Psychophysical experiment - *Reverse Correlation*

Aynaz ADL ZARRABI (FEMTO-ST, CNRS)

CONTENTS

What is a Psychophysical Experiment?

A controlled method to study the relationship between physical stimuli and perceptual responses, linking the external world to sensory processing.

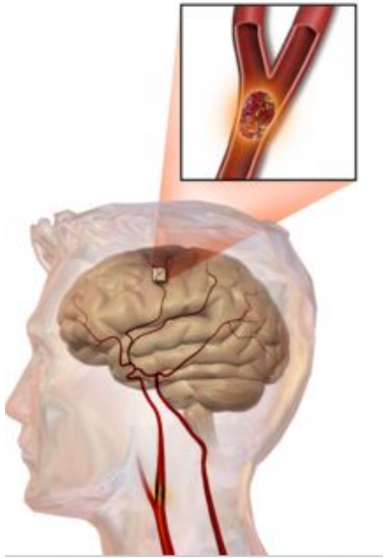
Key Concepts:

- Stimulus-Response Relationship:Quantifies how changes in a stimulus (e.g., sound intensity) influence perception or decision-making.
- Signal Detection Theory (SDT): Separates sensitivity (ability to detect a stimulus) from bias (tendency to respond in a particular way).

  Uses measures like d' (sensitivity) and criterion for decision-making.
- Wiener Kernel Analysis:A technique for modeling how a system responds to dynamic, time-varying stimuli.

  Identifies linear (first-order kernel) and nonlinear (higher-order kernels) components of perception.

STROKE & APROSODIA



Stroke (French: AVC) occurs when **blood flow to the brain is interrupted**, leading to brain cell death. It is one of the main causes of mortality in the world:

➔ The annual prevalence is a total of 15M each year (100,000 cases per year in France)

➔ About 30% of patients who have had a stroke have permanent disabilities, among which is "aprosodia"

Aprosodia is an **impairment in perceiving and producing "prosody", i.e. the melody of speech.** For instance, people with aprosodia may be unable to tell apart a question ("vraiment? really?") from an answer ("vraiment! really!").

NOT MANY TOOLS TO DIAGNOSE APROSODIA

Main tool to diagnose aprosodia : Montreal Evaluation of Communication (MEC), which consists of 12 sentences to evaluate, with a score out of 12.

For instance,
question: ***"Mary eats the cake ?"***
answer: ***"Mary eats the cake."***
order: ***"Mary, eat the cake !"***

MEC is very simple, but has two problems:

➔ a lot of false negatives : patients can have a perfect score (12/12), but still complain about aprosodia

➔ not specific : people can have 0/12, but for many different reasons: sensory (ex. bad internal representations of prosody) or cognitive (ex. attentional problems)

	P1	P2	P3	P4	P5	P6	P7	P8	P9
Désignation	55	72	72	72	72	72	65	72	67,5
Partie du corps	18,5	19	20	19	19	20	19,5	19	19
Exécution d'ordres	12	15	15	14	14	14	13	14	15
Répétition Prosodie	7	10	12	9	11	12	11	8	9
Compréhension Prosodie	5	8	9	0	10	9	6	6	6
Compréhension Questions Prosodie	1	4	4	0	4	2	0	2	2
Actes de langage indirect	30	35	30	31	32	33	32	33	33

Question méthodologique

The traditional diagnostic tool for aprosodia (the "Montreal Evaluation of Communication" battery - MEC) does not distinguish between representation and decision deficits. Can a more detailed psychophysical paradigm (reverse correlation) provide a better tool and help address our biological question?

Reverse Correlation Methodology:

The reverse correlation paradigm (revcor) involves a behavioral experiment where participants listen to numerous random prosody stimuli and respond to each pair of stimuli.These responses,**Y** , are analyzed using a computational subject model that makes linear comparisons between a latent representation $\boldsymbol{\beta}$ and the random stimuli, **X** to perform the task. Yes/no responses are coded as 1 and 0. An extended model incorporates noise, $\boldsymbol{\varepsilon}$ into this formulation to better represent the human response process.

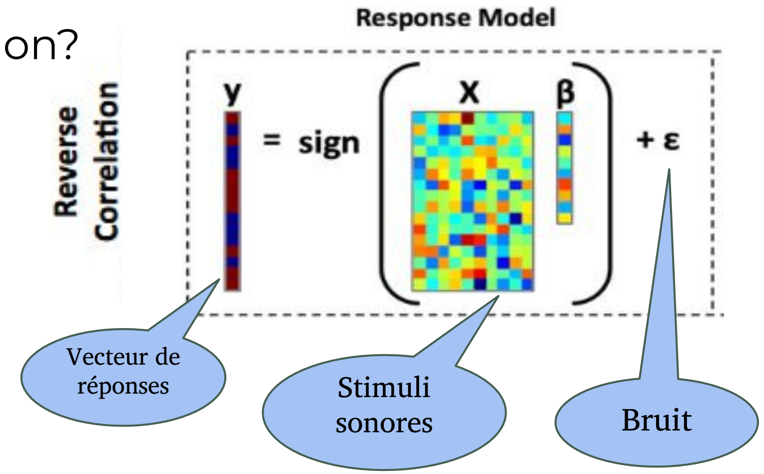
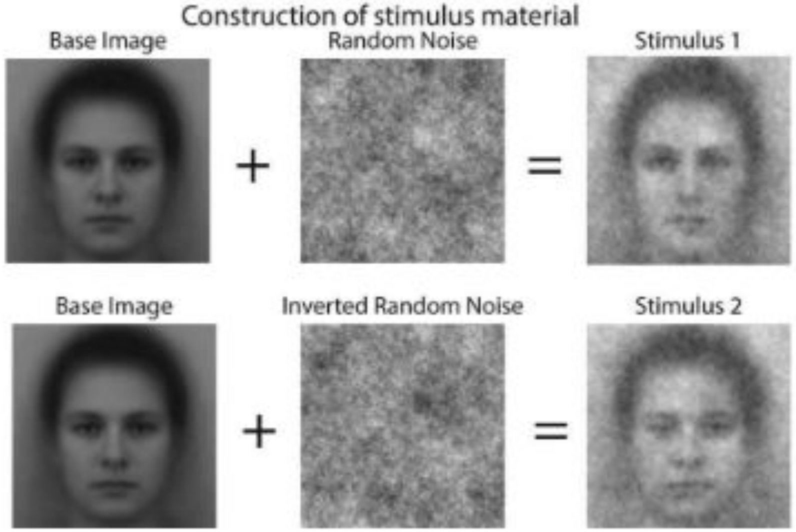
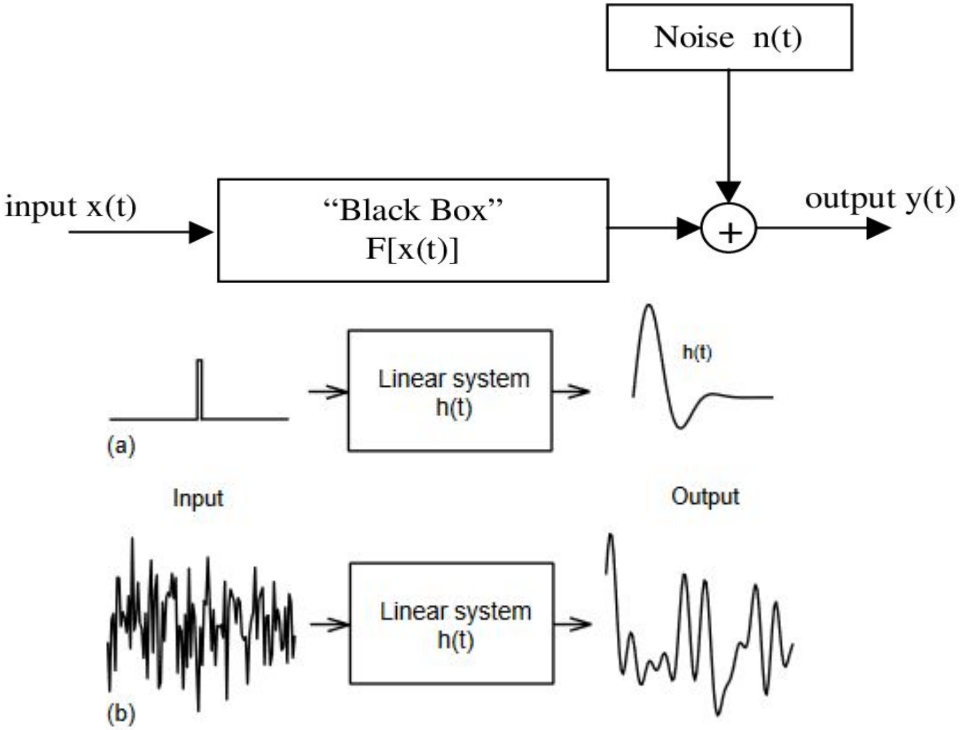


Figure adaptée de Roop et al. 2023

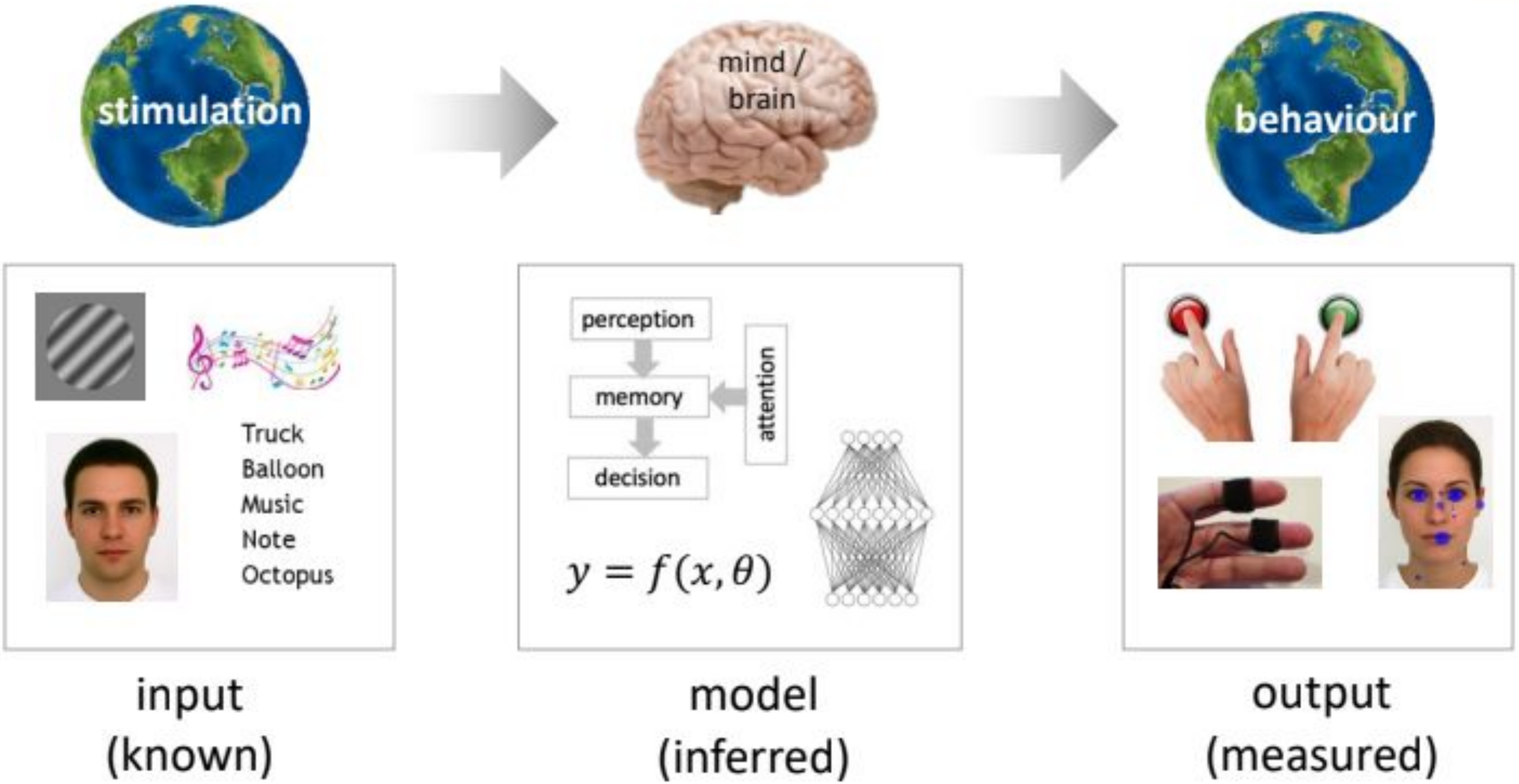
CLASSIFICATION IMAGES

The **“classification images”** method is an experimental technique called “data-driven” to estimate how a participant makes a decision based on a stimulus (visual or audio). The participant is presented with a large number of random stimuli, made by superimposing noise patterns on a base stimulus. We then correlate the participants' responses to each of these noise patterns, to estimate a sort of “transfer function” of the system called “image classification” or “mental representation”. This technique is widely used in visual psychophysics (e.g. below on images of faces - Dotsch & Todorov, 2012). We adapt it here to the perception of prosody.





Murray (2011). Classification images: A review. Journal of vision, 11:5

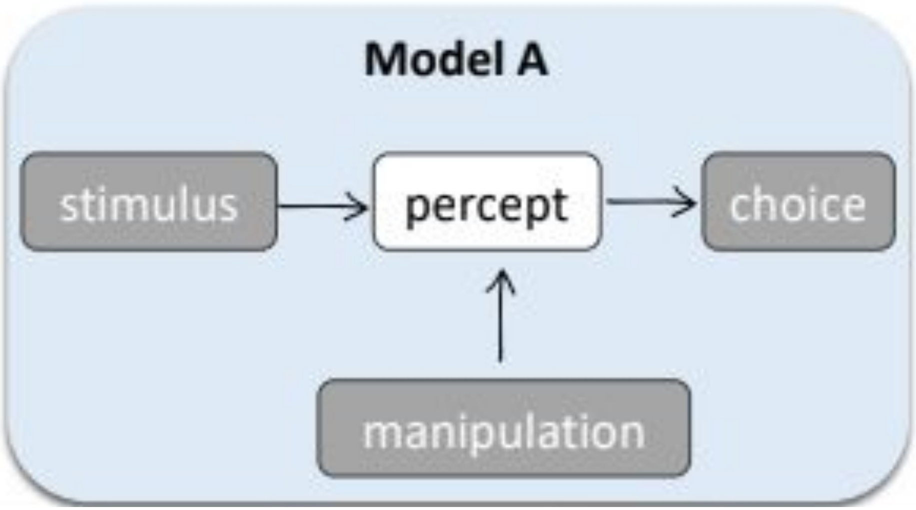

stimulation
mind /
brain
behaviour
perception
memory
attention
decision
$y = f(x, \theta)$
Truck
Balloon
Music
Note
Octopus
input
(known)
model
(inferred)
output
(measured)

Convert model A to statistical model:

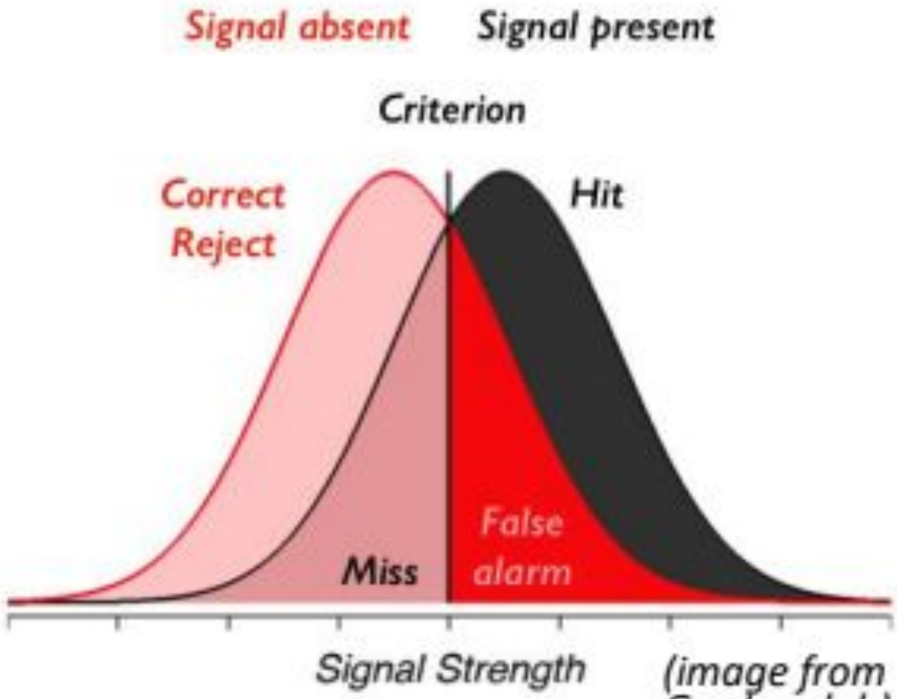
percept: $\hat{s} = s + \epsilon$

ϵ sensory noise drawn from zero-mean Gaussian, variance σ_d^2 in deactivation trials, σ_m^2 in control trials

choice: Right if $\hat{s} > 0$, Left otherwise



Signal detection theory



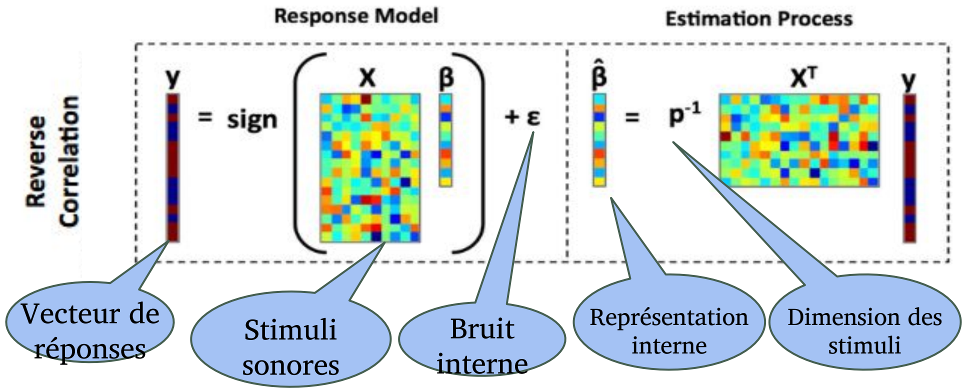
(image from Gardner lab)

State of the art to estimate kernel representation and noise

To estimate the latent representation $\boldsymbol{\beta}$ and the noise $\boldsymbol{\varepsilon}$, the subject's response model is "inverted" using different methods:

In most experiments, the latent representation (or kernel)$\boldsymbol{\beta}$ is estimated using the "classification image" method: the mean of the stimuli that elicit a "no" response is subtracted from the mean of the stimuli that elicit a "yes" response. (Note: Other methods exist, e.g., GLM, Knoblauch, K., & Maloney, L. T. (2008)).

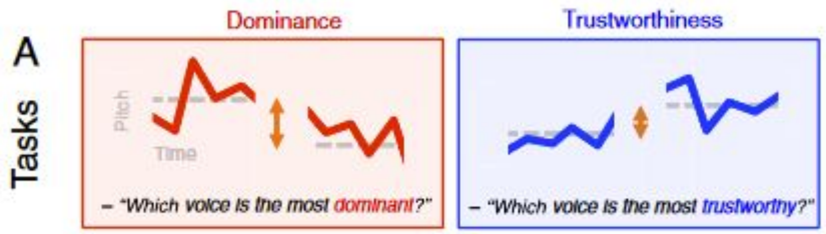
To estimate internal noise, the "double-pass" method is used: A small number of trials (pairs of stimuli in a 2AFC experiment) are repeated, and the subject's percentage of disagreement across the two repetitions is measured. The noise level required to produce this percentage of disagreement is determined through simulation. (Neri, 2010). Note: Other methods exist, such as "equivalent noise" - Vilidaite, Baker, 2016.

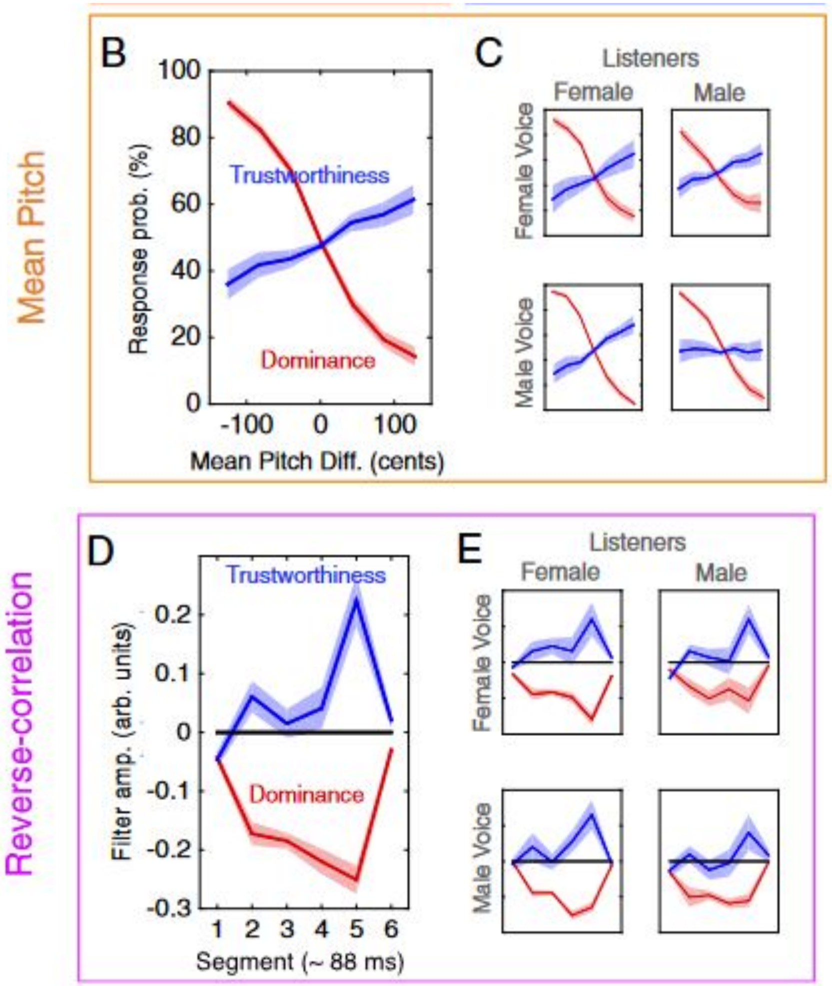


W. Roop et al. 2023

REVERSE CORRELATION IN SOCIAL TRAITS

- the social perceptions of dominance and trustworthiness in speech prosody using the word "hello."
- Using an experimental paradigm that combined voice transformation algorithms with psychophysical reverse correlation, allowing to manipulate the pitch dynamics of recorded voices to create novel utterances of "hello" with randomly varied pitch contours.
- Two groups of participants were presented with pairs of random pronunciations of "hello" by male and female speakers and asked to evaluate the social traits of the speakers.
- specific pitch contours in the utterance of "hello" significantly influenced perceptions of dominance and trustworthiness. These pitch trajectories remained stable across different genders of speakers, indicating that listeners inferred social traits irrespective of the speaker's sex or mean pitch.





Ponsot et al.(2018). Cracking the social code of speech prosody using reverse correlation

femto-st SCIENCES & TECHNOLOGIES

CONTENTS

EXPERIMENT

you can start now…

https://neuro-xp.femto-st.fr/xp/prosavc/new

participant: your name

password: prosavc

mention your level of french proficiency from 0 to 5 in your name

like mine: Aynaz_5

FEEDBACK

- your level of tiredness
- difficulty you faced
- what is our hypothesis in this experiment?
- was it enough the pause time that you had?
- did you feel that you're hearing the same sounds sometimes?
- how you were comparing the sounds ? between the sounds that you were hearing at one time or in a different manner?
- ...

EXPERIMENT

This experiment aims to investigate how individuals perceive the interrogative intonation of the word "vraiment? = really?". We seek to understand the nuances of linguistic prosody , particularly how subtle changes in prosody can alter the perceived meaning of a word.

you will hear 150 pairs of audio clips, each containing different intonations of the word "vraiment" and will listen to each pair of audio clips and judge which of the two sounds more like a question; The key aspect is to identify how pitch shifting affect the perception of interrogative intent.

Expected Outcomes:

Insights into how people distinguish between a question and a statement based solely on intonation.

Understanding of the variability in perceiving interrogative prosody among different individuals.

Discussion Points:

Challenges faced by participants in distinguishing the interrogative tone.

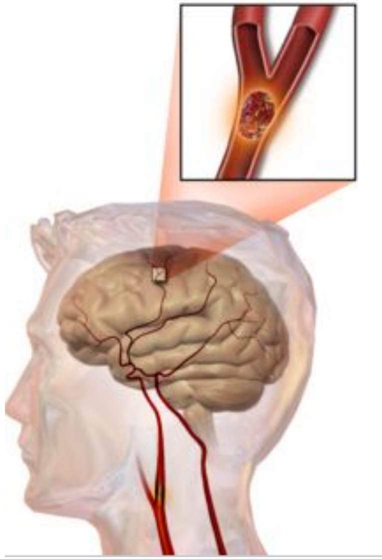
Talking about your judgments decisions parameters

CONTENTS

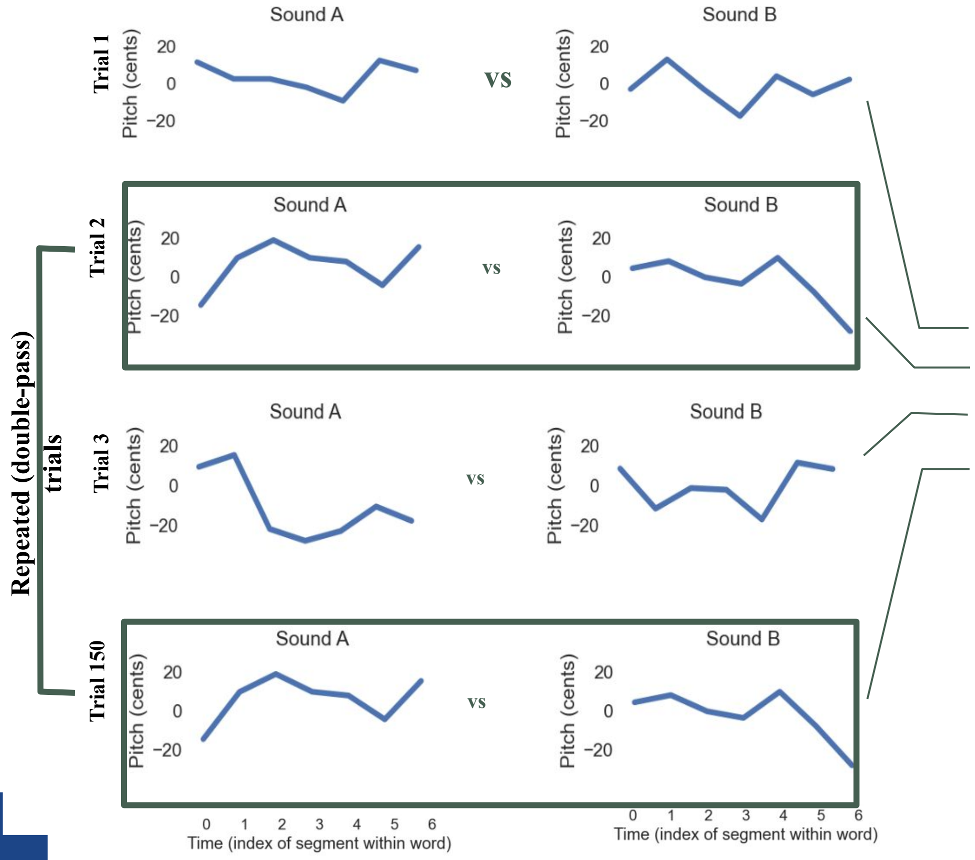
Because MEC has so many problems,

GOAL OF THE STUDY

Investigate the use of a new method, based on a simple idea of **“linear system identification”**, for replacing MEC when evaluating impairments of prosody perception after stroke.

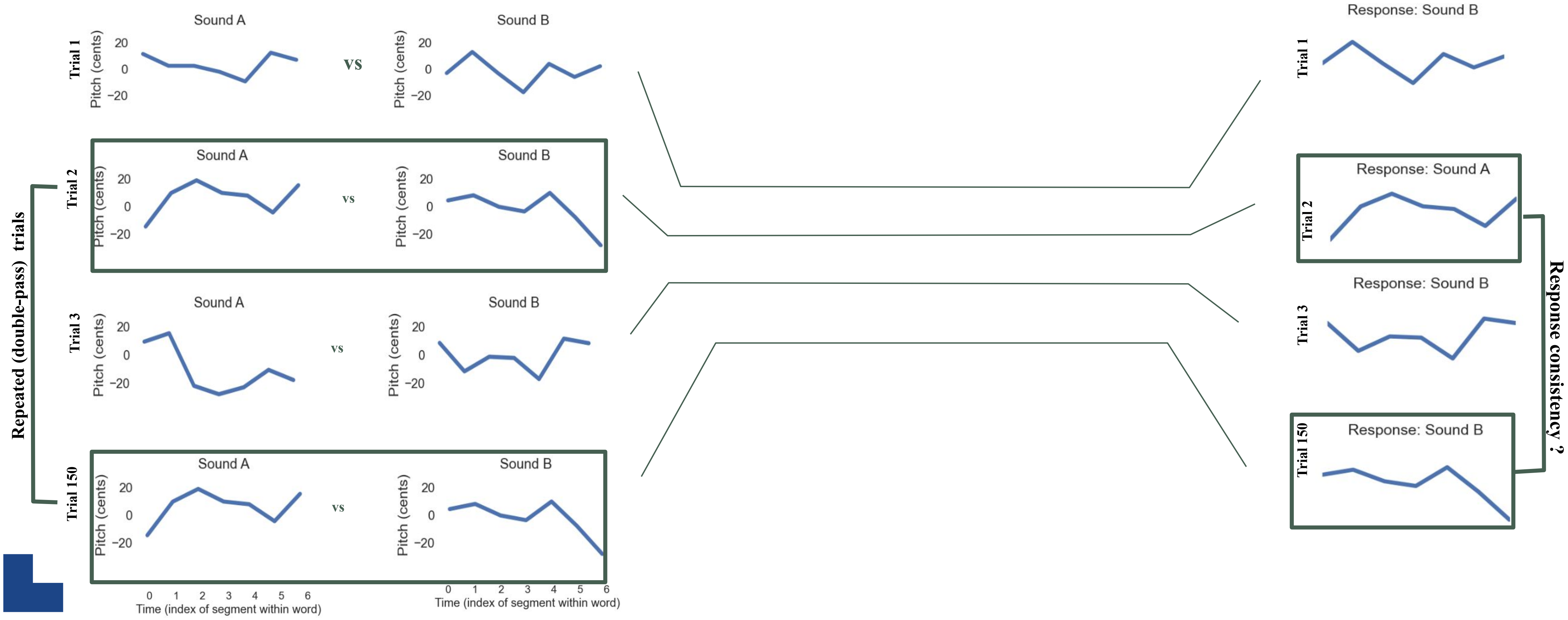


(1) Build an experiment in which patients listen to many random examples of prosody



(1) Build an experiment in which patients listen to many random examples of prosody

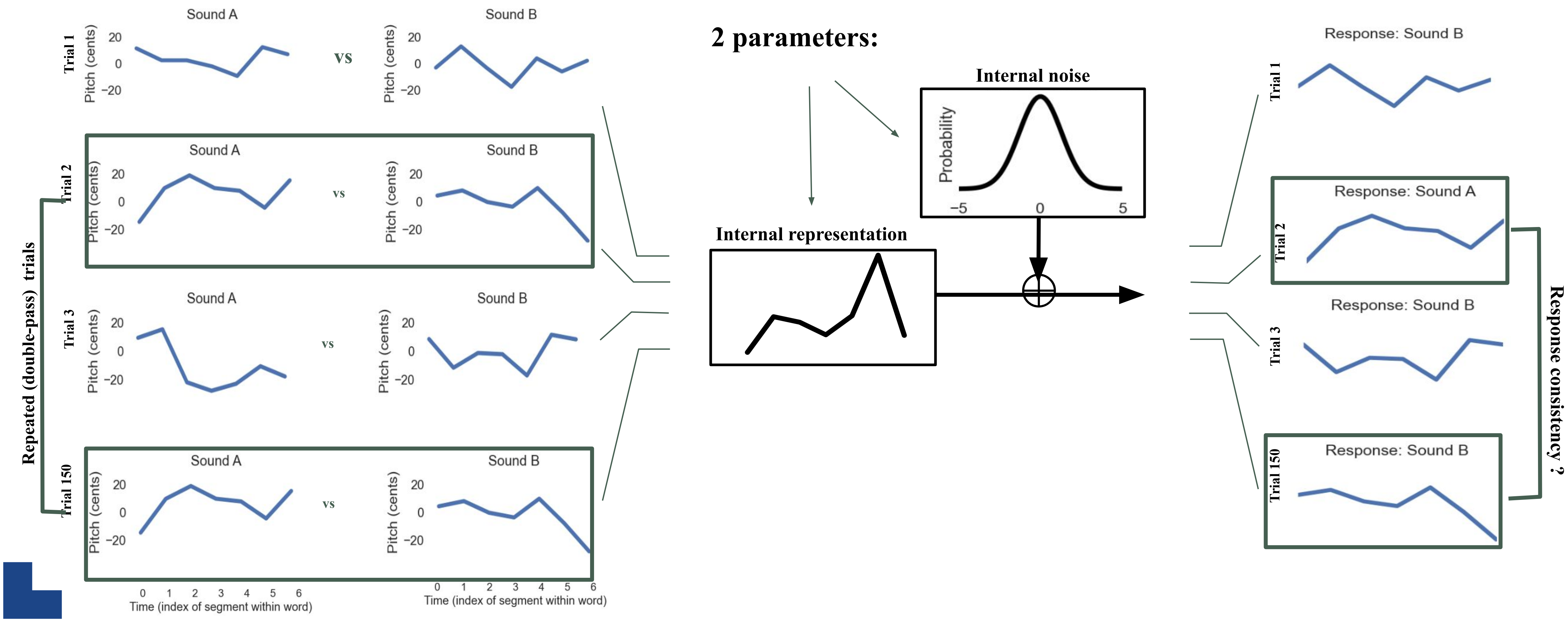
(2) Patients give responses to each examples, and from these responses…



(1) Build an experiment in which patients listen to many random examples of prosody

(3) we build a computational model that explains patient behaviour, and it is the parameters of *that* model which serve as markers of aprosodia

(2) Patients give responses to each examples, and from these responses…



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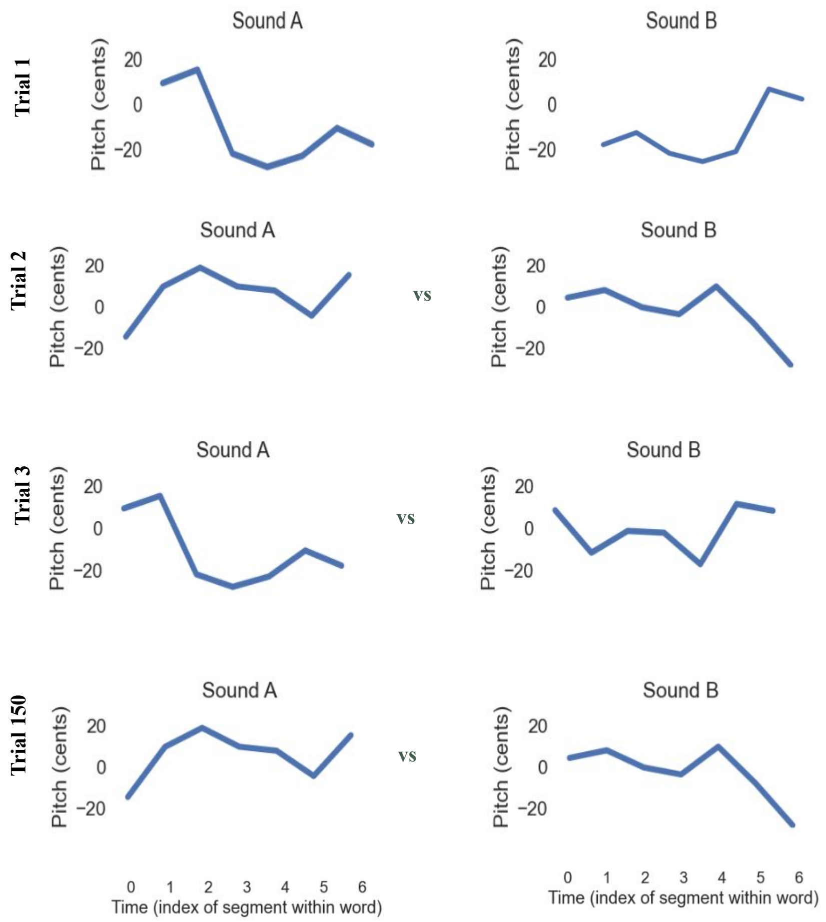

In more details:

- Patients are presented with pairs of 2 random pronunciations of the word “really” (French: “vraiment?”)

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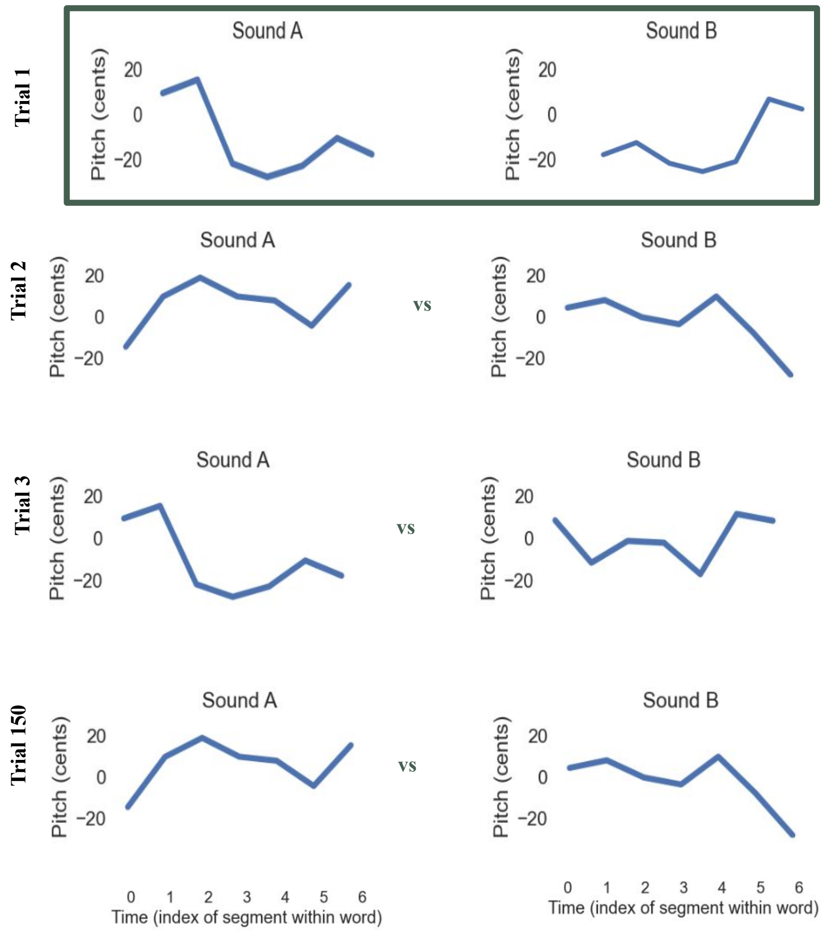

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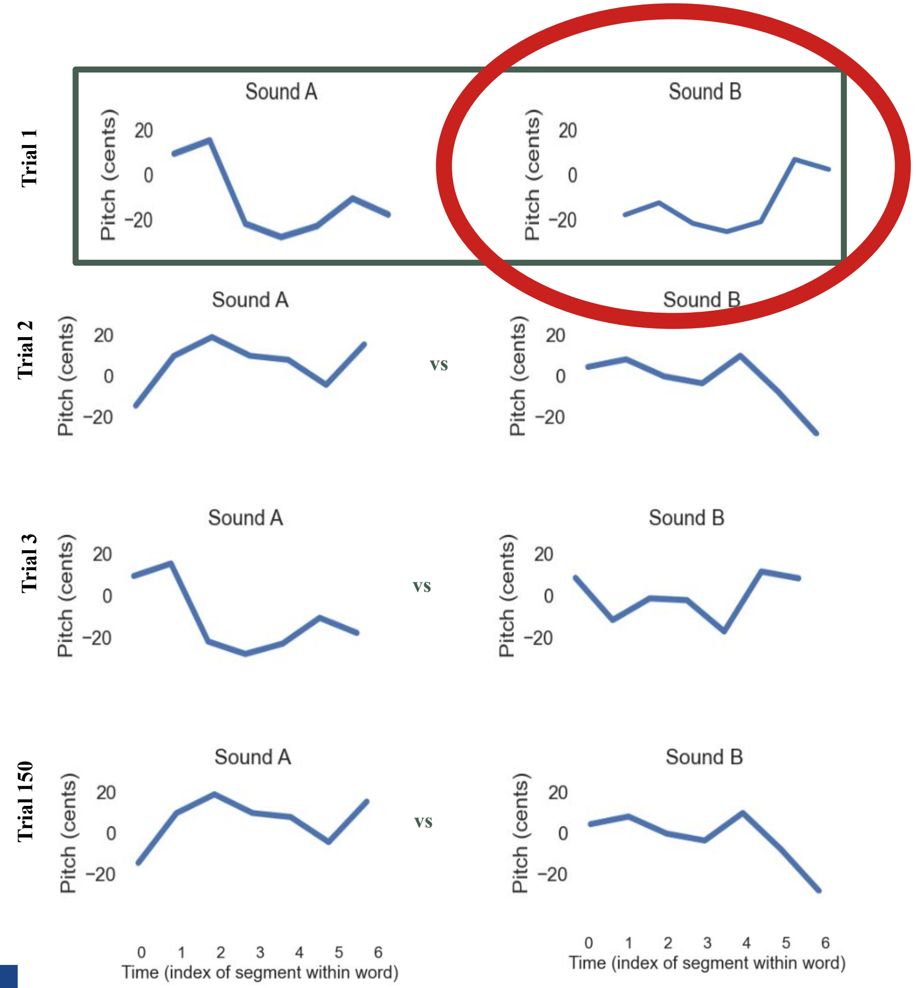

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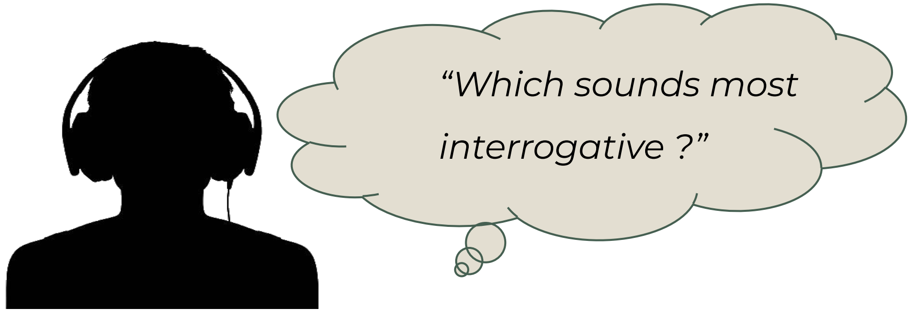
- For each pair, they have to decide which of the 2 pronunciation sounds most like a question



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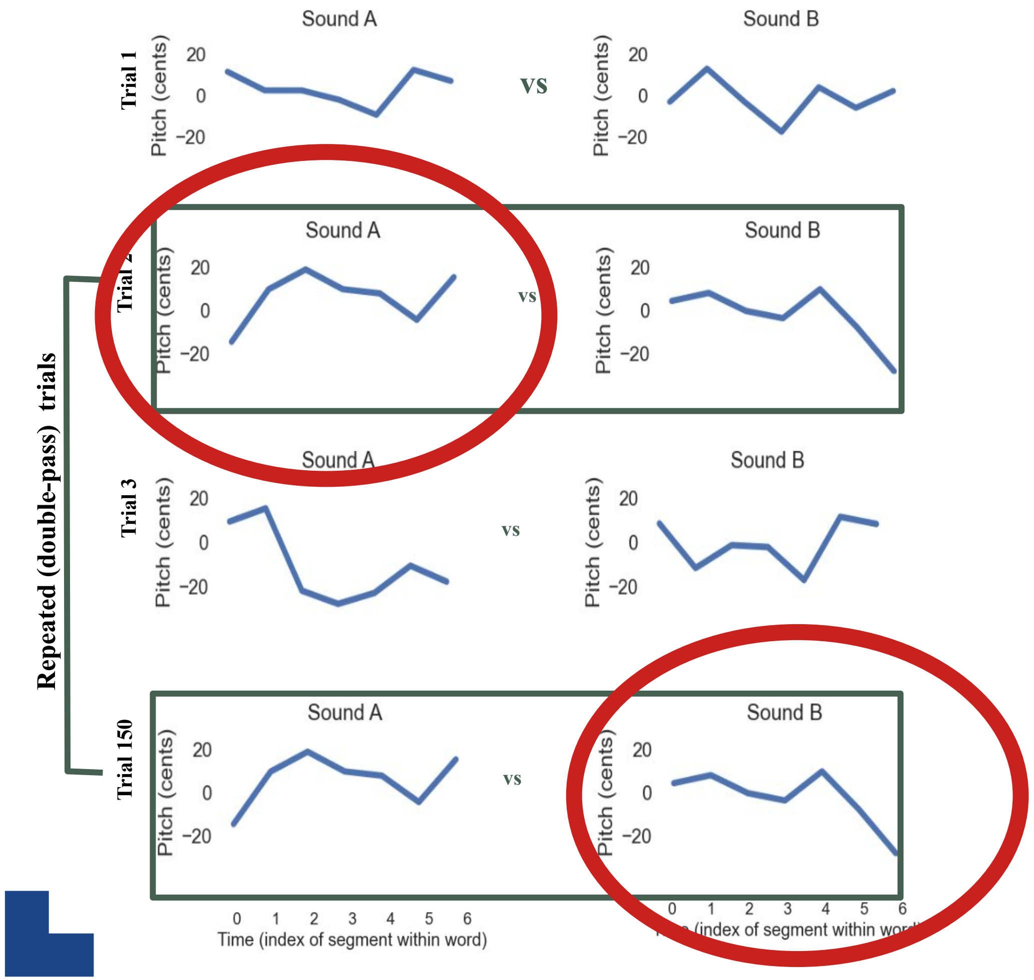

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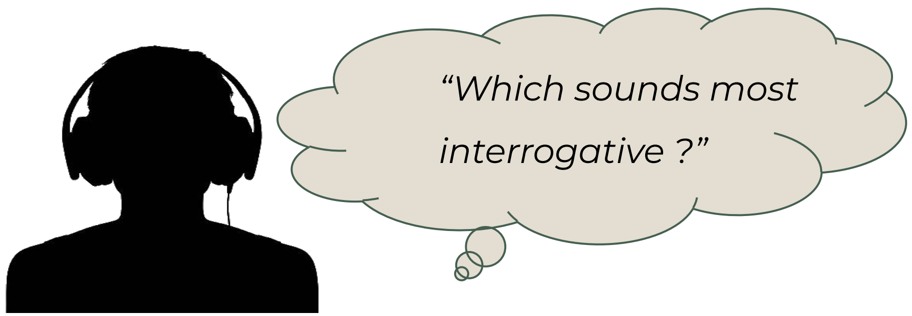
- Patients are presented with pairs of 2 random pronunciations of the word "really" (French: "vraiment?")
- For each pair, they have to decide which of the 2 pronunciation sounds most like a question
- There are 150 pairs (10 minutes), and some pairs are repeated (t.b.d.)



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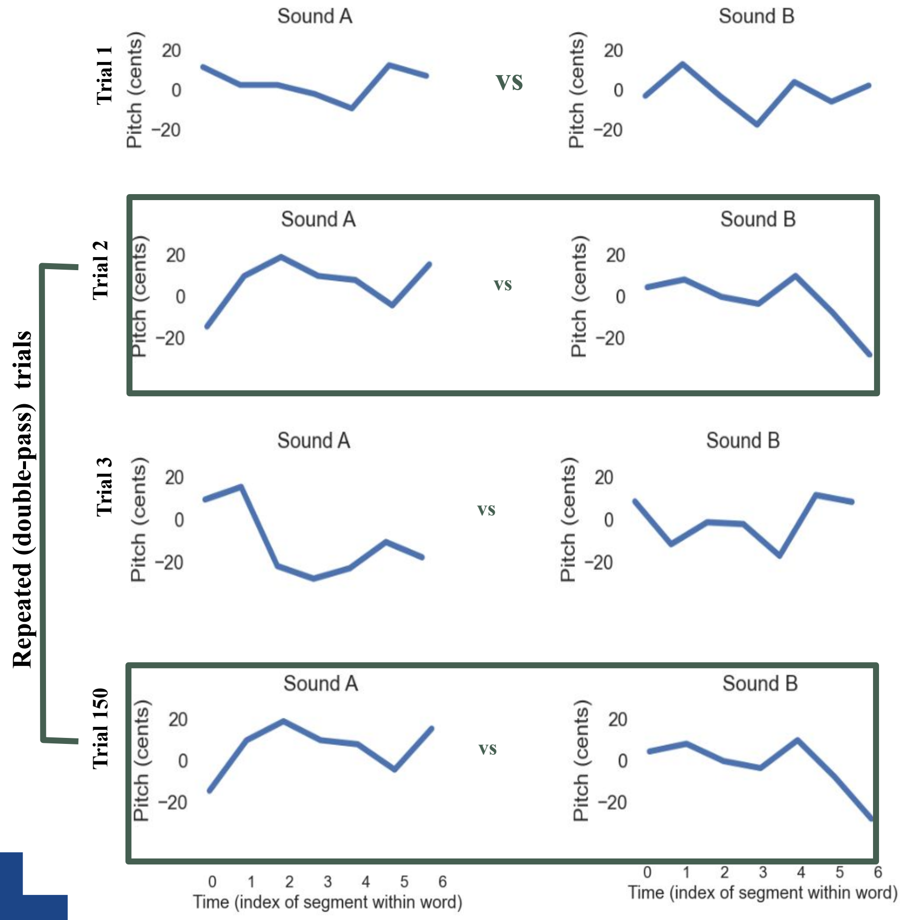

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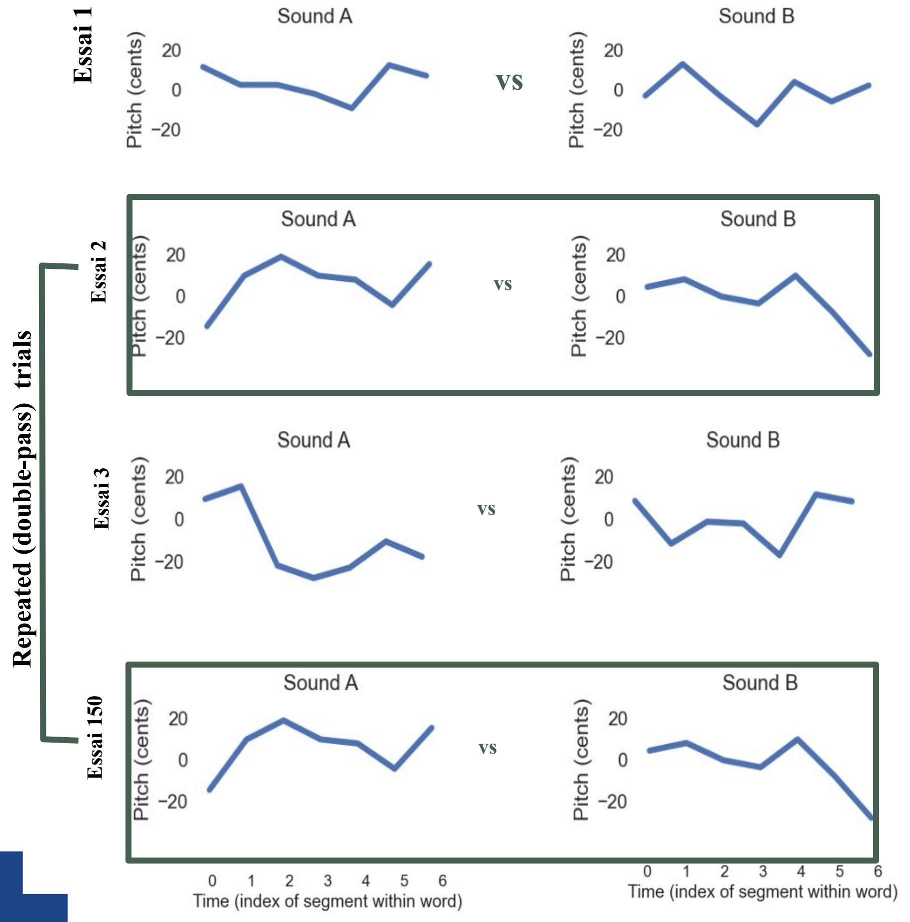
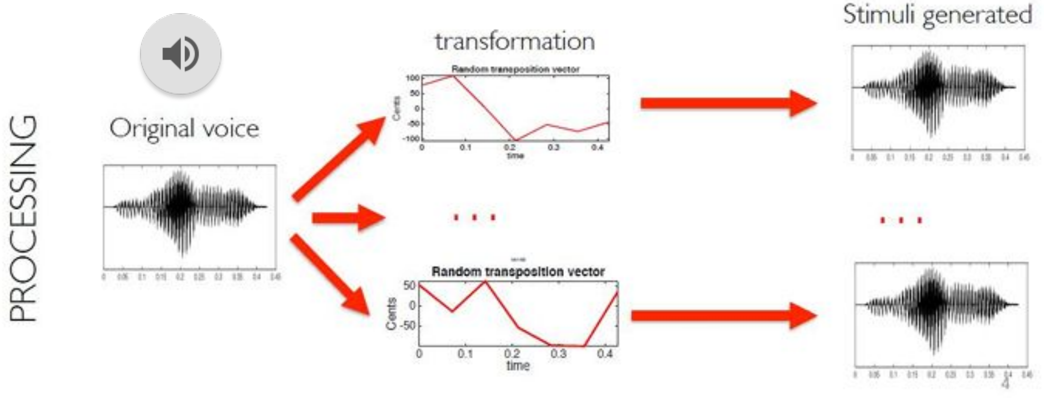
- Patients are presented with pairs of 2 random pronunciations of the word “really” (French: “vraiment?”)
- For each pair, they have to decide which of the 2 pronunciation sounds most like a question
- There are 150 pairs (10 minutes), and some pairs are repeated (t.b.d.)
- The random pronunciations are generated with computer software (CLEESE: open-source python toolbox)

LINK: https://github.com/neuro-team-femto/cleese

(1) Construire une expérience dans laquelle les patients écoutent de nombreux exemples aléatoires de prosodie

- Les prononciations aléatoires sont générées avec un logiciel informatique (CLEESE : open-source python)

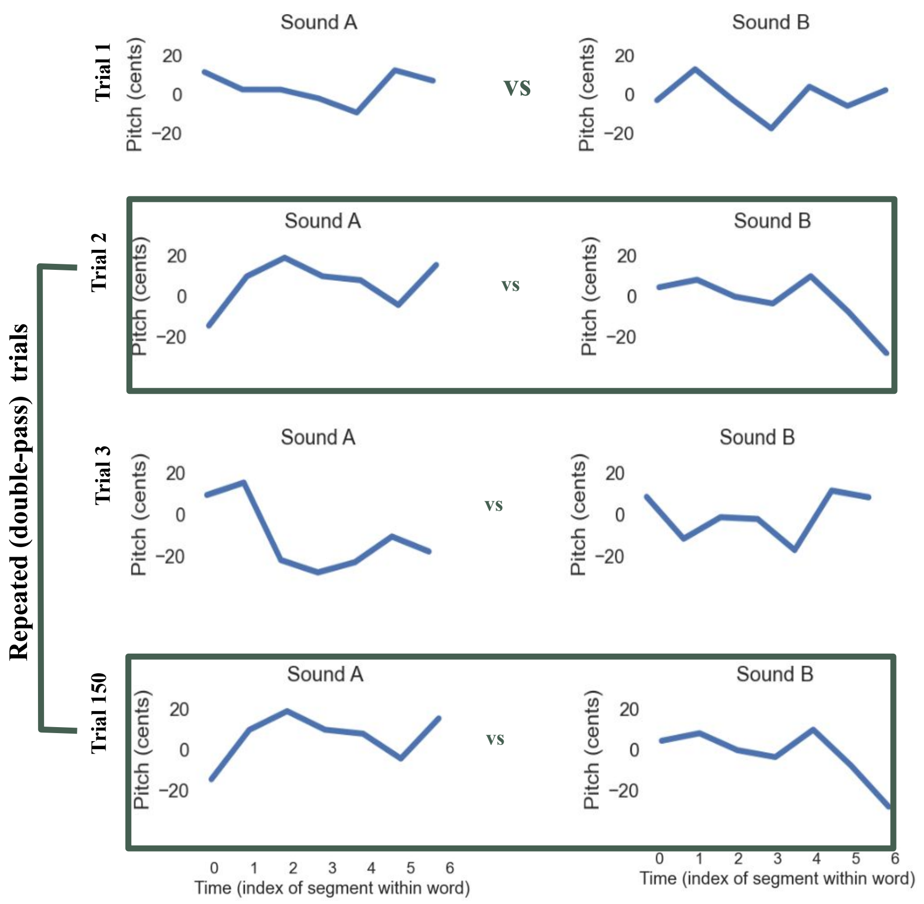




Lien:https://github.com/neuro-team-femto/cleese

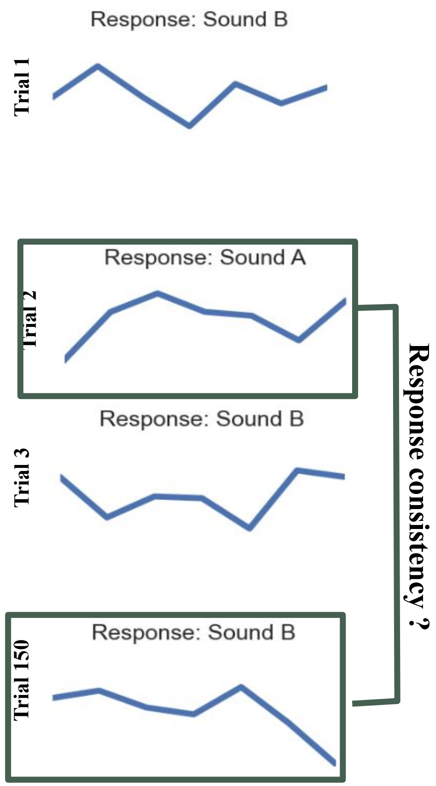
(2) Patients give responses to each of these trials

A. Experimental stimuli



(including perhaps different responses to repeated trials)

B. Patient responses

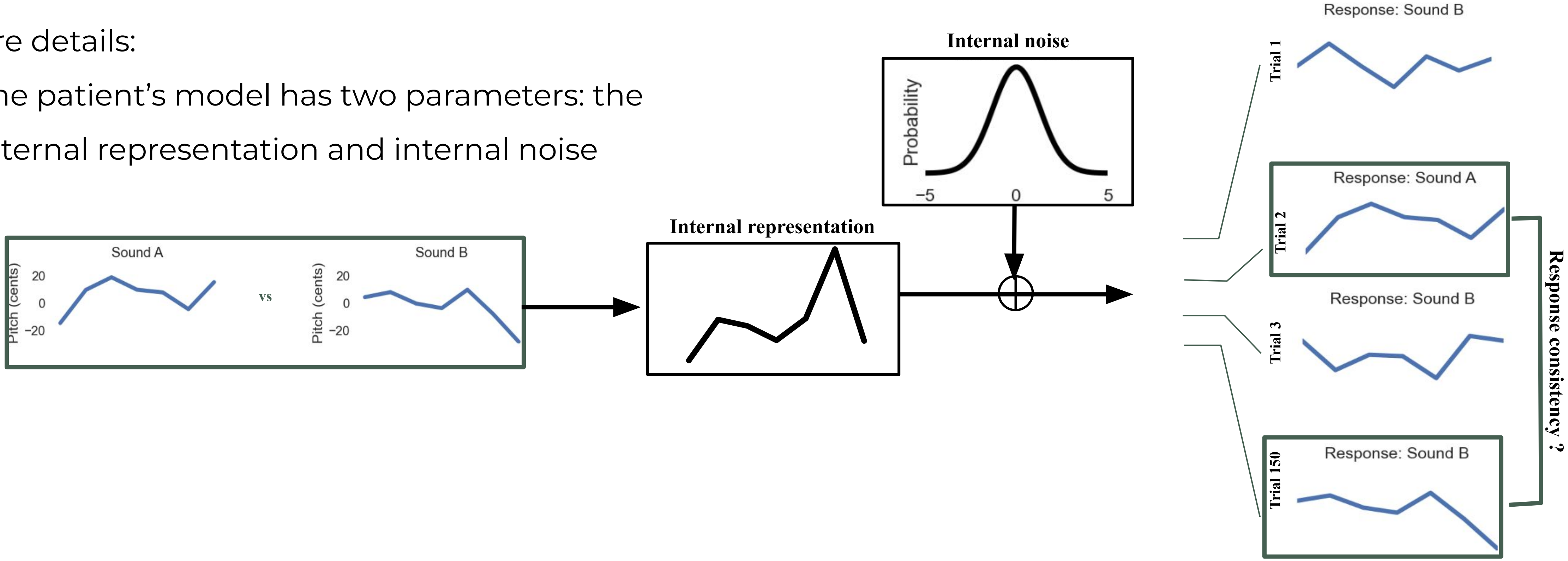


Which sounds most interrogative ?

(3) we build a computational model that explains these responses

In more details:

- The patient’s model has two parameters: the internal representation and internal noise



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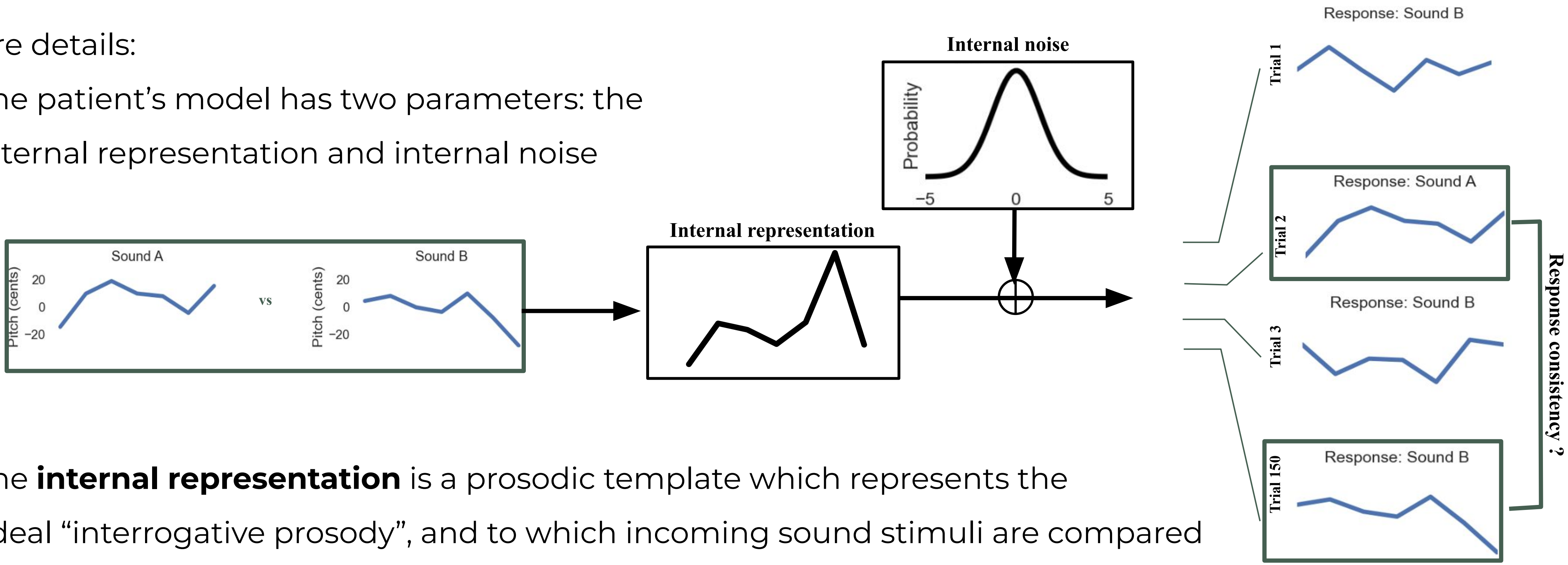
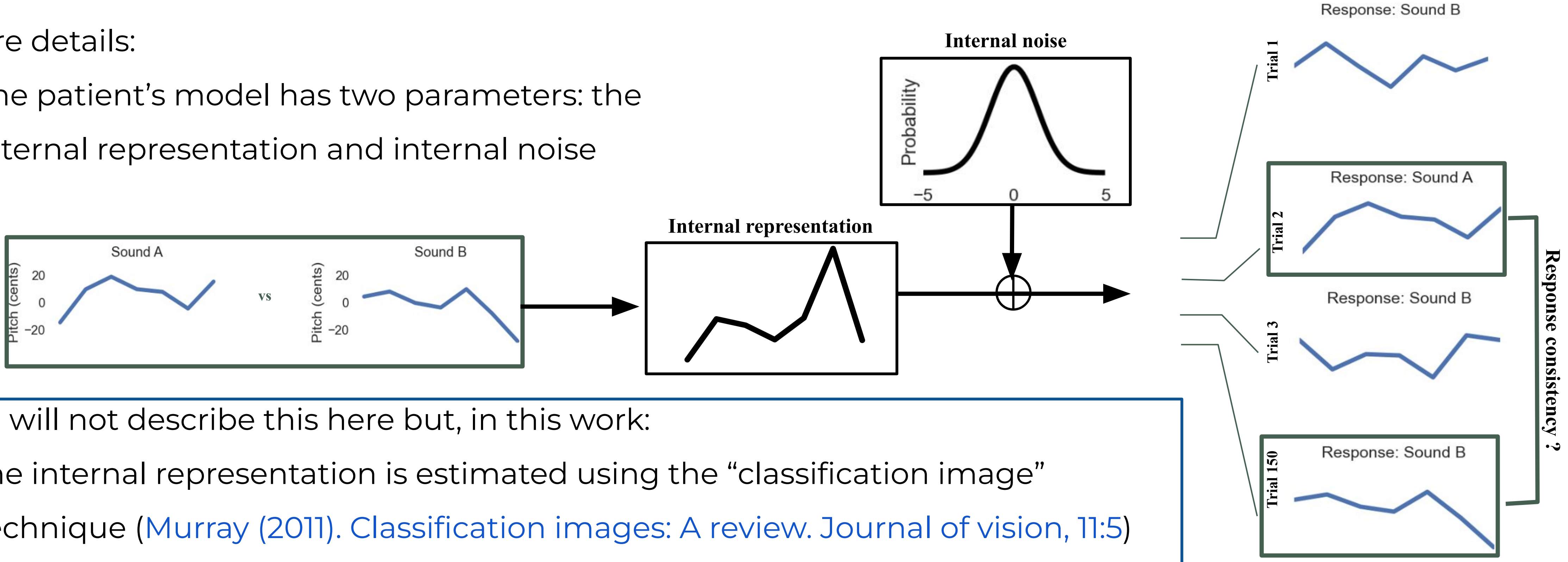


- The **internal representation** is a prosodic template which represents the ideal "interrogative prosody", and to which incoming sound stimuli are compared
- The **internal noise** is additive gaussian noise which controls how consistently this representation is applied to incoming stimuli (the more noise, the less consistent)

(3) we build a computational model that explains these responses

In more details:

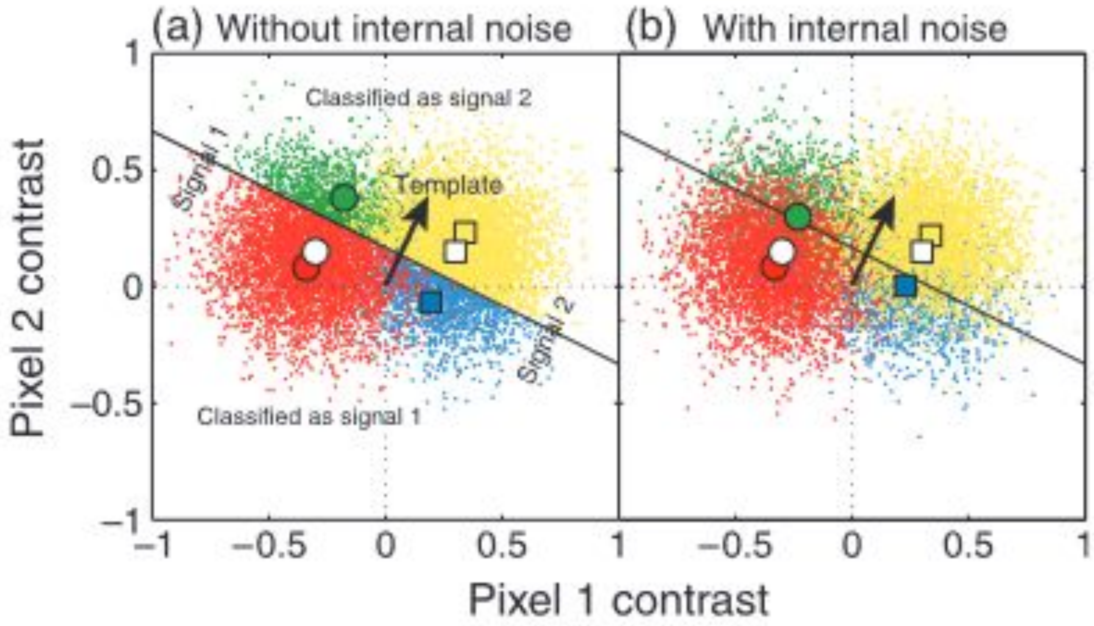
- The patient's model has two parameters: the internal representation and internal noise



Note: I will not describe this here but, in this work:

- the internal representation is estimated using the "classification image" technique (Murray (2011). Classification images: A review. Journal of vision, 11:5)
- internal noise is estimated from the probability of agreement on repeated trials, using the simulation procedure of Neri (2010). How inherently noisy is human sensory processing? Psychonomic Bulletin & Review, 17(6)

NOISE

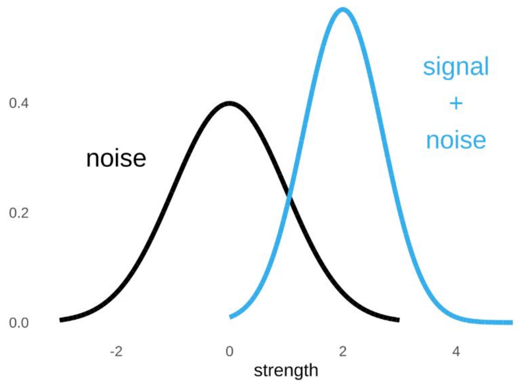


Murray.(2011)

Decision space for a linear observer (a) without internal noise and (b) with internal noise

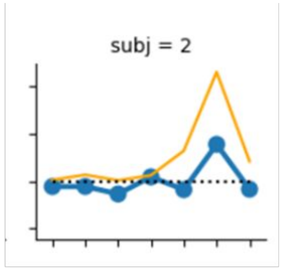
The black arrow is the hypothetical observer's template, and the oblique black line is the decision line that the observer used to decide whether to identify a stimulus as signal 1 or signal 2.

This internal response is inherently noisy. Even when there is not the true pronunciation of really, present (no-signal trials) there will be some internal response (sometimes more, sometimes less) in the participant's sensory system.



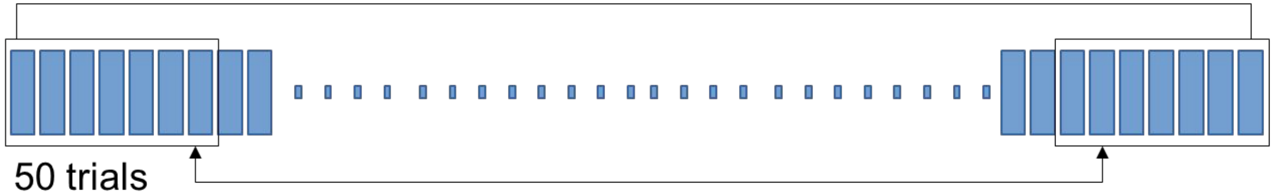
Discriminability index (dprime)

DOUBLE-PASS PARADIGM



Distance du kernel du patient au kernel « contrôle »

200 trials



50 trials identiques en « double pass »

Probability of agreement
Prob. of responding “1”

$$\cancel{l = \mathbf{w}^T(\mathbf{s}^k + \mathbf{n}) + z,} \quad r = \begin{cases} 1 & \text{if } d < a \\ 2 & \text{otherwise} \end{cases}$$

INTERNAL NOISE COMPUTATION

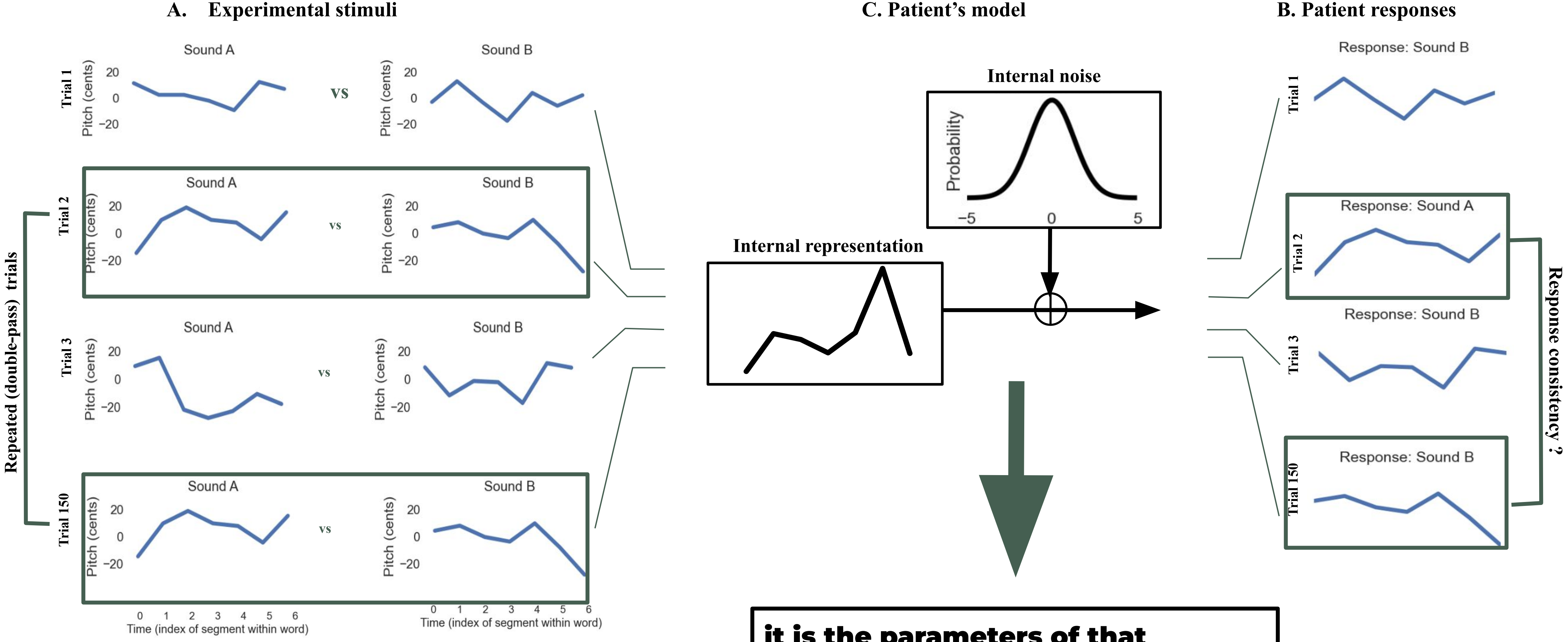
$$d = \mathbf{w}^T\cancel{(\mathbf{s}^k + \mathbf{n})} + z, \quad r = \begin{cases} 1 & \text{if } d < a \\ 2 & \text{otherwise} \end{cases}.$$

Observed variables — Probability of agreement; Prob. of responding “1” $\xrightarrow{\textbf{what we want to do}}$ internal noise z; criteria a

Hidden “internal” variables

Predicted variables — Probability of agreement; Prob. of responding “1” $\xleftarrow{\textbf{compute by simulation}}$ internal noise z; criteria a

SUMMARY



it is the parameters of that model *(i.e. representation + noise)* which serve as markers of aprosodia

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OPEN

A simple psychophysical procedure separates representational and noise components in impairments of speech prosody perception after right-hemisphere stroke

Aynaz Adl Zarrabi[1,5], Mélissa Jeulin[2,5], Pauline Bardet[2], Pauline Commère[2], Lionel Naccache[2,3], Jean-Julien Aucouturier[1], Emmanuel Ponsot[4] & Marie Villain[2,3]

CLINICAL STUDY

We studied a group of **22 patients** who had had a right-hemisphere stroke (about 4 months before)

Each patient did the experiment (150 pairs of sounds), and we computed their internal representation and internal noise.

We compared with their MEC score, and with the parameters of a control group (N=9, matched in age)

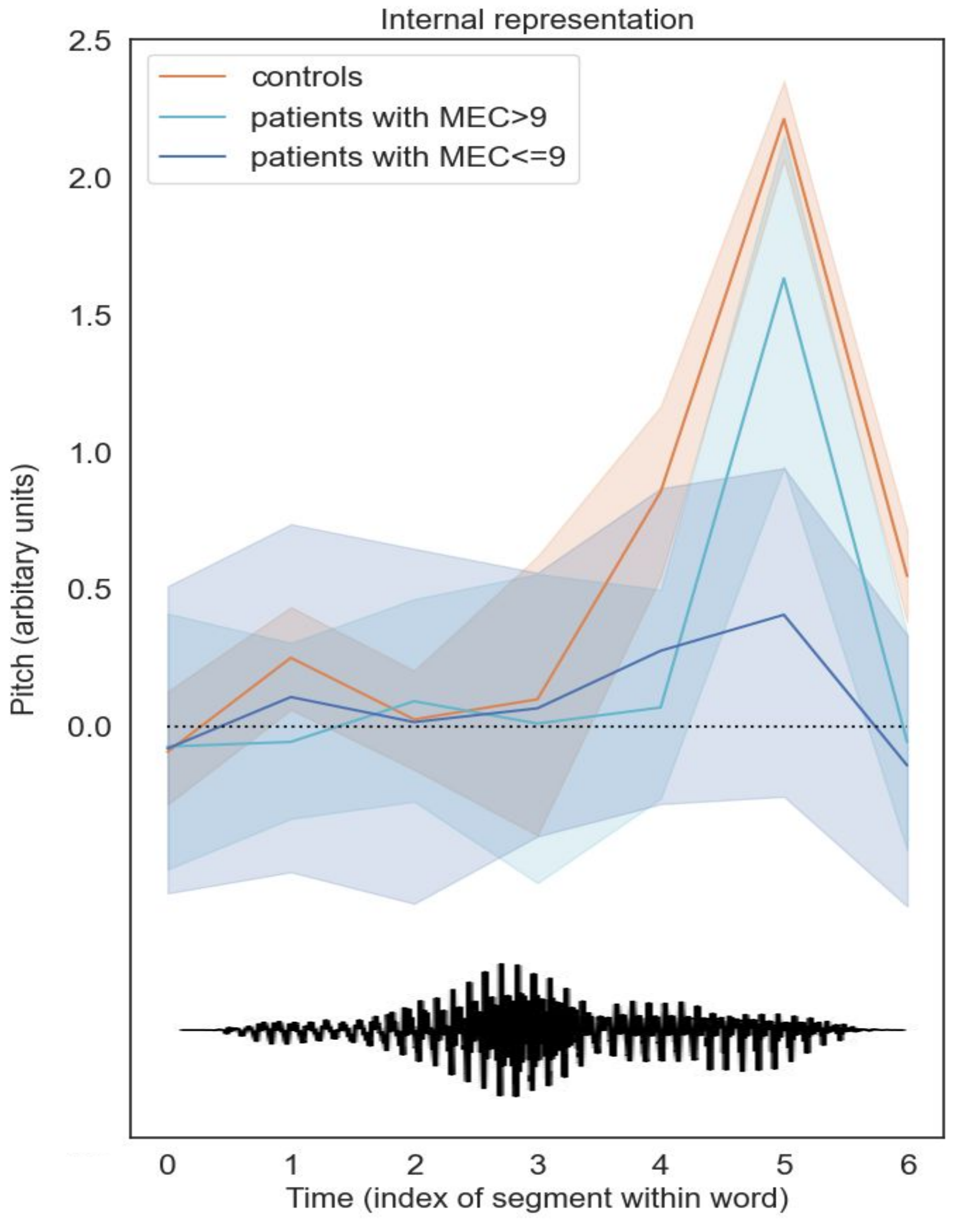
		Controls	Patients
n		21	22
Sex, n (%)	f	8 (38.1%)	5 (22.7%)
	m	13 (61.9%)	17 (77.3%)
Age, median [min, Q1, Q3, max]		58 yo [27,52,64,82]	60.5 yo [28,52.2,63,74]
Month after stroke, median [min, Q1, Q3, max]			4 mo [0,1,5,17]
Stroke type, n (%)	HEM		3 (33.3%)
	ISCH		6 (66.7%)
NIH stroke scale (NIHSS), median [min, Q1, Q3, max]			Available: N = 11(50%) 10 [2,5.5,16,20]
MEC Prosody Comprehension item, median [min, Q1,Q3, max]			Available: N = 22 (100%) 9 [0,8,11,12]
MEC Prosody Repetition item, median [min, Q1, Q3, max]			Available: N = 22 (100%) 11 [7,10,12,12]
MEC Total, median [min, Q1, Q3, max]			Available: N = 22 (100%) 21 [9,18.2,22.8,24]
BDAE command execution item, median [min, Q1, Q3, max]			Available: N = 22(100%) 14 [5,14,15,19]
Audiogram left-ear, median dBHL at 1000 Hz [min, Q1, Q3, max]		0 dBHL [0,0,15,35]	Available: N = 7(31%) 20 dBHL [10,15,30,60]
Audiogram right-ear, median dBHL at 1000 Hz [min, Q1, Q3, max]		5 dBHL [0,0,20,30]	Available: N = 7(31%) 15 dBHL [5,7.5,37.5,45]
Vocal audiogram, median% detection at 40 dB [min, Q1, Q3, max]			Available: N = 13(59%) 99. % [85,94,100,100]
LAMA Sustained auditory attention score accuracy, median [min, Q1, Q3, max]			Available: N = 12(54%) 30 [29,29.8,30,30]
LAMA Sustained auditory attention reaction time (sec), median [min, Q1, Q3, max]			Available: N = 12(54%) 92.5 [63,85.8,137,192]
MBEA (Montreal Battery of Evaluation of Amusia), median [min, Q1, Q3, max]			Available: N = 13(59%) 60 [48,57,71,85]
AIRTAC2 (Auditory discrimination), median [min, Q1, Q3, max]			Available: N = 13(59%) 44 [36,42,47,48]
HADS (depression + anxiety), median [min, Q1, Q3, max]			Available: N = 13(59%) 18.5 [7,11.2,24.8,35]

Results for internal representations

In the control group, internal representations of interrogative prosody (orange) had a **rising pitch contour at the end of the word**

In the patient group, internal representations had a lower amplitude and their shape were more variable across individuals

The lower the MEC, the more atypical was the representation

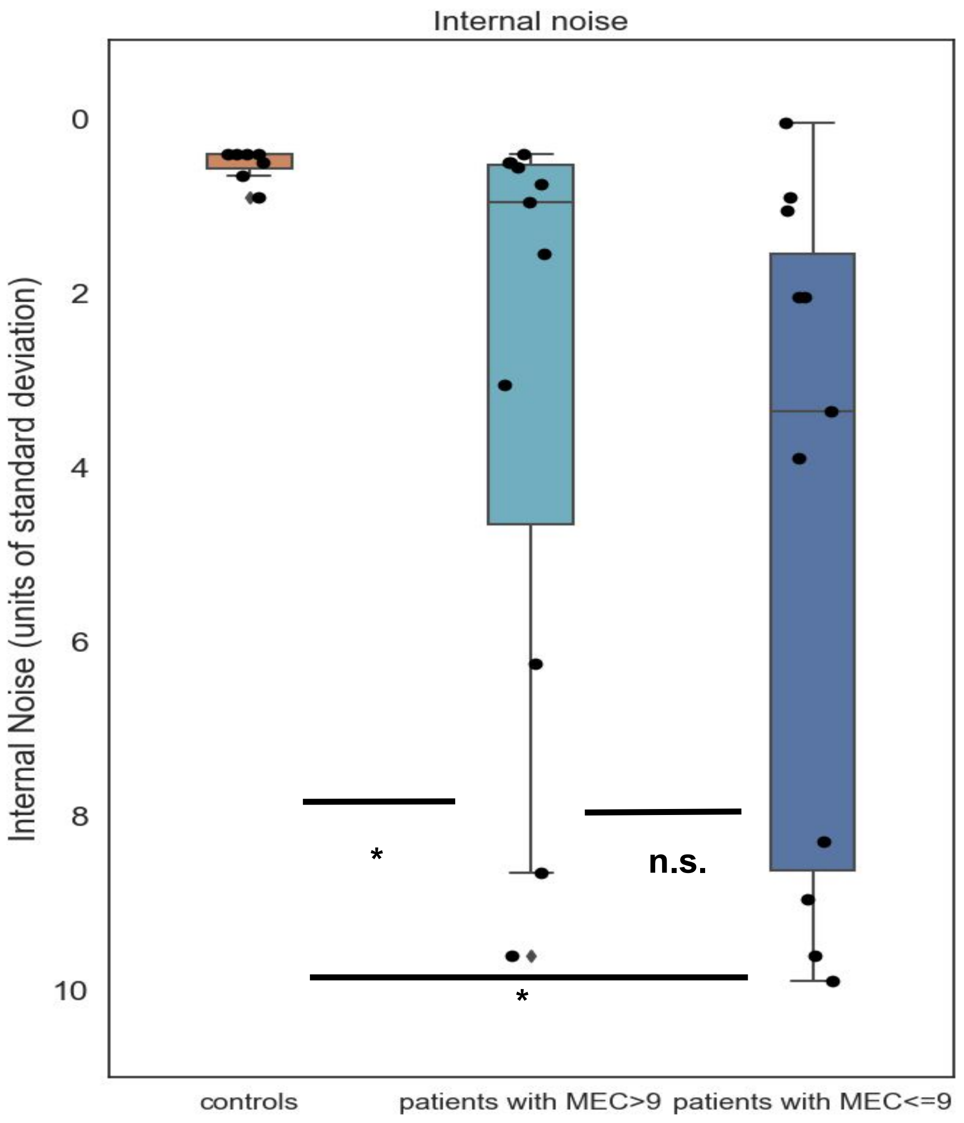


Results for internal noise

Control participants has a low internal noise value (< 1 standard deviation), which means they were very consistent in repeated trials

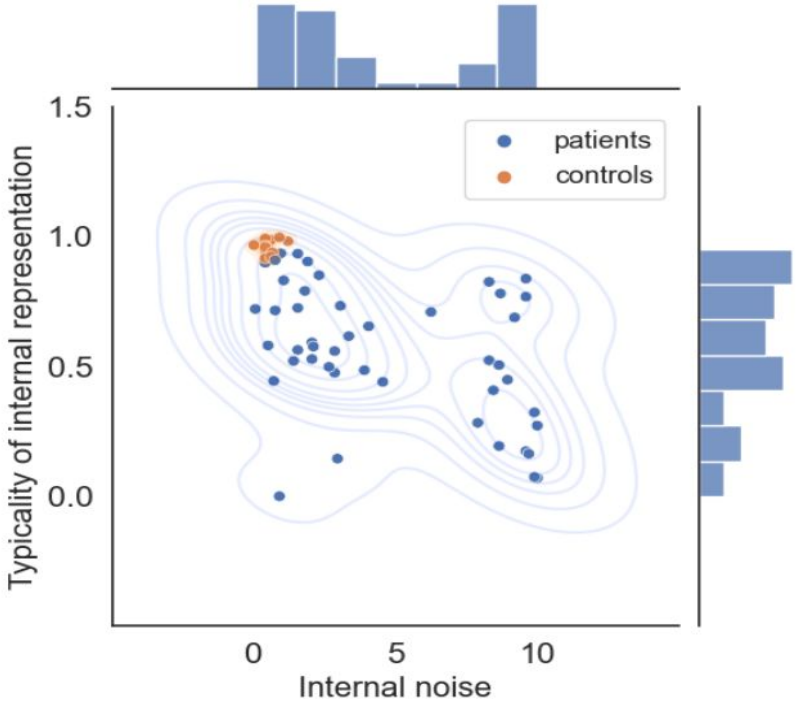
Patients' internal noise level were larger and more variable across individuals.

As for representations, the lower the MEC, the bigger the internal noise (less consistent).



Types of patients

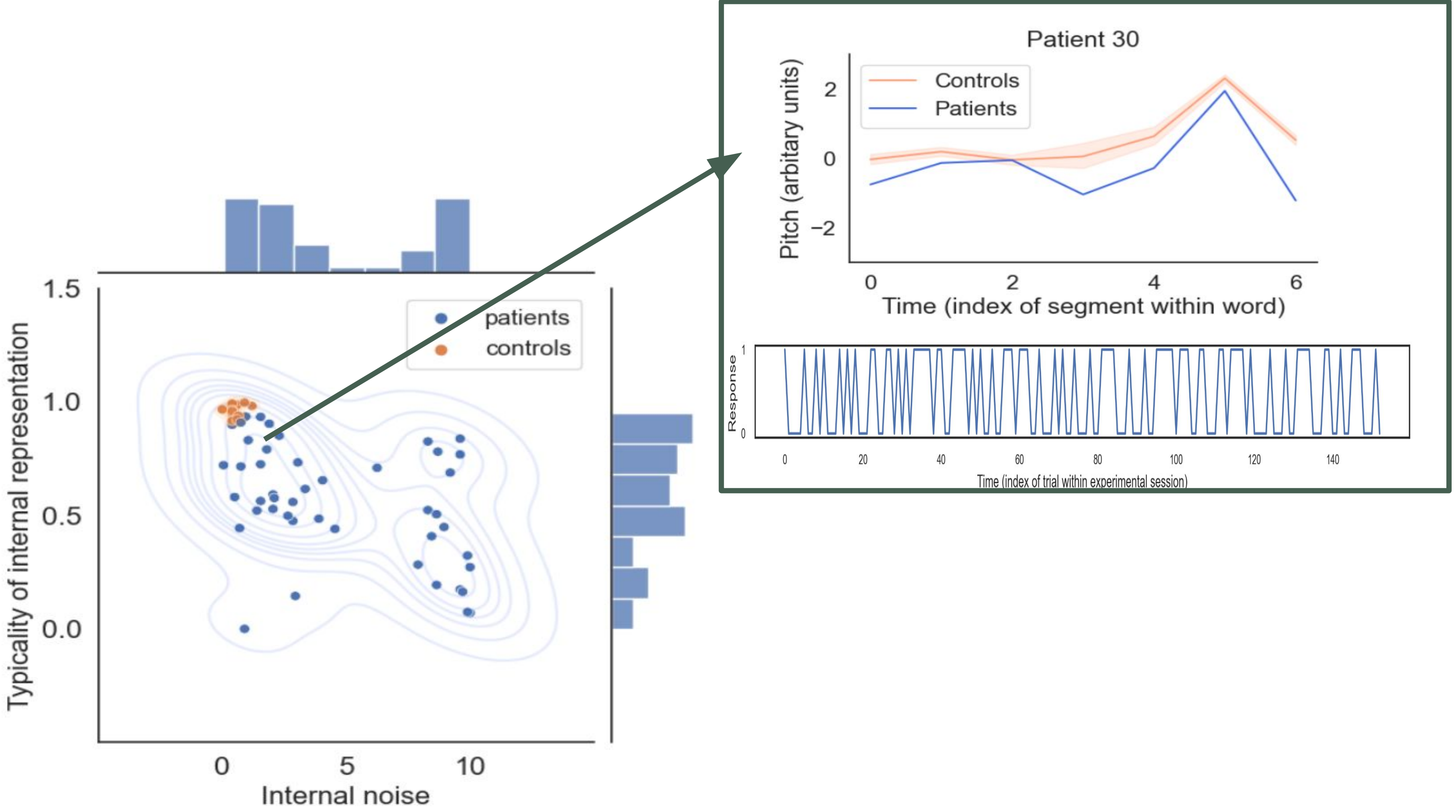
When we combine the 2 parameters of internal representation and internal noise, we can identify several types of patients:



Types of patients

When we combine the 2 parameters of internal representation and internal noise, we can identify several groups of patients:

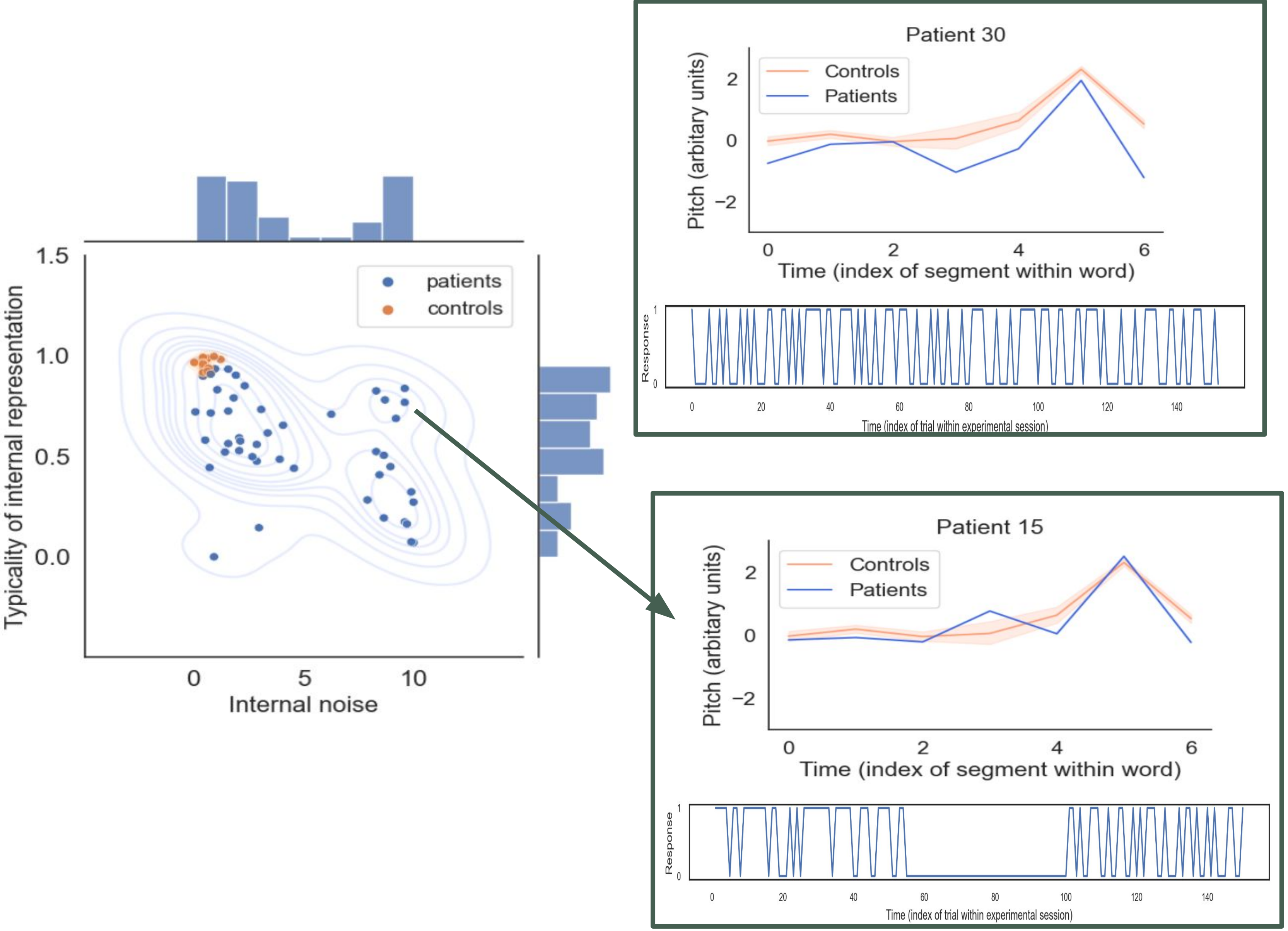
- patients who have good representations and low noise (a bit like controls)



Types of patients

When we combine the 2 parameters of internal representation and internal noise, we can identify several groups of patients:

- patients who have good representations and low noise
- patients who have good representations, but high noise (ex. they have executive function problems such as perseveration)



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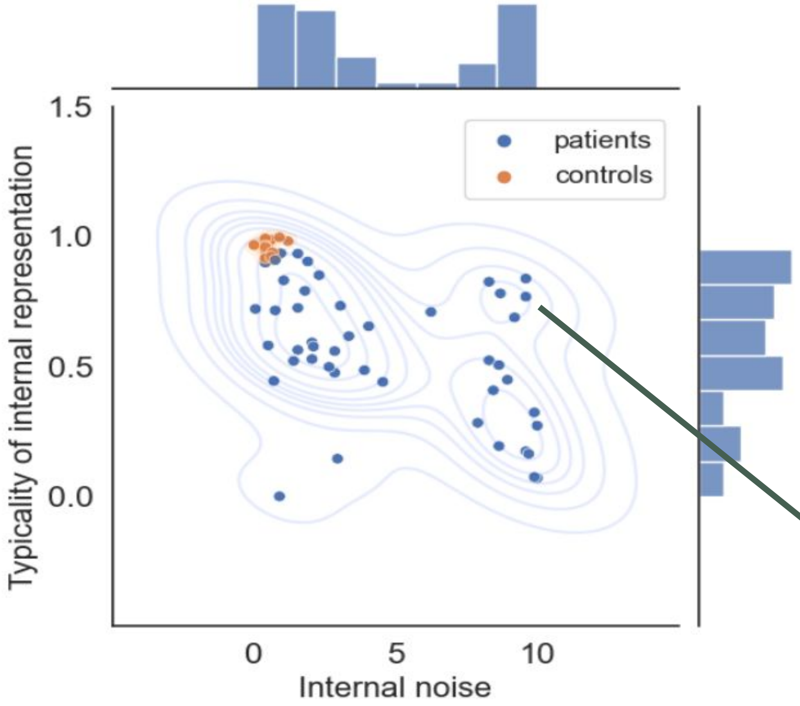
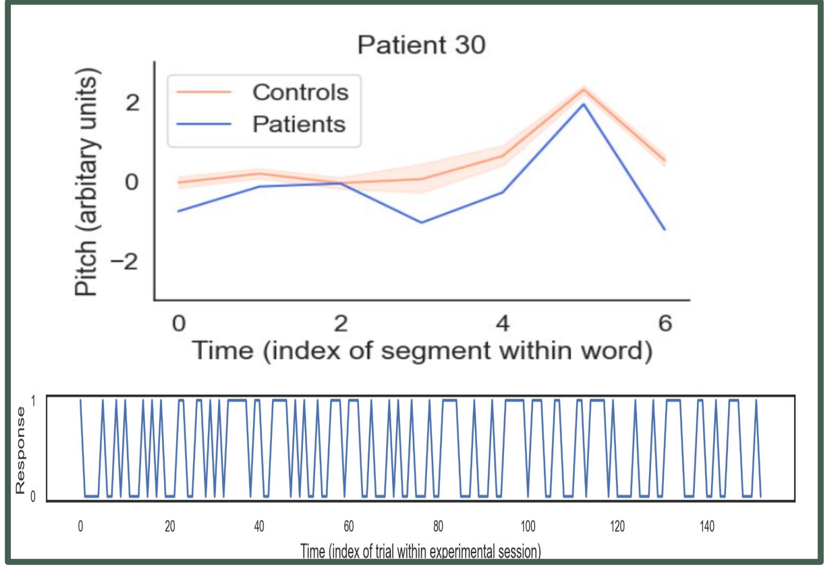
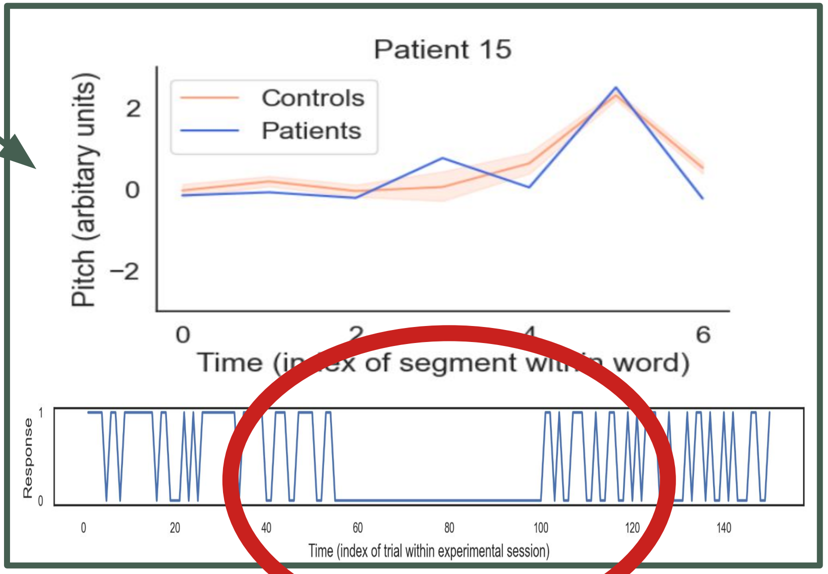


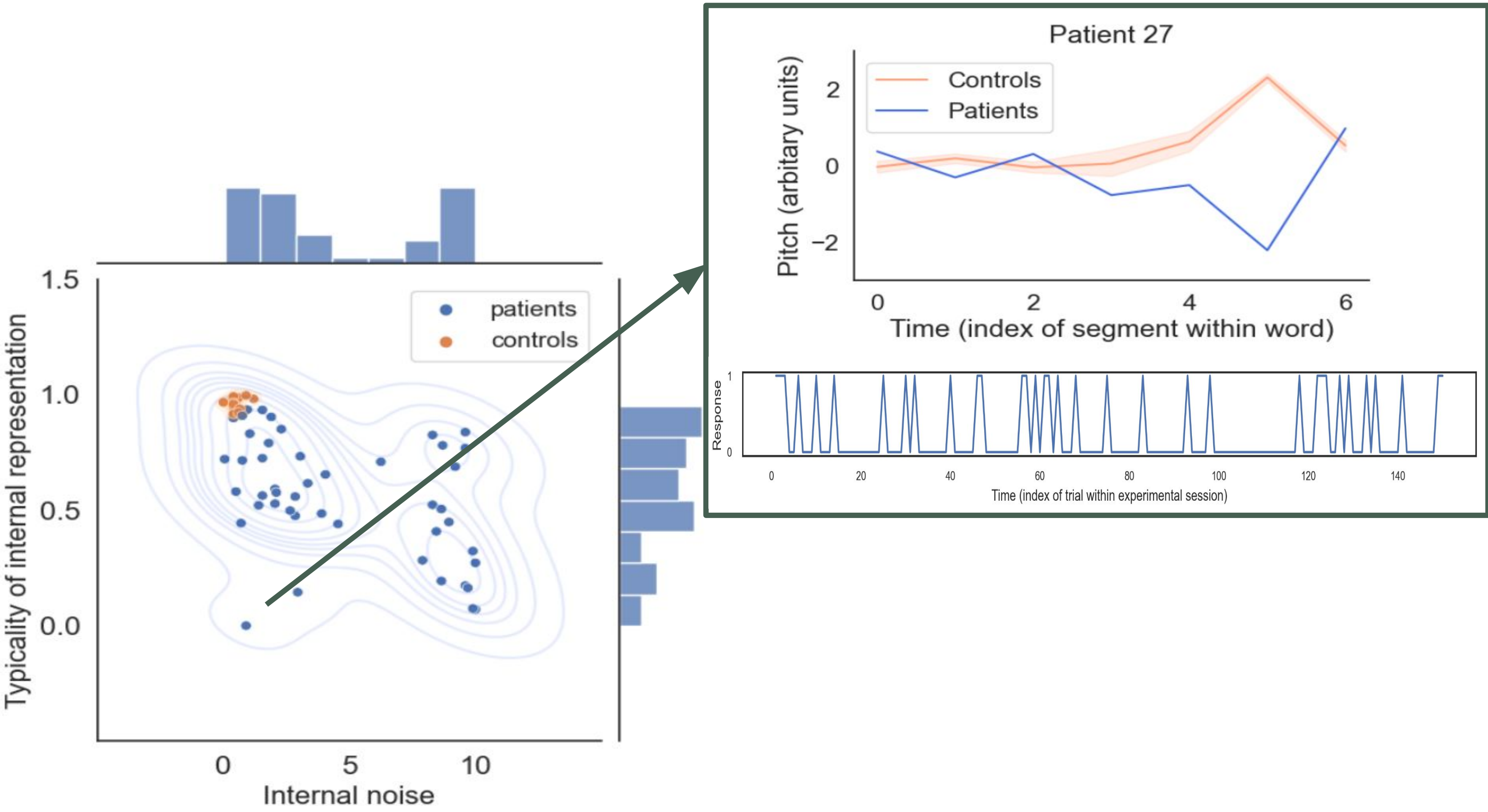




Types of patients

When we combine the 2 parameters of internal representation and internal noise, we can identify several groups of patients:

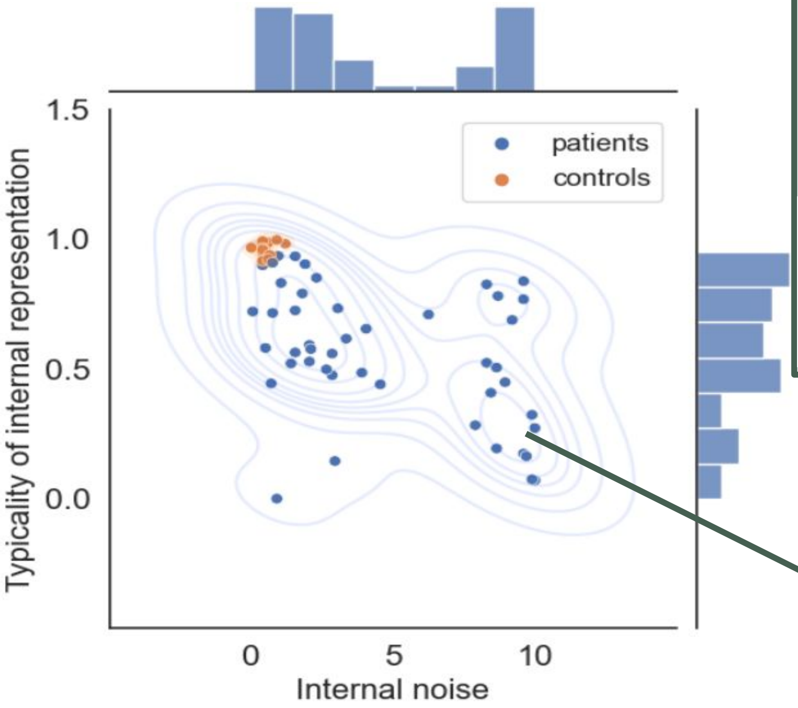
- patients who have good representations and low noise
- patients who have good representations, but high noise
- patients who have wrong representations, but are consistent (low noise)

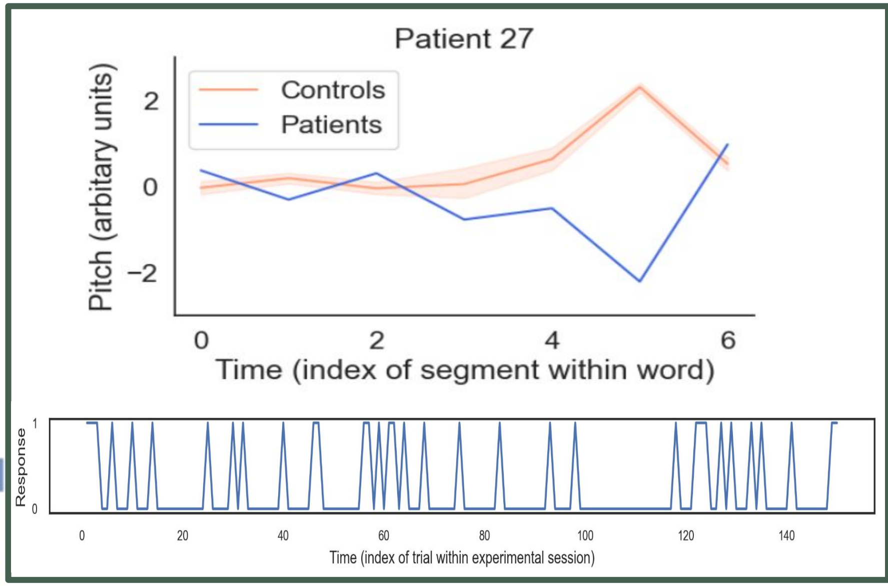


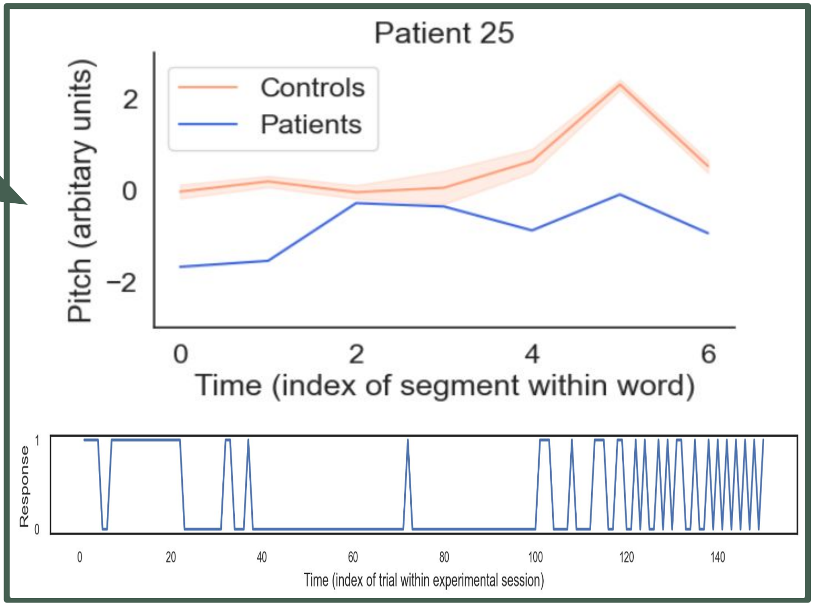
Types of patients

When we combine the 2 parameters of internal representation and internal noise, we can identify several groups of patients:

- patients who have good representations and low noise
- patients who have good representations, but high noise
- patients who have wrong representations, but are consistent (low noise)
- patients who have both bad representations and bad noise



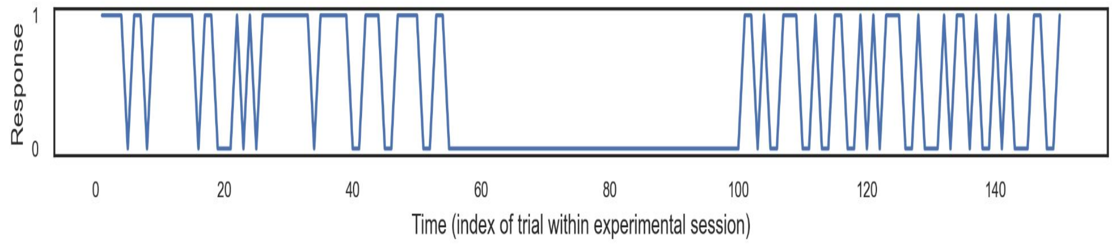


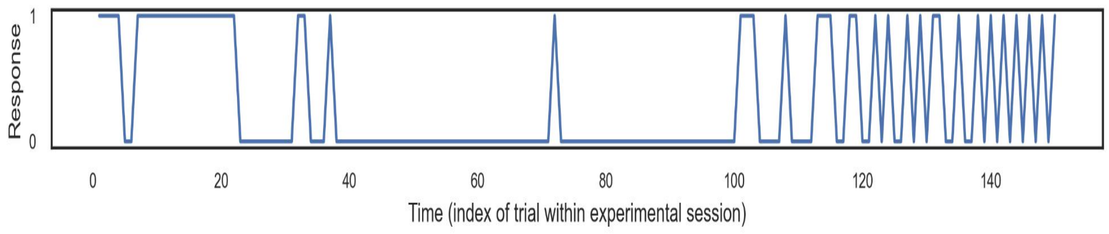


Linear model to probabilistic models

We employed a reverse correlation experiment using a data-driven approach to find biomarkers of aprosodia in stroke patients by estimating the internal sensory representations and noise. For the representation we computed the difference of the two response class means based on the judgments and to model the relationship between stimulus (input) and response (output). For noise estimation, we used a double-pass procedure, measuring response consistency across repeated trials, and inferred the level of internal noise by simulating how varying degrees of Gaussian noise affected response patterns. These 2 parameters which are static across the experiment, are key factors in differentiating behaviors among stroke patients.

While investigating these parameters, we observed that patient responses exhibited **perseveration**, a repetitive response tendency, which appeared to evolve over time and until now we were assuming a single, unchanging strategy across trials. This unexpected variation led us to investigate on generative model because it describes the process of generating observable data by modeling both the latent states and how they produce the observed responses. We hypothesize the existence of hidden states that influence patient behavior during the experiment. We believe that modeling these hidden states and inferring the parameters from the states could provide deeper insights into the dynamic nature of the patients' responses and their underlying cognitive processes.





GLM

We can model the relationship between the behavioral response (binary outcome) and the stimulus (regressors) using a bernoulli Generalized Linear Model (GLM). The core idea behind Logistic Regression is to transform the output of a linear combination of input features using a sigmoid function, making the predicted values range between 0 and 1.

Input (x): The input x could be the stimulus or some other covariate data that feeds into the model.

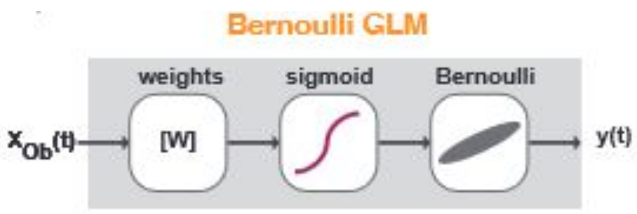
Linear Mapping : The input is linearly transformed using a weight; how the input (stimuli or other covariates) affect the probability of the binary output (decision). The weights are learned during model training are updated in such a way that they maximize the likelihood of the observed data given the model.

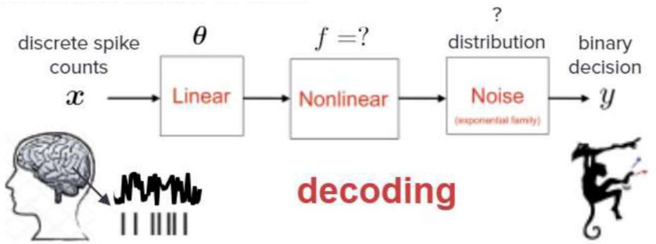
Nonlinearity (σ): After the linear transformation, a nonlinear activation function is applied to map the weighted sum into a probability space. Here, the sigmoid function $\sigma(\cdot)$ is used, which is typical in logistic regression. This transforms the output into a value between 0 and 1, interpreted as the probability of making one of the two binary decisions- likelihood of the binary outcome .

Noise: Since this is a probabilistic model, noise is incorporated, meaning the final decision isn't deterministic but follows a probability distribution, such as the Bernoulli distribution in this case (binary outcome).

Output (y): The output y is a binary decision (0 or 1) based on the probability computed by the model.

Importantly, in this model, w remains constant over time, suggesting that the response function does not change during stimulus presentation.





$$z(t) = W_1 \cdot x_1(t) + W_2 \cdot x_2(t) + \cdots + W_n \cdot x_n(t) + \epsilon(t)$$

$$p(t) = \sigma(z(t)) = \frac{1}{1+e^{-z(t)}} = \frac{1}{1+e^{-(W \cdot x_{\text{obs}}(t)+\epsilon(t))}}$$

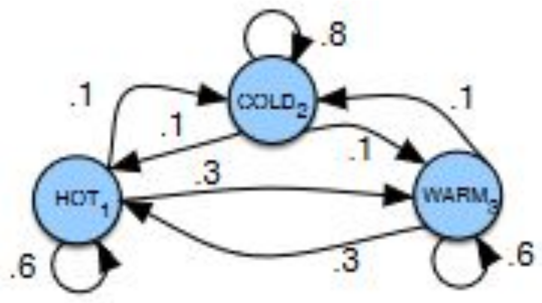
$$P(y(t)=1 \mid x(t)) = \frac{1}{1+e^{-(x(t) \cdot W + \epsilon(t))}}$$

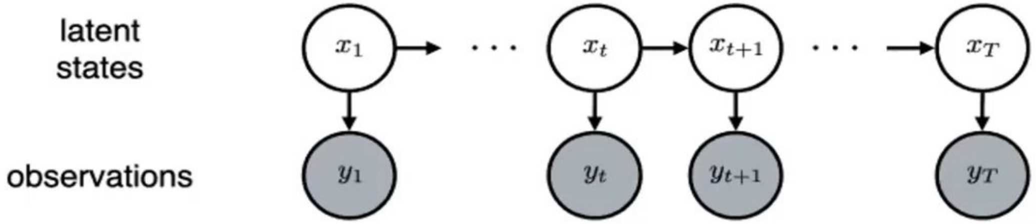
Hidden Markov Models for the Stimulus-Response Relationships of Multistate Neural Systems, Sean 2011

State space models (HMMs)

With simple statistical framework as generalized linear models which does not change in time(static), we can transform the input into a probability of output , to explain many of observed patterns but not different types of behavior that are difficult to predict; particularly when the subjects' internal states or external conditions shift during the experiment. These kind of missing variance can be explained by allowing an internal variable that alters with time like hidden markov models. The hidden states in these models are found through a fitting procedure rather than through manual annotation.

- **Hidden Markov Model (HMM)** is a statistical Markov model in which the system being modeled is assumed to be a Markov process with unobserved (i.e. hidden) states.
- In probability theory, a Markov model is a stochastic model used to model randomly changing systems. It is assumed that future states depend only on the current state, not on the events that occurred before it (the Markov property).





Nuts and Bolts of Modern State Space Models,
Scott Linderman, 2023

Vanilla HMM

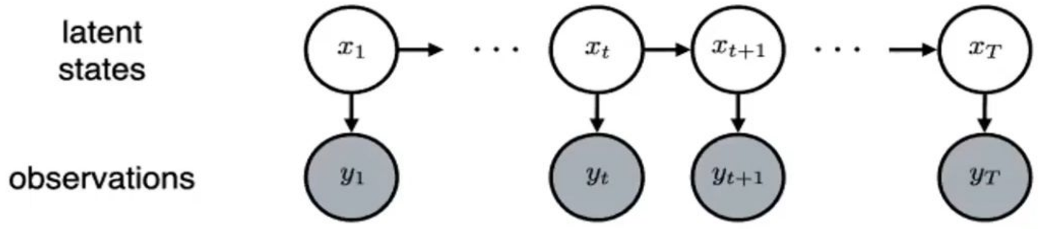
A **Hidden Markov Model (HMM)** is a statistical model in temporal space, which the observed events (observations) are influenced by hidden or **latent states** that cannot be directly observed. The model has two components:

Latent State Process: Follows the **Markovian property**, meaning the current state only depends on the previous state. The transitions between these states are governed by a **transition probability matrix** $A \in R^{K \times K}$, where each element represents the probability of moving from state j to state k: $\mathbf{p(z_{t+1}=k | z_t=j)}$

Observation Model (emission probabilities): The observable data at time t, x_t, depends only on the current latent state z_t, and not on previous observations: $\mathbf{p(x_t|x_1,x_2,\ldots,x_{t-1},z_t)=p(x_t|z_t)}$. This can be modeled using **Gaussian Emission Models**, where each hidden state generates observations following a Gaussian (normal) distribution. In this case, the emission probability for a given hidden state z_t is modeled as:

$$p(x_t \mid z_t = k) = \mathcal{N}(x_t; \mu_k, \Sigma_k)$$

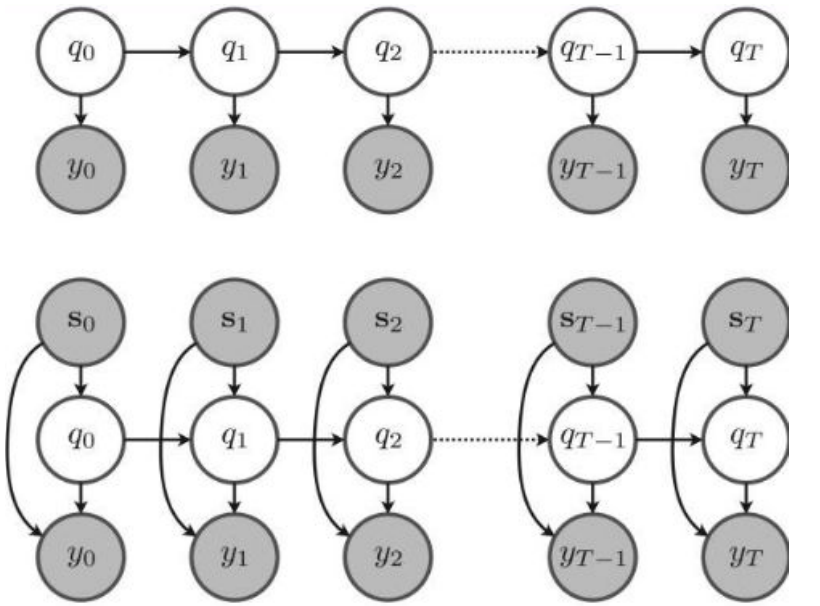
Here, μ_k is the mean and Σ_k is the covariance matrix of the Gaussian distribution associated with hidden state k. Alternatively, other distributions like **Gaussian Mixture Models (GMMs)** can be used to capture more complex state-dependent behaviors.



Nuts and Bolts of Modern State Space Models, Scott Linderman, 2023

IO-HMM

An **Input-Output Hidden Markov Model (IO-HMM)** is an extension of the standard HMM that incorporates input variables, allowing it to model the relationship between input covariates and both the hidden states and the observed outputs. Unlike standard HMMs, which only account for hidden states and observations, an IO-HMM conditions both the hidden states and the observable outputs on external inputs.



- **State Dependencies on Inputs**: In an IO-HMM, the hidden states can persist over a large number of trials and are influenced by external inputs such as stimuli or covariates. This allows the model to capture the impact of input variables on the evolution of hidden states over time.
- **Output Dependencies on Inputs**: The observed outputs $Y_{1:T}$ are also conditioned on input variables $X_{1:T}$, allowing the model to account for how the input affects both the hidden states and the outputs.
- **Key Difference from HMM**: In a standard HMM, the hidden states and outputs depend only on previous states and observations. In contrast, the IO-HMM framework adds input dependencies, making it more flexible in modeling systems where external variables influence the *transitions and emissions*.
- **Single Model Training**: Unlike HMMs, where a different model might be trained for each class, an IO-HMM trains a single model to handle multiple classes by incorporating the input variables directly into the state and output distributions.

Hidden Markov Models for the Stimulus-Response Relationships of Multistate Neural Systems, Sean 2011

GLM-HMM

The GLM-HMM is a latent state model, combining Hidden Markov Models (HMMs) with multiple sets of per-state Generalized Linear Models (GLMs). Like the IO-HMM, which conditions outputs on input variables, the GLM-HMM incorporates external covariates to influence the state-specific decision process.

- **Latent States**: Represent different cognitive or decision-making strategies, with each state parameterized by a unique set of GLM weights.
- **Discrete States**: A discrete random variable models internal states over time, governed by an HMM.
- **Mapping**: A sigmoidal function (logistic regression) maps the human's binary decision to a weighted representation of covariates (e.g., stimulus, trial history, bias), just like in the IO-HMM, but with state-specific GLM weights.
- **GLM as Emission Model**: Each state-specific GLM describes how covariates are integrated to make a decision. The GLM calculates the output probability in each state based on a linear combination of the covariates.
- **Transition Between States**: Probabilistic transitions between states occur after each trial, governed by a fixed transition probability matrix, allowing states to evolve over time.

By combining the strengths of both GLMs and HMMs, the GLM-HMM captures both the hidden state dynamics and how participants make decisions based on the covariates, unlike the IO-HMM that transition probabilities between hidden states and emission probabilities of the outputs are both conditioned on the external inputs but hidden state transitions may be independent of inputs in GLM-HMM.

Bernoulli GLM component of a **GLM-HMM:**

$$p(y_t = 1 | \mathbf{x}_t, z_t = k) = \frac{1}{1 + e^{-\mathbf{x}_t \cdot \mathbf{w}_k}}$$

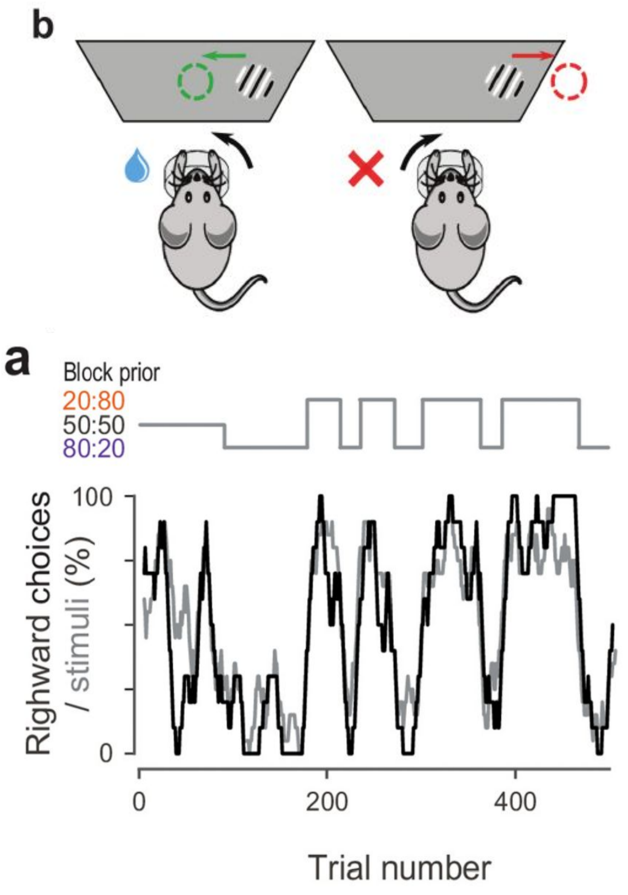
Probabilistic Models for Characterizing Animal Learning and Decision-Making - Ashwood 2022

Example IBL dataset

In this task, mice detect the direction of a Gabor patch on the screen and turn a wheel to the center to indicate whether the stimulus direction is to the right or left. The researchers (Ashwood et al. 2021) applied the **GLM-HMM** model to describe the behavior of mice making right–left decisions based on the contrast of a visual stimulus (input).

Mice exhibit at least two distinct internal states. In one state of **high engagement**, they perform the perceptual task with high sensitivity and low bias, accurately responding to the stimulus. However, in a **lower-performance state**, the mice tend to ignore even easy-to-discriminate stimuli and make biased responses, favoring one direction regardless of the stimulus. Mice often switch between these states, alternating several times and sometimes staying in one state for tens of trials or more.

This analysis using **GLM-HMM** effectively captures these hidden states, providing insights into how internal cognitive factors affect decision-making behavior.



Standardized and reproducible measurement of decision making in mice - international brain laboratory 2021

Lapse model

In the classic lapse model (2-state GLM-HMM), the decision-making process is modeled with two states: "engaged" and "lapse."

- **Engaged**: In this state, the decision-making is based on the stimulus with a higher probability of making a correct choice (P(correct) = 0.8).
- **Lapse**: In this state, decisions are assumed to be random, meaning the individual might still make a correct choice purely by chance (P(correct) = 0.2), but without being influenced by the stimulus.

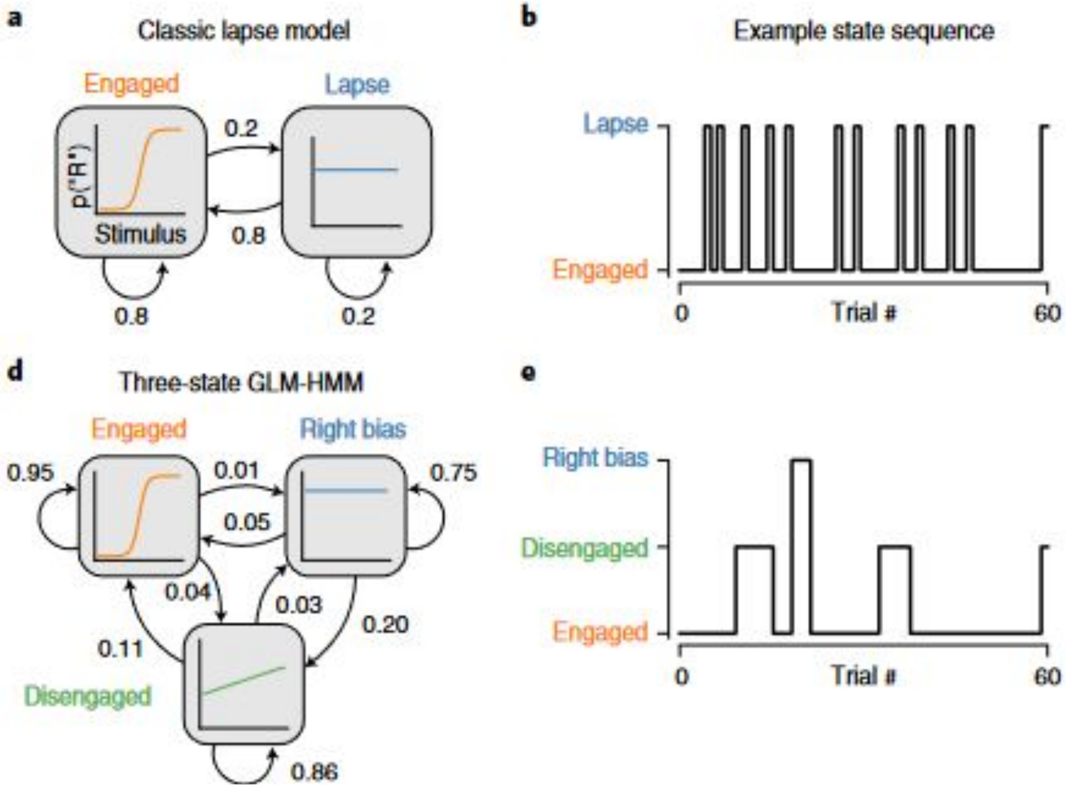
The lapse model assumes that animals alternate between these two strategies. However, this model has limitations, as it treats lapses as independent, random events, not accounting for the possibility that lapses might still be weakly influenced by the stimulus or other external factors and it lapse state last for only one trial not more.

In contrast, the 3-state GLM-HMM model provides a more detailed view, incorporating:

- **Engaged**: A high-performing state where decisions are strongly guided by the stimulus.
- **Disengaged**: A state where decision-making is disconnected from the stimulus (similar to the lapse state but distinct in dynamics).
- **Right Bias**: A third state that represents a bias in decision-making towards a particular choice (e.g., right-sided decisions).

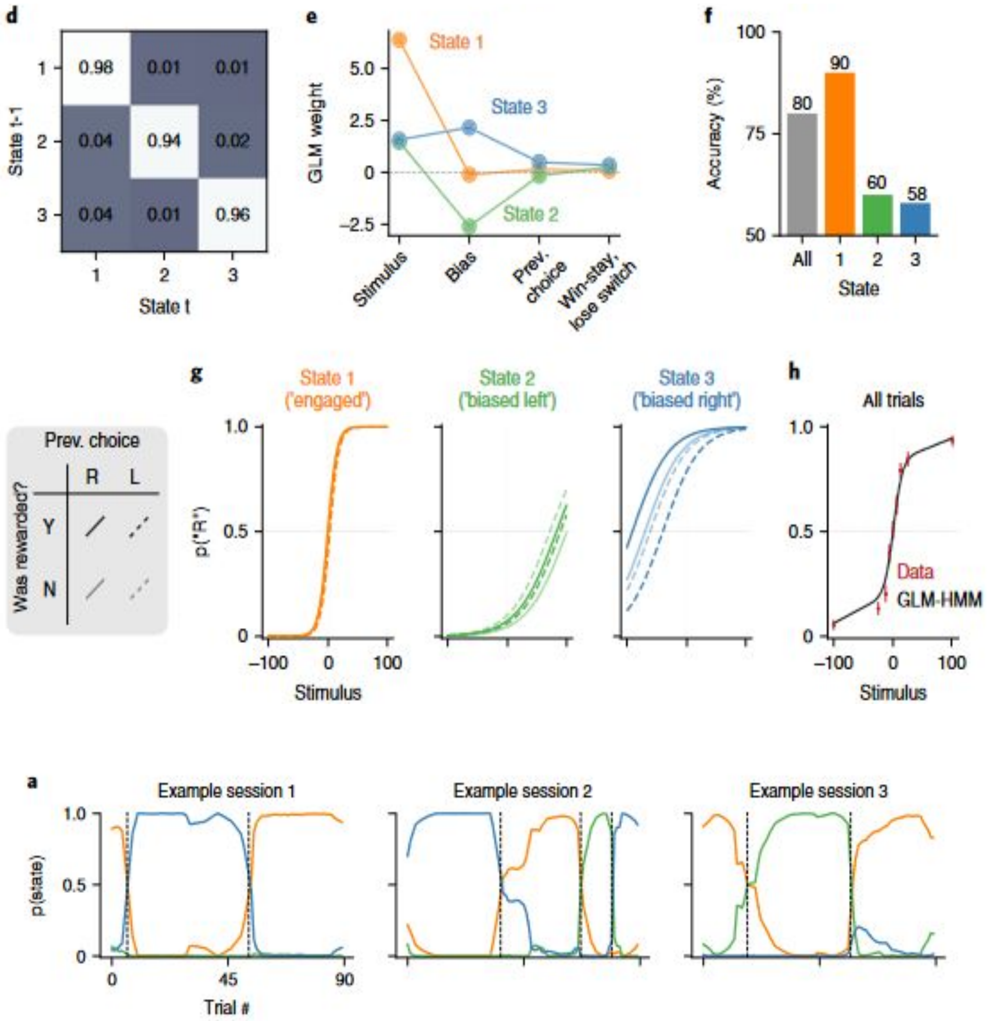
And contrary to lapse model , states intended to persist for many trials in a row.

$$p(y_t = 1 \mid \mathbf{x}_t) = \begin{cases} \frac{1}{1+e^{-\mathbf{w}\cdot\mathbf{x}_t}}, & z_t = \text{“engaged”} \\ \frac{\gamma_r}{\gamma_r+\gamma_l}, & z_t = \text{“lapse”}, \end{cases}$$



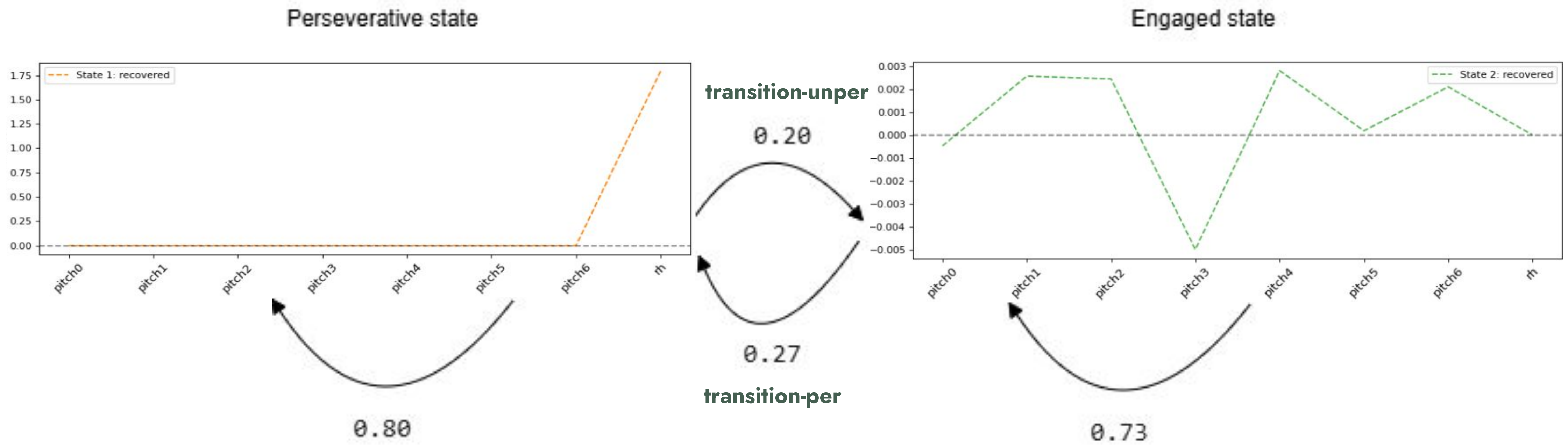
Probabilistic Models for Characterizing Animal Learning and Decision-Making - Ashwood 2022

IBL analysis

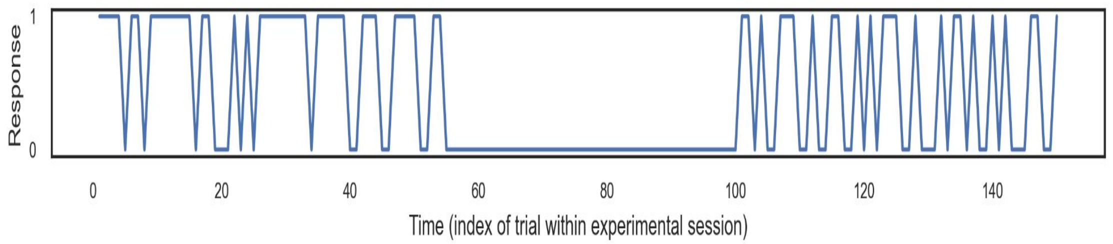


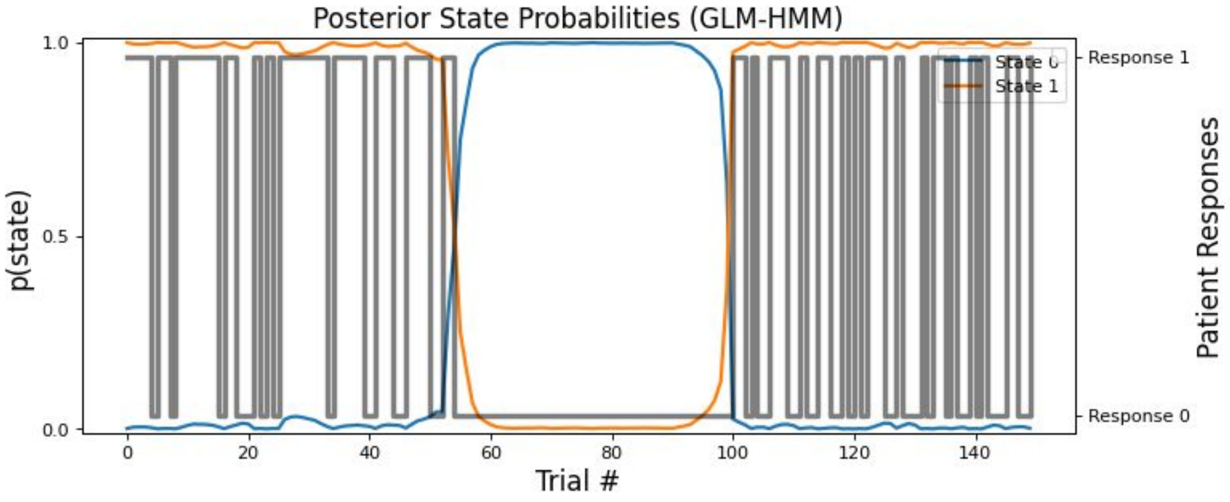
Probabilistic Models for Characterizing Animal Learning and Decision-Making - Ashwood 2022

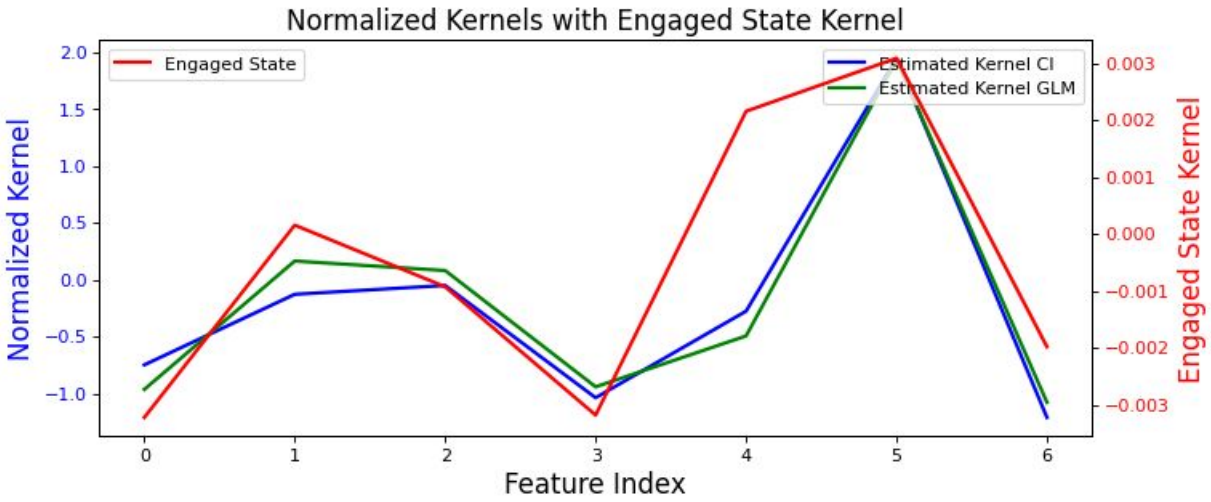
2state GLM-HMM engaged-perseverative patients



Results of GLM-HMM patient 40







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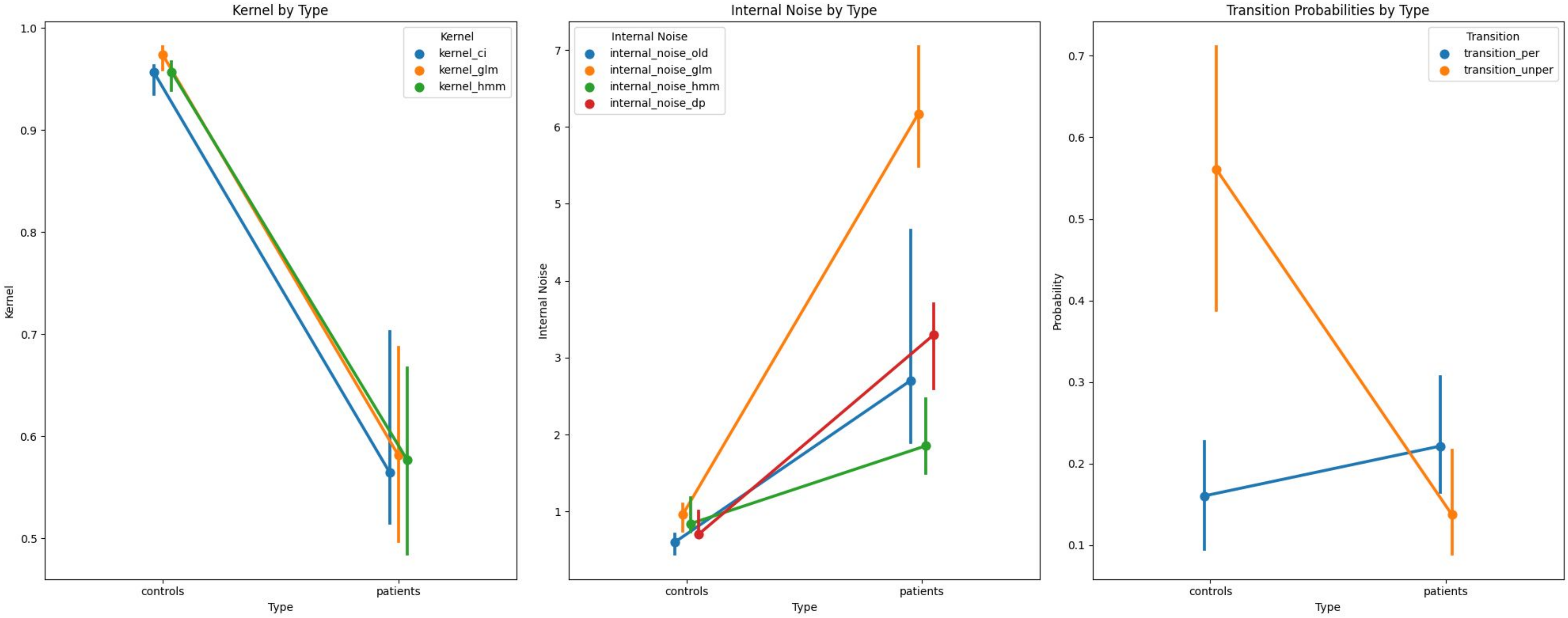

A quick palin tutorial

General architecture

This is the general palin simulation structure:

- we create an Experiment (here, a `DoublePassExperiment`, with 1000 2AFC trials + repeat the last 1000, i.e. 2000 trials on the whole). Experiments are subclasses of the `Experiment` abstract class, for now 2 are implemented: `SimpleExperiment` and `DoublePassExperiment`
- we create an Observer (here, a LinearObserver with kernel, internal_noise, and bias/criteria). Again, Observer classes are subclasses of the basic `Observer` class (we have `LinearObserver`, but we could also have `PerseveratingObserver`, etc.)
- we let the observer respond to the experiment, by `obs.respond_to_experiment(exp)`. This generates a list of responses (here, 0,1,0,0,0,1,1, etc...). Obviously if there are sources of stochasticity (e.g. the observer has non-zero internal_noise), every call to `respond` will generate different responses
- there is a utility in the `Analyser` class (read more about Analysers below) to gather the info about each of the `exp` trials + their corresponding response into a single dataframe (`to_df(exp, responses)`)

following palin data analysis in the notebook

CONCLUSION

- We have proposed a new experimental method to characterize impairment of prosody perception in patients who had a right-hemisphere stroke
- The method uses stimuli with random prosody generated by computer software, and builds a simple model (representation + noise) to simulate patient responses
- Both internal representation and internal noise allow separating patients from controls, and correlate with the severity of aprosodia measured by MEC
- When we combine the two parameters, we can identify several types of patients who have different “ways” to have bad scores at the MEC, for instance they have the good representation of prosody but they are inconsistent, or on the contrary they are consistent but their mental representation of what is a question is wrong