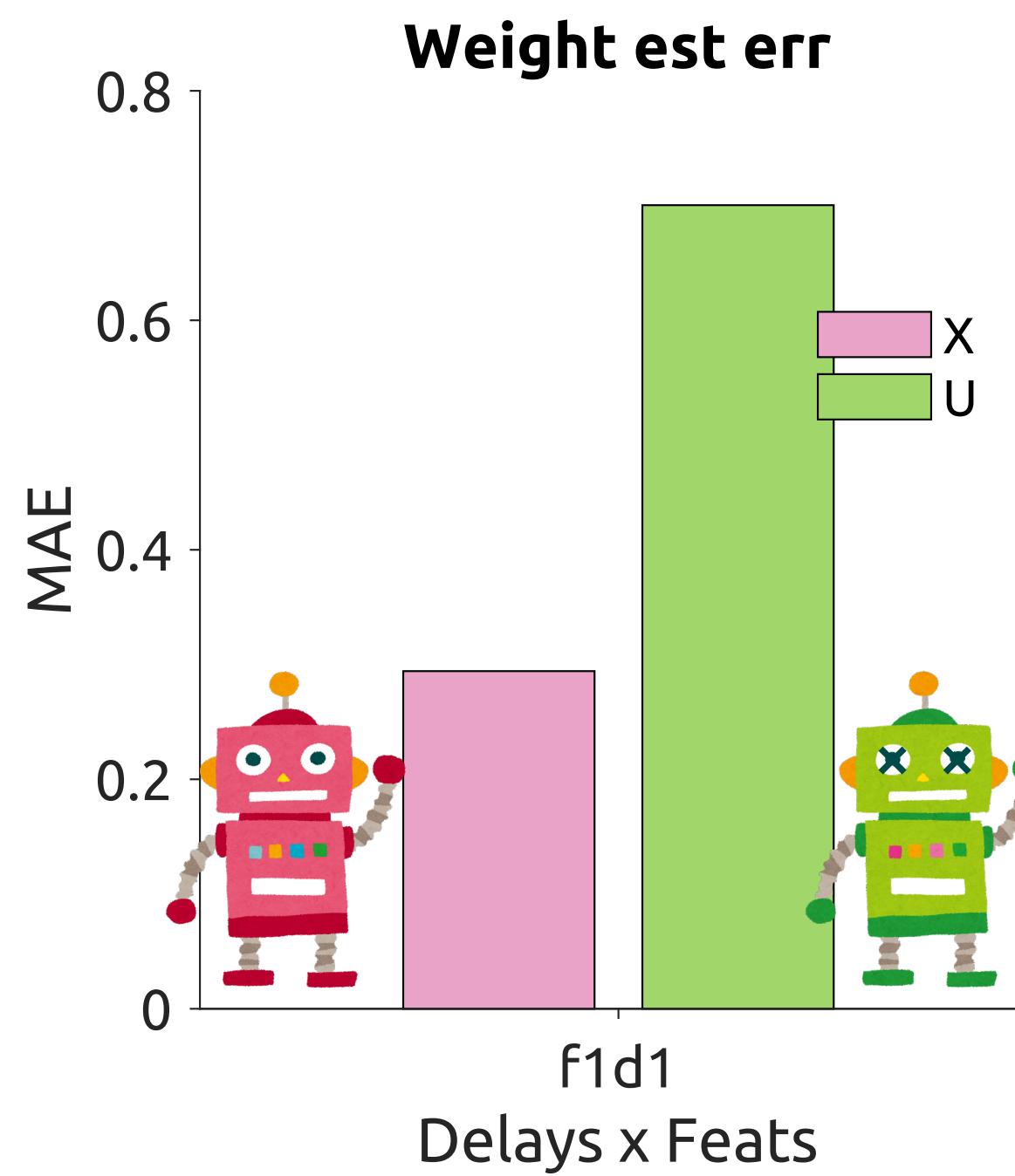
Prediction performances | #Sims = 100

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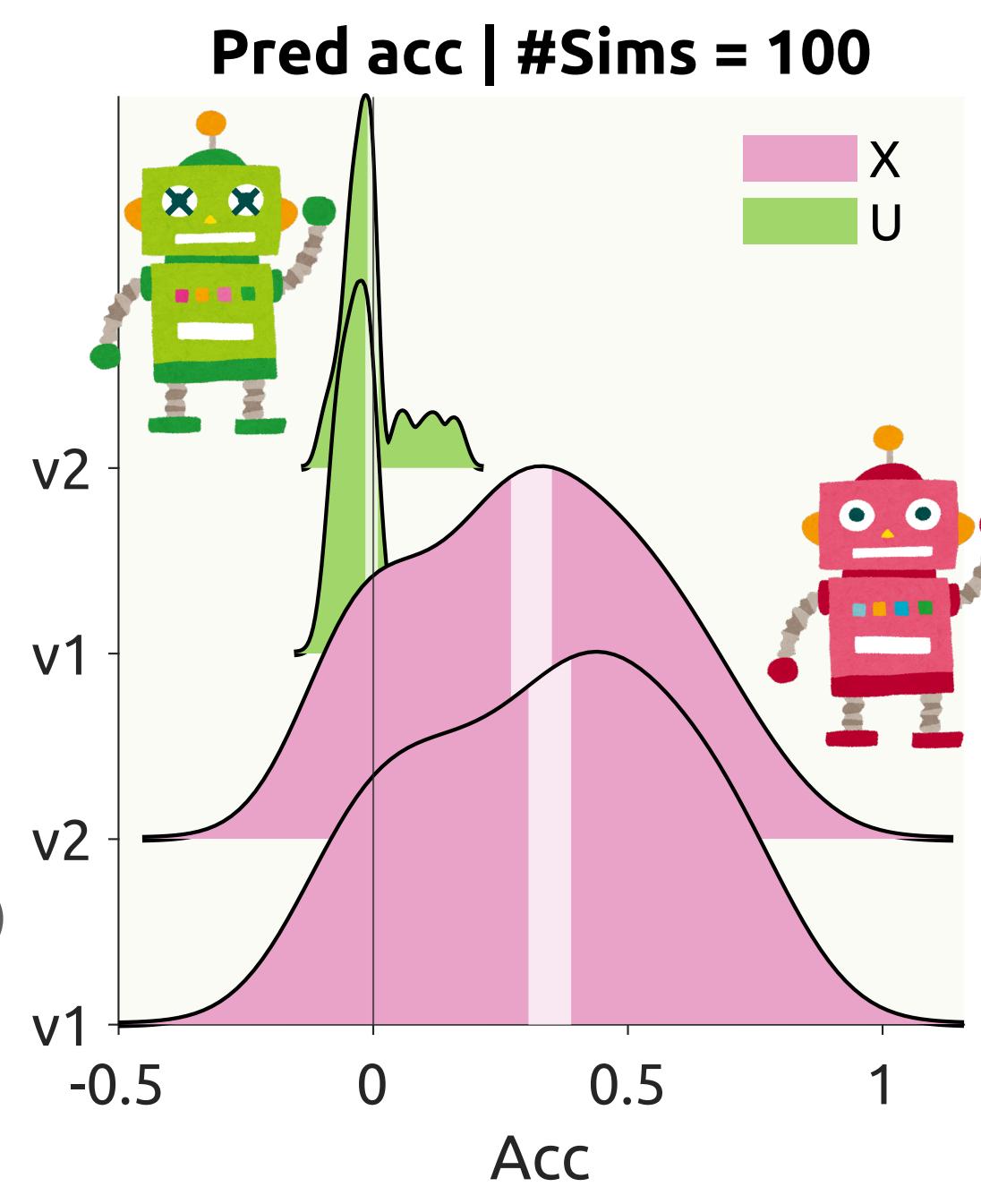
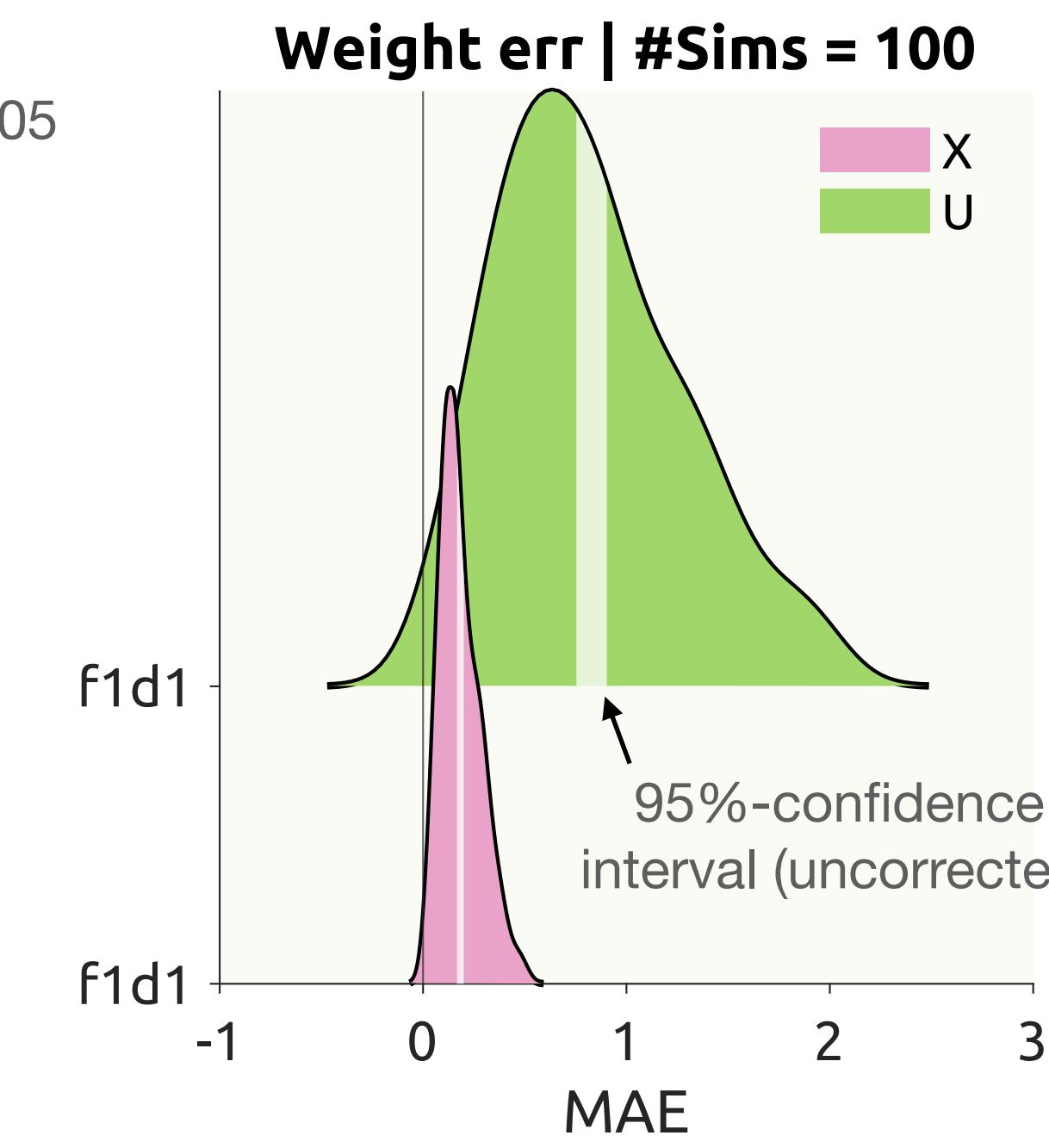
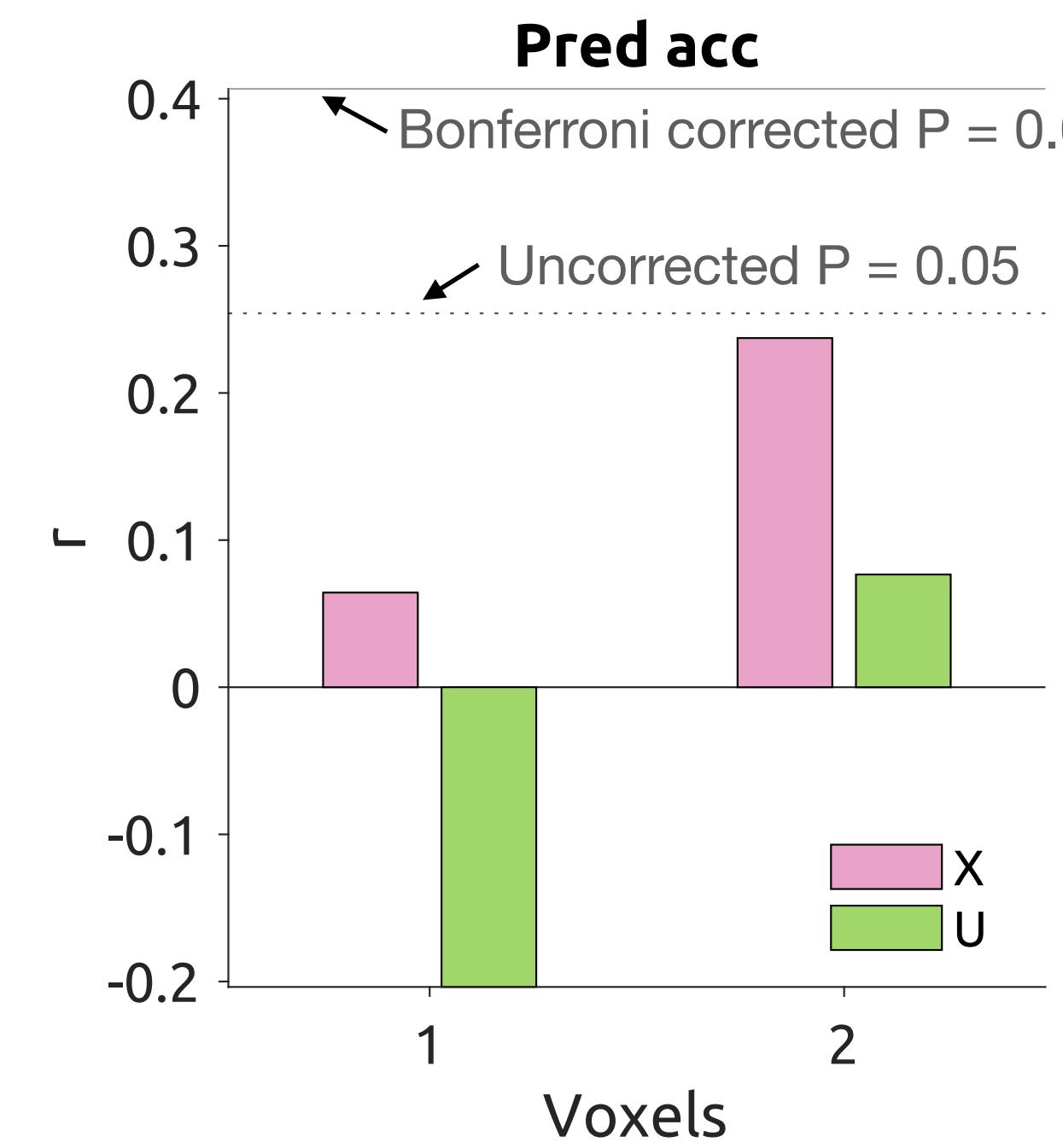
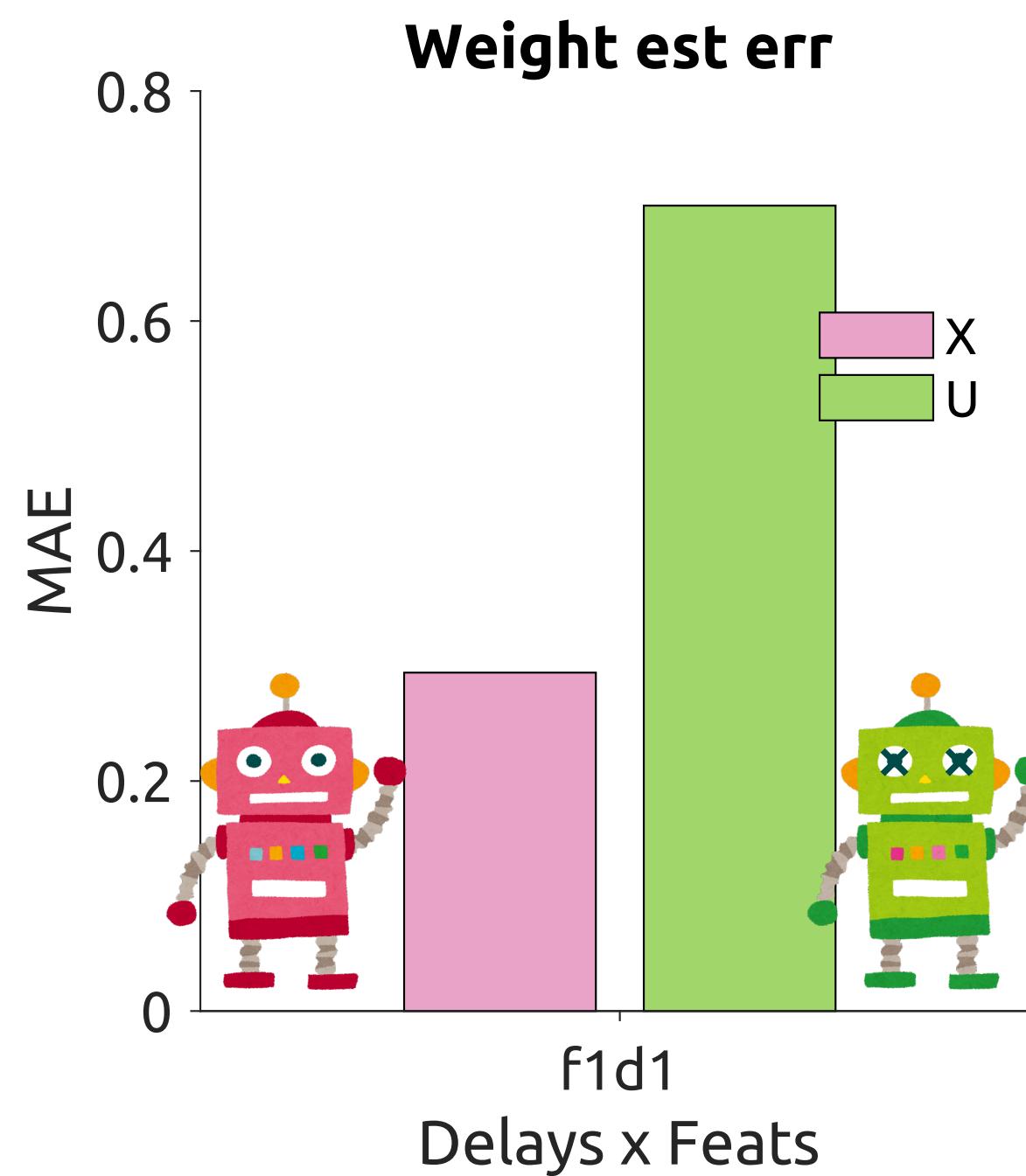
Prediction performances | #Sims = 100

MAE: mean absolute error; r: Pearson correlation

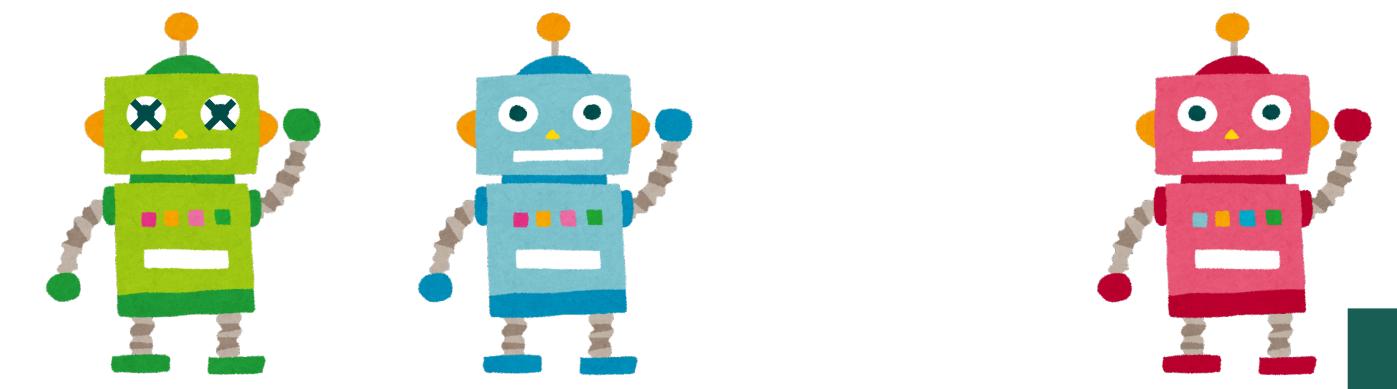


Prediction performances | #Sims = 100

MAE: mean absolute error; r: Pearson correlation

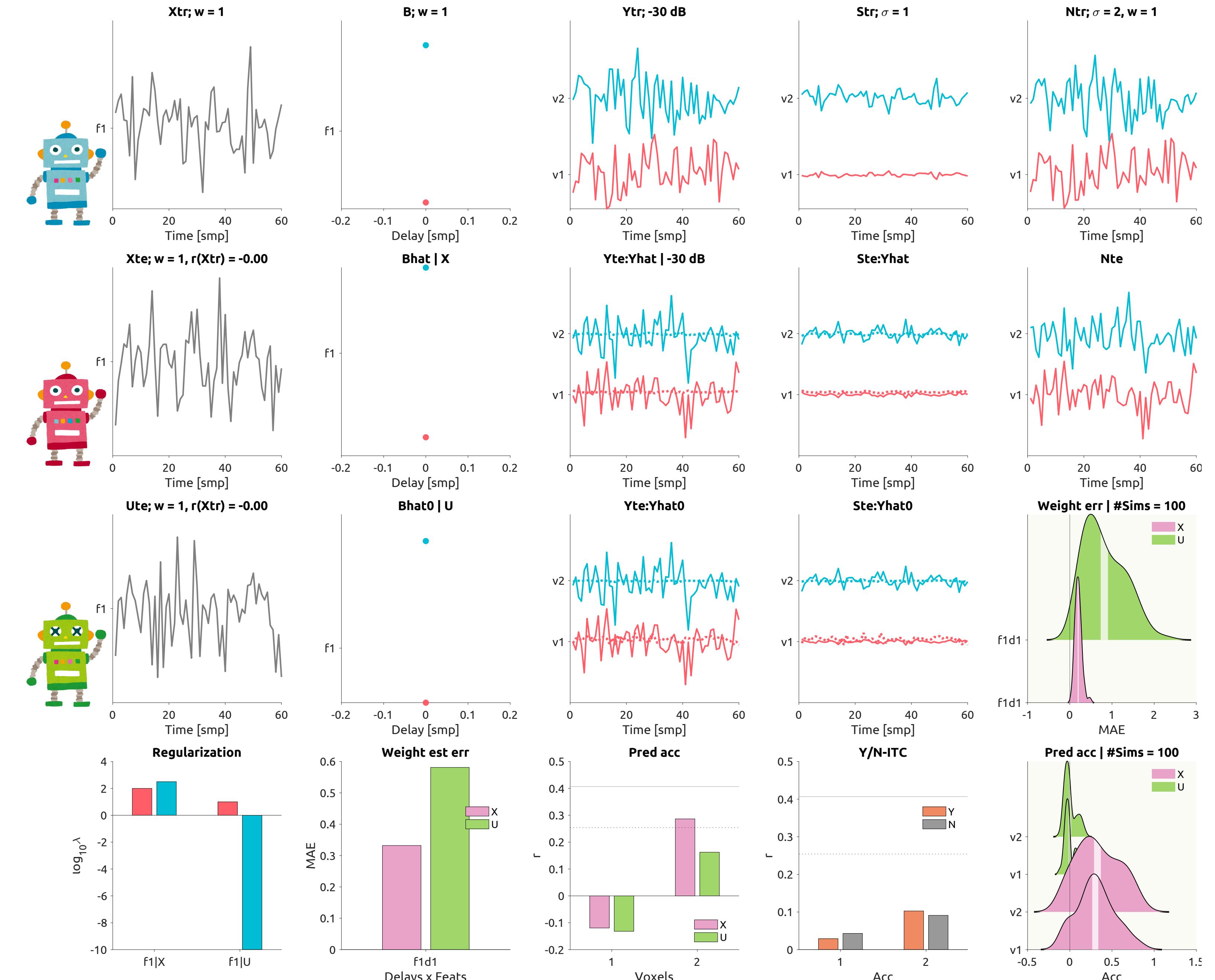


So far so good?



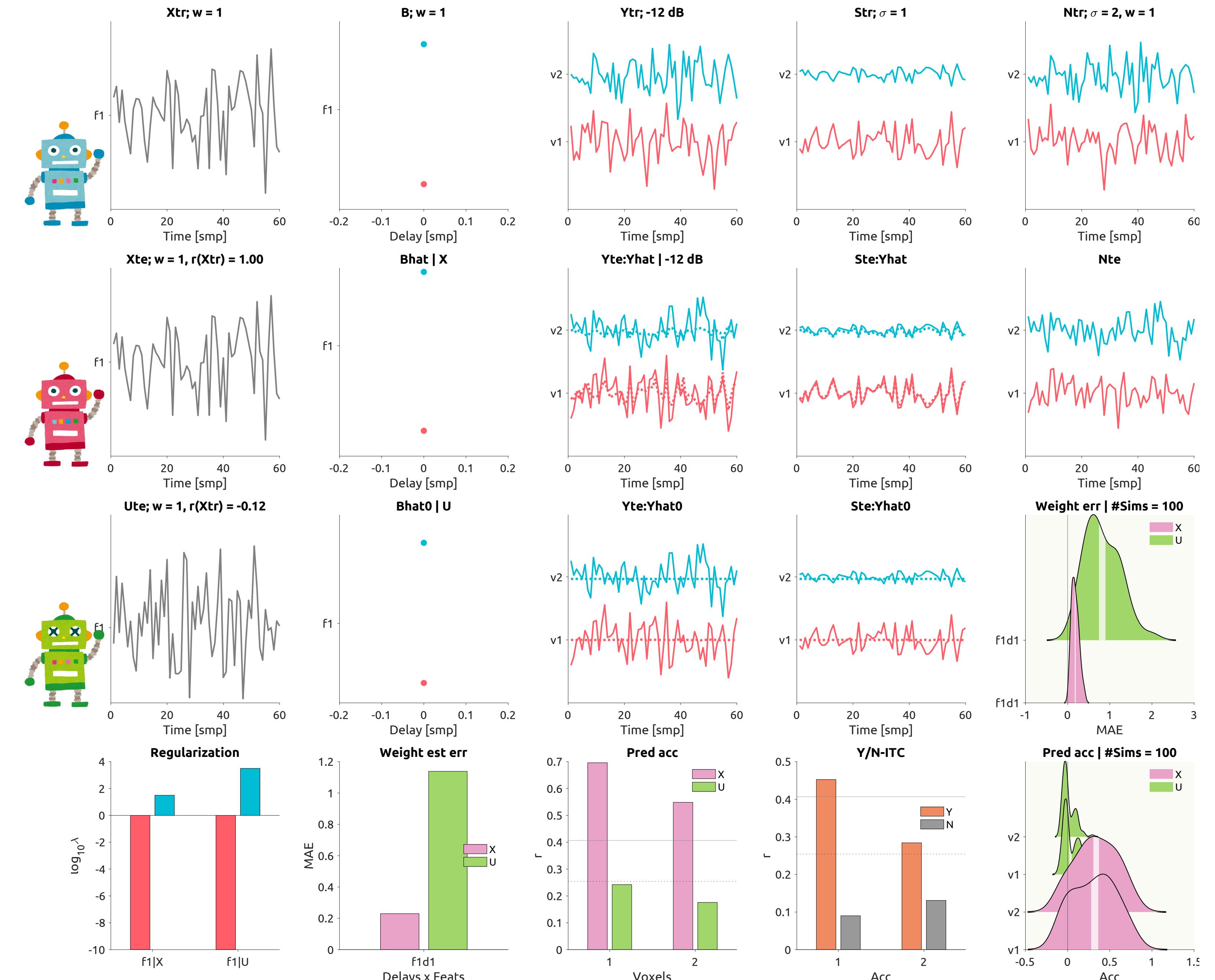
Simulation A0

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



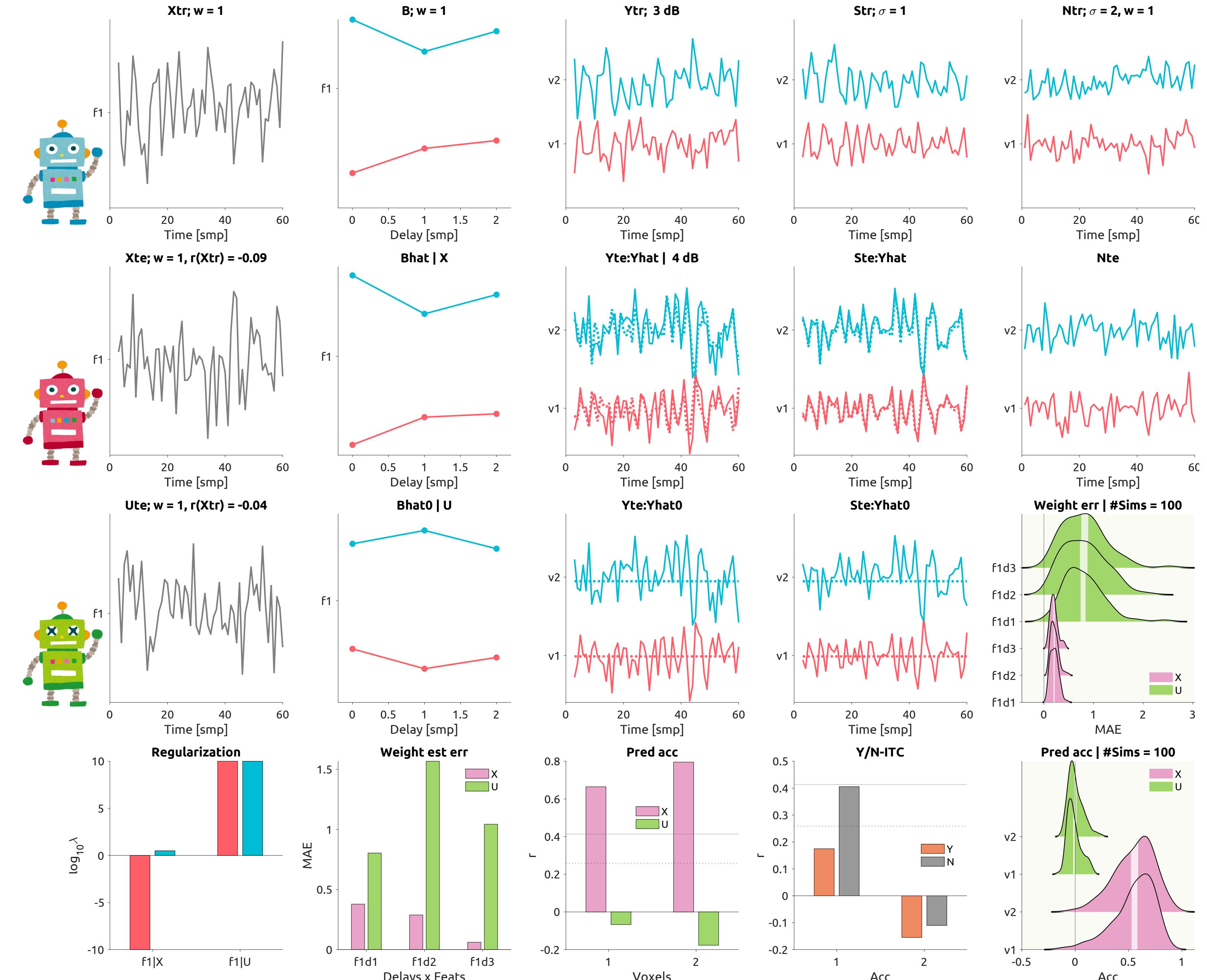
Simulation A1

- #Timepoints = 60
- #Voxels = 2
- #Features = 1
- #Delays = 1 | delay = [0]
- $\sigma[\text{noise}] = 2$
- Feature smoothness = 1
- Weight smoothness = 1
- Noise smoothness = 1
- **Repeated stimulus**



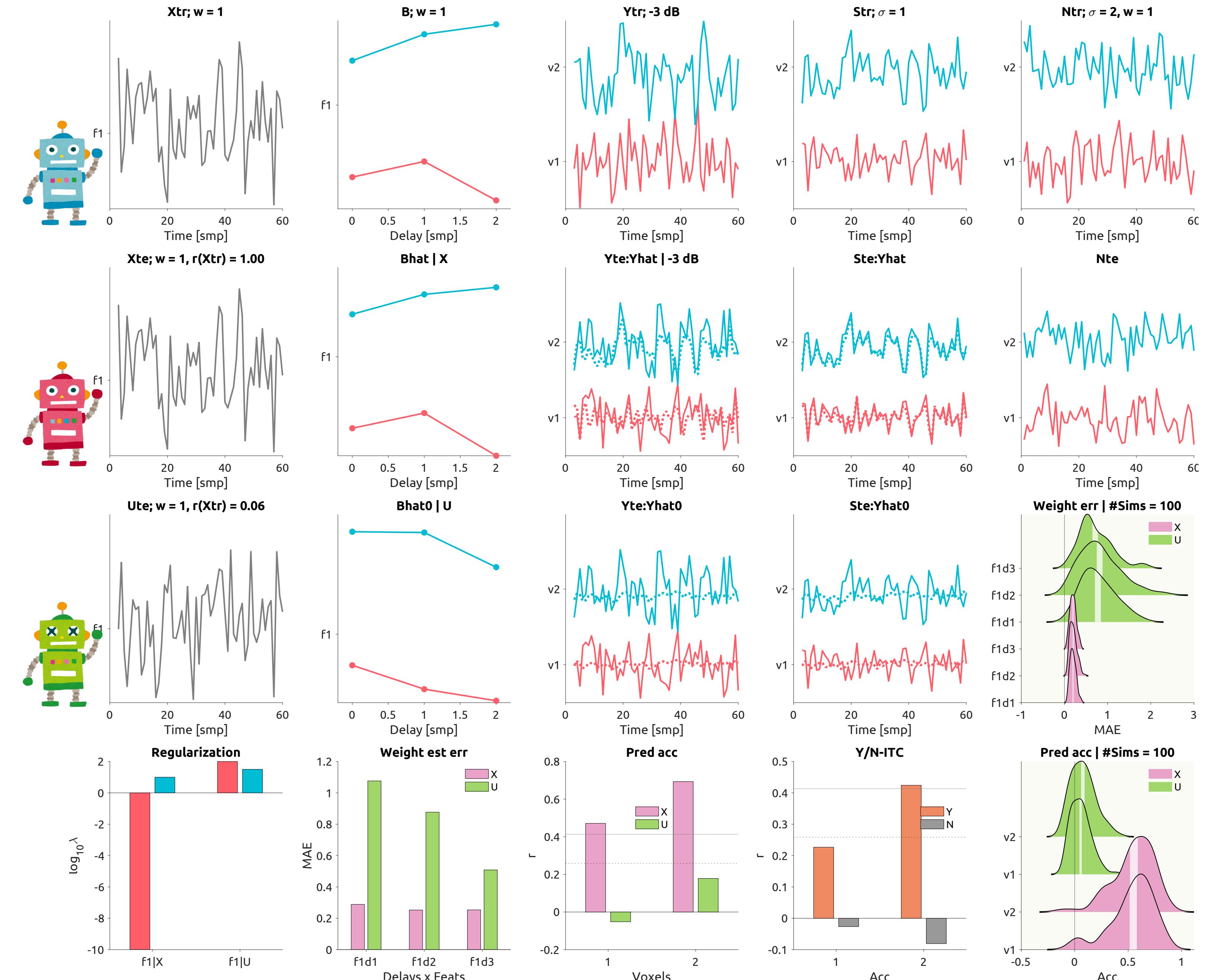
Simulation B0

- #Timepoints = 60
- #Voxels = 2
- #Features = 1
- #Delays = 3 | [0,1,2]
- $\sigma[\text{noise}] = 2$
- Feature smoothness = 1
- Weight smoothness = 1
- Noise smoothness = 1
- Independent stimuli



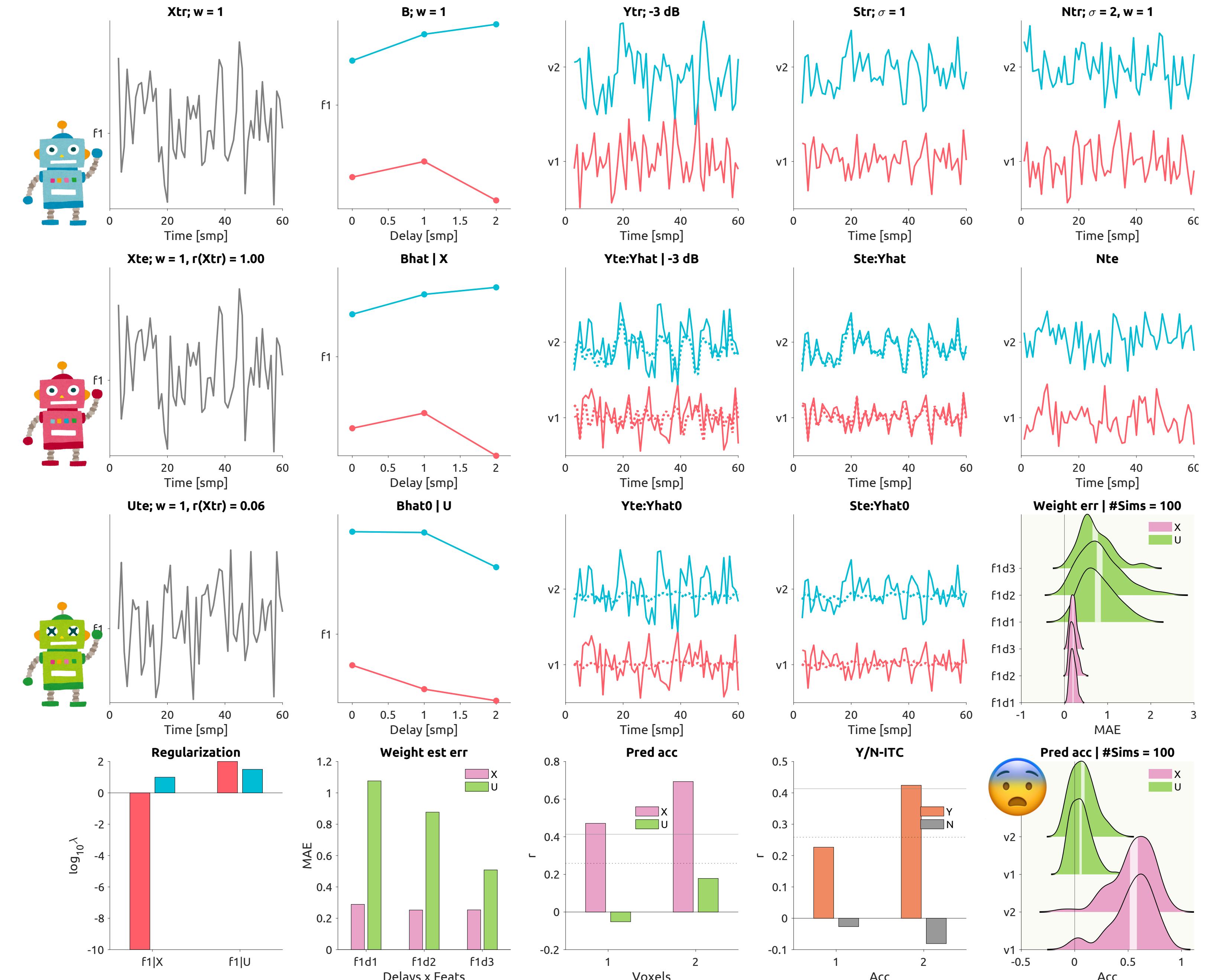
Simulation B1

- #Timepoints = 60
- #Voxels = 2
- #Features = 1
- #Delays = 3 | [0,1,2]
- $\sigma[\text{noise}] = 2$
- Feature smoothness = 1
- Weight smoothness = 1
- Noise smoothness = 1
- **Repeated stimulus**



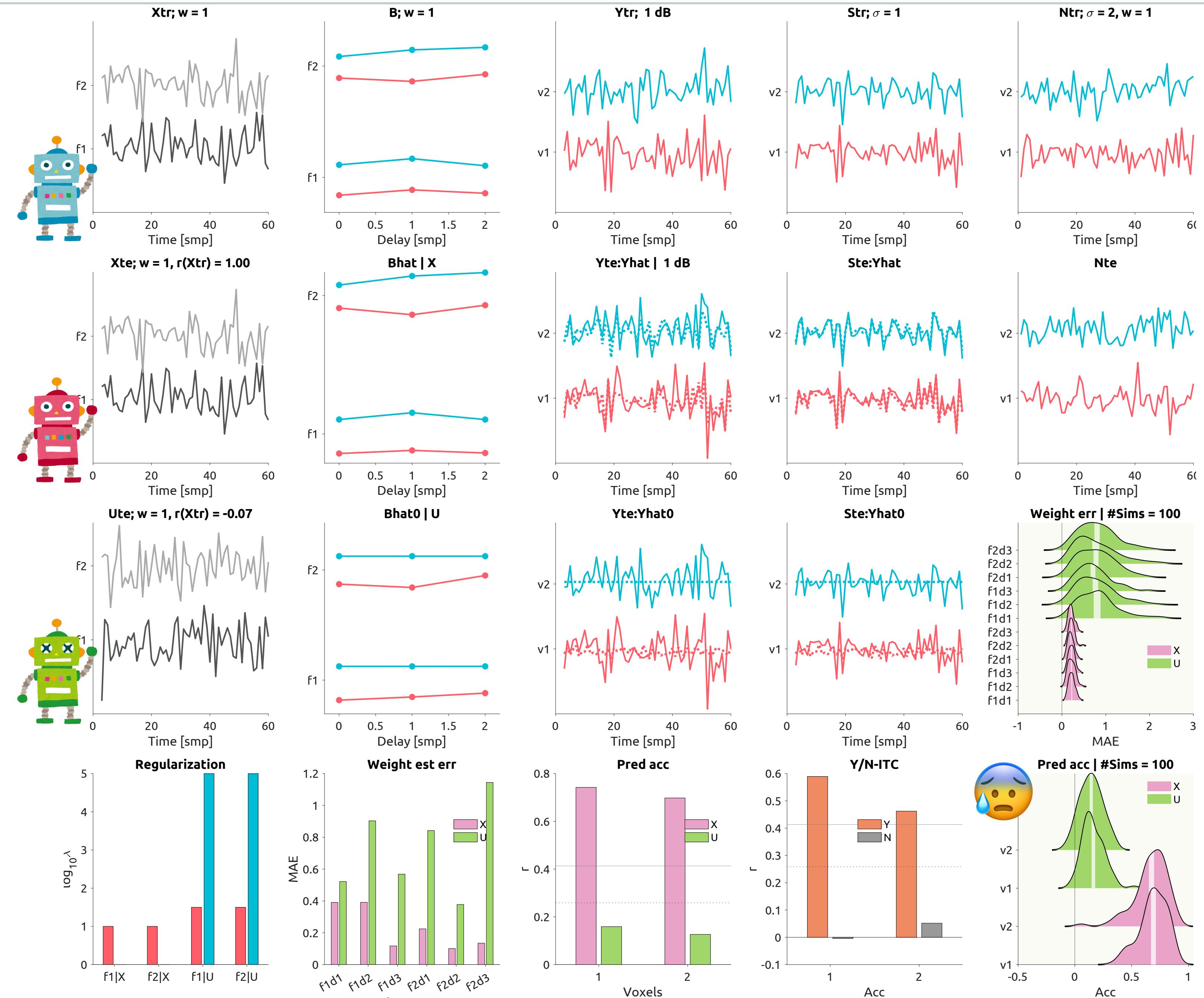
Simulation B1

- #Timepoints = 60
- #Voxels = 2
- #Features = 1
- #Delays = 3 | [0,1,2]
- $\sigma[\text{noise}] = 2$
- Feature smoothness = 1
- Weight smoothness = 1
- Noise smoothness = 1
- **Repeated stimulus**



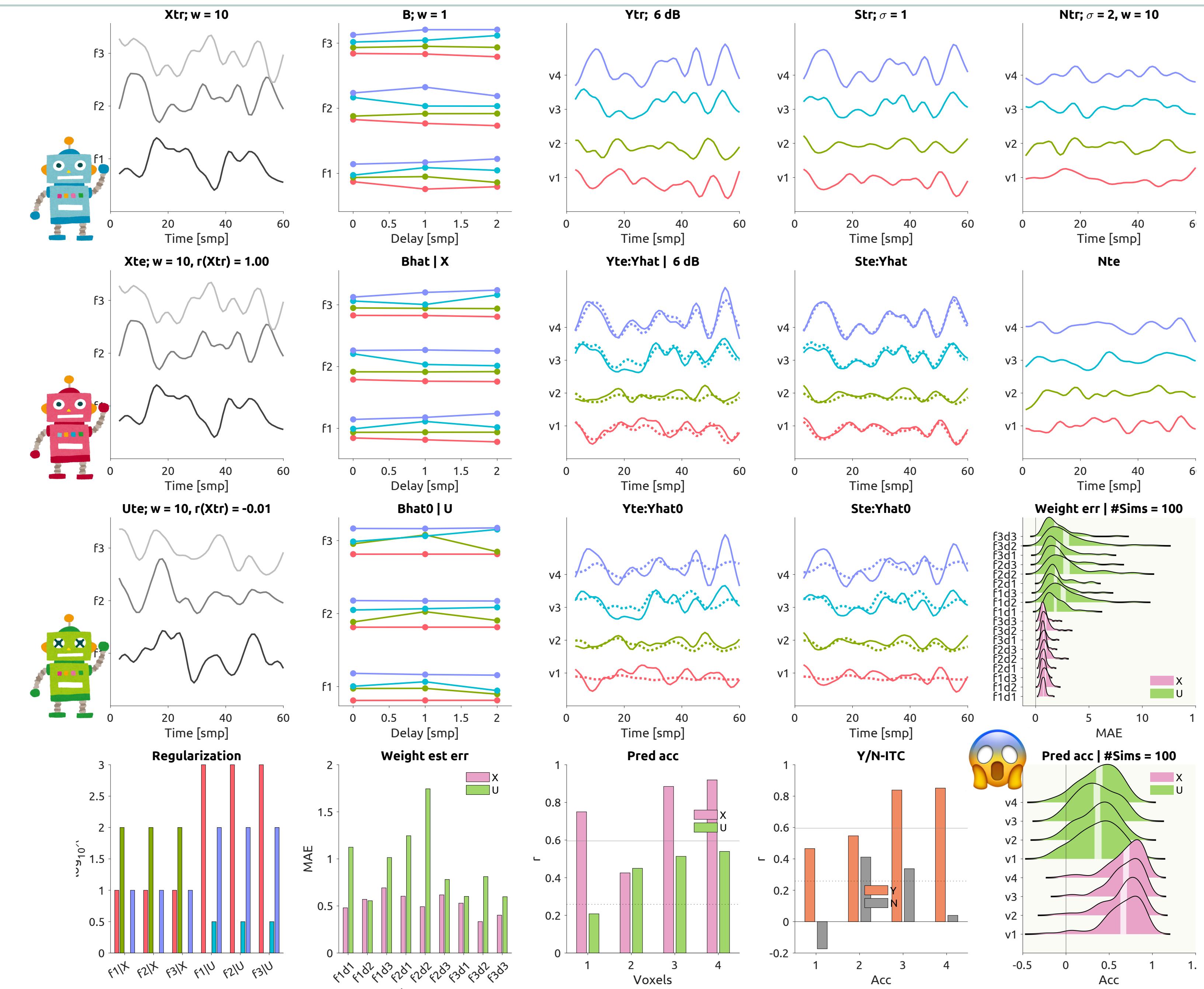
Simulation C1

- #Timepoints = 60
- #Voxels = 2
- #Features = 2
- #Delays = 3 | [0,1,2]
- $\sigma[\text{noise}] = 2$
- Feature smoothness = 1
- Weight smoothness = 1
- Noise smoothness = 1
- **Repeated stimulus**



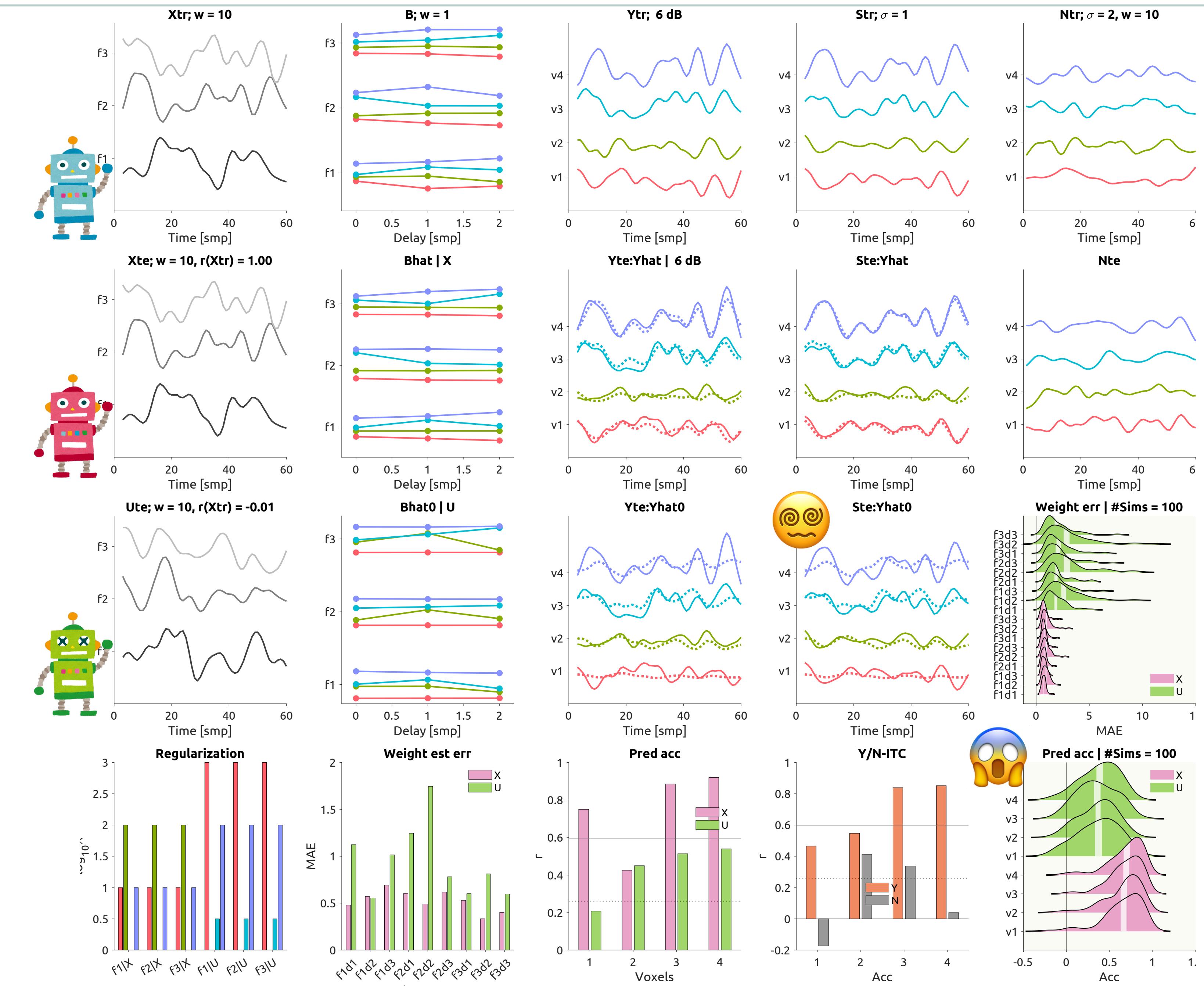
Simulation D1

- #Timepoints = 60
- #Voxels = 4
- #Features = 3
- #Delays = 3 | [0,1,2]
- $\sigma[\text{noise}] = 2$
- Feature smoothness = 10
- Weight smoothness = 10
- Noise smoothness = 10
- Repeated stimulus



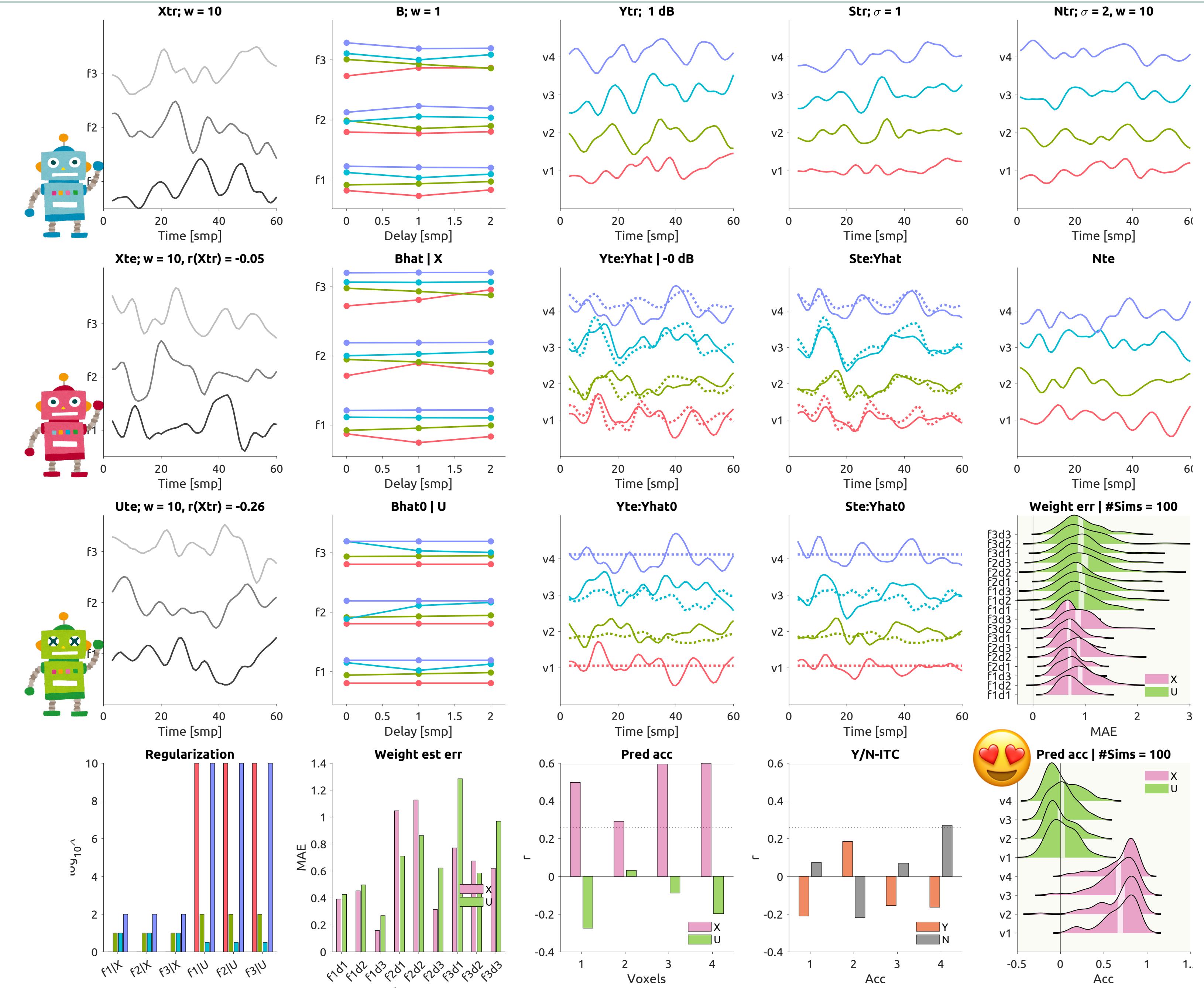
Simulation D1

- #Timepoints = 60
- #Voxels = 4
- #Features = 3
- #Delays = 3 | [0,1,2]
- $\sigma[\text{noise}] = 2$
- Feature smoothness = 10
- Weight smoothness = 10
- Noise smoothness = 10
- Repeated stimulus



Simulation D0

- #Timepoints = 60
- #Voxels = 4
- #Features = 3
- #Delays = 3 | [0,1,2]
- $\sigma[\text{noise}] = 2$
- Feature smoothness = 10
- Weight smoothness = 10
- Noise smoothness = 10
- Independent stimuli

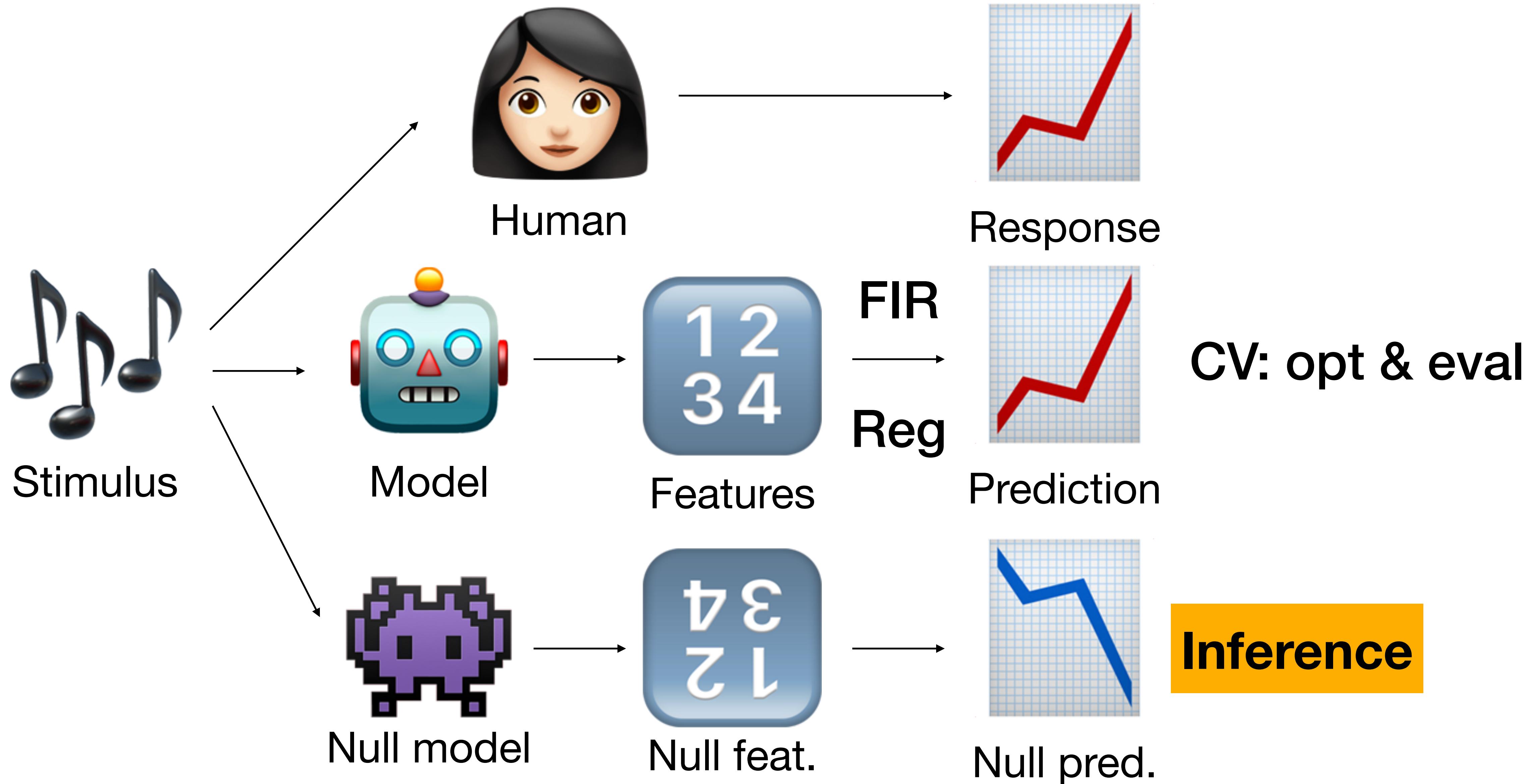


Summary [3/4]: Cross-validation

Nested cross-validation

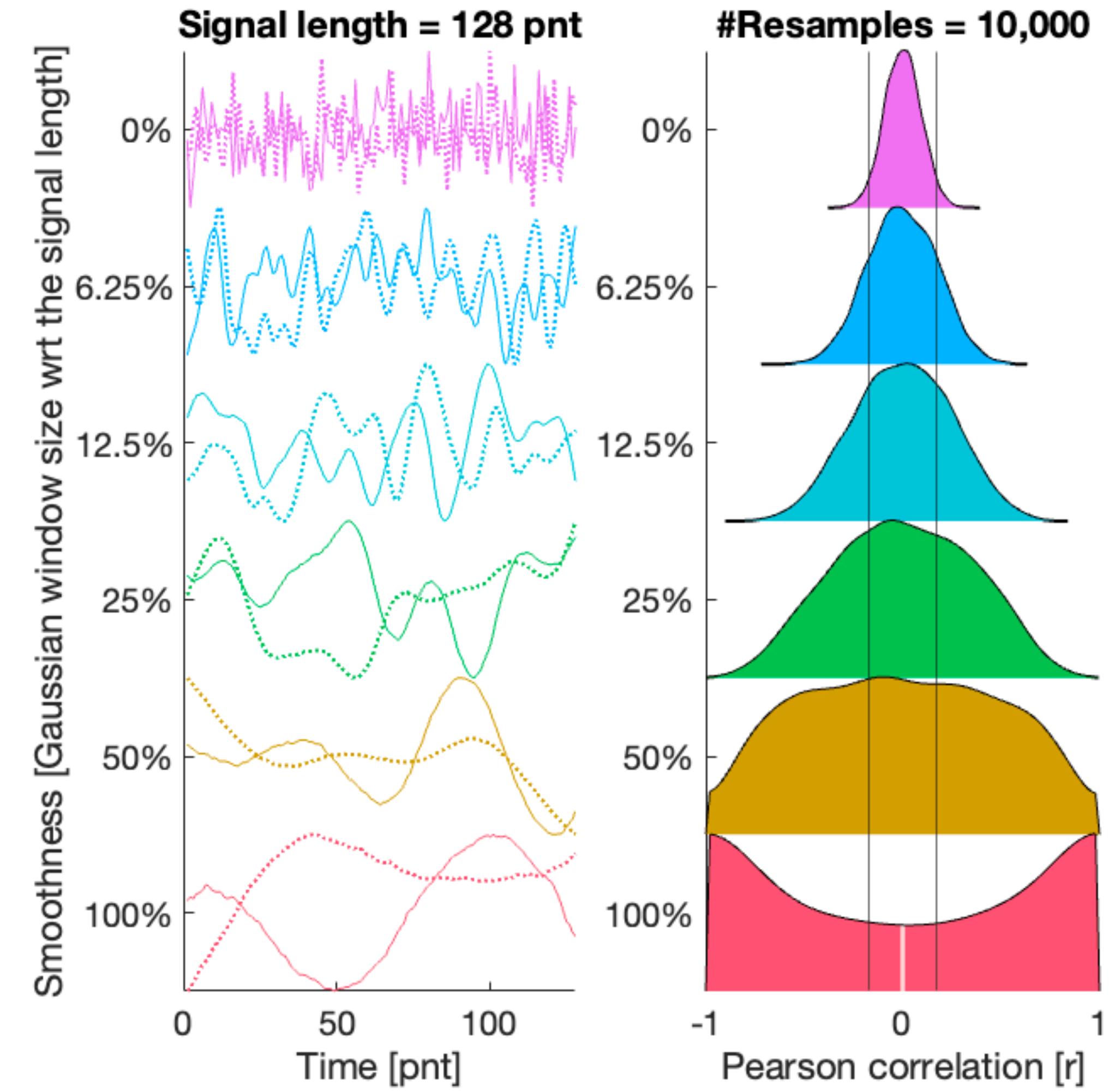
- We use an **outer** CV to evaluate the **generalizability** of a model.
- We use an **inner** CV to optimize the **hyperparameters** of a model.
- All partitions (train, optimization, and test) must be water-tightly **independent**. Otherwise, a leakage will fool you ("{:tongue_out:} my model predicts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

Linearized encoding analysis overview (HOWs)



Correlation between two time series

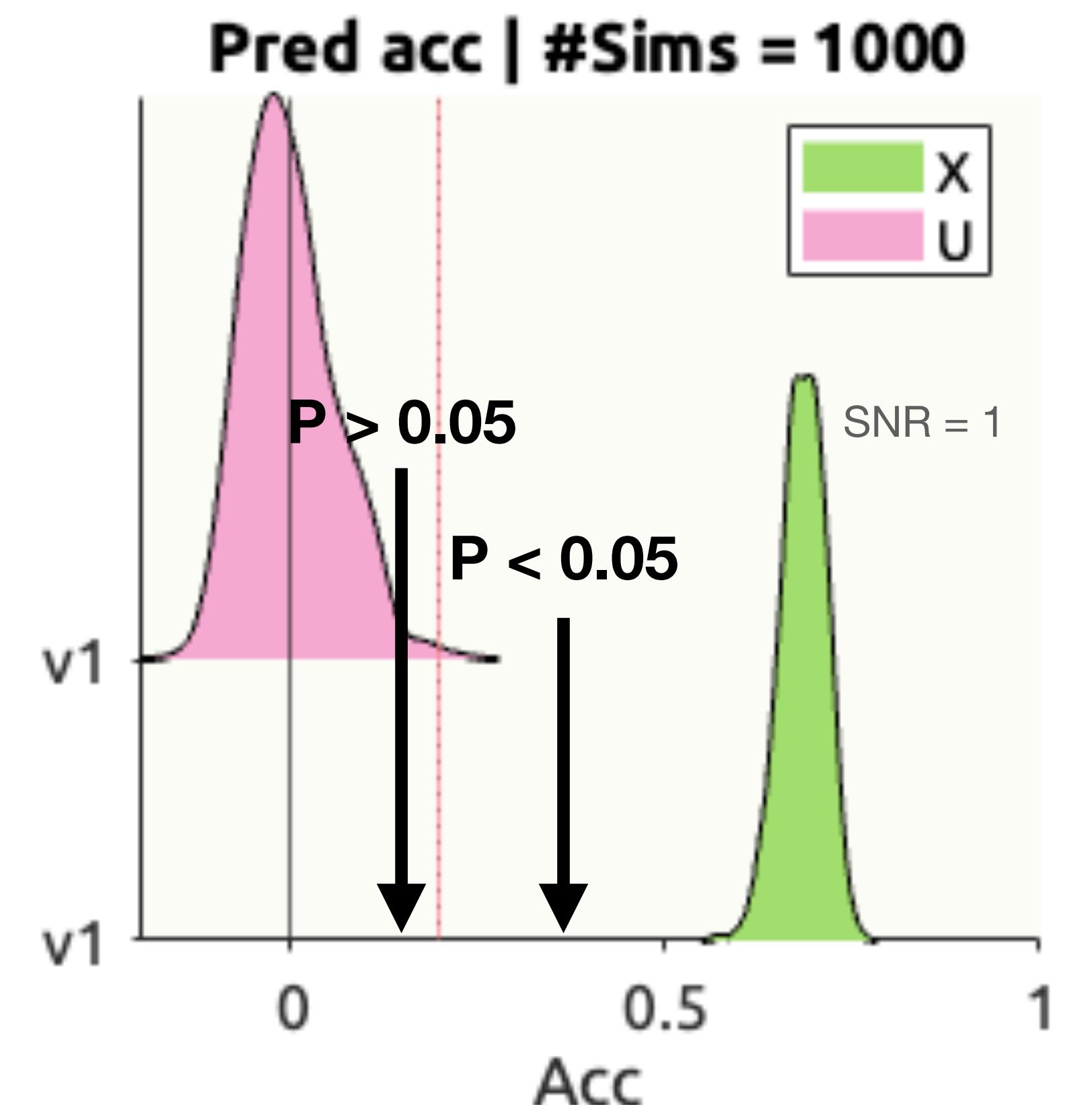
Spurious correlation in smooth (slow) time series



Noise floor & ceiling of performance

Prediction performance of time series

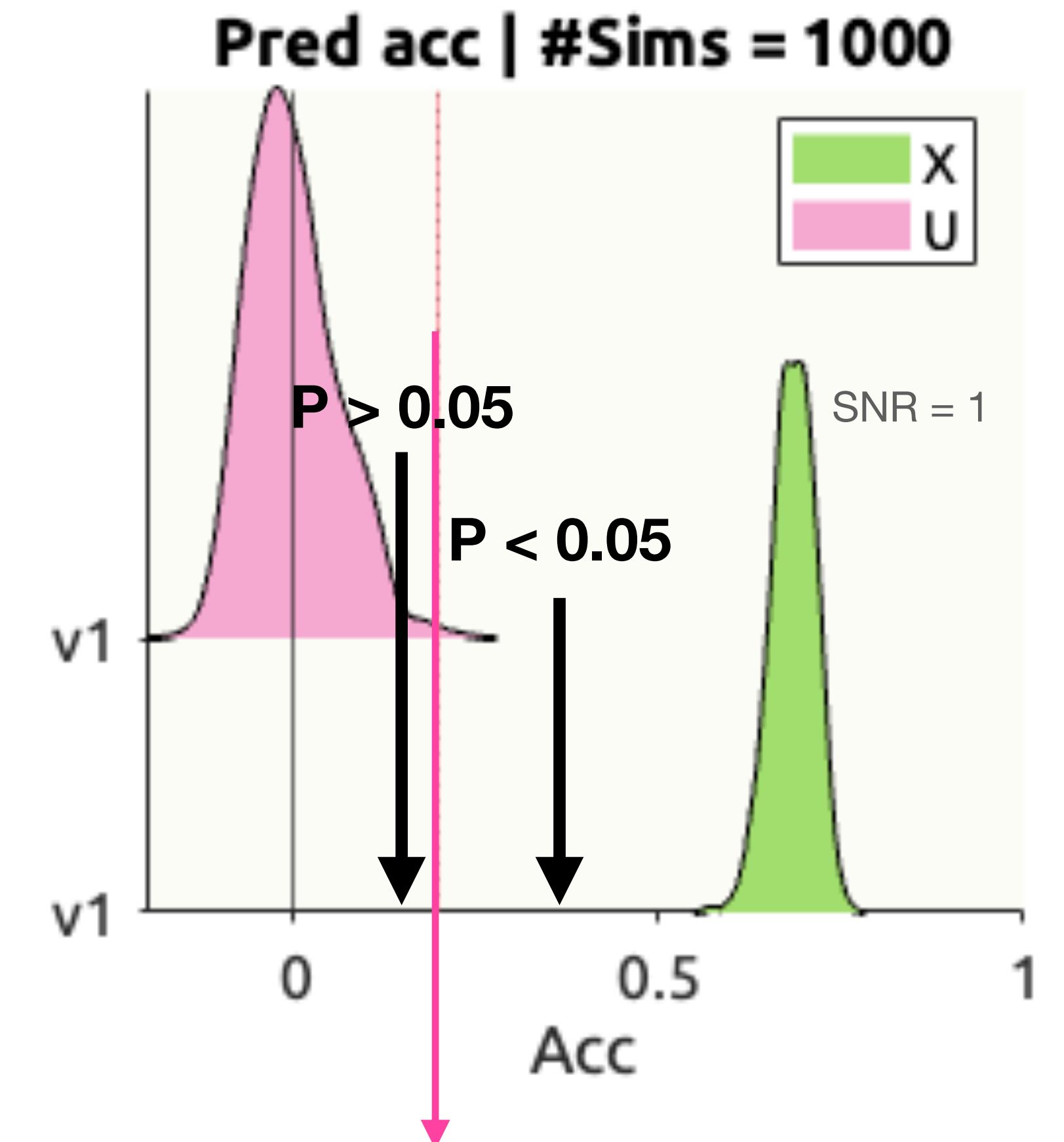
- **Noise floor:** $r_{null} > 0$ while $E(r_{null}) = 0$
- **Noise ceiling:** due to noise in the data, even with the perfect model, $E(r_{perfect}) < 1$ ("explainable variance")
- NOTE: Sometimes people use correction using the noise ceiling (i.e., 70% of the noise ceiling of $r=0.1$; that is, $r=0.07$),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



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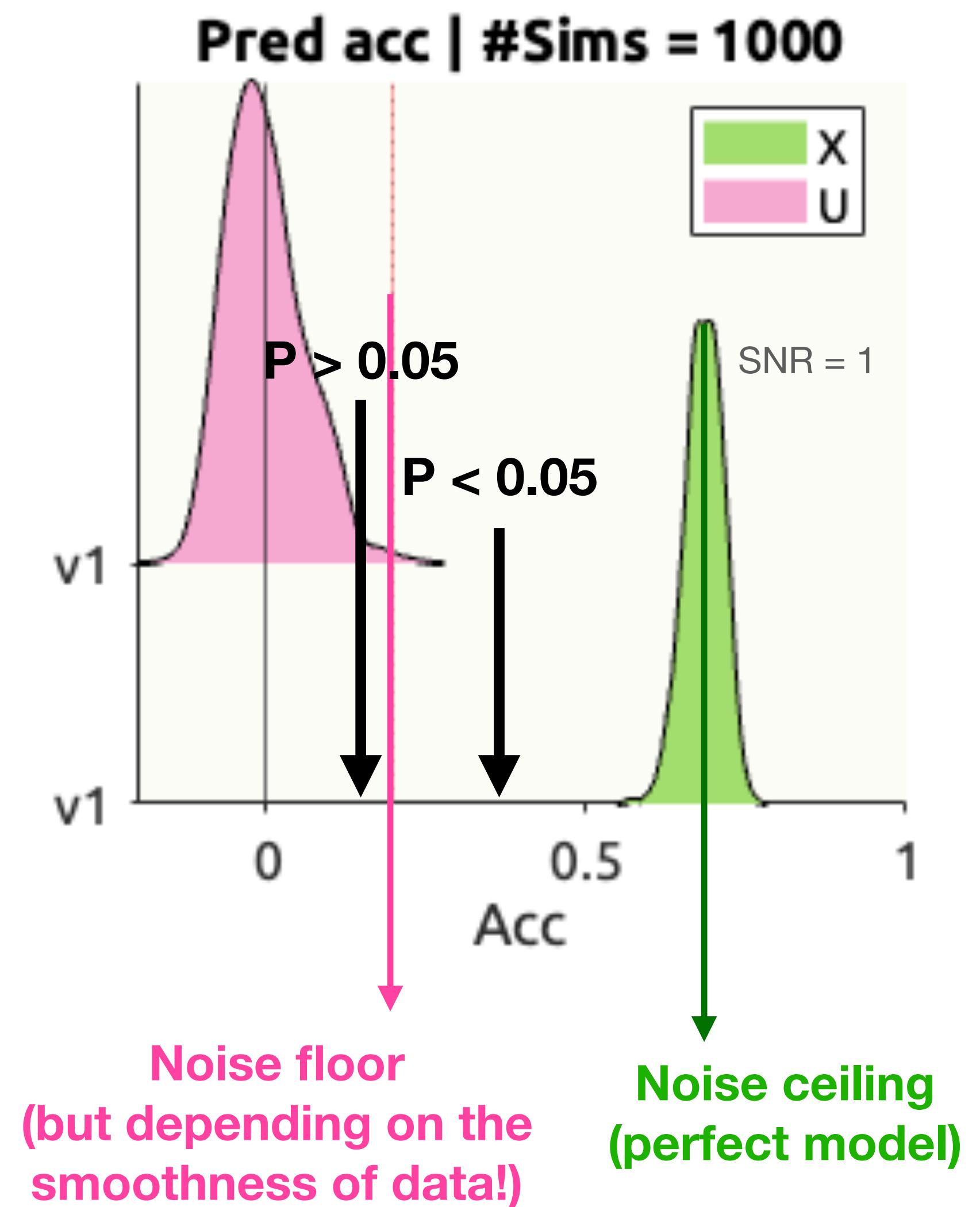


(but depending on the
smoothness of data!)

Noise floor & ceiling of performance

Prediction performance of time series

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- 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?)



What about real data?

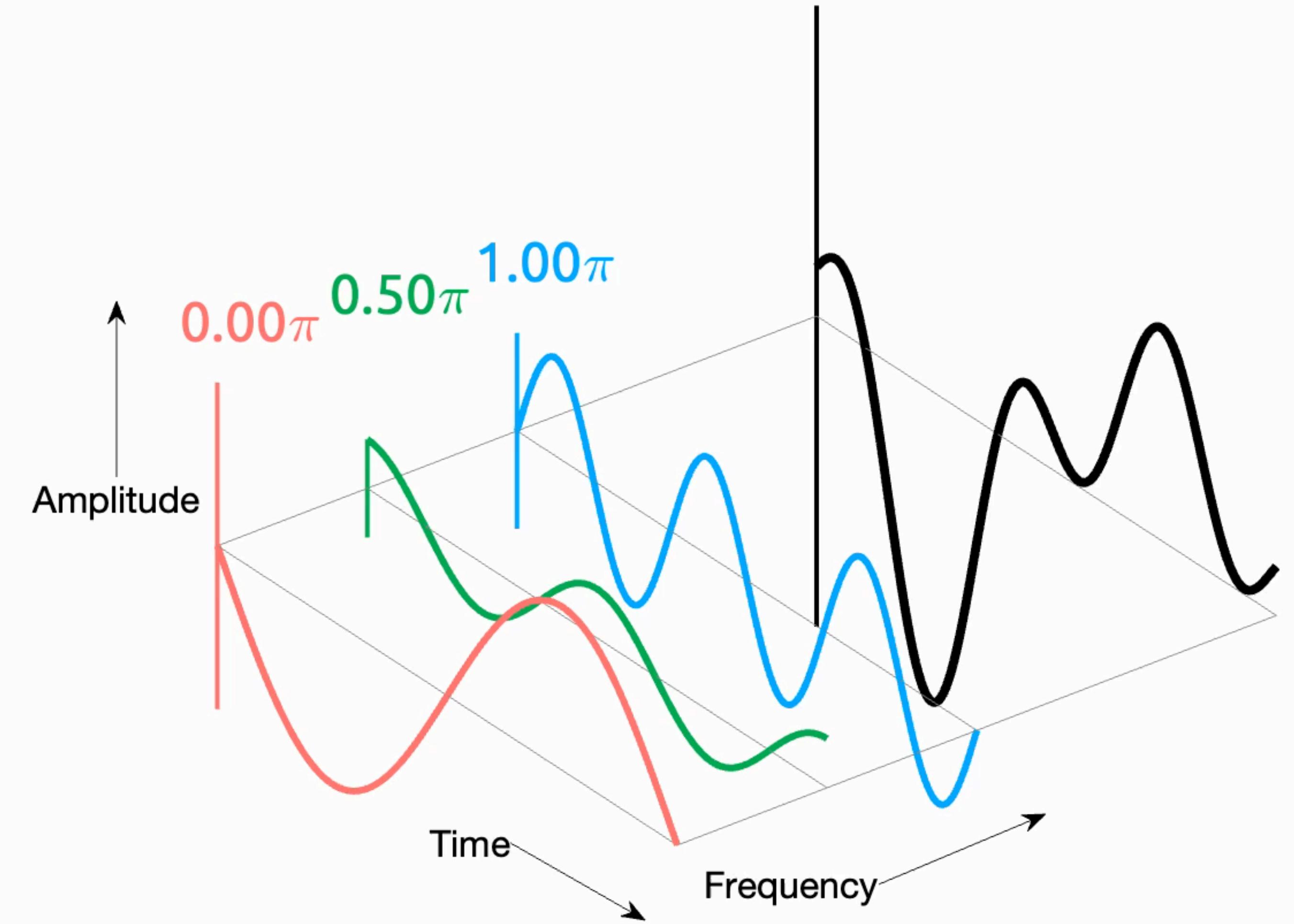
We don't know the correct null distribution!

- 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

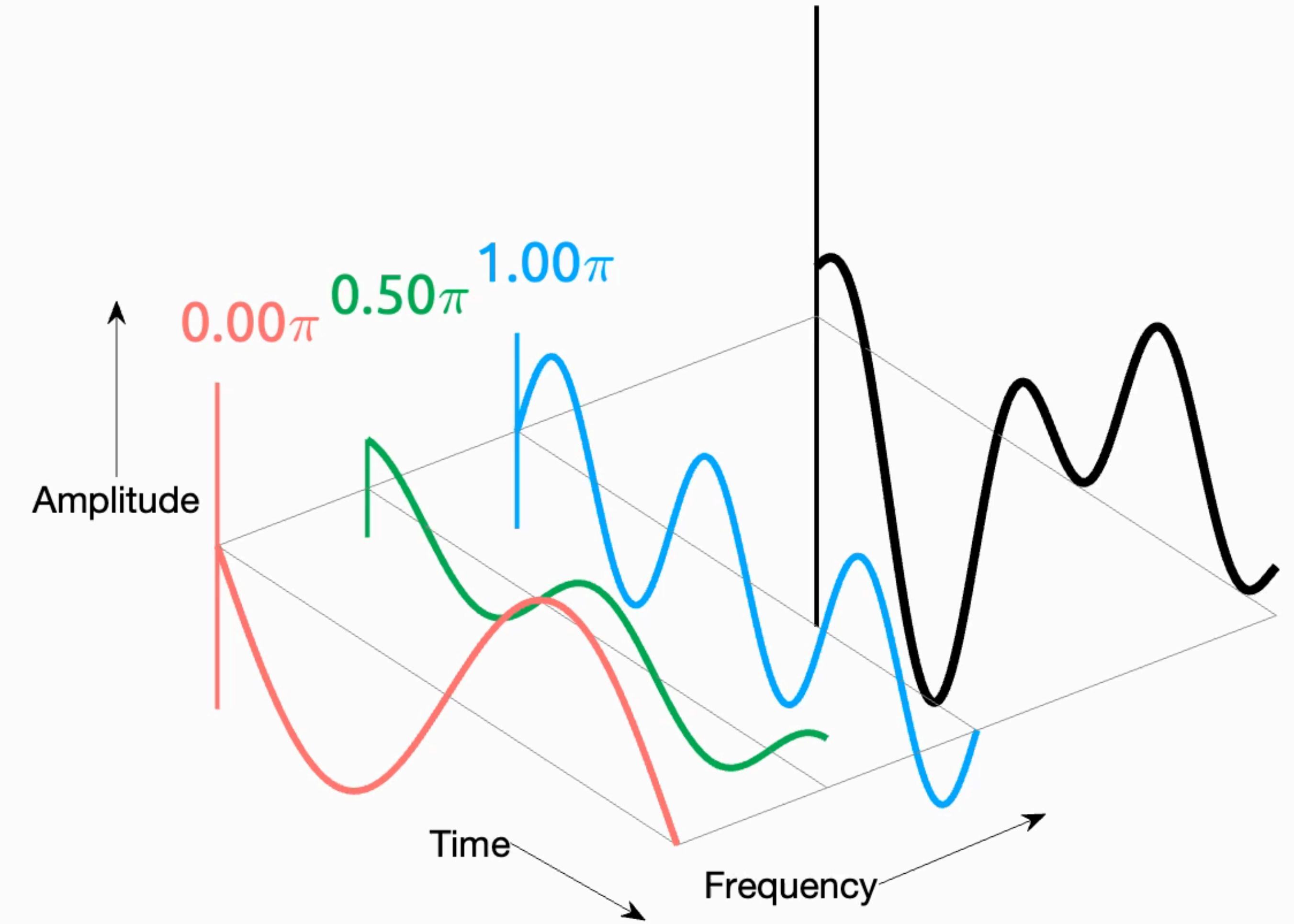
- A complex waveform is a sum of simple (sine) waves at different frequencies and **phases** (is it the beginning of the cycle? in the middle? or the end?)
- Using a super cool method called "Fourier analysis" we can decompose and recompose complex waveforms! 😊



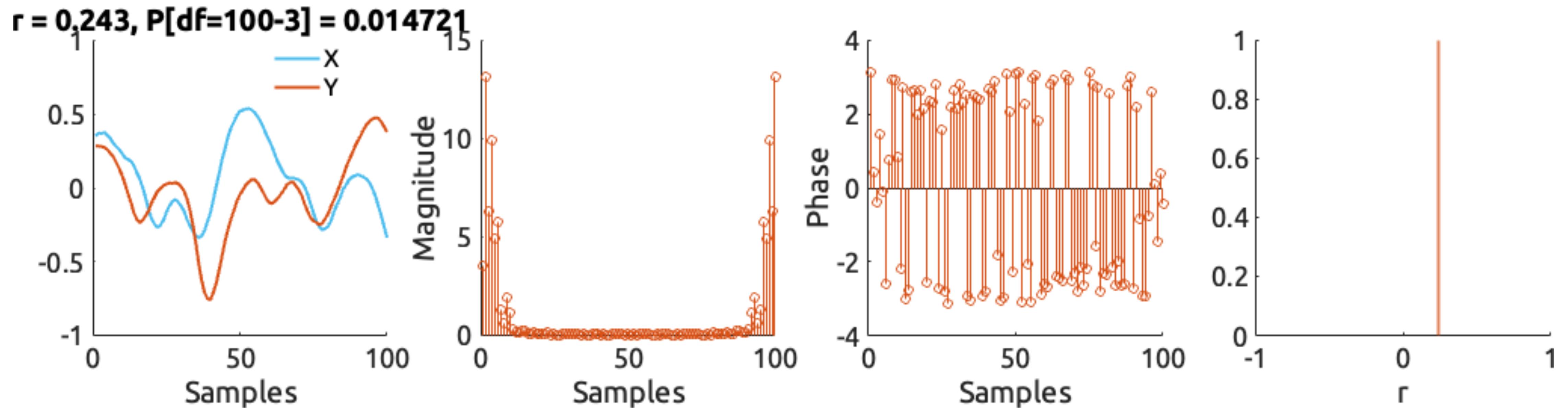
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A (dangerously) quick explanation of Fourier analysis

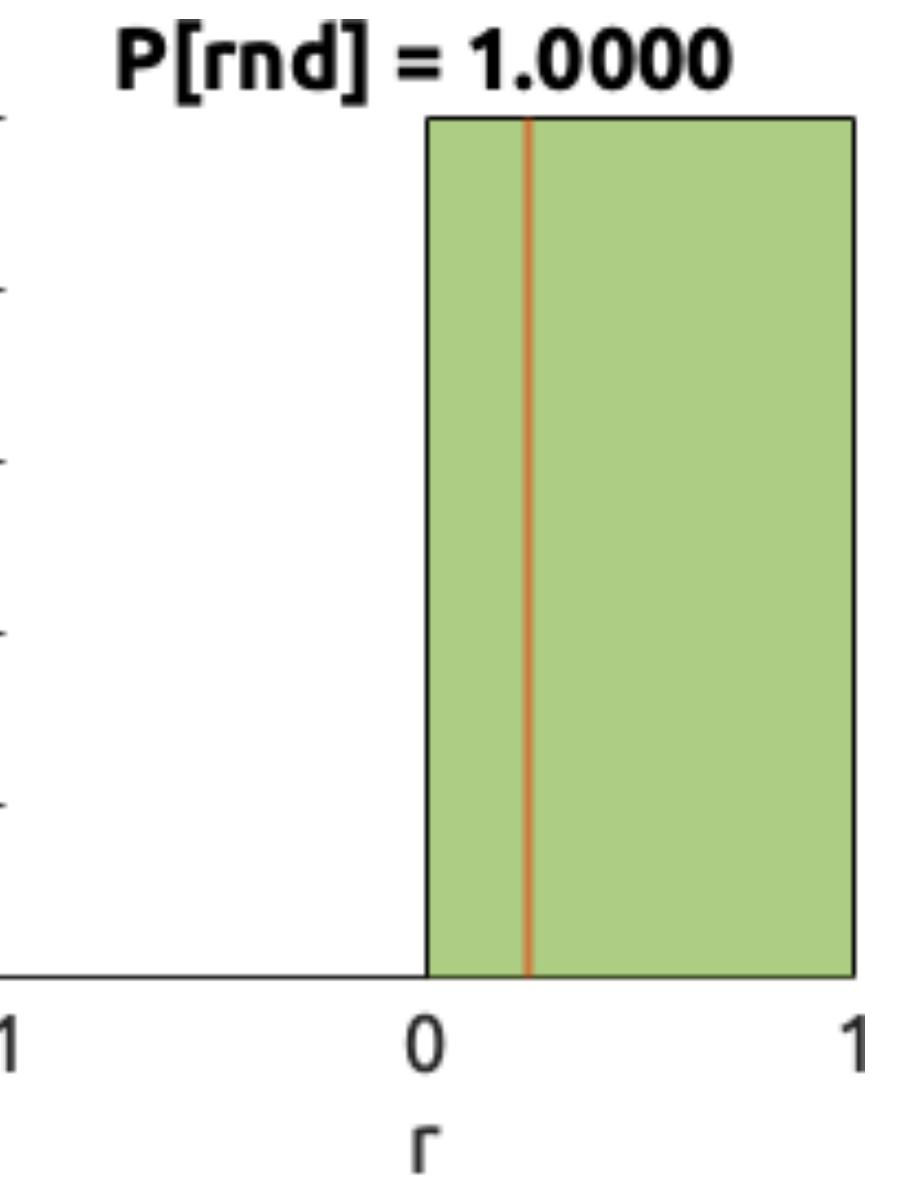
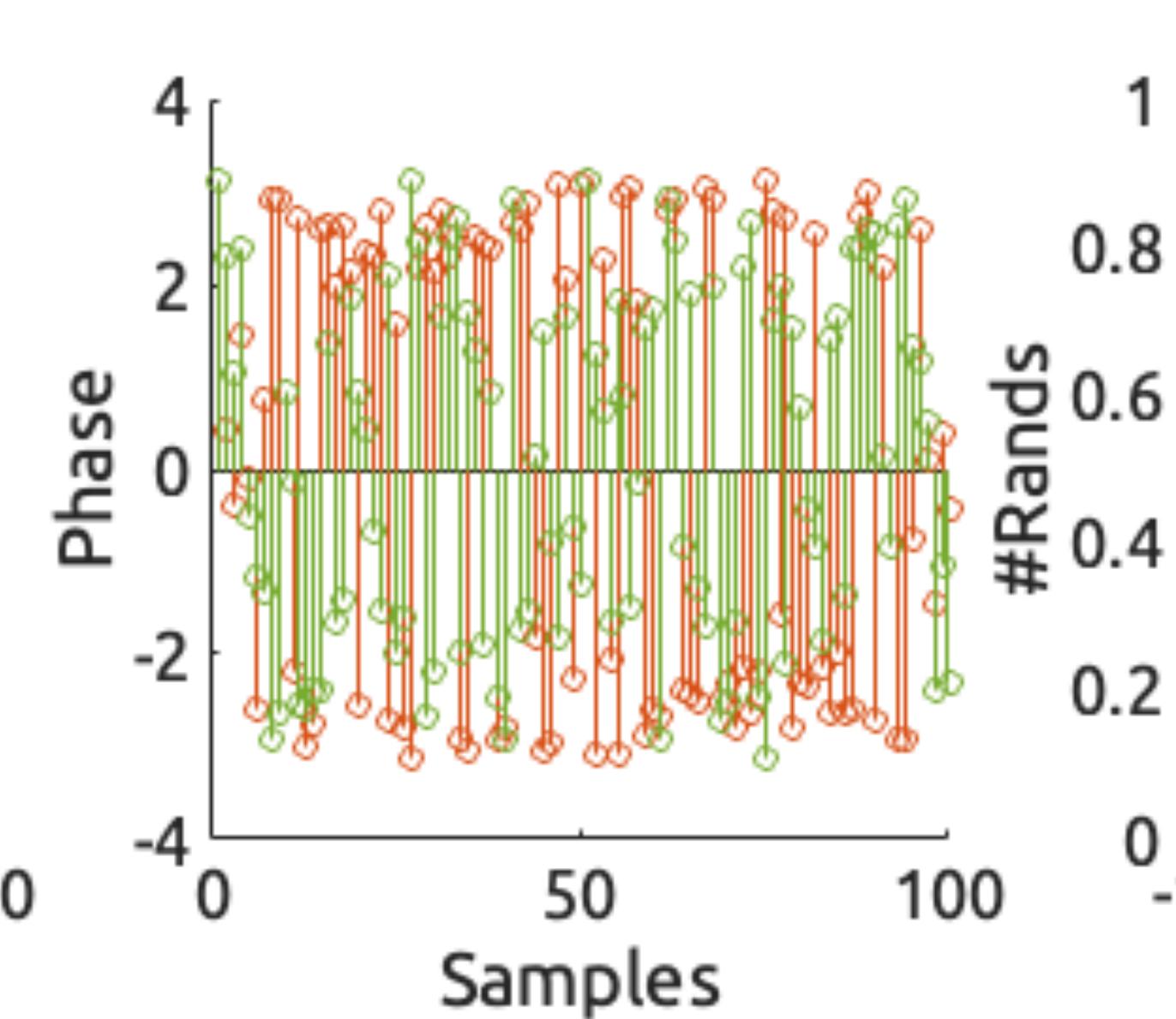
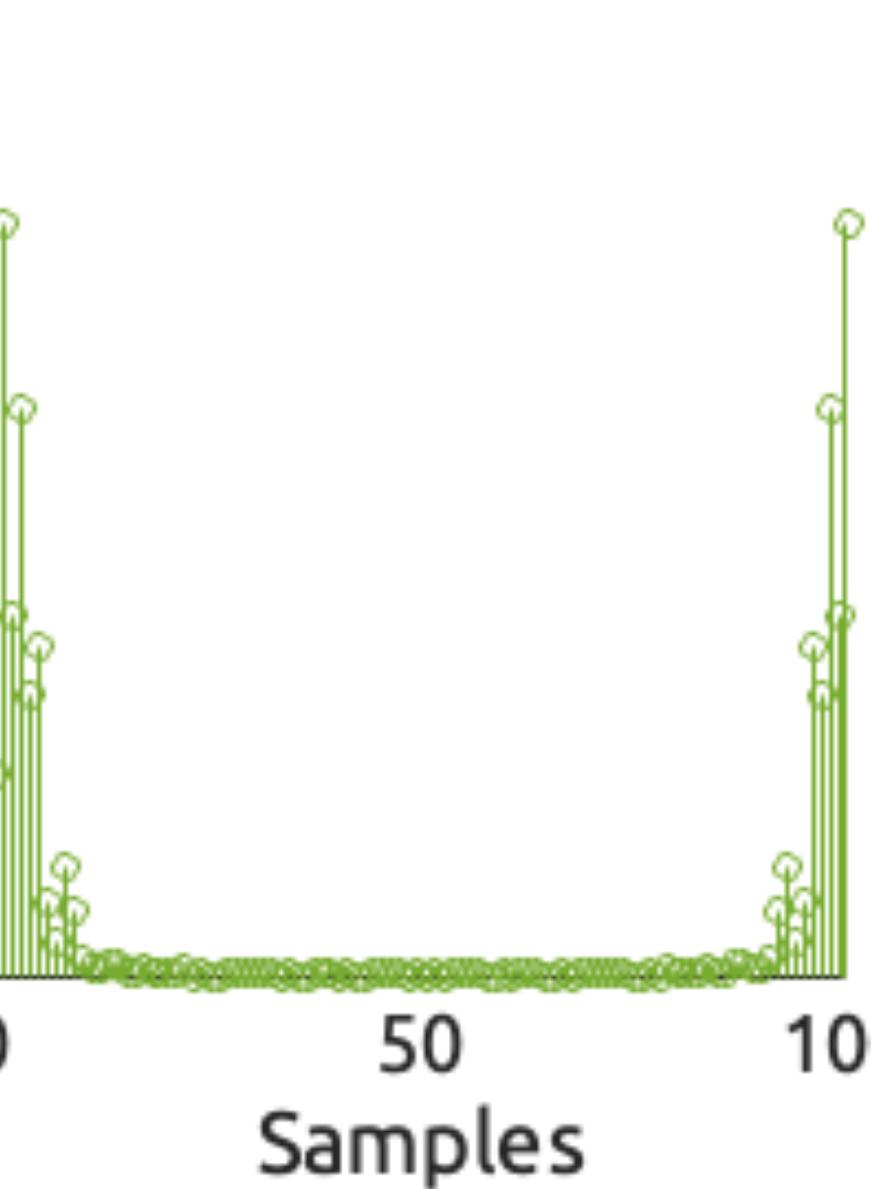
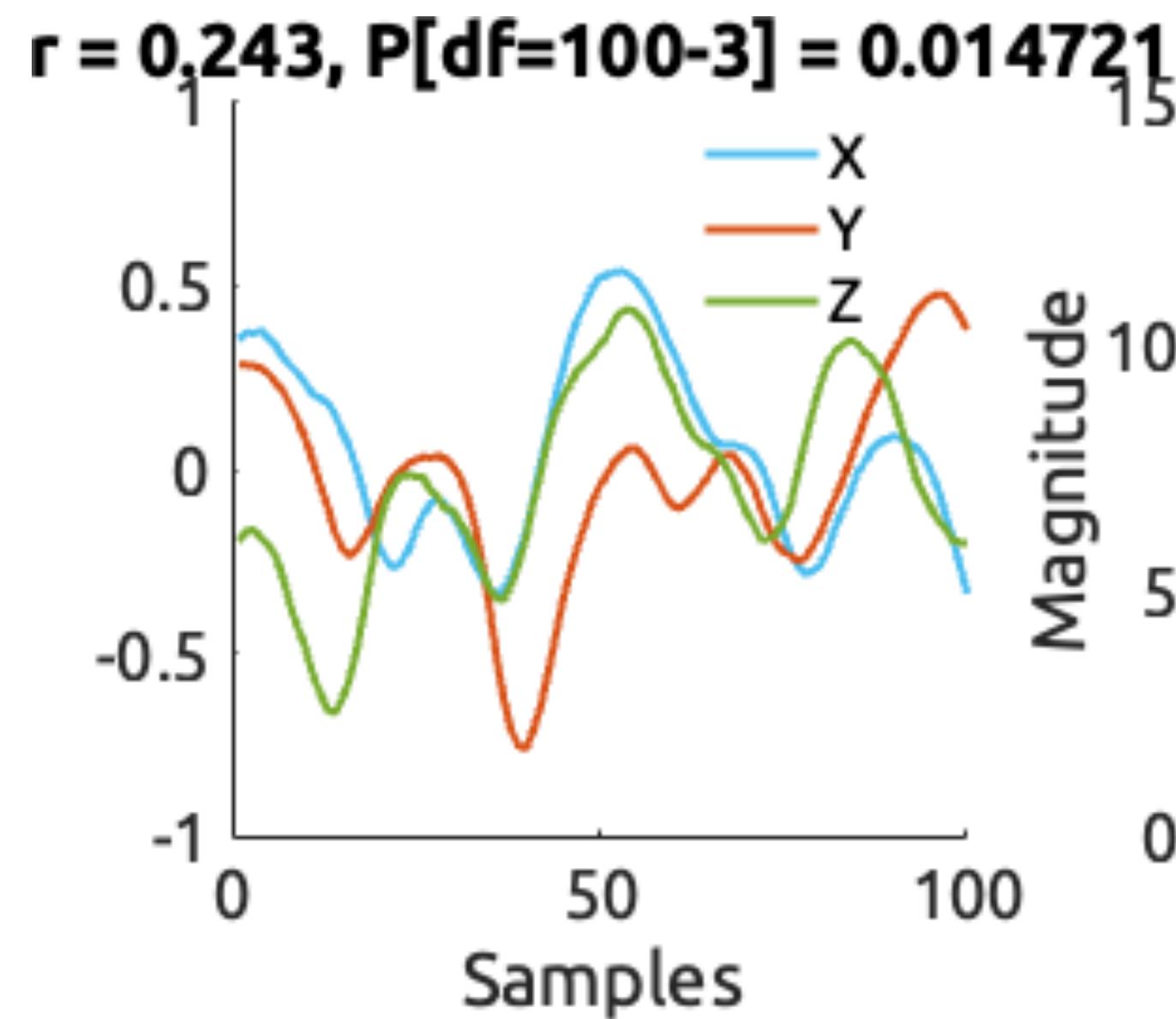
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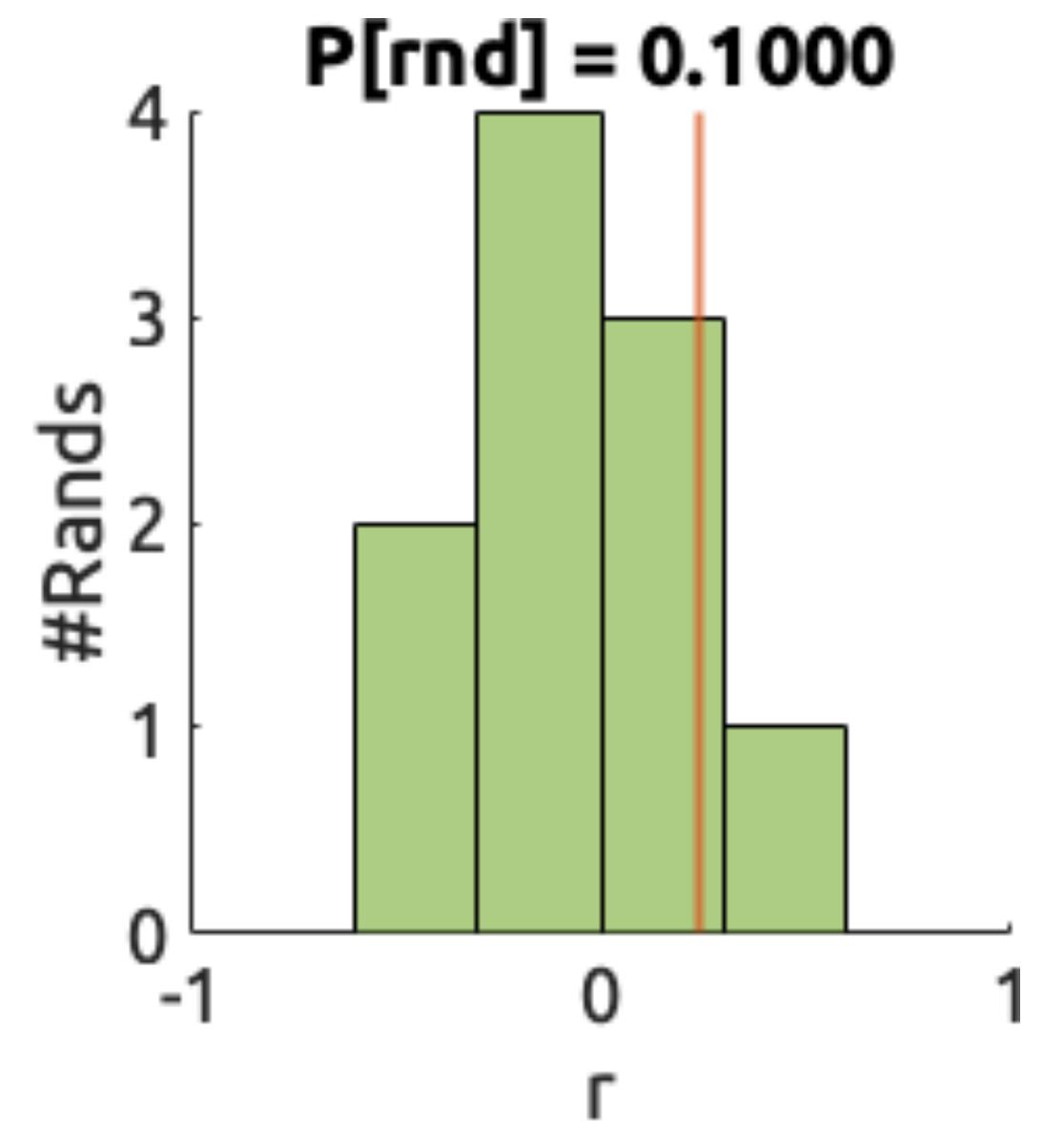
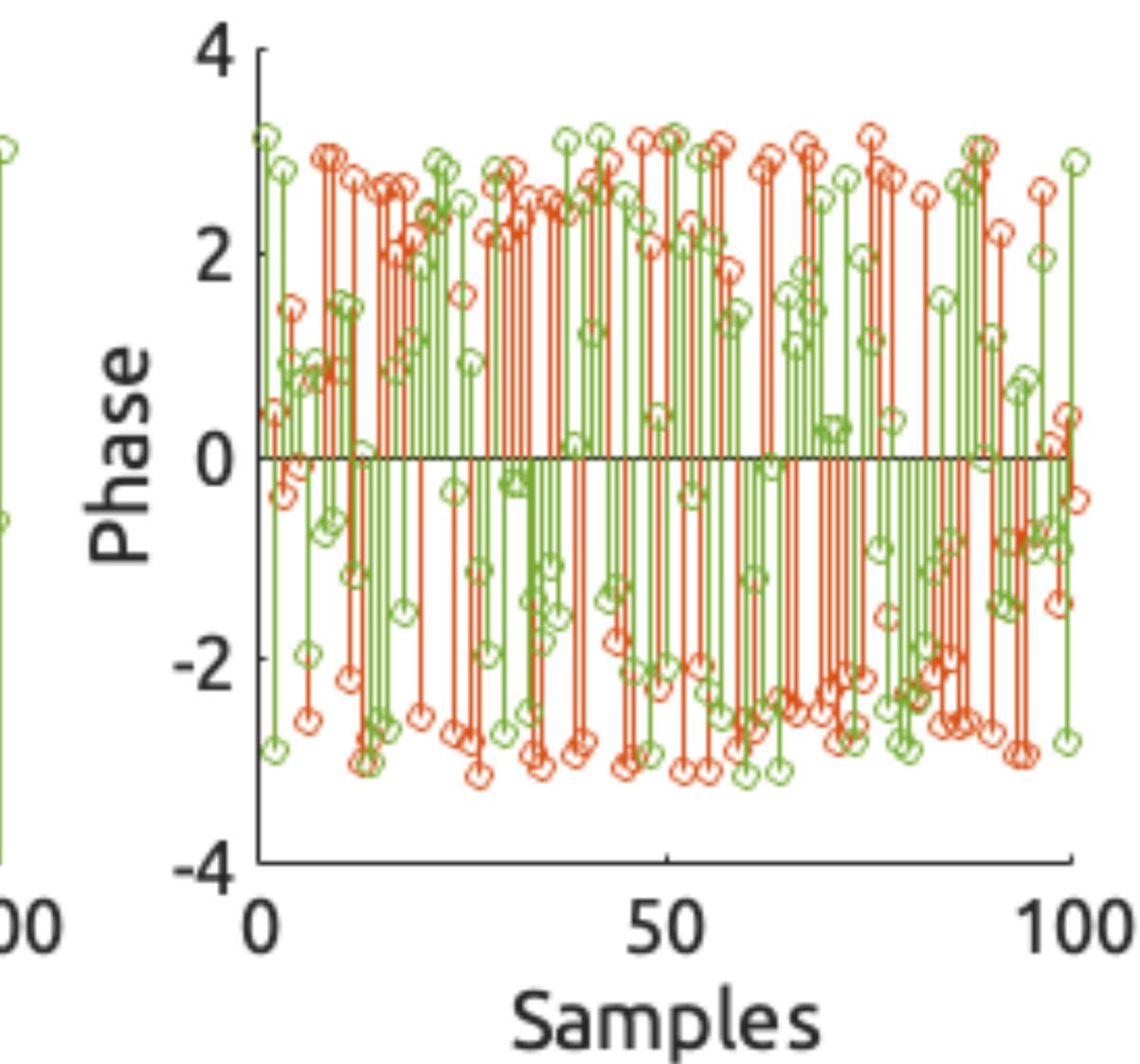
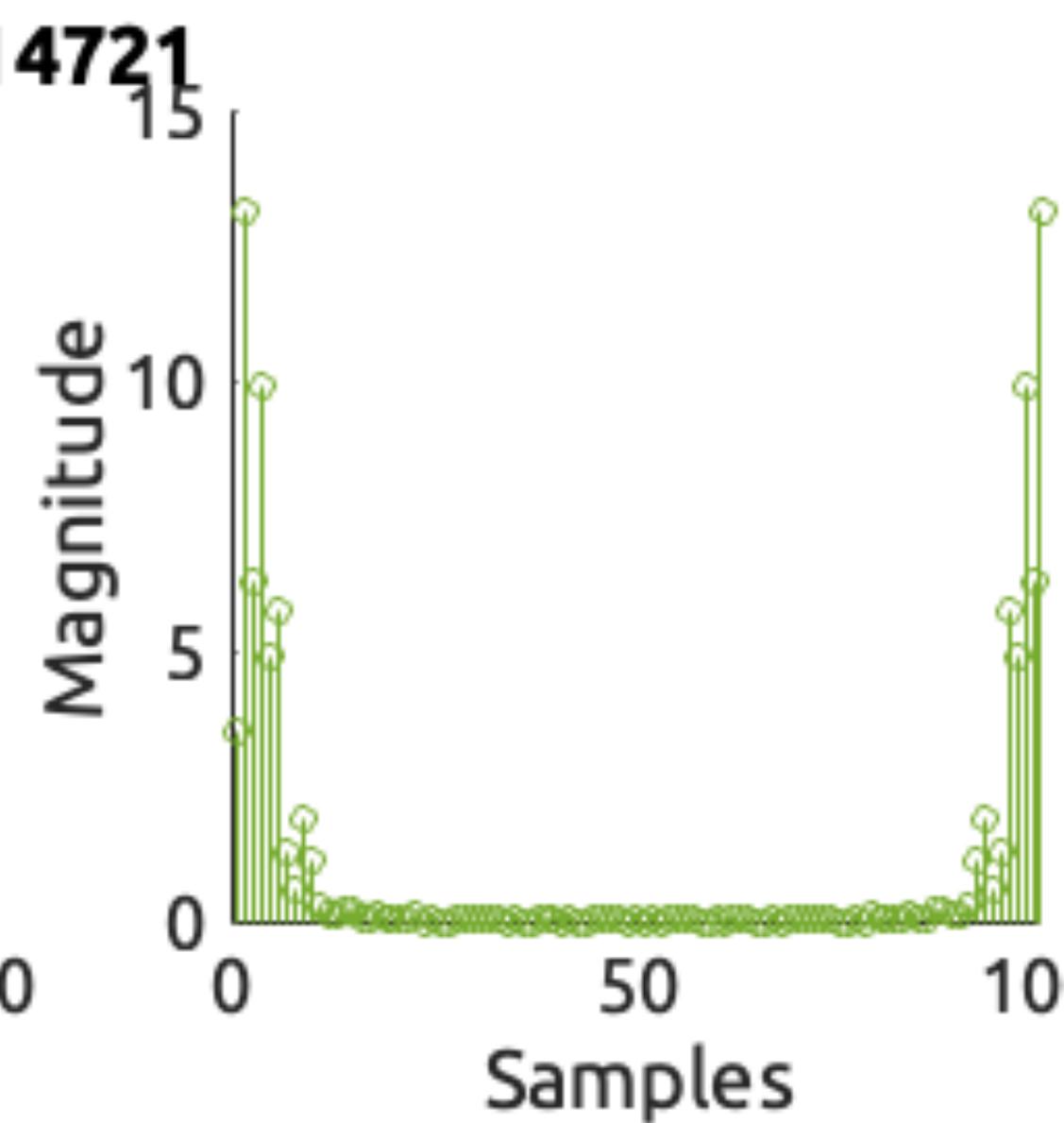
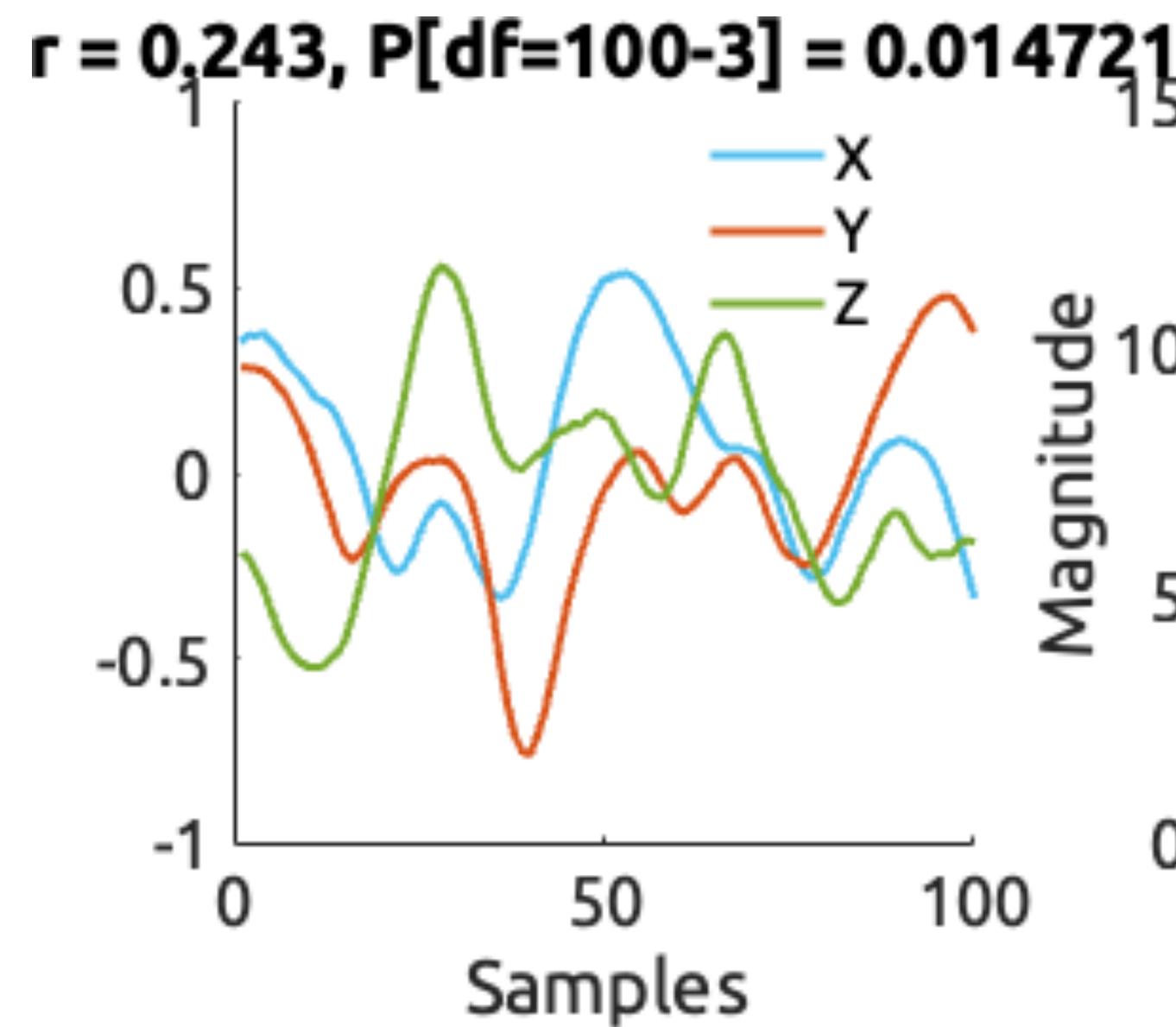
Null distribution from phase randomization



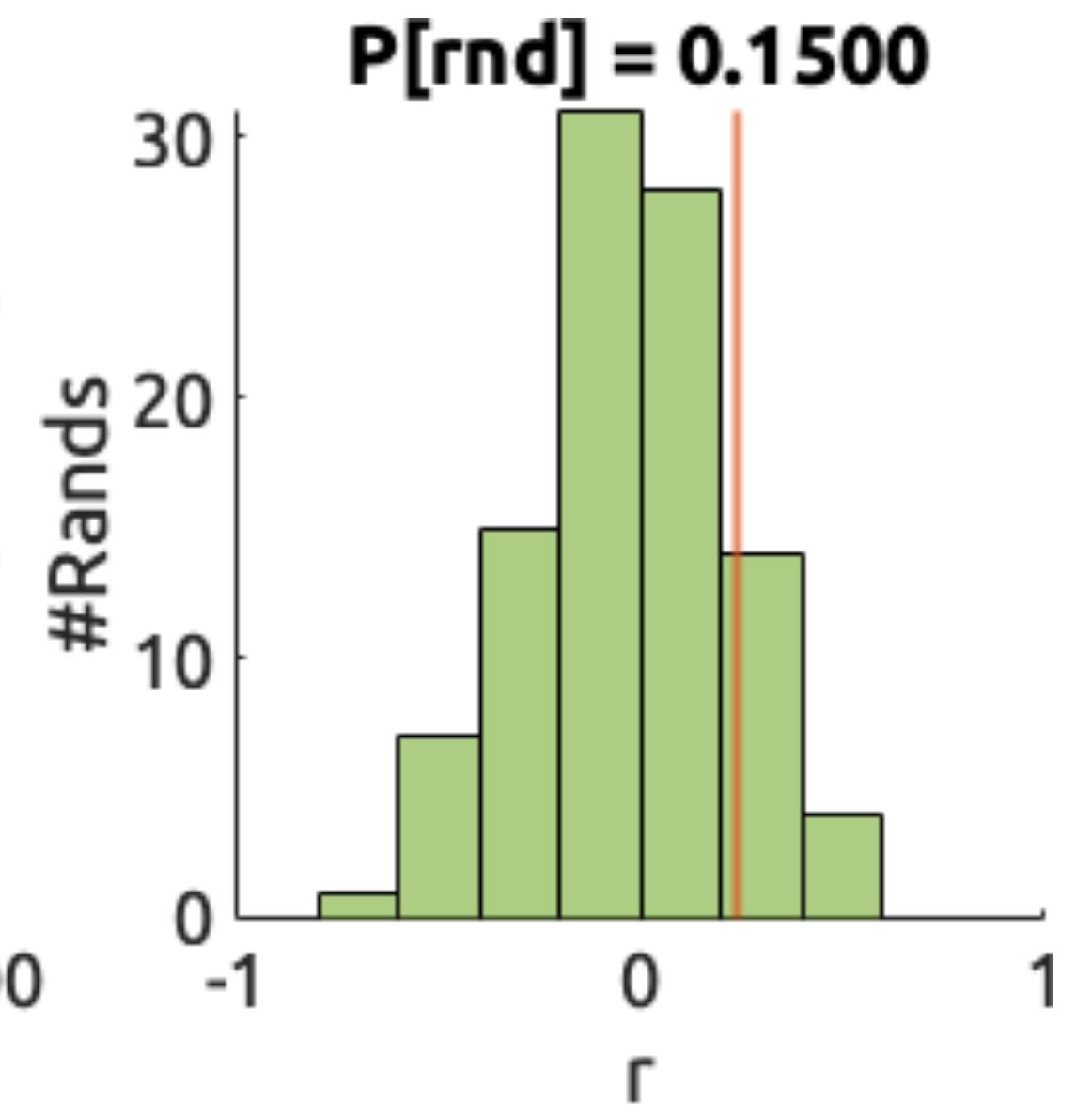
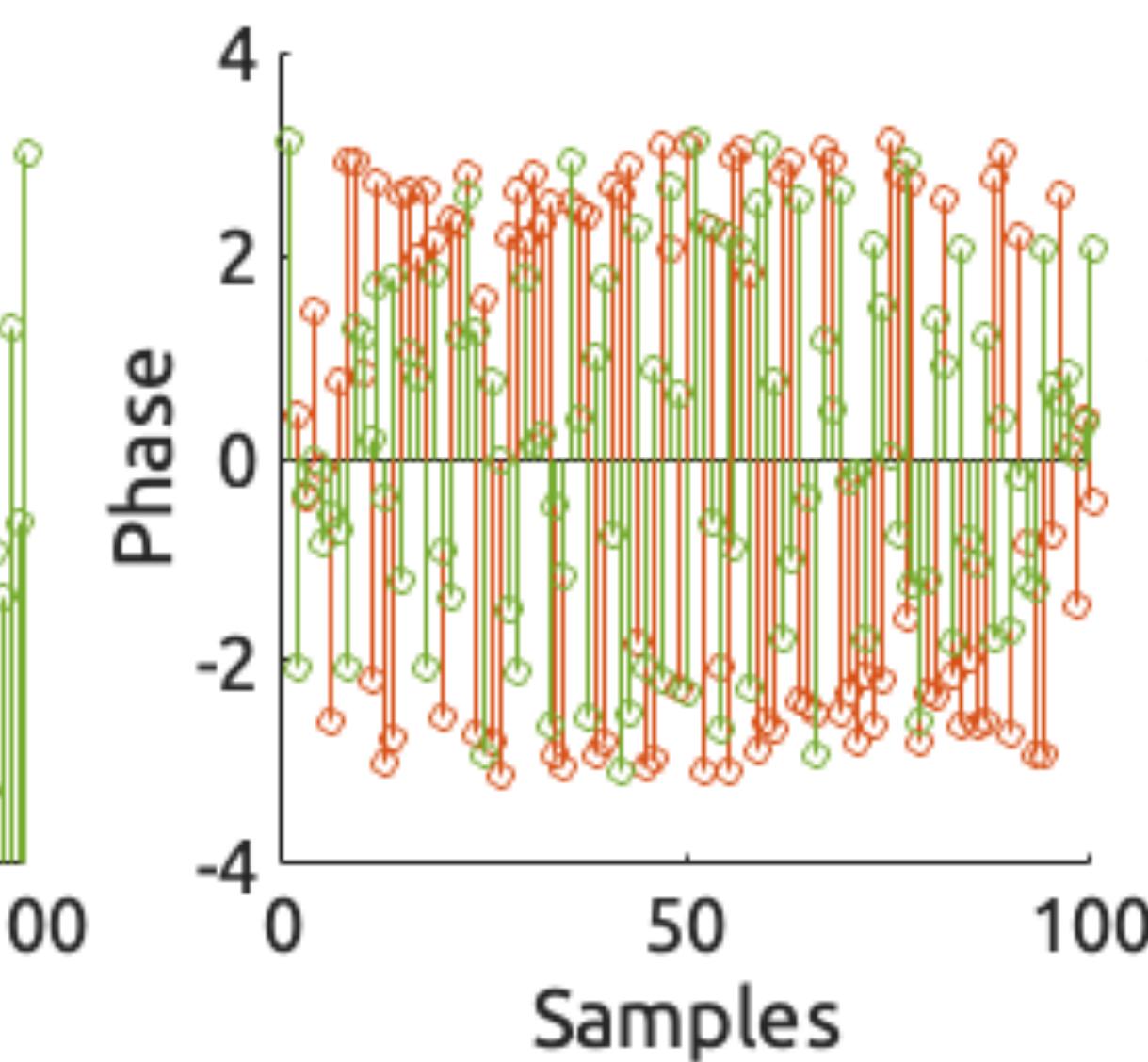
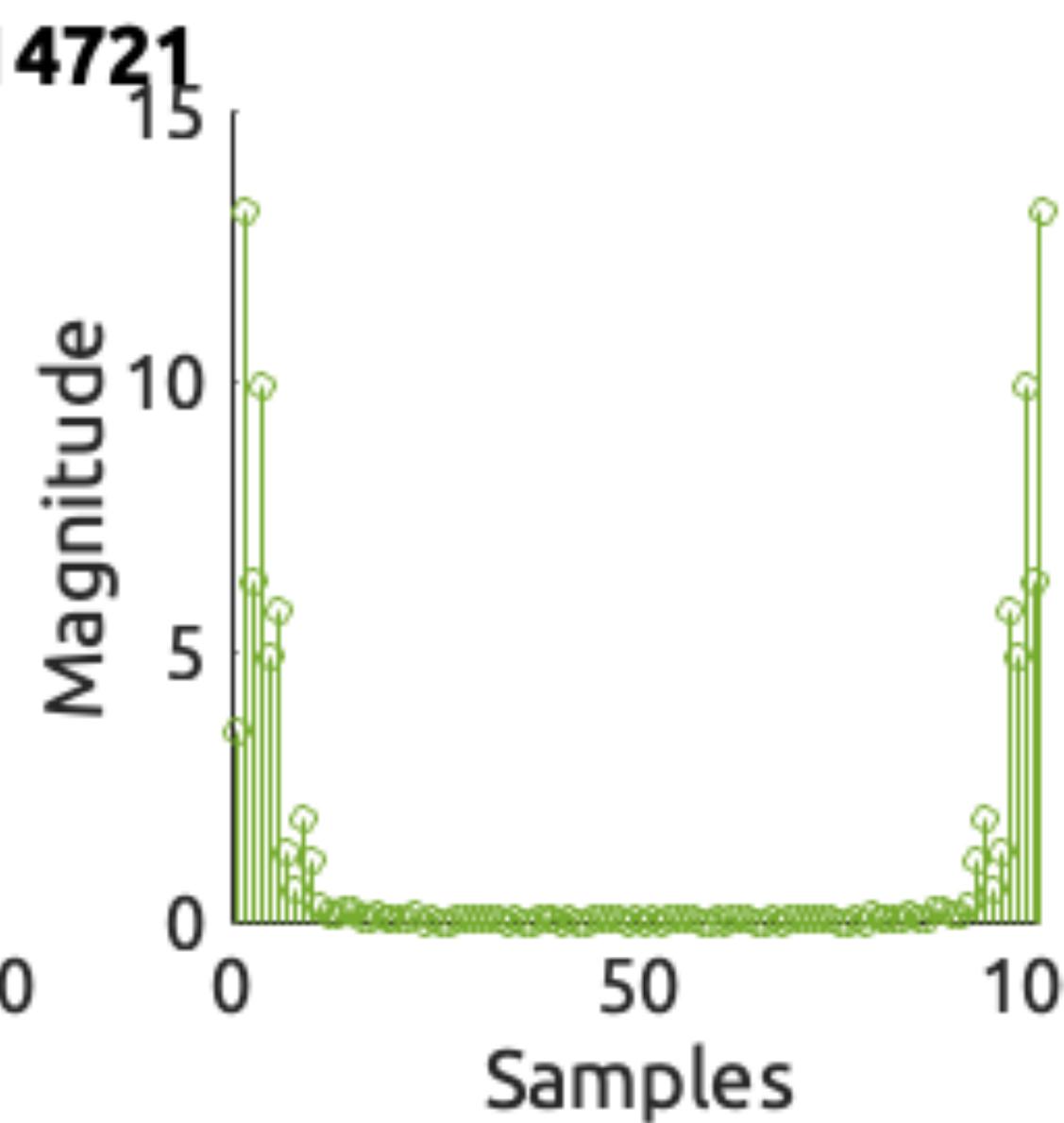
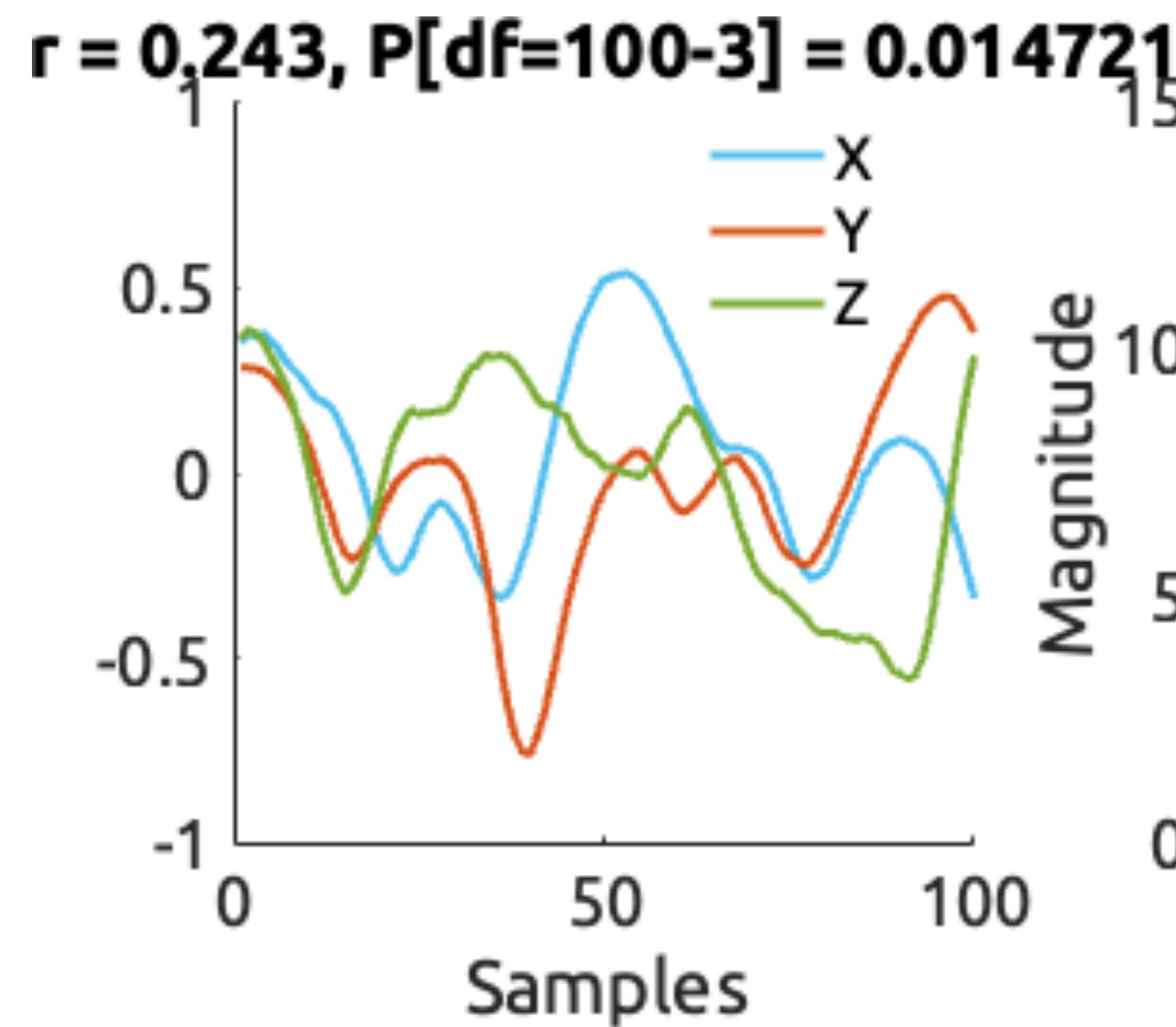
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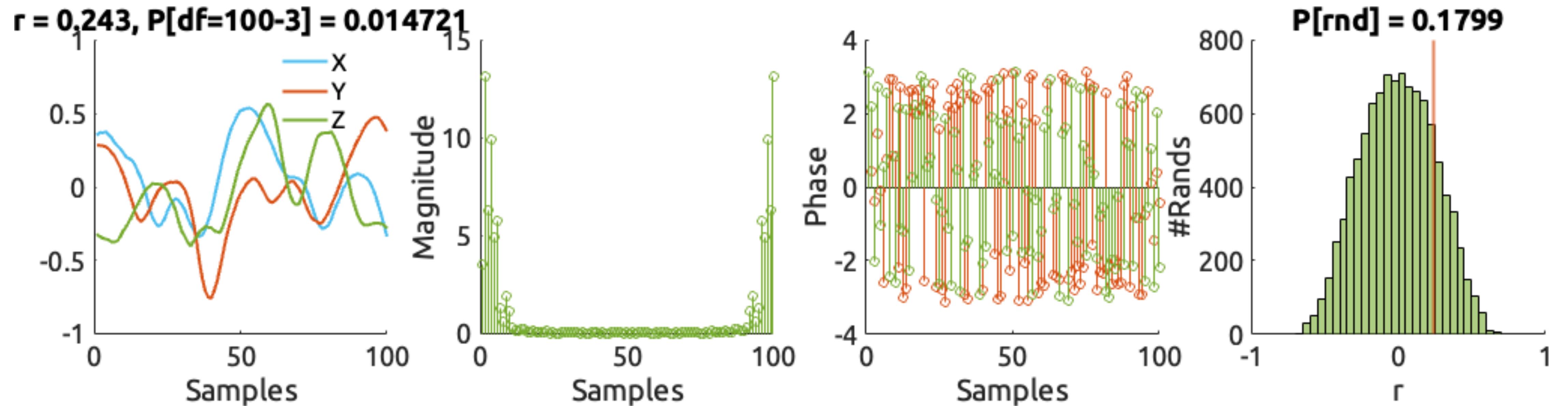
Null distribution from phase randomization



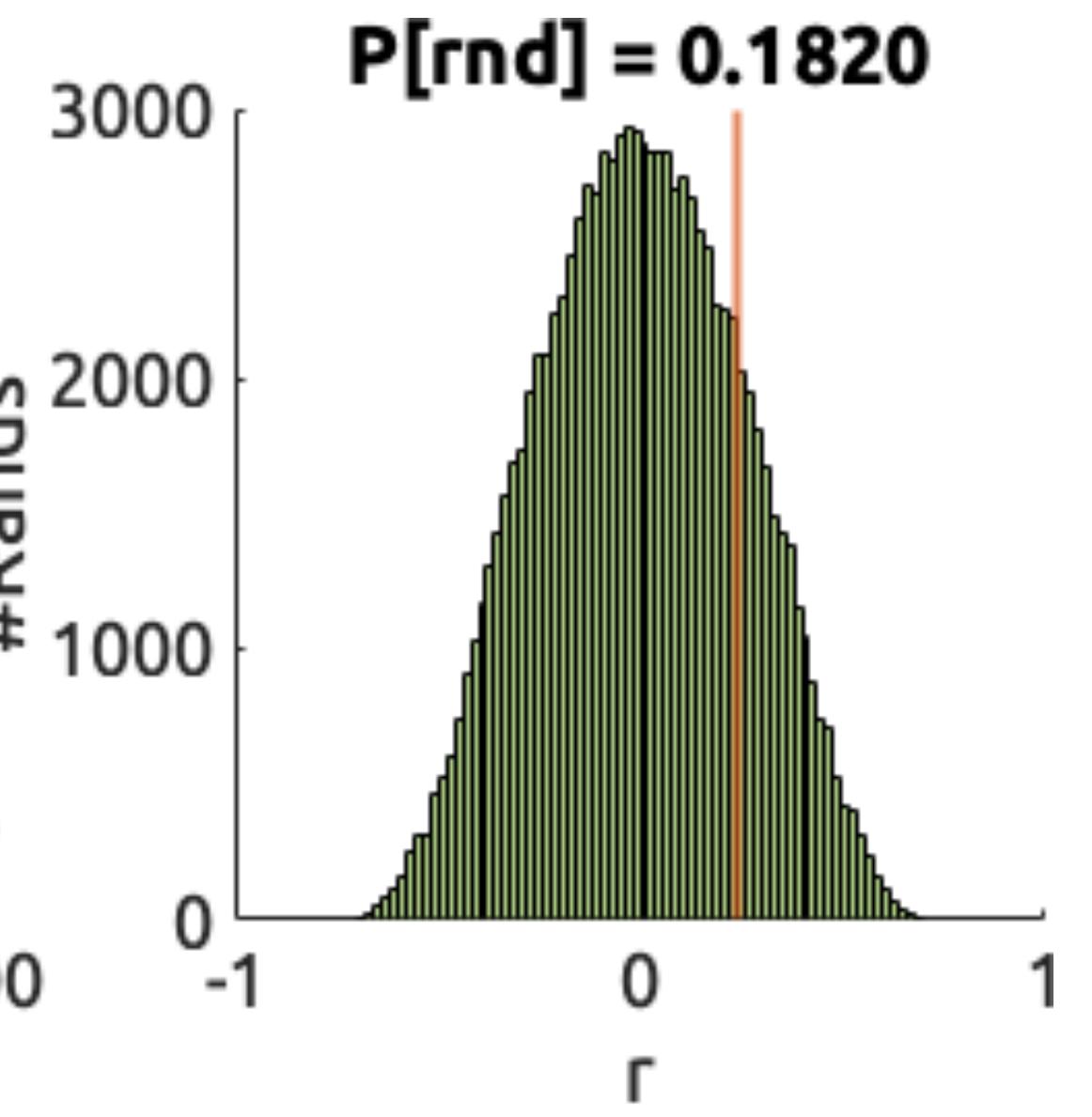
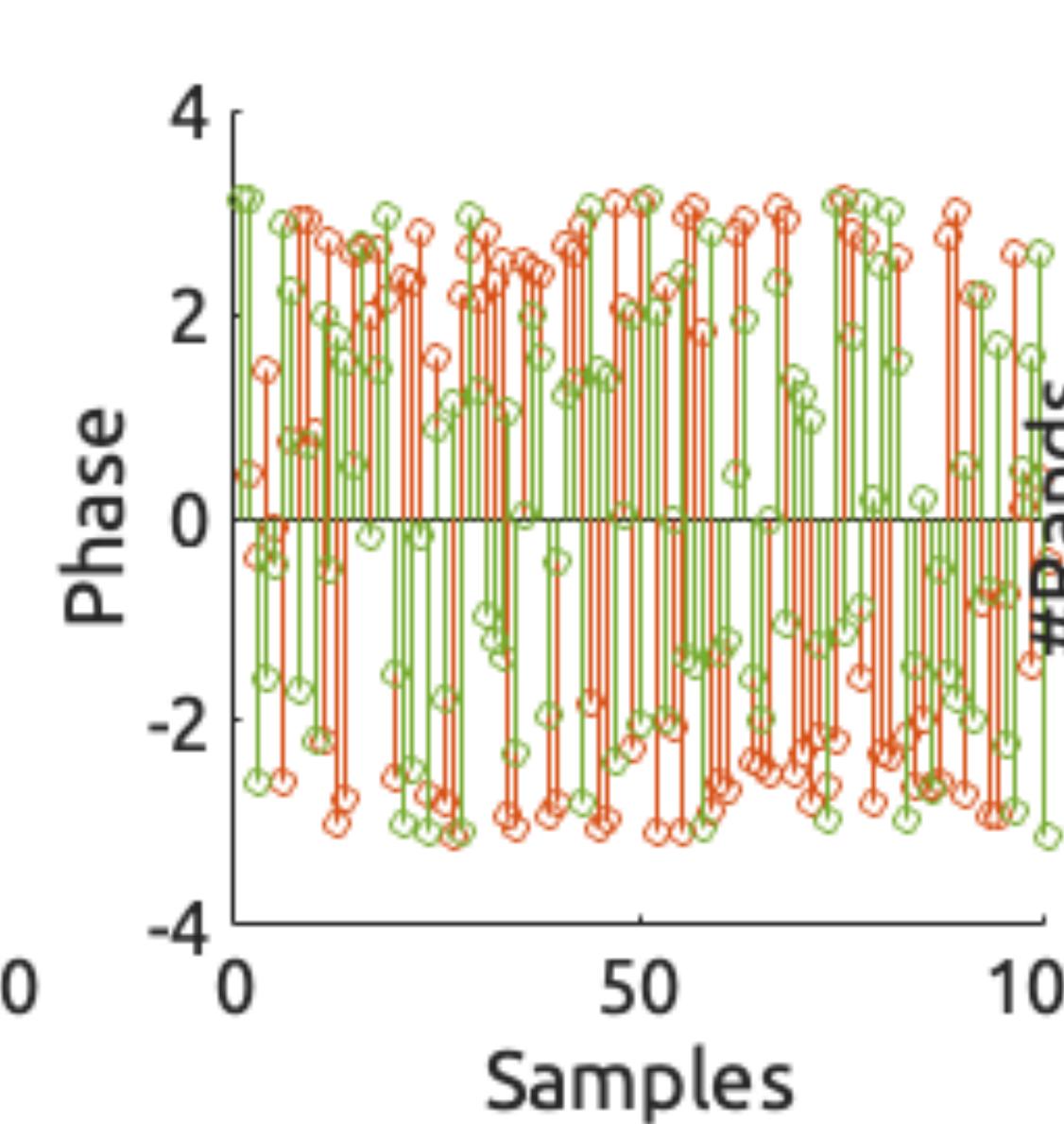
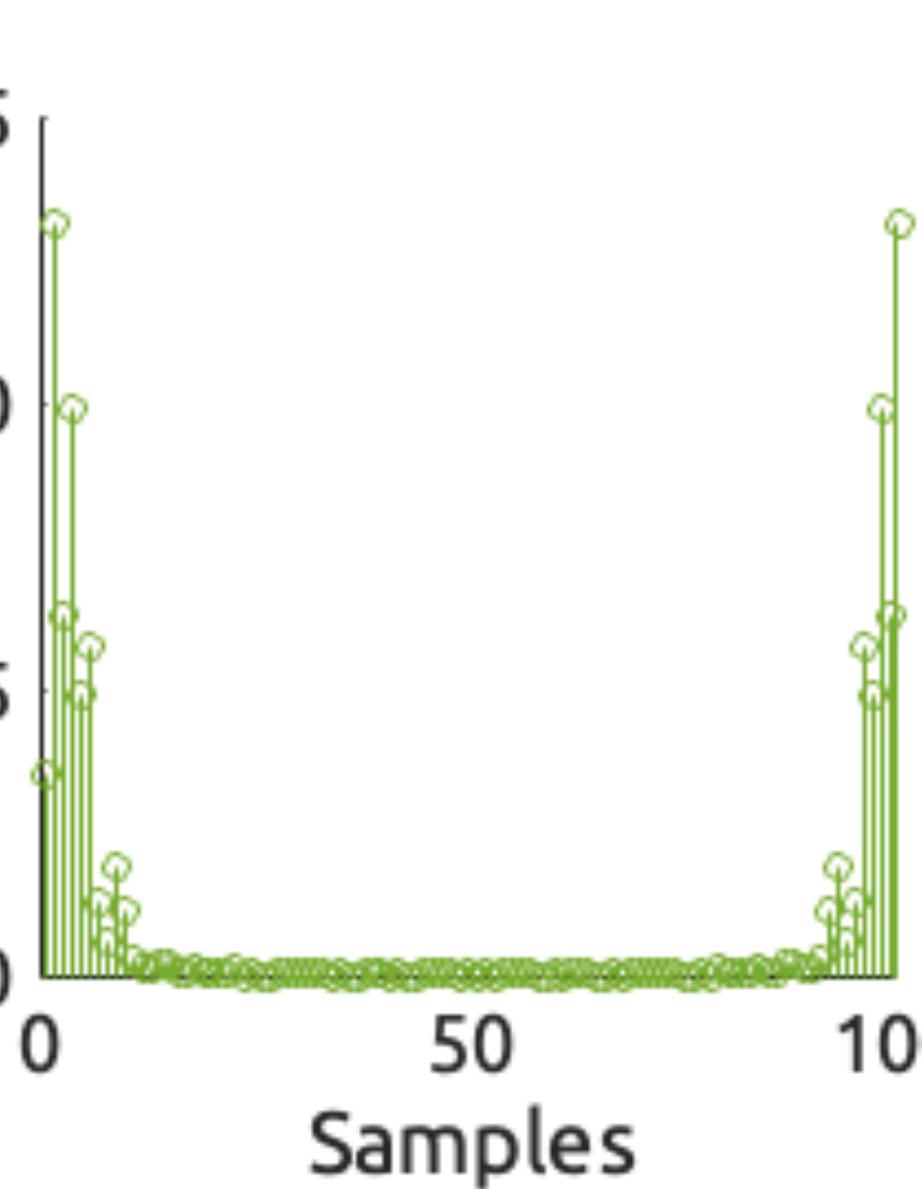
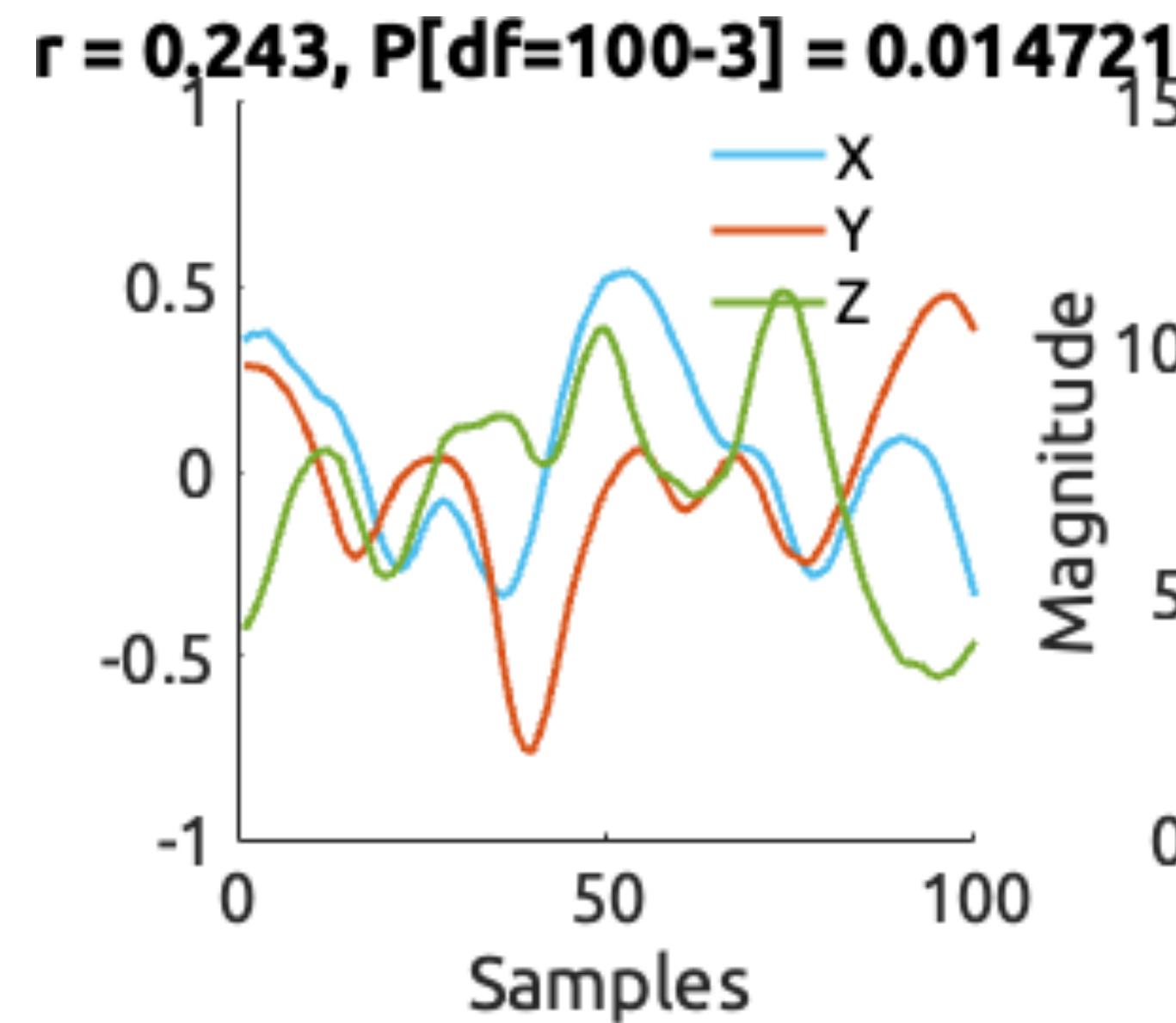
Null distribution from phase randomization



Null distribution from phase randomization



Null distribution from phase randomization



Summary [4/4]: Inference

Randomization test for time series

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).

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.

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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Linearized encoding analysis

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

Summary: Methods

Linearized encoding analysis

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- **Delay modeling:** finite impulse response modeling

Summary: Methods

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- **Optimization & Evaluation:** nested cross-validation

Summary: Methods

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 😈)

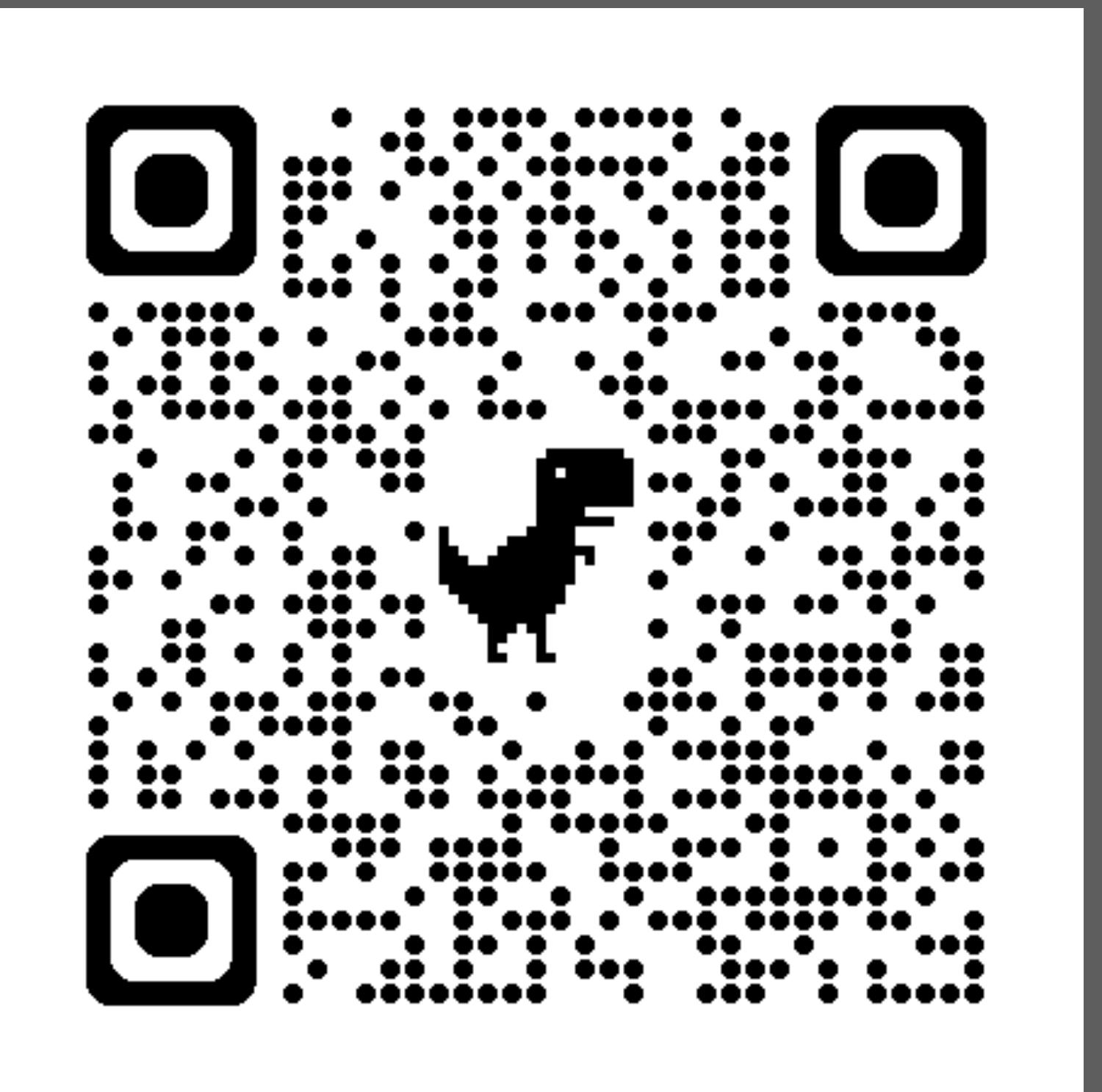
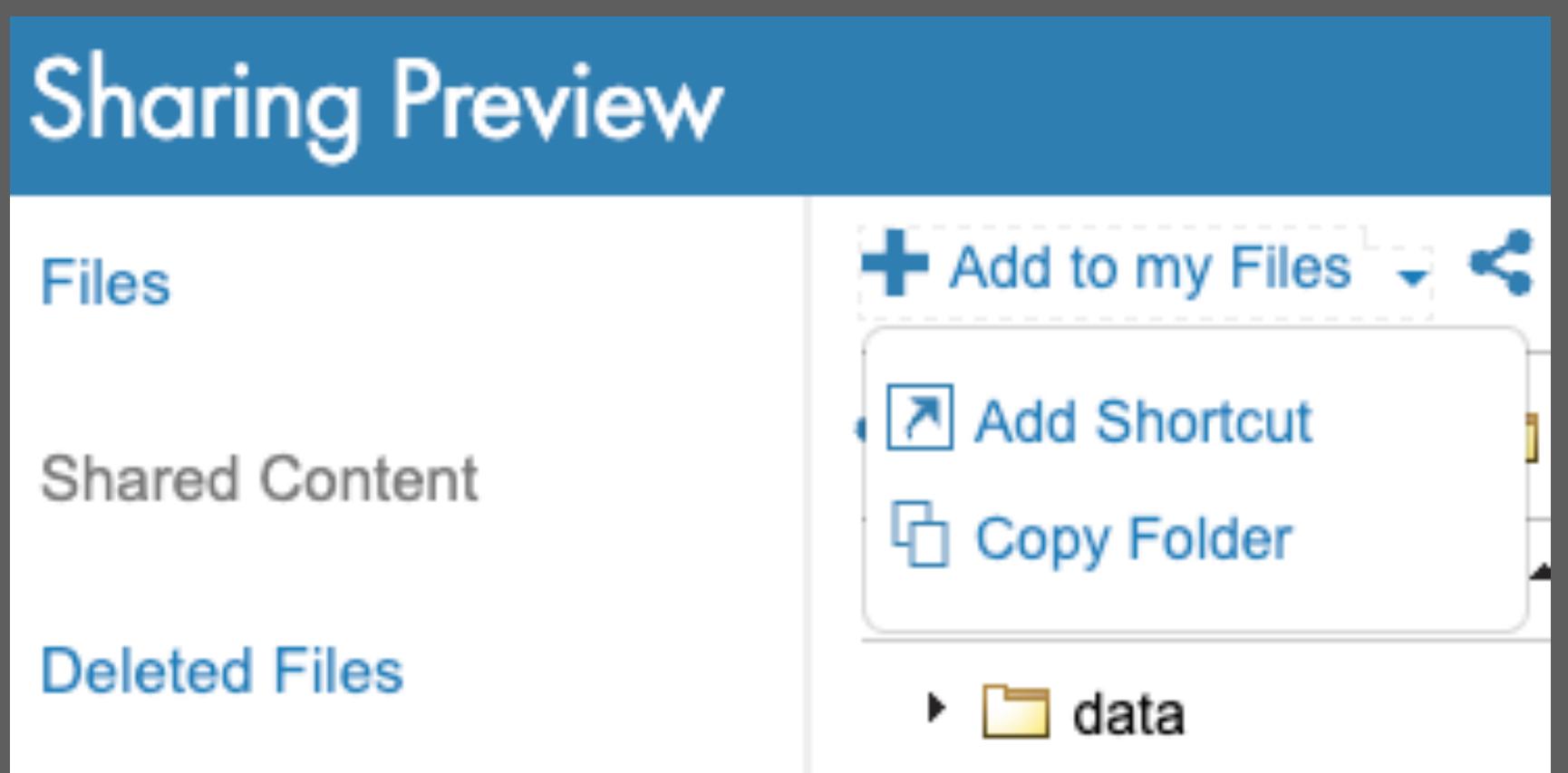


[Go back to SESSION PLAN](#)

Hands-on -1: MATLAB ONLINE

How to accept the SHARE INVITATION?

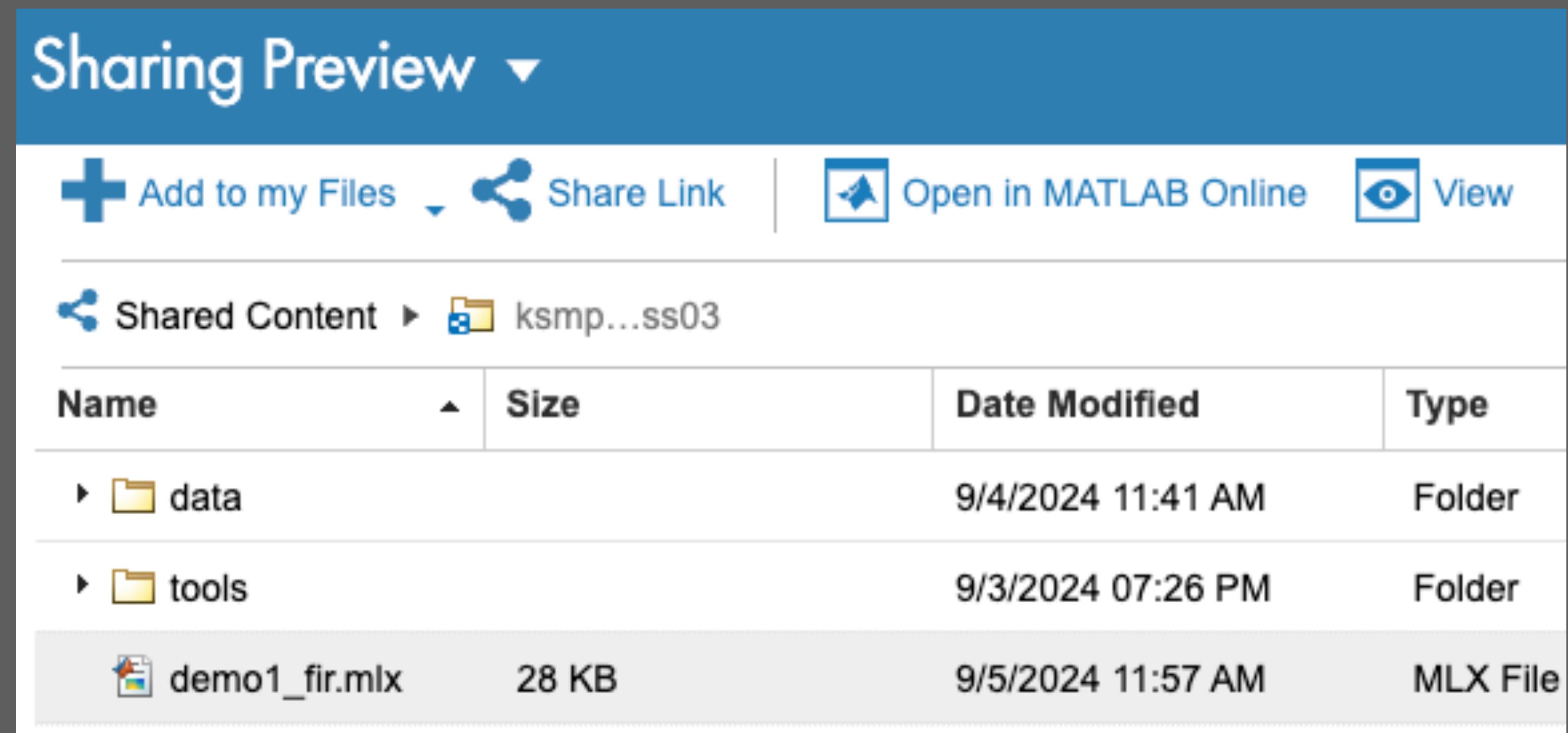
1. log in to [HTTPS://MATLAB.MATHWORKS.COM](https://MATLAB.MATHWORKS.COM)
2. Scan/click on the share link [<https://drive.mathworks.com/sharing/6852c95ab53f-4be0-bbe5-b6e4f7f8c6ae/>]
3. Clink on "Add to my Files" and "Copy Folder"



Hands-on -1: MATLAB ONLINE

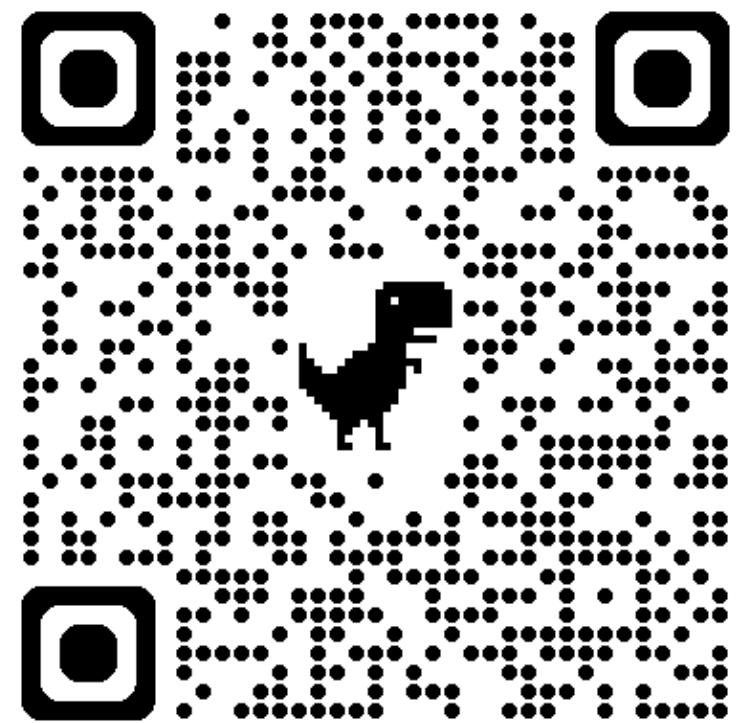
How to open a MLX (matlab live script) file?

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



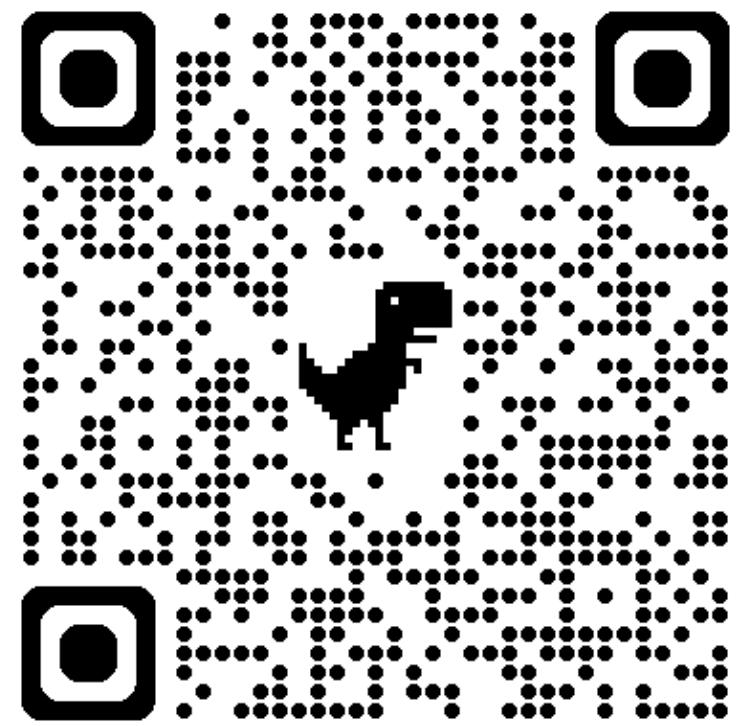
The screenshot shows a 'Sharing Preview' interface for a MATLAB Drive folder. At the top, there are buttons for 'Add to my Files', 'Share Link', 'Open in MATLAB Online' (which is highlighted in blue), and 'View'. Below this, the path 'Shared Content > ksmp...ss03' is shown. A table lists the contents of the folder:

Name	Size	Date Modified	Type
▶ data		9/4/2024 11:41 AM	Folder
▶ tools		9/3/2024 07:26 PM	Folder
 demo1_fir mlx	28 KB	9/5/2024 11:57 AM	MLX File



Hands-on 0: Launch MATLAB Online todo0_matlab mlx

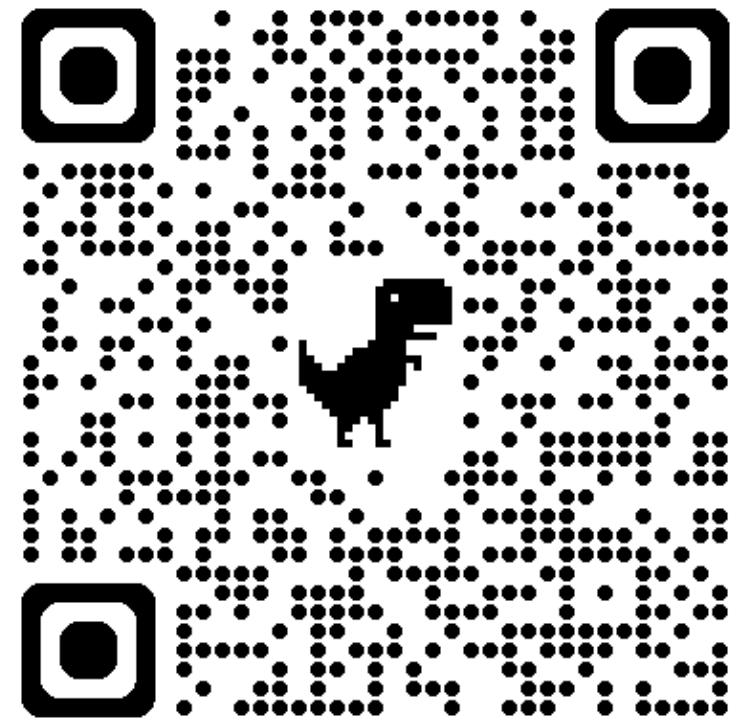
[Go back to SESSION PLAN](#)



Hands-on 1: Toy Example

 todo1_toy.mlx

[Go back to SESSION PLAN](#)



Hands-on 2:

🌟 Real data analysis
todo2_real mlx

[Go back to SESSION PLAN](#)



Summary of the session

Music and the Brain 🎵🧠

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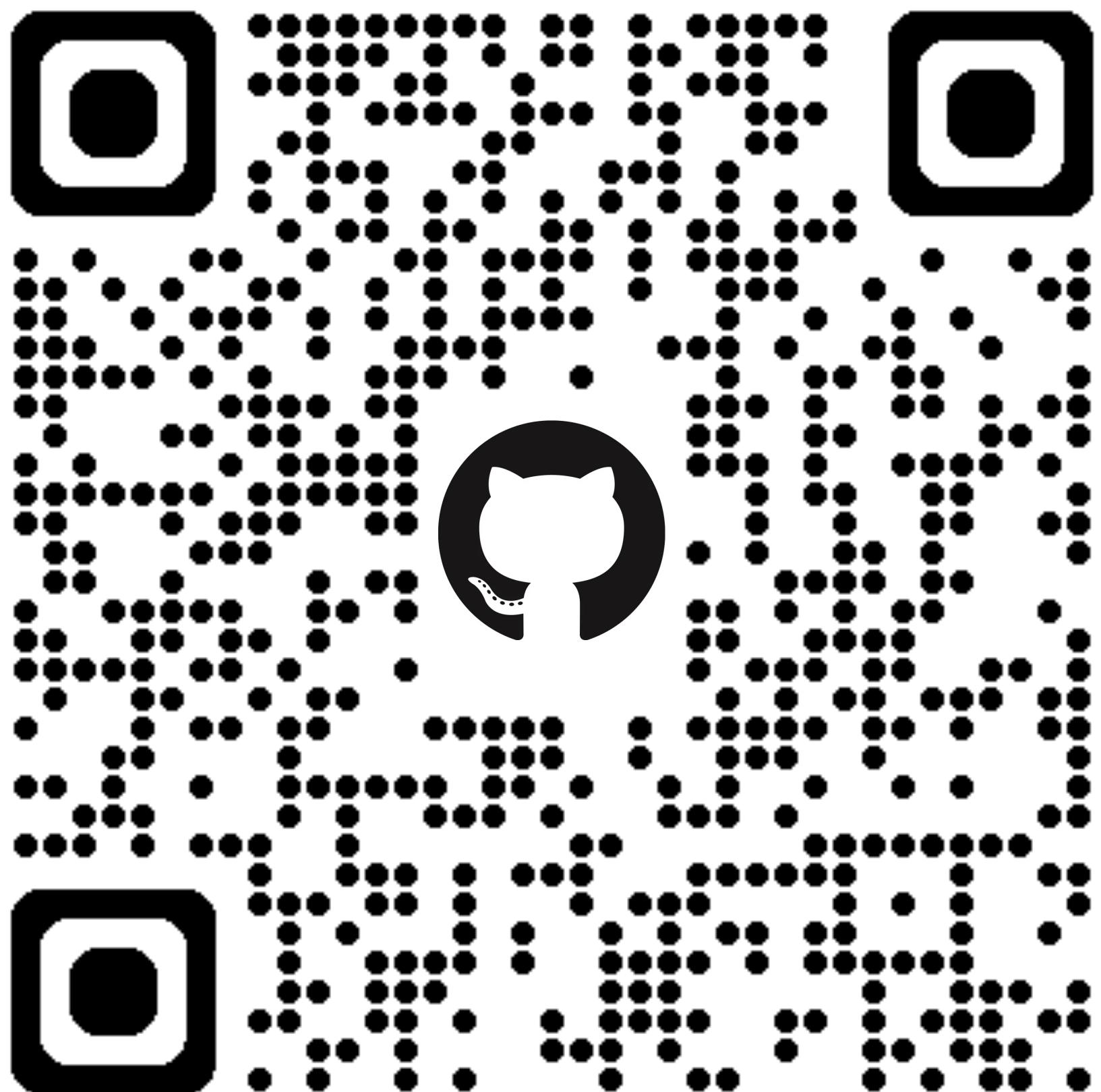
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- Statistical inference must account for **dependency structure** of the data (time series, N-D images, ...)



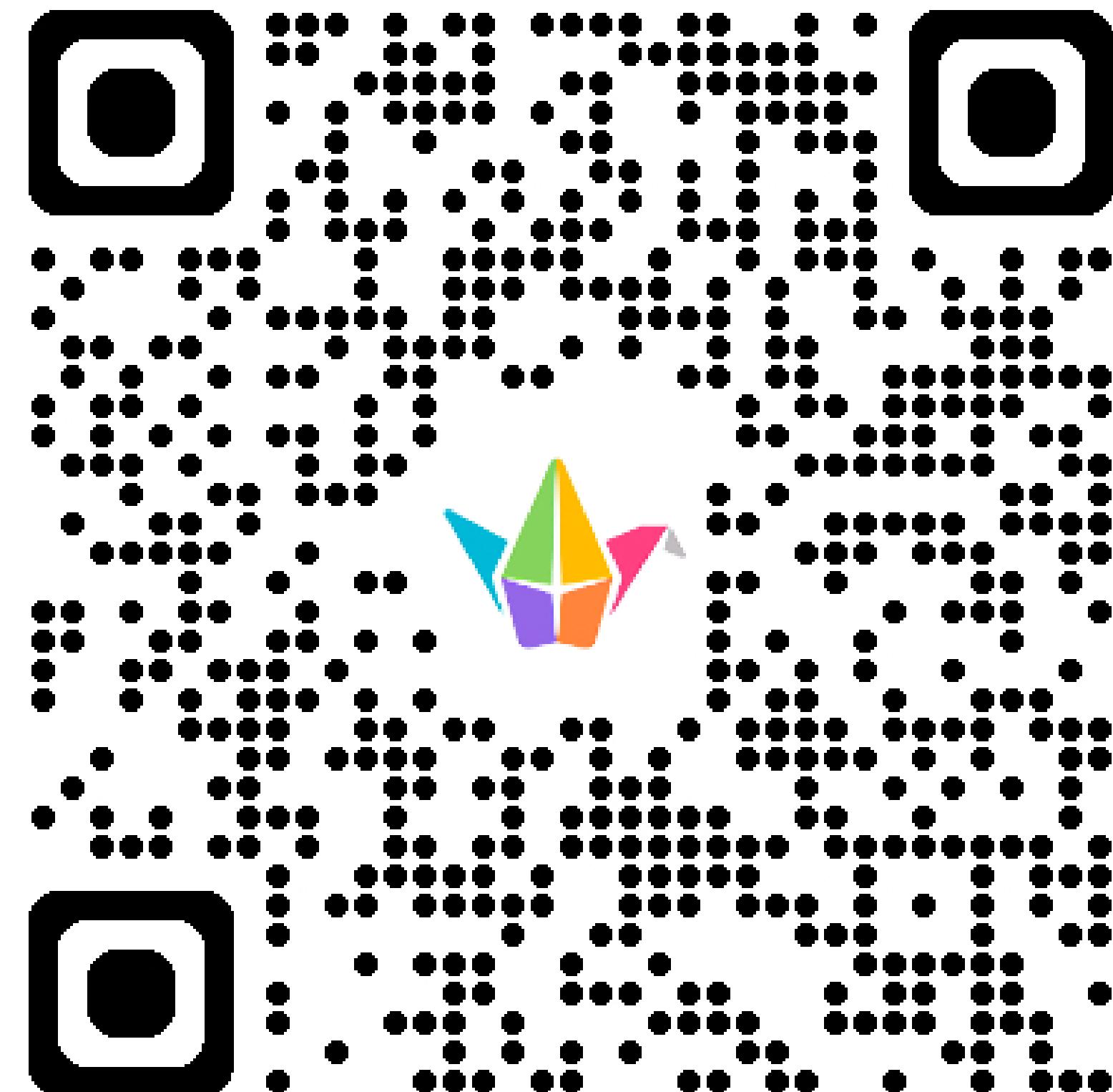
Resources

<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!

