A PREDICTIVE CODING PERSPECTIVE ON OSCILLATORY TRAVELING WAVES

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Lausanne, December 2024

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https://artipago.github.io/

NeuroAi CerCo UMR5549 cnrs

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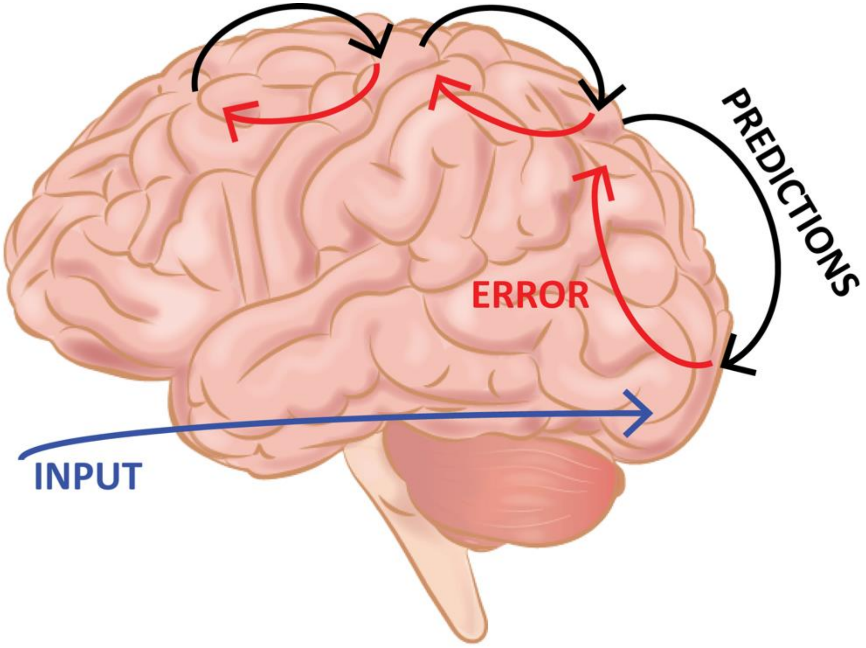
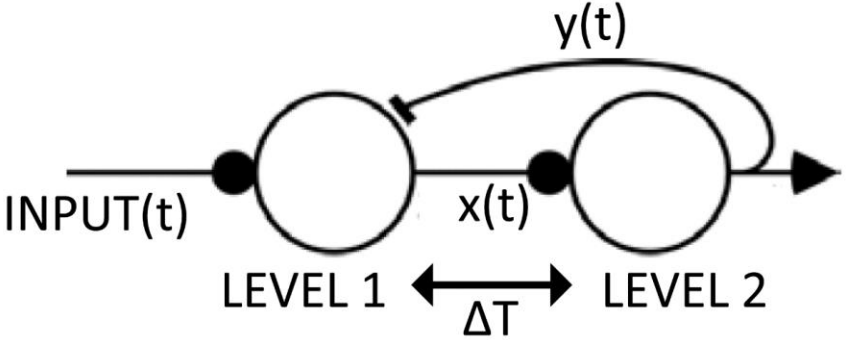
PREDICTIVE CODING IN SHORT



Mumford 1992, Rao & Ballard 1999, Friston 2009, Huand & Rao 2011, Spratling 2017…

- Higher regions generate **predictions** to explain **sensory input**.
- **Prediction-errors** update predictions over time.
- The brain fully represents the incoming sensory information.

THE SIMPLEST PC MODEL



$$\frac{dy}{dt} = \frac{1}{\tau} x(t-\Delta T) - \frac{1}{\tau_D} y(t)$$

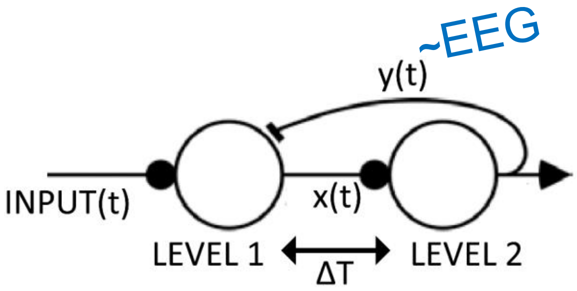
~15ms

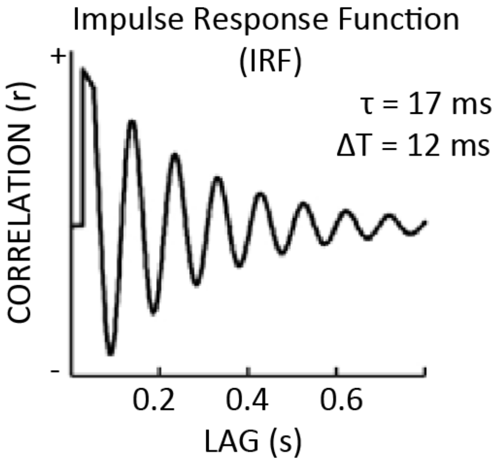
$$x(t) = \text{input}(t) - y(t-\Delta T)$$

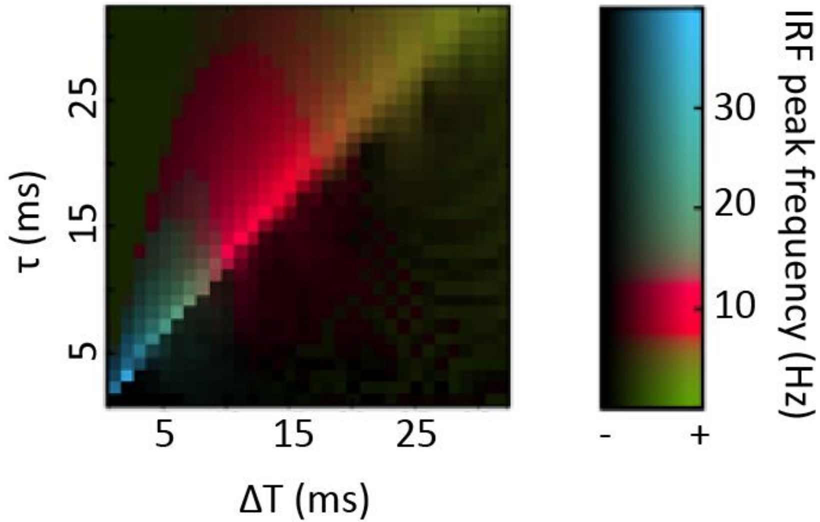
200ms

Alamia & VanRullen (2019)

SIMPLE MODEL RESULTS

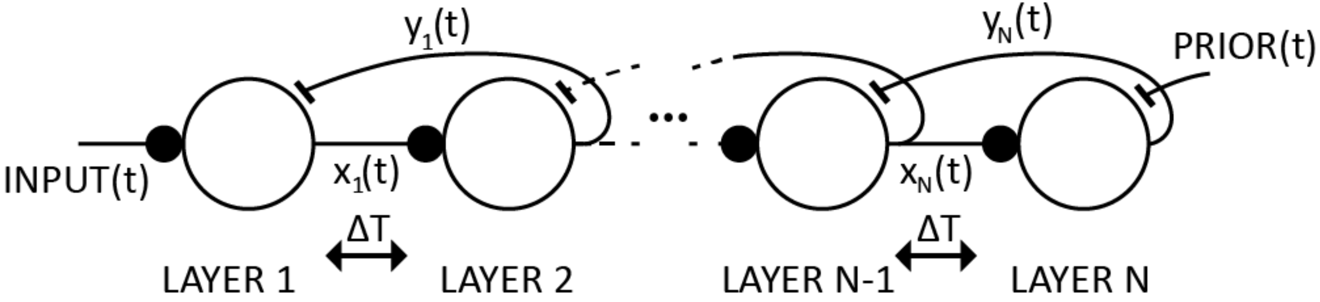






Alamia & VanRullen (2019)

A MULTI-LAYER PC MODEL

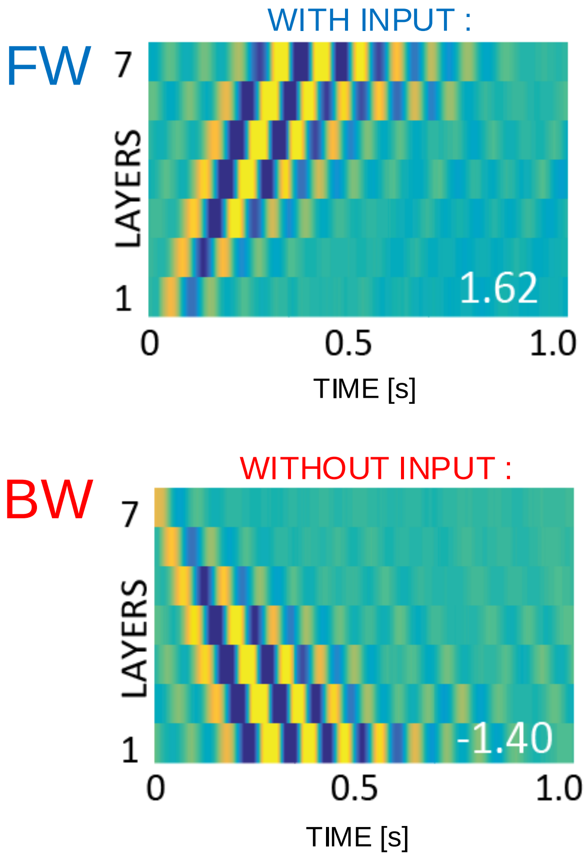


$$\frac{dy_L}{dt} = \frac{1}{\tau} x_L(t-\Delta T) - \frac{1}{\tau_D}\left(y_{L+1}(t-\Delta T) - y_L(t)\right)$$

$$x_L(t) = y_{L-1}(t) - y_L(t-\Delta T)$$

Alamia & VanRullen (2019)

MULTI-LAYER MODEL RESULTS

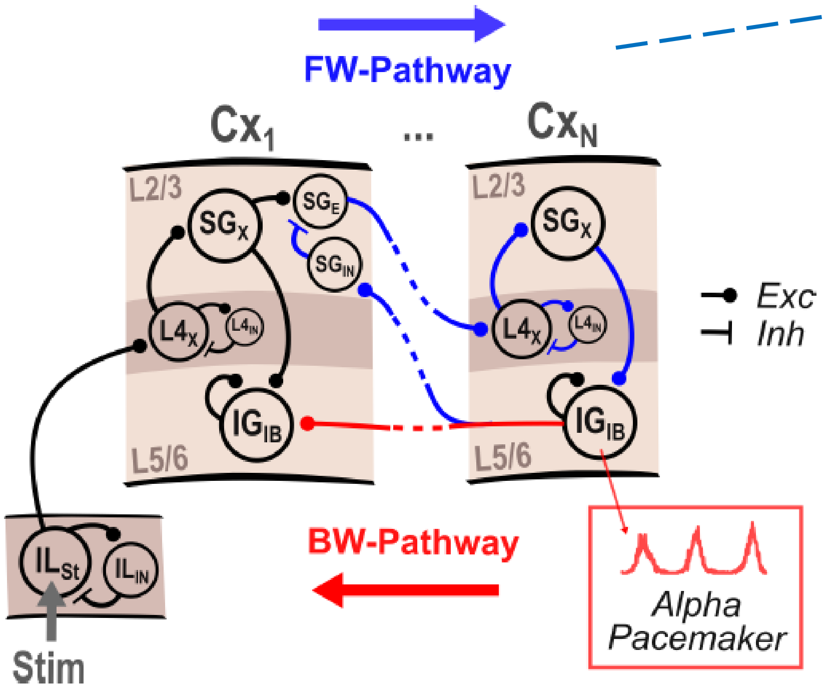


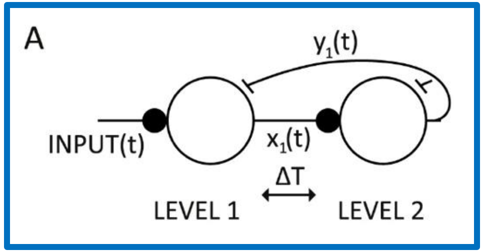
- y_i have an oscillatory behavior (no need to compute the IRFs);
- Oscillations are **TRAVELLING WAVE,** propagating **FORWARD** or **BACKWARD** depending on the cognitive state of the system.

Alamia & VanRullen (2019)

A MORE PLAUSIBLE MODEL

Three layers model of the cortex.
Two pathways: infragranular (IG) and the “Predictive Coding” one (as in previous model).

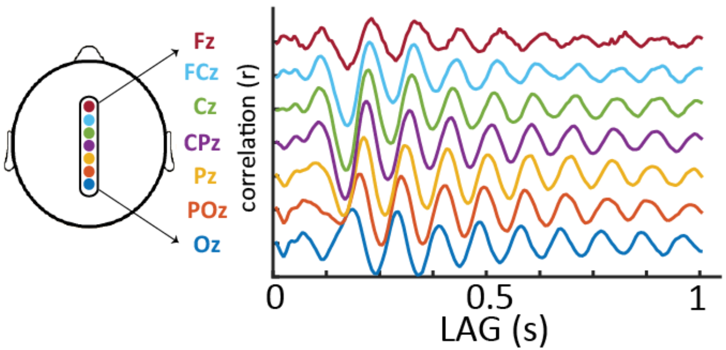


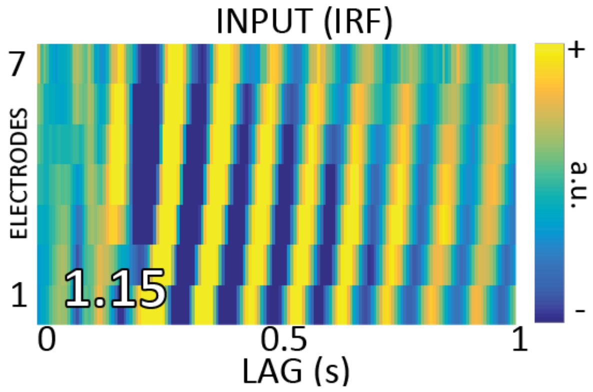


Jakob Schwenk

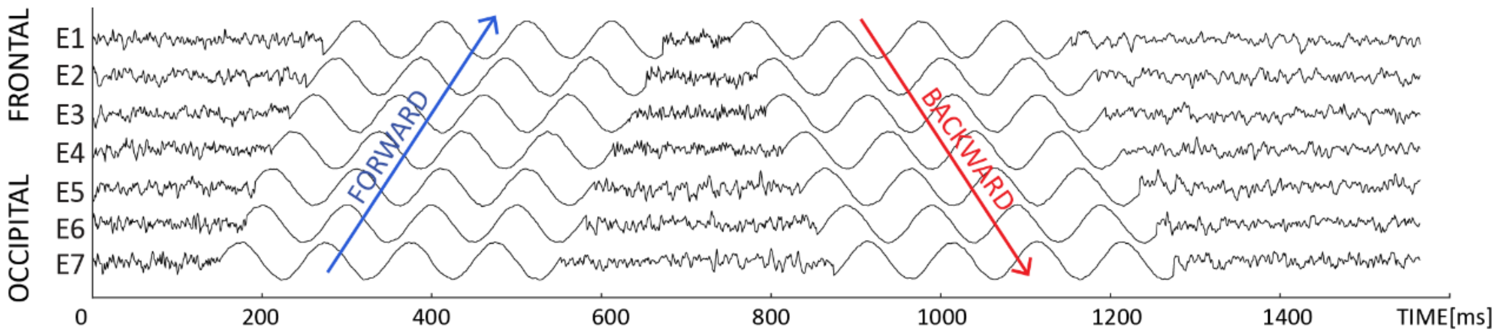
Schwenk & Alamia (2024)

WAVES IN REAL DATA

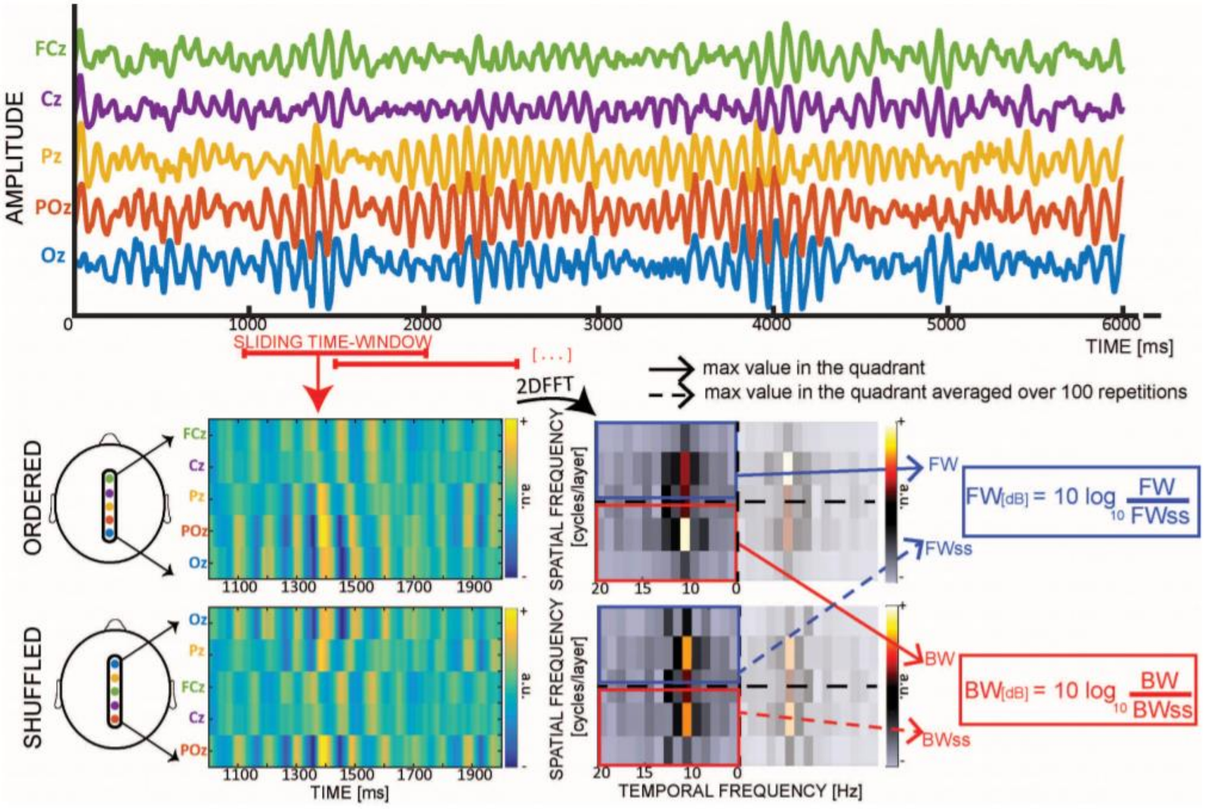




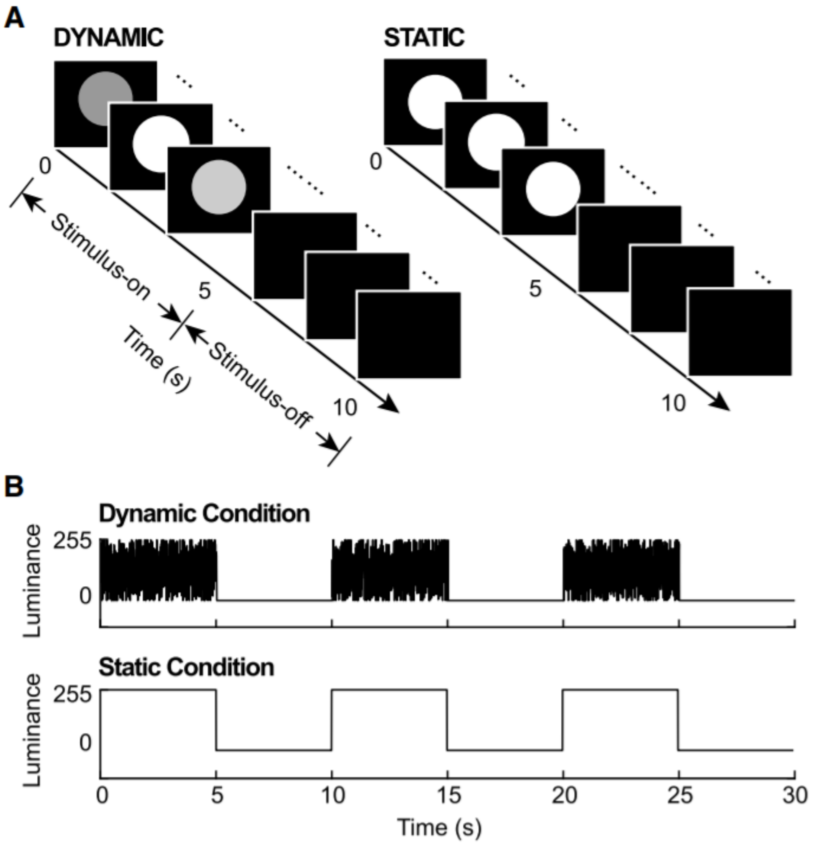
How can we quantify waves' direction?



QUANTIFYING WAVES DIRECTION



TRAVELING WAVES AND VISUAL PERCEPTION



Turning the Stimulus On and Off Changes the Direction of α Traveling Waves

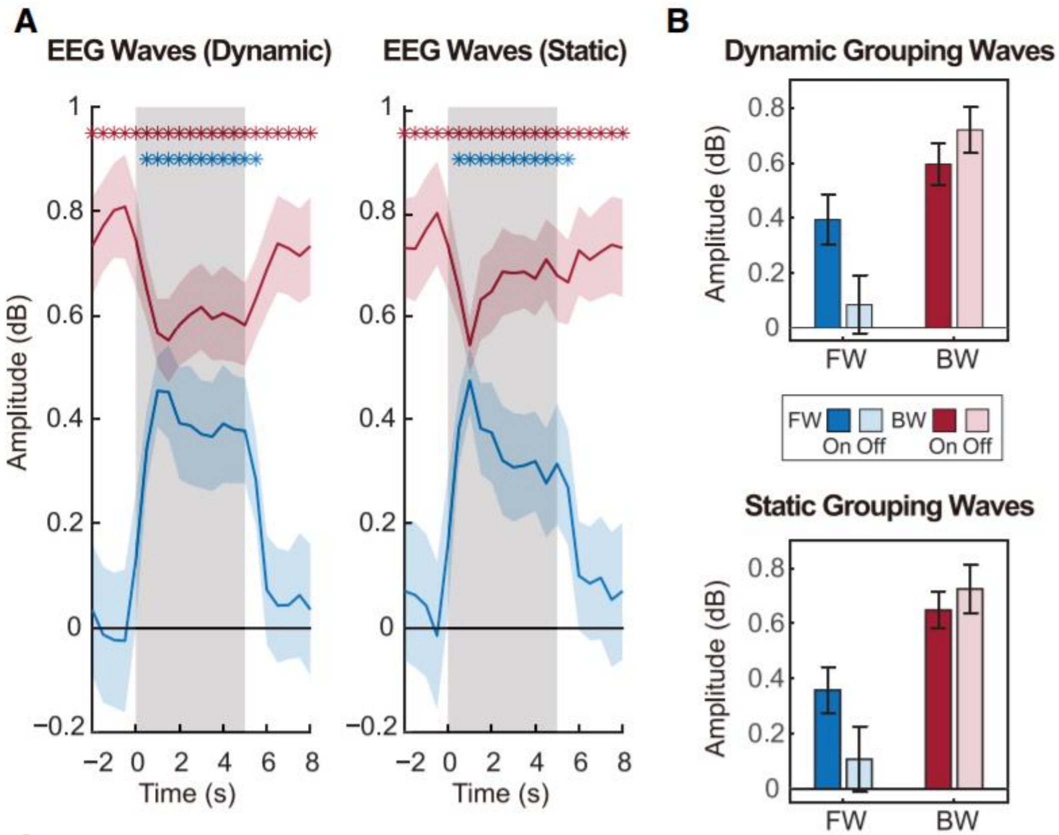
Zhaoyang Pang (庞兆阳),[1] Andrea Alamia,[1] and Rufin VanRullen[1,2]

eNeuro

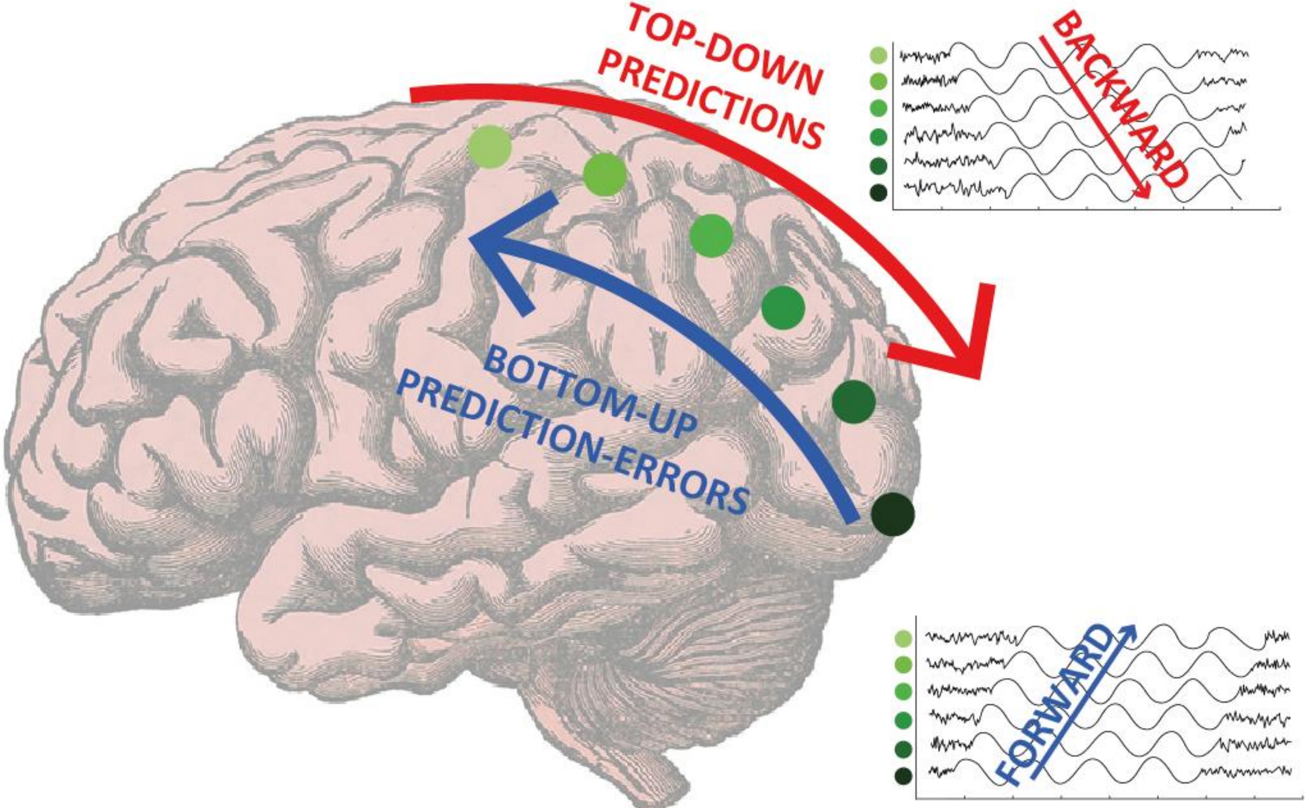
Zhaoyang Pang

Pang Z., Alamia A, VanRullen R (2020)

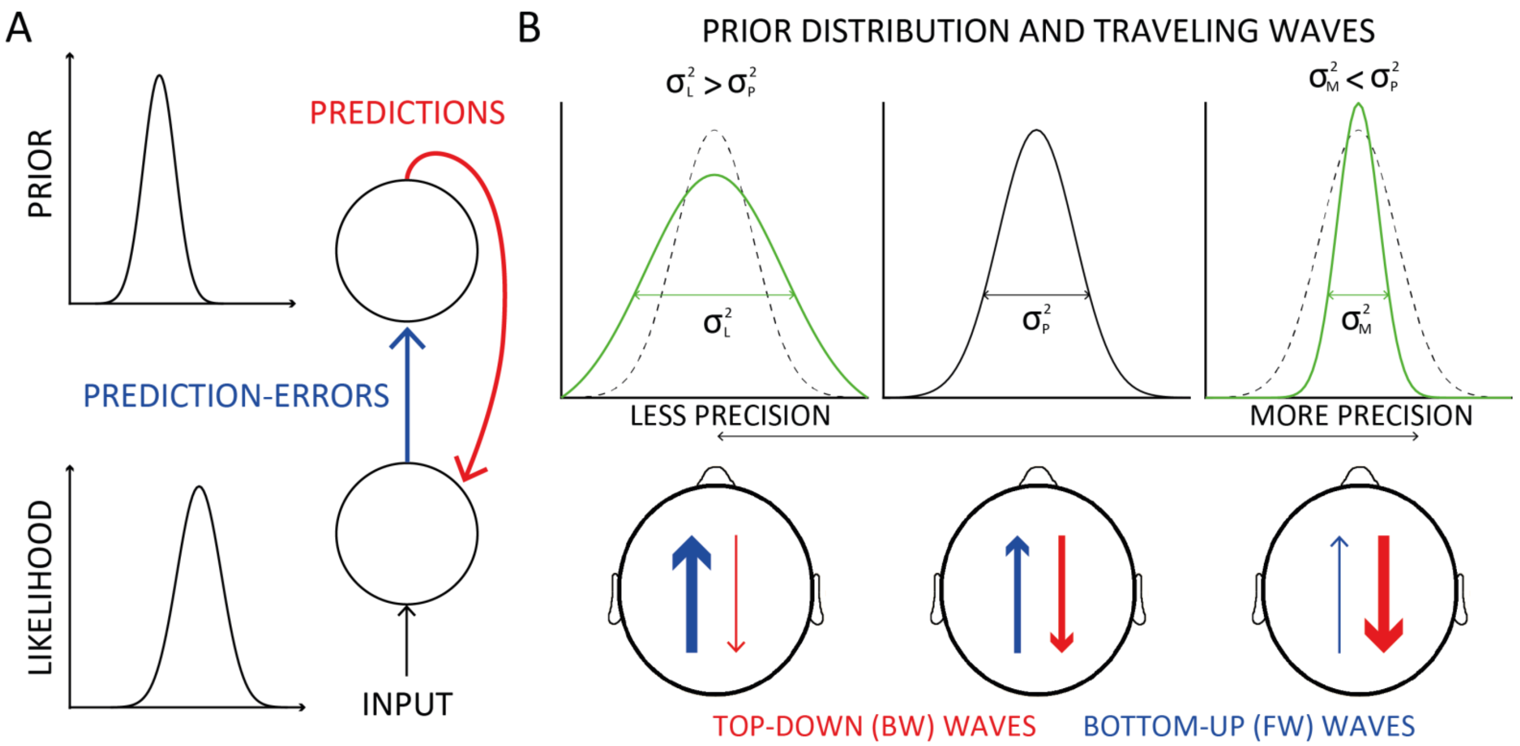
ALPHA WAVES AND VISUAL PERCEPTION



WAVES AND PREDICTIVE CODING



WAVES AND PREDICTIVE CODING



WAVES AND PSYCHEDELICS

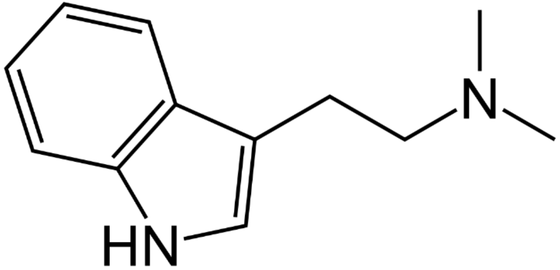
R. Carhart-Harris

C. Timmermann

“ [..] psychedelics work to relax the precision of high-level priors or beliefs, thereby liberating bottom-up information flow, particularly via intrinsic sources such as the limbic system.”

Carhart-Harris and Friston (2019)

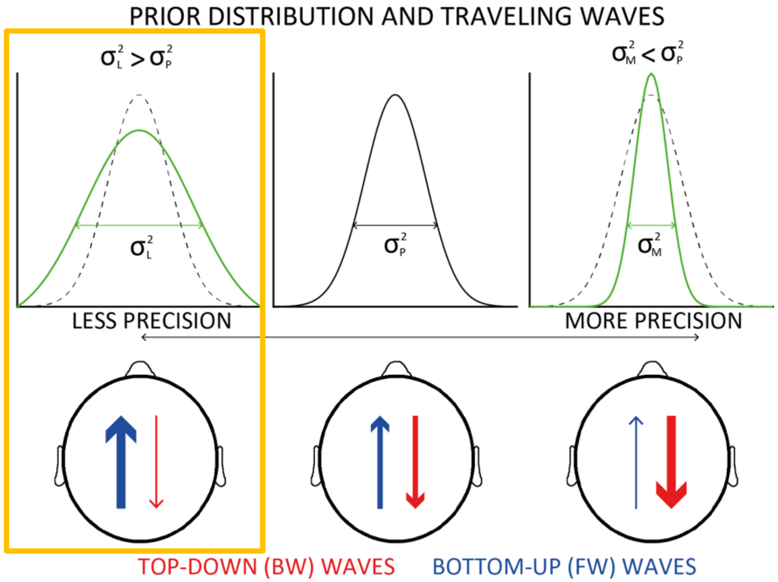
N,*N*-Dimethyltryptamine (DMT)



Alamia A., Timmermann C., Nutt DJ., VanRullen R., Carhart-Harris R. (2020)

WAVES AND PSYCHEDELICS

R. Carhart-Harris *C. Timmermann*



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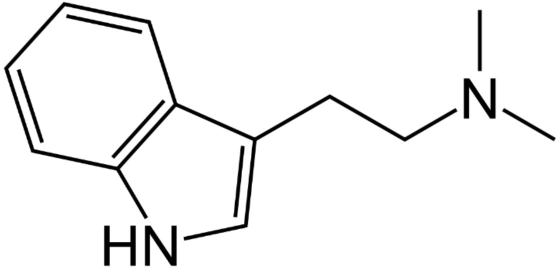
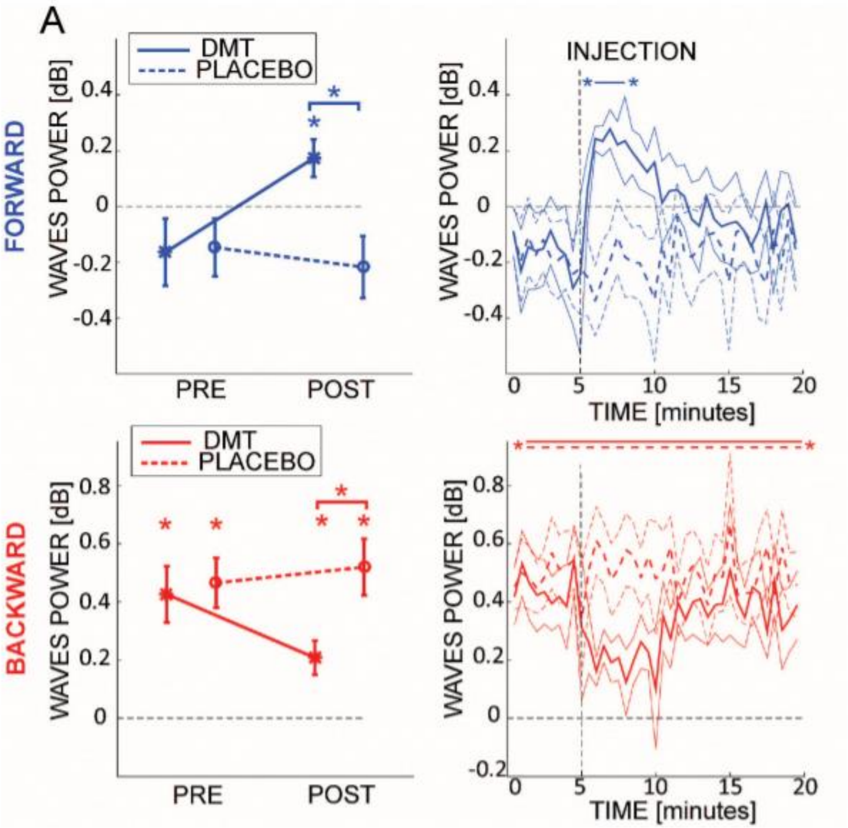


Alamia A., Timmermann C., Nutt DJ., VanRullen R., Carhart-Harris R. (2020)

PSYCHEDELICS MODULATE WAVES

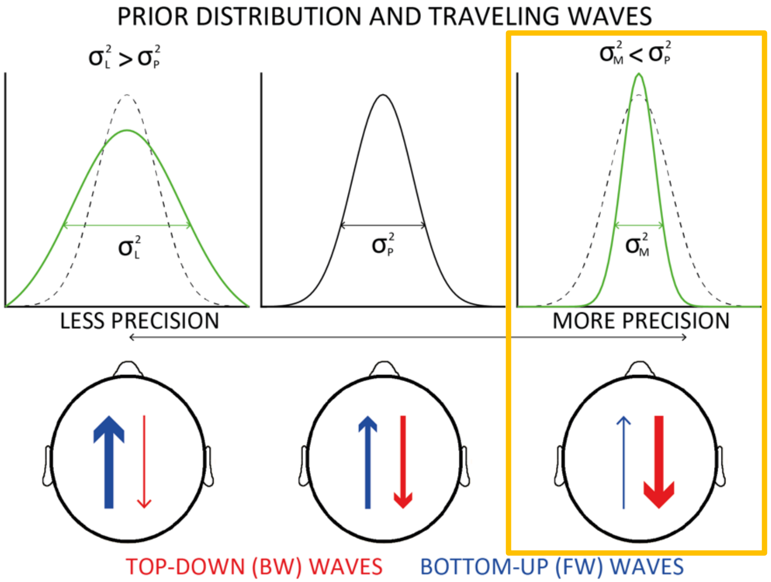


Despite participants had closed eyes, DMT alters cortical activity, as during visual stimulation.

WAVES IN SCHIZOPHRENIA

D. Gordillo

M. Herzog

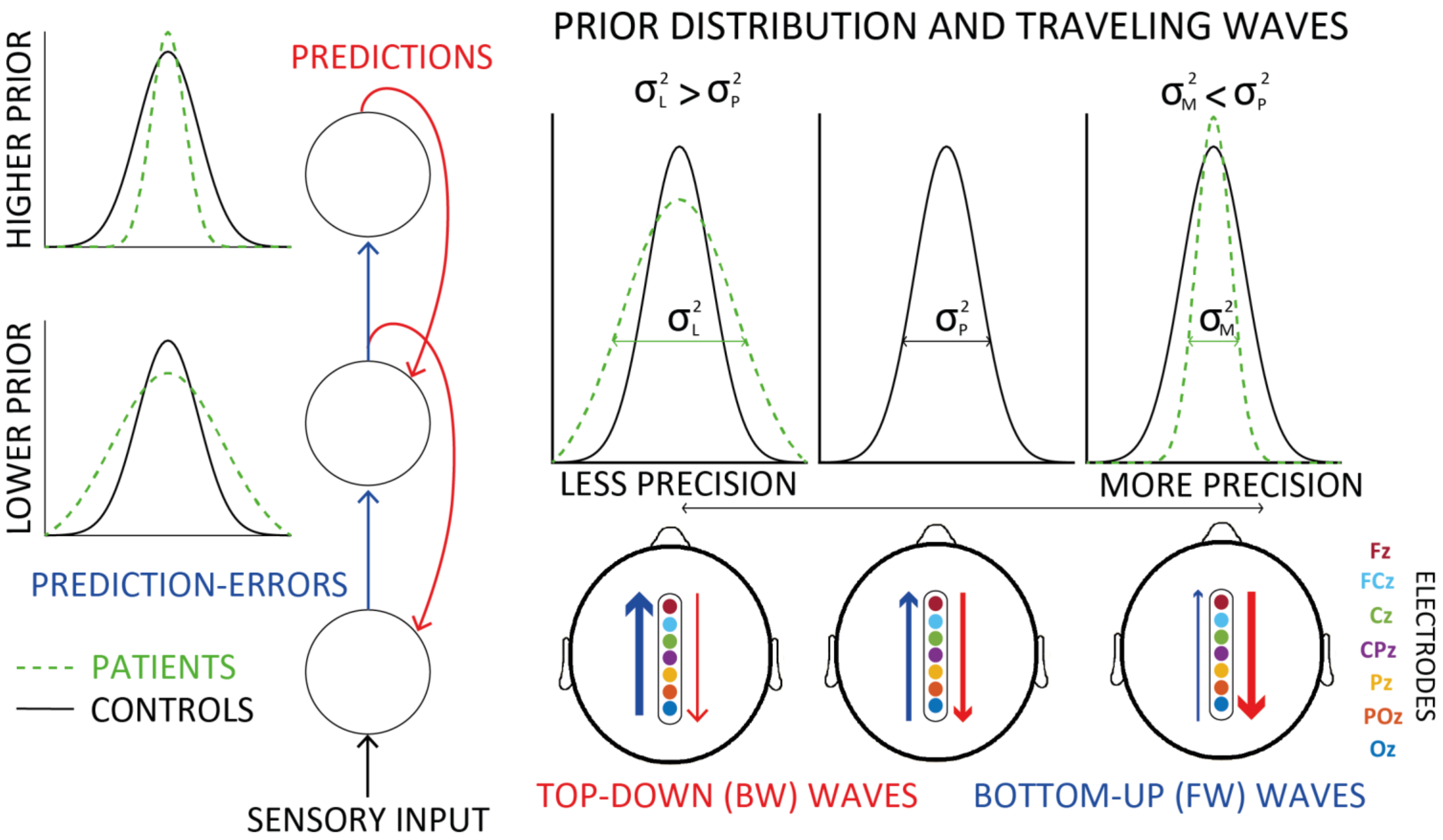


Hypothesis: alteration in the priors? *(Friston et al 2014, 2016, Fogelson 2014, Sterzer 2018, Tarasi et al. 2022, …)*

Opposite to DMT's study predictions, should we observe a decrease in FW waves and increase in BW waves?

Alamia, Gordillo*,…, Herzog (2024)*

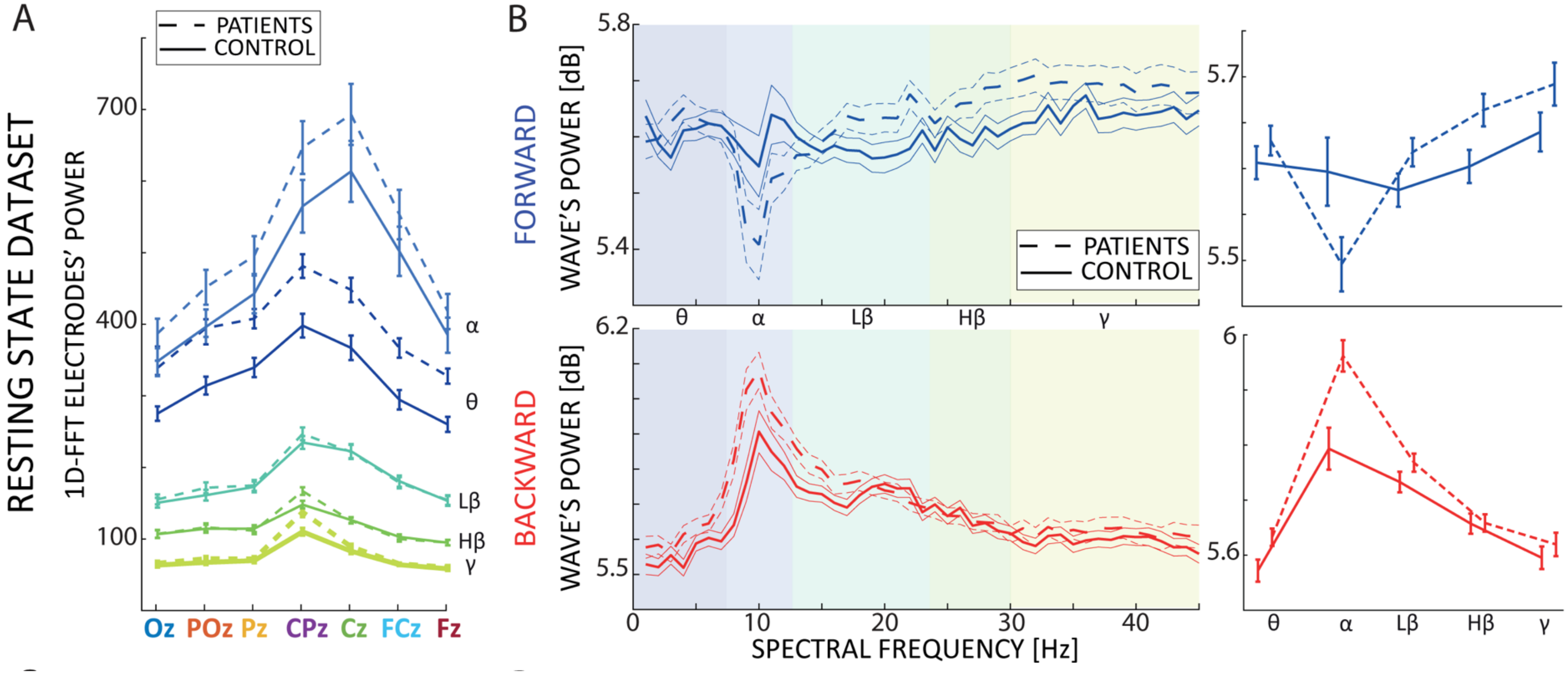
WAVES IN SCHIZOPHRENIA



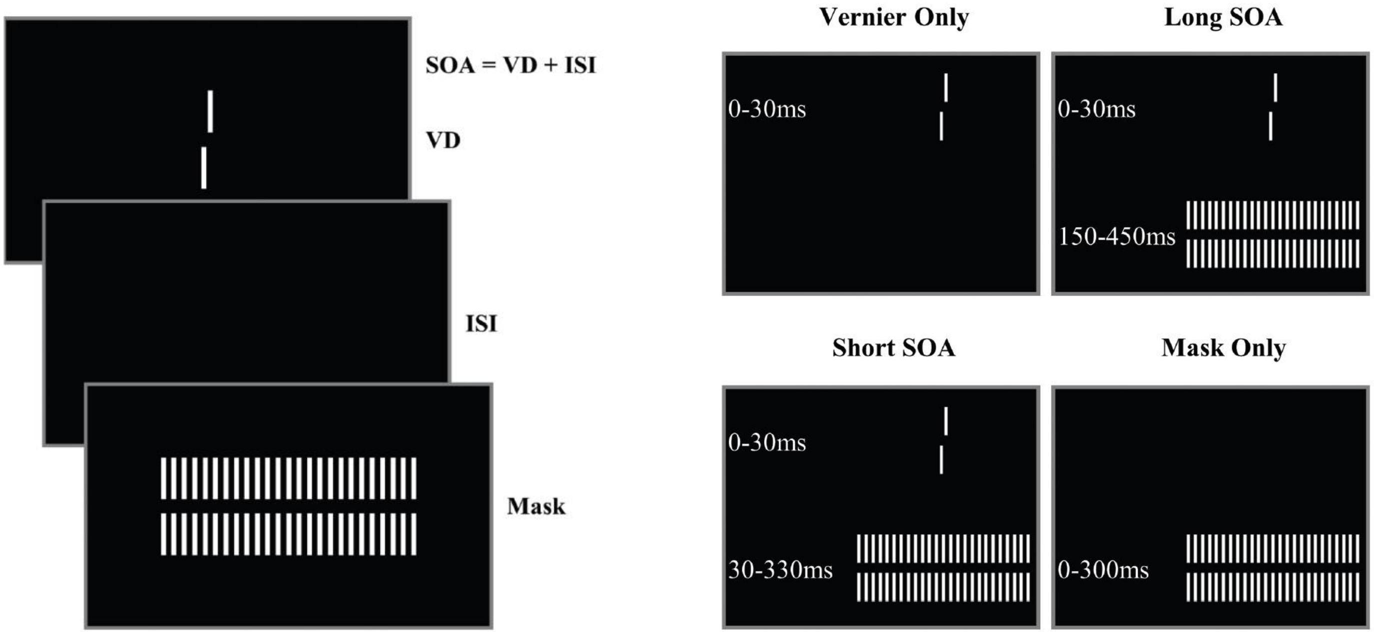
Sterzer 2018, Corlett 2019

WAVES IN SCHIZOPHRENIA

N = 121 (patients); N = 75 (control)



Vernier visual task.



WAVES IN SCHIZOPHRENIA

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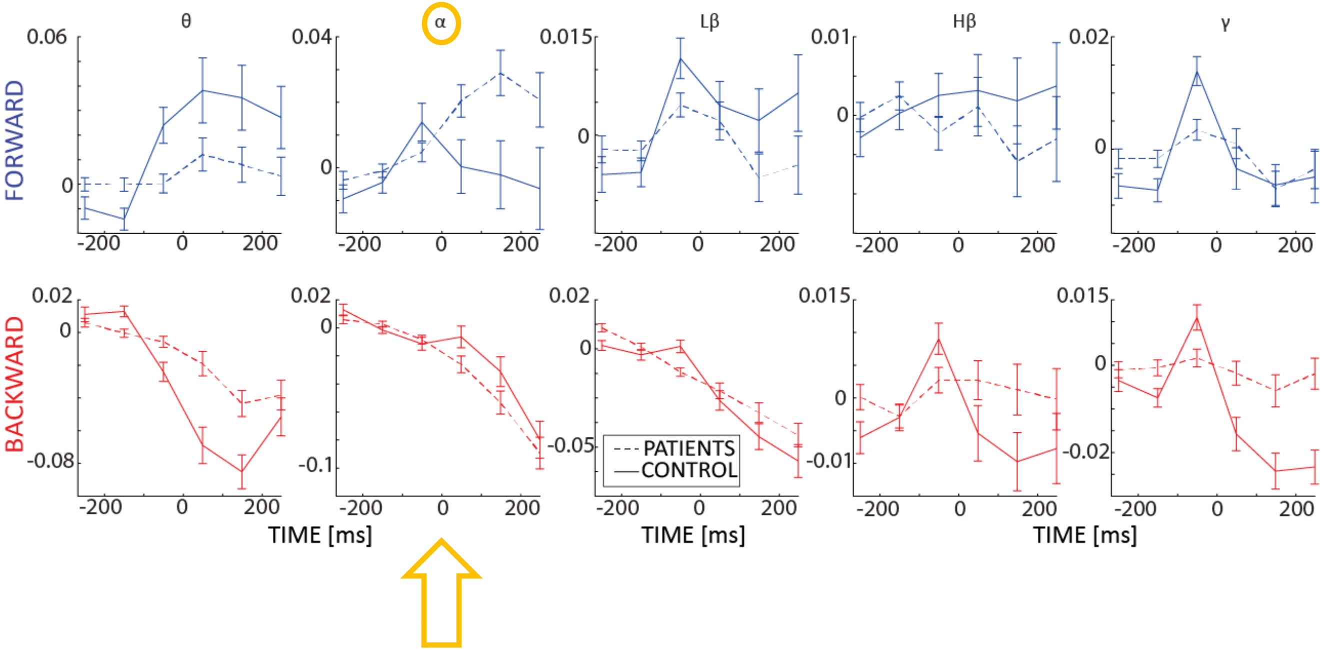
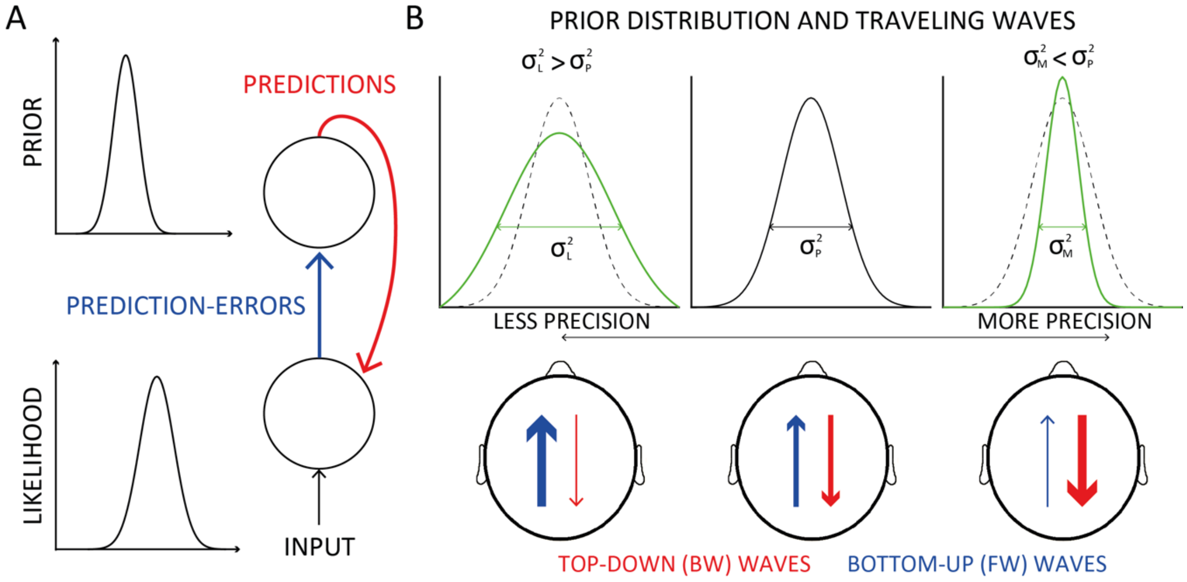


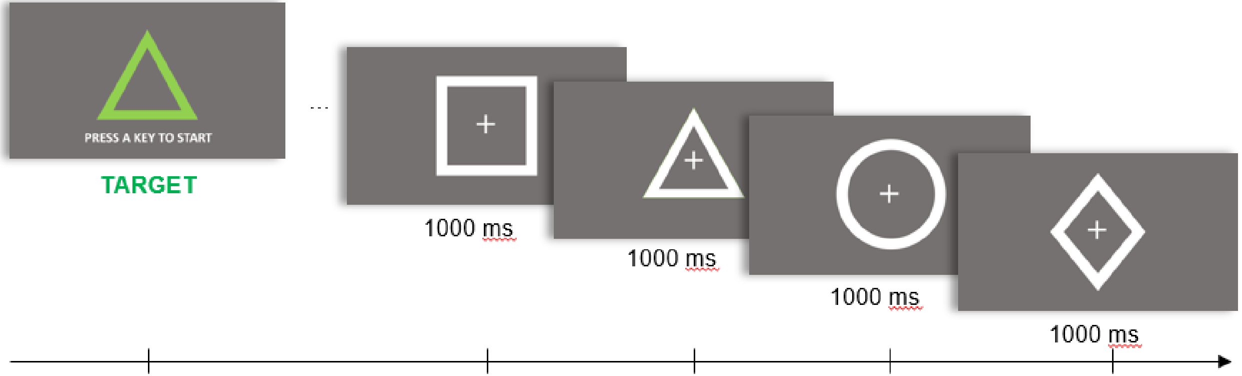
GOING FURTHER

- Find a way to test directly this fascinating hypothesis that **TW reflect Predictive Coding processes** (with modeling & experiments).



EXPERIMENTAL DESIGN: STATISTICAL LEARNING

Participants performed 15 blocks of 70 shapes each. The target changes every 18 shapes.



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Measured variables:

- Behavioral (RT and Scores)
- Pupil size
- EEG (TW)

Pasqualetti & Alamia (in preparation)

MANIPULATING PROBABILITIES

$H = 0.3944$

	□	○	△	◇
□	✖	5	5	90
○	90	✖	5	5
△	5	90	✖	5
◇	5	5	90	✖

$H = 0.6309$

	□	○	△	◇
□	✖	10	10	80
○	80	✖	10	10
△	10	80	✖	10
◇	10	10	90	✖

$H = 0.8570$

	□	○	△	◇
□	✖	5	47.5	47.5
○	47.5	✖	5	47.5
△	47.5	47.5	✖	5
◇	5	47.5	47.5	✖

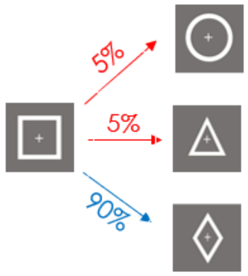
$H = 0.9503$

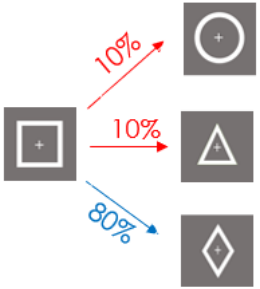
	□	○	△	◇
□	✖	20	20	60
○	60	✖	20	20
△	20	60	✖	20
◇	20	20	60	✖

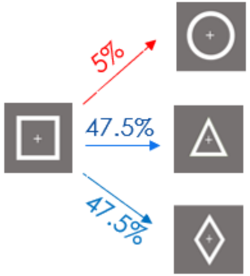
$H = 1.0977$

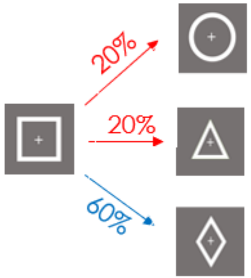
	□	○	△	◇
□	✖	33	33	33
○	33	✖	33	33
△	33	33	✖	33
◇	33	33	33	✖

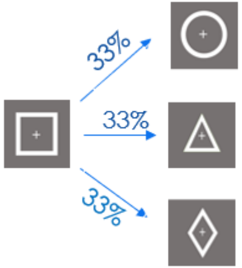
$$H = -\sum P(x) \log P(x)$$











MANIPULATING PROBABILITIES

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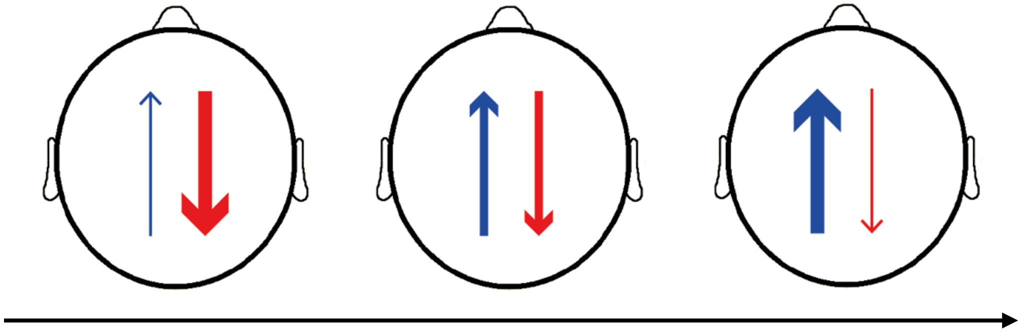
○	60	✖	20	20
△	20	60	✖	20
◇	20	20	60	✖

$H = 1.0977$

	□	○	△	◇
□	✖	33	33	33
○	33	✖	33	33
△	33	33	✖	33
◇	33	33	33	✖

- *Hypothesis I:*

Increase in BW waves with predictability.



Entropy (non Predictability)

MANIPULATING PROBABILITIES

$H = 0.3944$

	□	○	△	◇
□	✖	5	5	90
○	90	✖	5	5
△	5	90	✖	5
◇	5	5	90	✖

$H = 0.6309$

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□	✖	20	20	60
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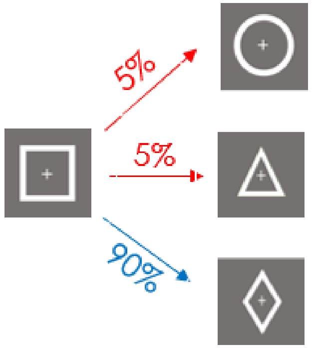
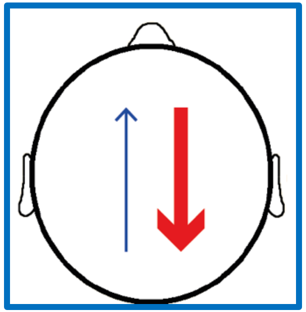
$H = 1.0977$

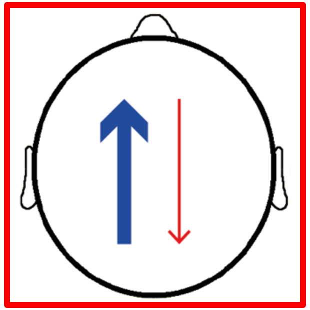
	□	○	△	◇
□	✖	33	33	33
○	33	✖	33	33
△	33	33	✖	33
◇	33	33	33	✖

- *Hypothesis II:*

Increase in FW waves with the rare transition (i.e., the Prediction Error).



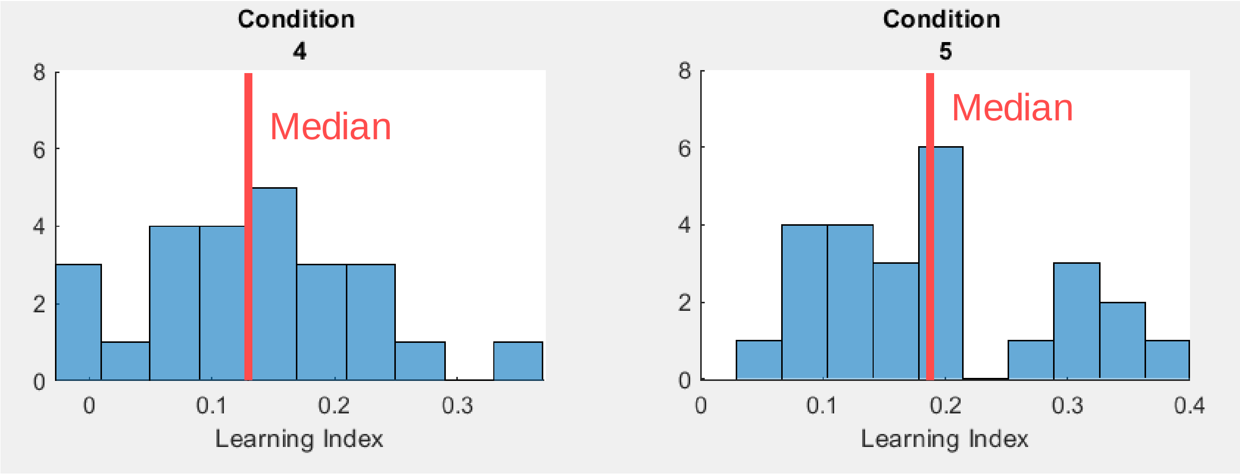




LEARNERS vs NON-LEARNERS

We split participants based on how much they use the regularities.

Learning index (LI) : RT(rare) – RT(expected)



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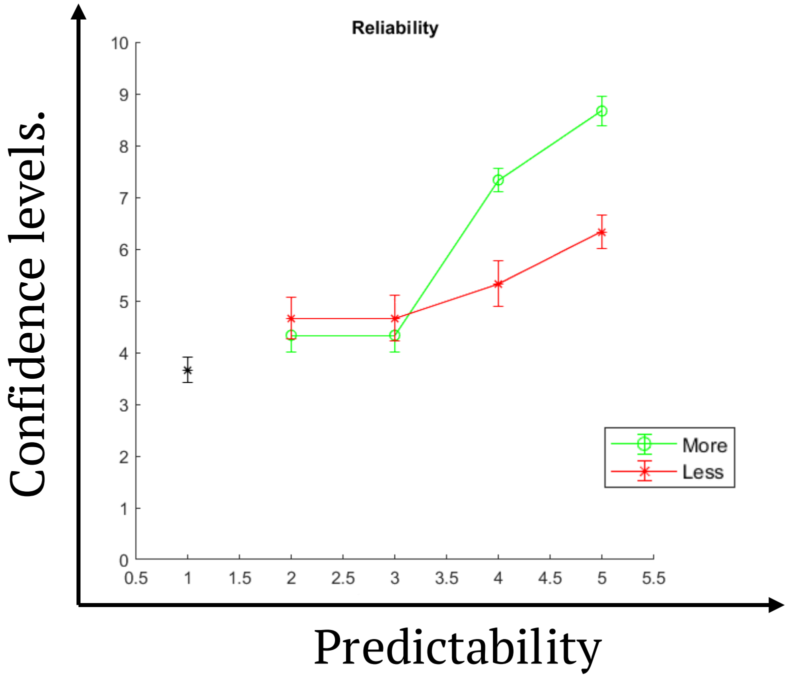
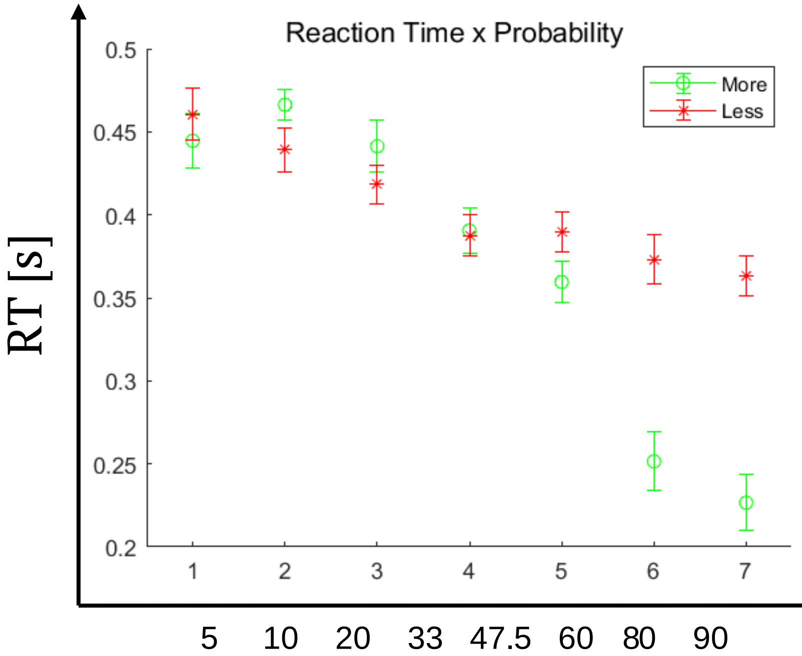
TW DURING STATISTICAL LEARNING

Behavioral results (N=30). Participants learn explicitly the regularities.





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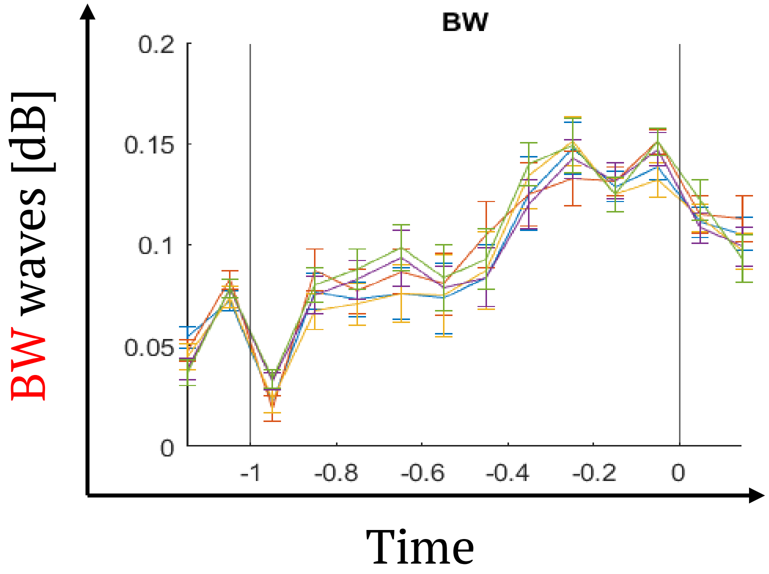
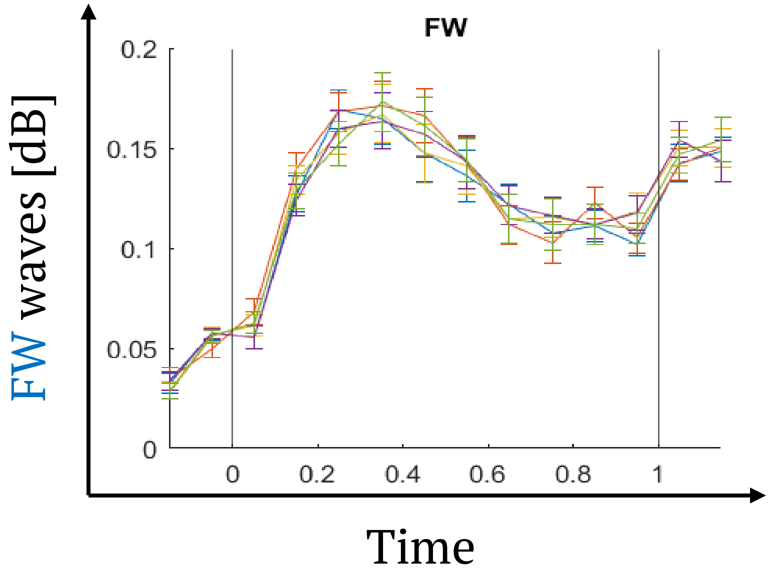
TW DURING STATISTICAL LEARNING

BW waves increase before stimuls onset, FW waves after stimulus onset.





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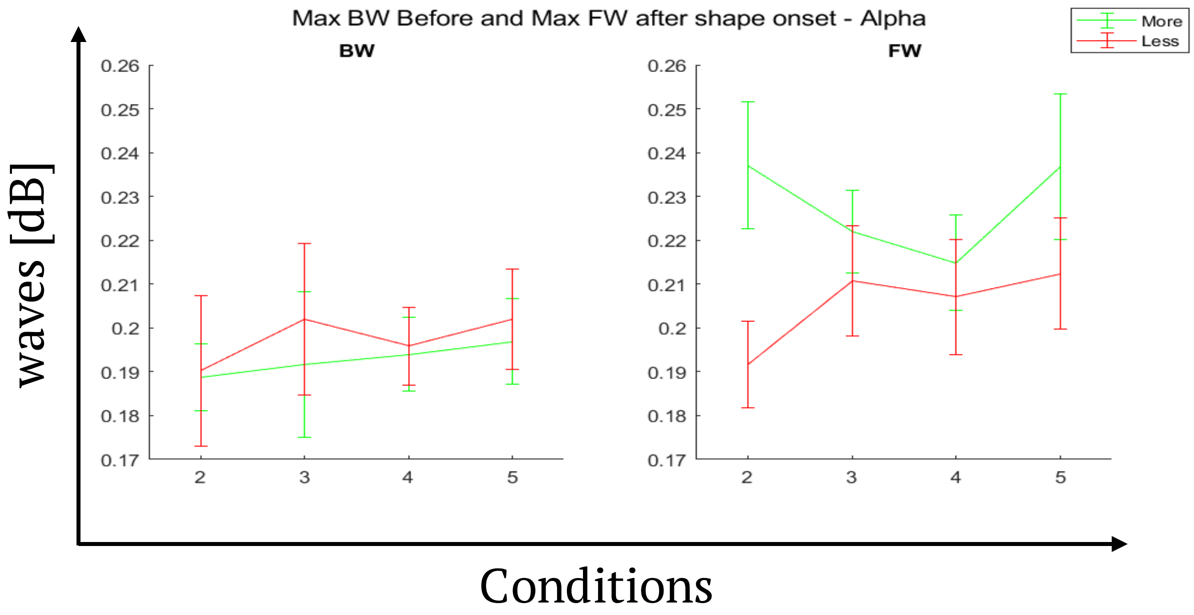
TW DURING STATISTICAL LEARNING

Hyp I : Sequence predictability doesn’t modulate BW or FW waves (BF<0.3).



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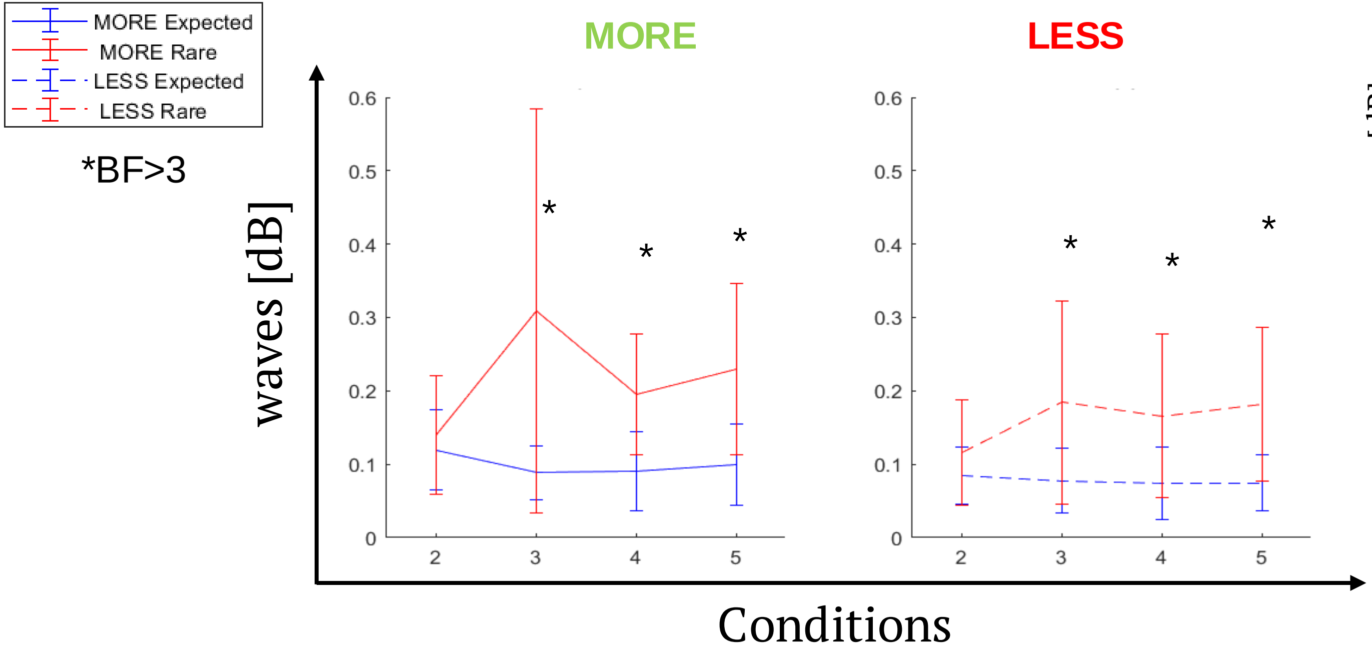
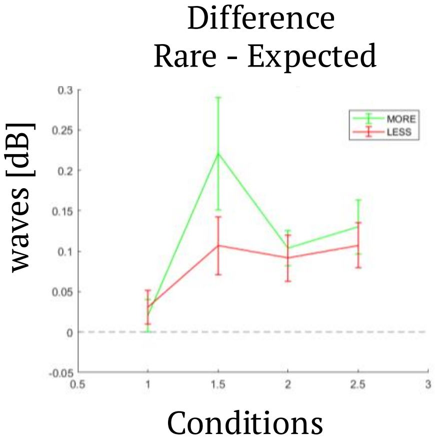
TW DURING STATISTICAL LEARNING

Hyp II : difference between rare and expected in FW waves.





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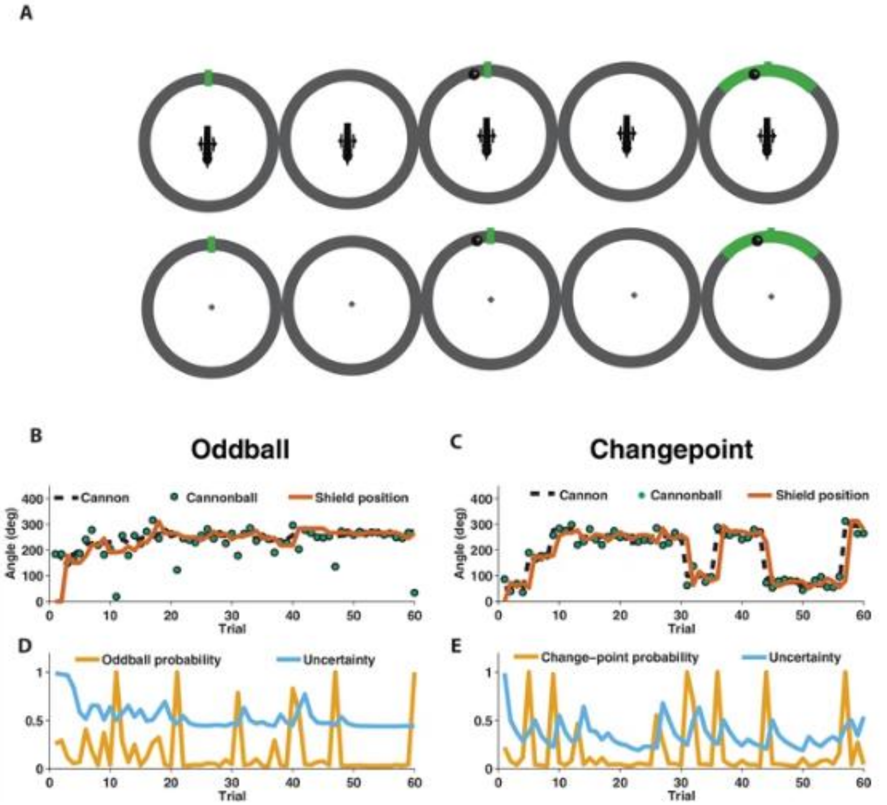
TW AND THE CANNONBALL



Nassar, Matthew R., Rasmus Bruckner, and Michael J. Frank. *"Statistical context dictates the relationship between feedback-related EEG signals and learning."* elife 8 (2019): e46975.

Matthew Nassar

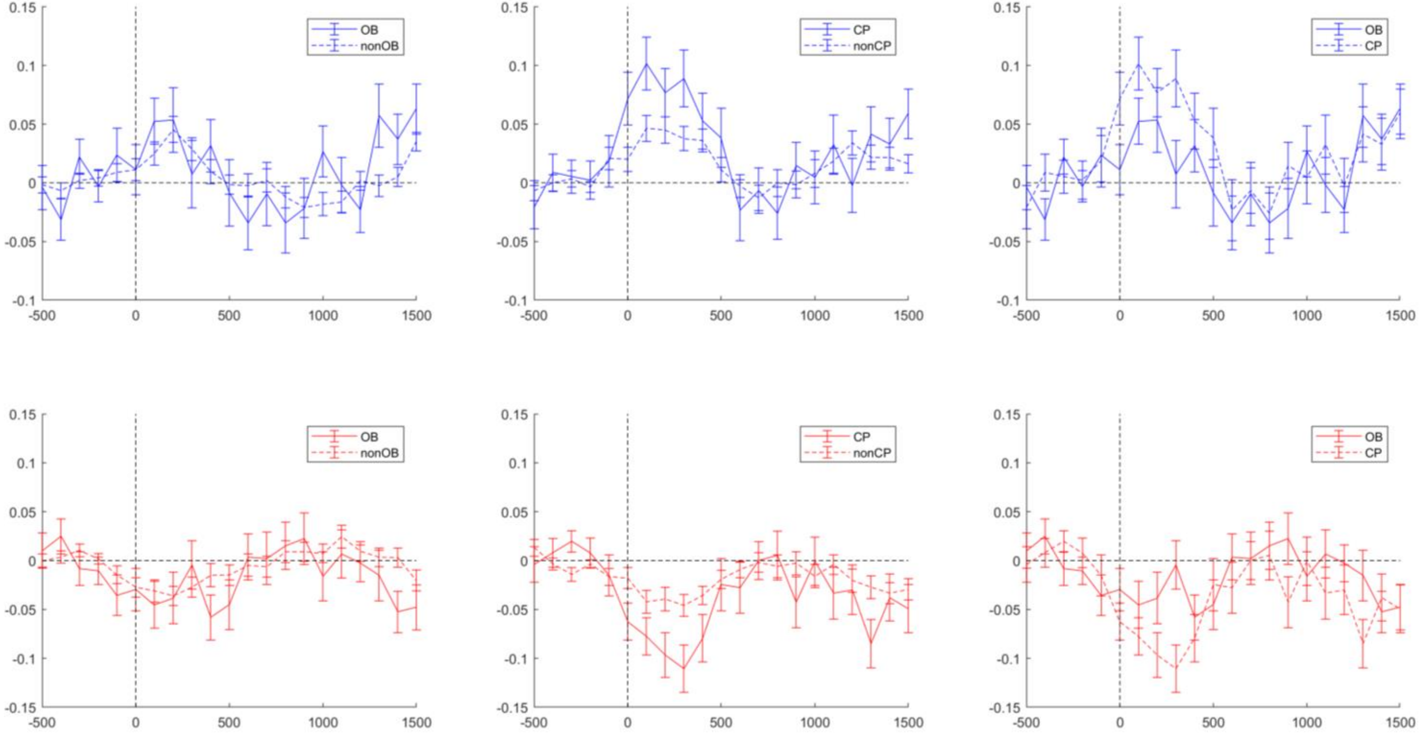
Do TW reflect changes in the model? (i.e., changepoint vs oddball).

TW AND THE CANNONBALL

OddBall (OB) | ChangePoint (CP) | OB vs CP

FORWARD

BACKWARD



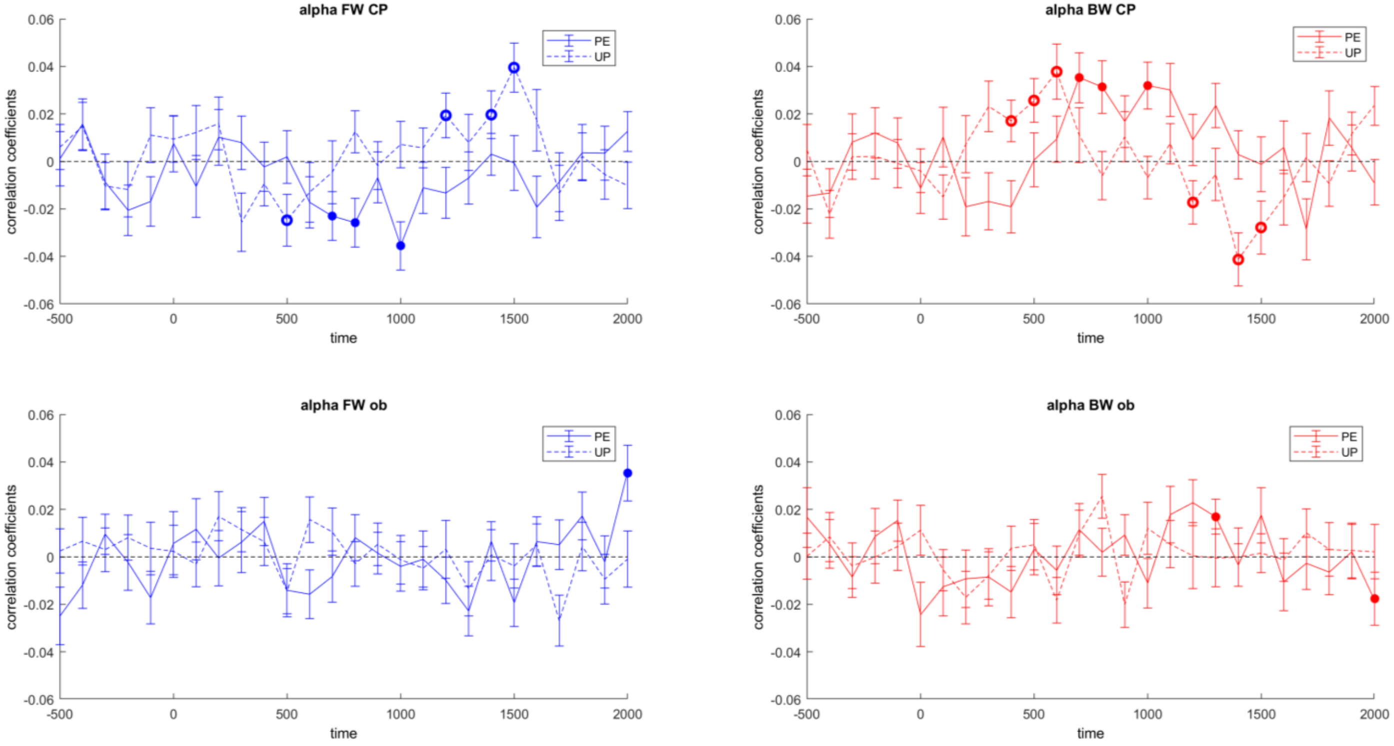
TW AND THE CANNONBALL

FORWARD

BACKWARD

CP

OB



CONCLUSIONS

Considering oscillations as Travelling Waves help us understanding their role in different cognitive functions.

- Forward waves relate to visual stimulation.
- Backward waves reflect inhibition and attentional modulation.
- Both modulated by psychedelics drugs (DMT), and in Schizophrenia patients.
- Ongoing work to test their link with Predictive Coding.

- Ongoing work investigating travelling waves and Binocular Rivarly, Working Memory and computational mechanisms.

THANKS!!

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C.Timmermann

M.Nassar

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NeuroAI team

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NeuroAi

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UMR5549

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European Research Council
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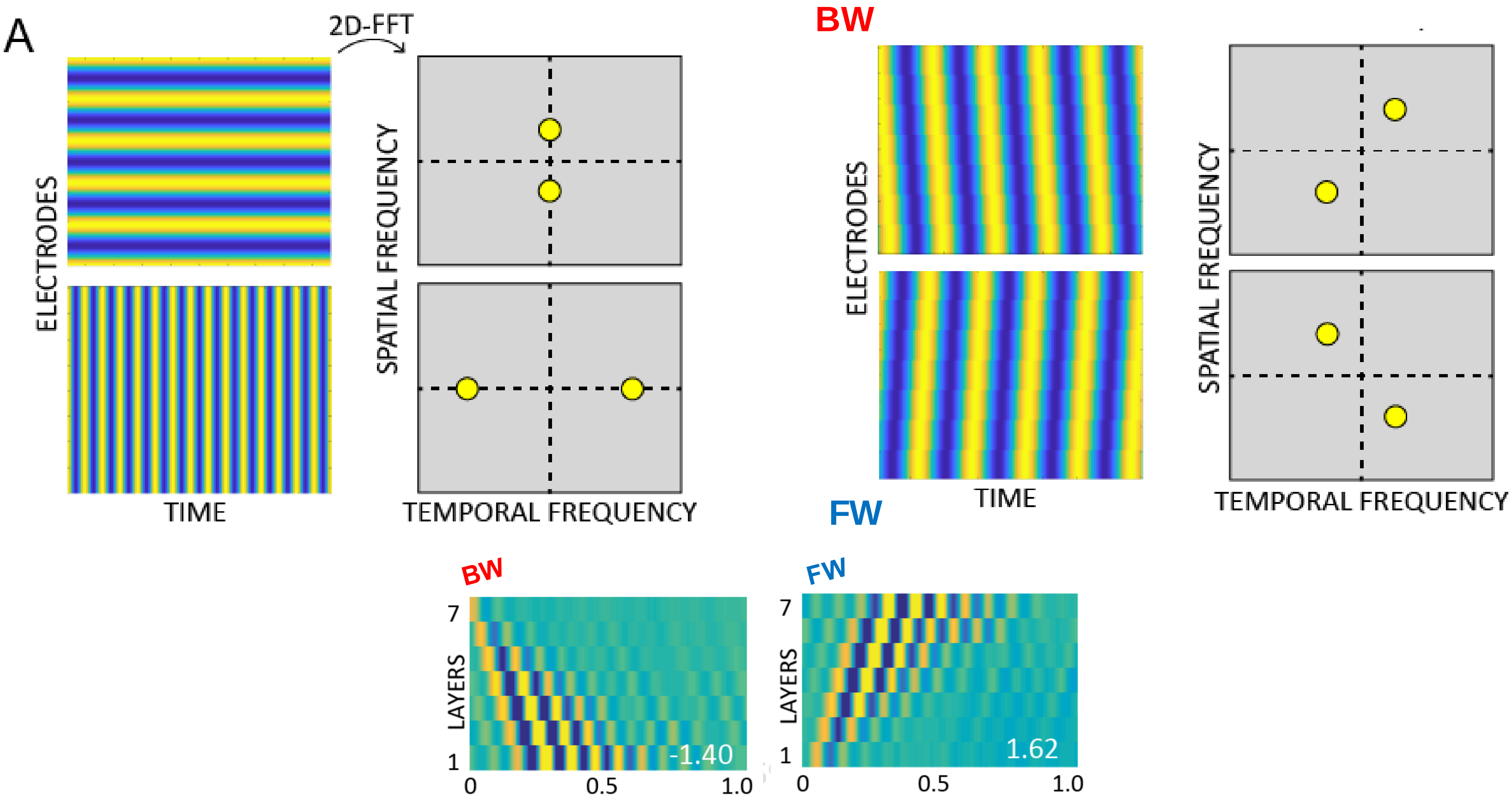
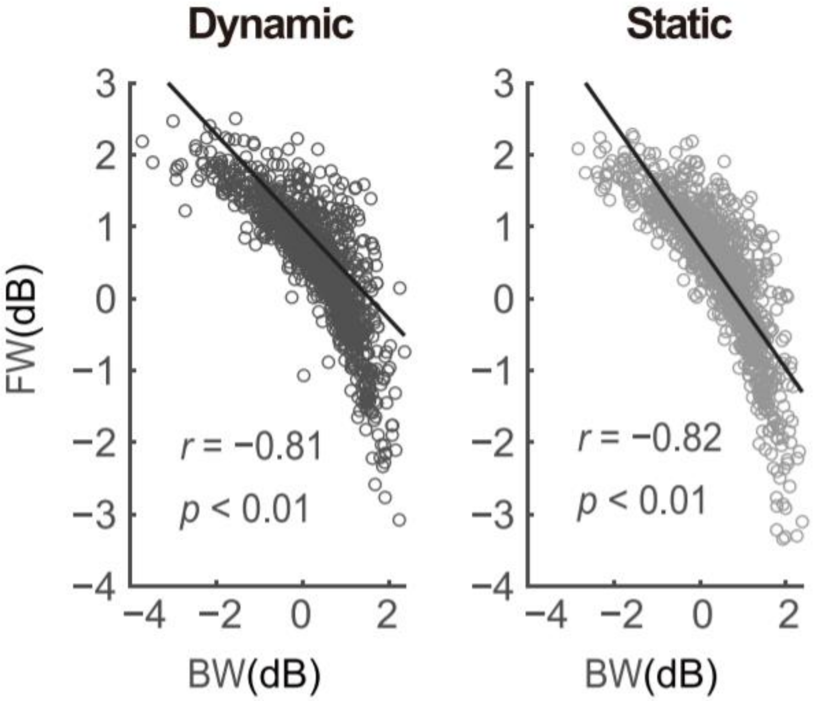
QUANTIFYING WAVES DIRECTION



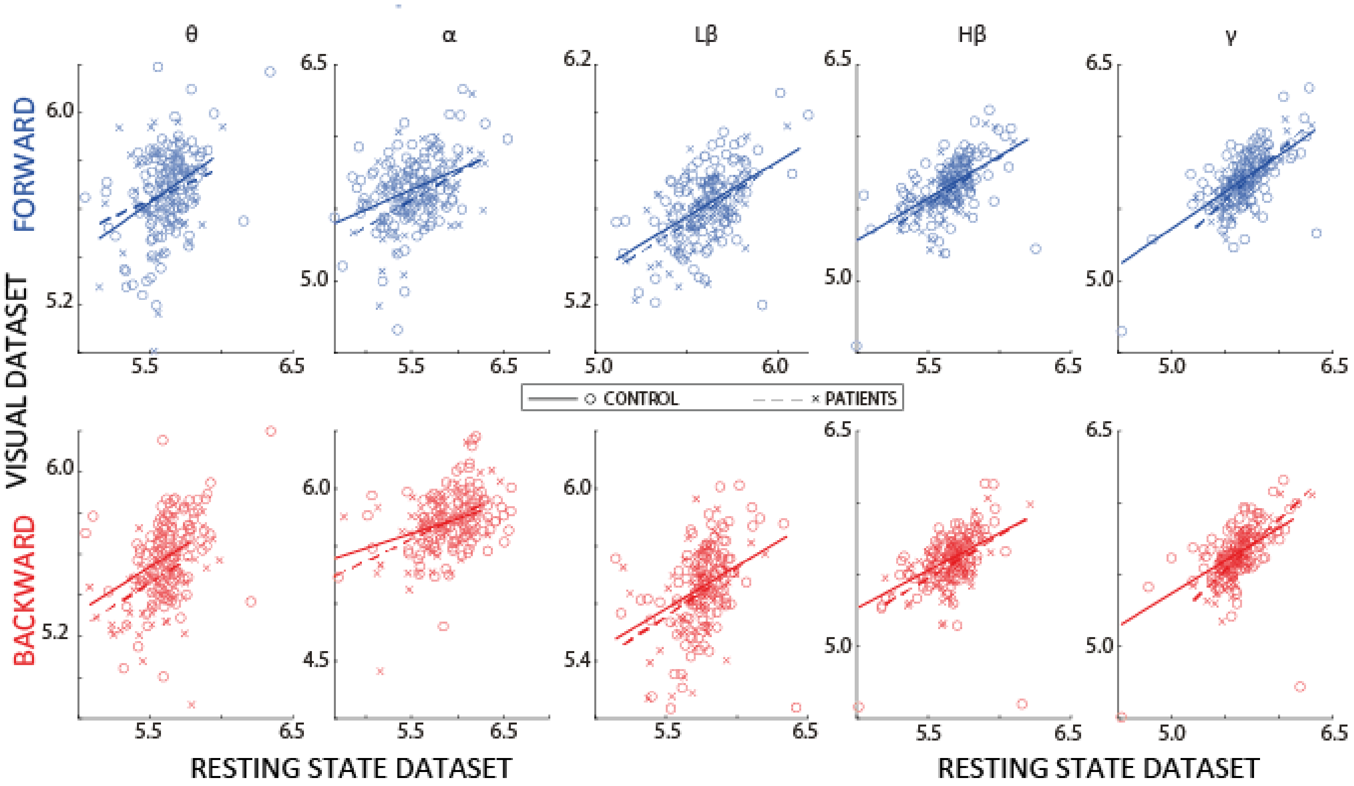
CORRELATING FW AND BW WAVES



Forward and backward waves related to visual stimulation.

WAVES IN SCHIZOPHRENIA

Do waves correlate between datasets?



WAVES IN SCHIZOPHRENIA

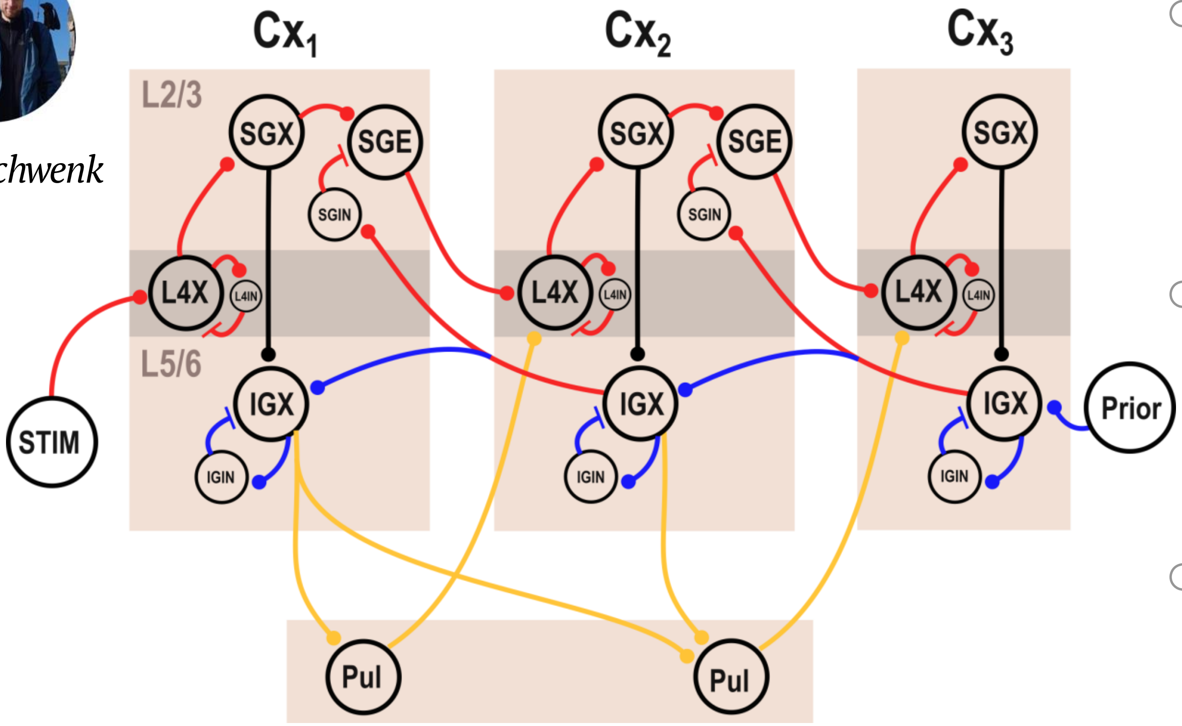
Do waves correlate with pharmacological drugs (CPZ equivalent)? NOPE

Do waves correlate with positive symptoms? NOPE

Do waves correlate with negative symptoms? NOPE

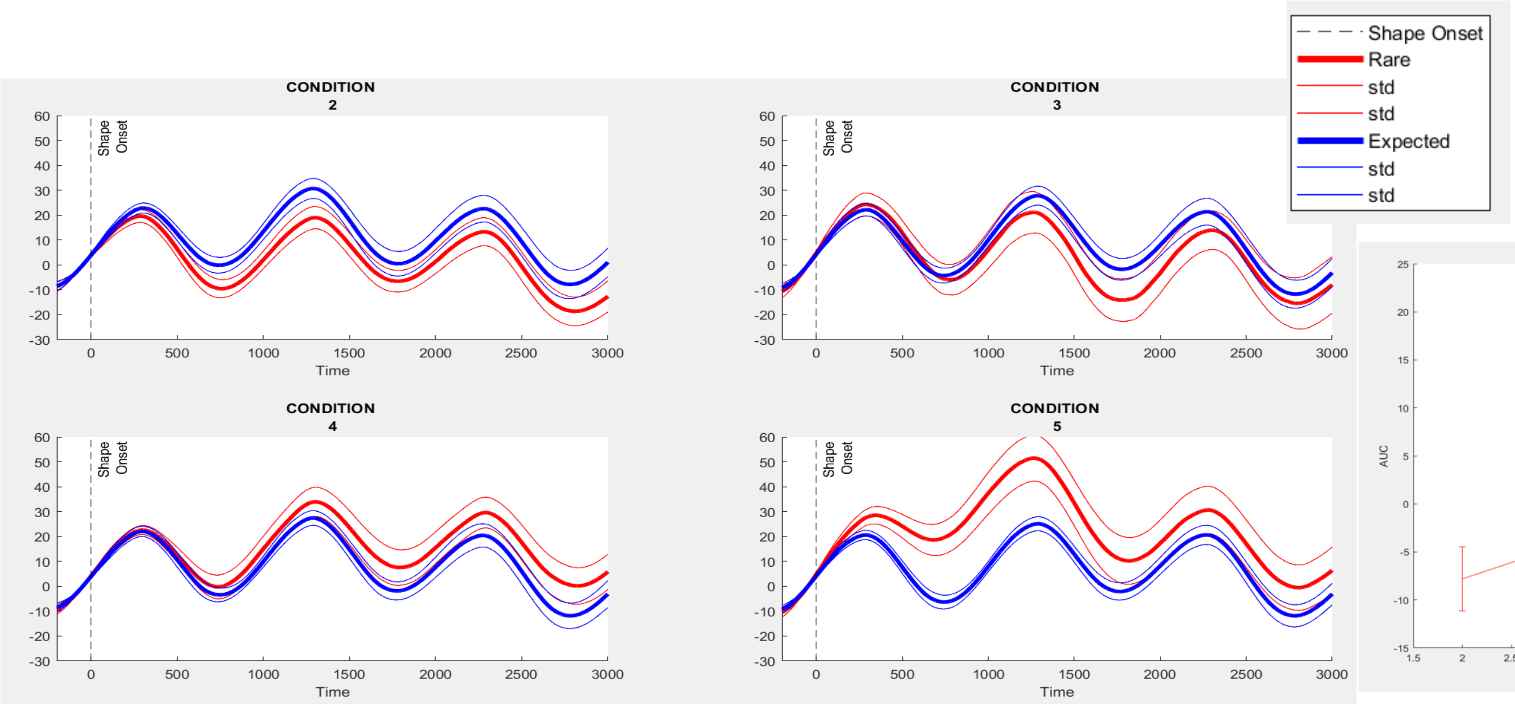
PROJECT STRUCTURE

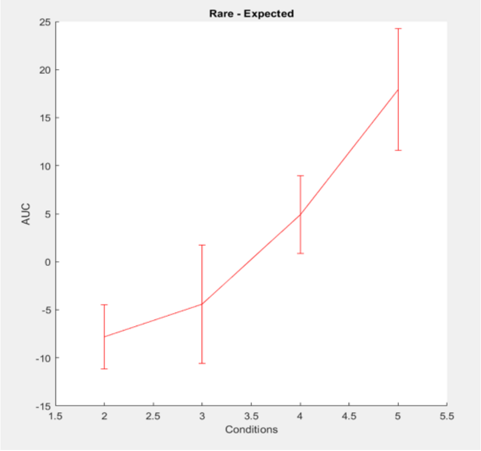
Jakob Schwenk



- Mean field model showing FW and BW waves in a PC framework.
- Pulvinar modulates TWs, biasing FW and BW competition in favor of FW waves.
- Waves drive gamma-band coherence and causality (mean field + spiking network).

PUPIL IN THE STATISTICAL LEARNING





[60 20] [47.5 5] [80 10] [90 5]

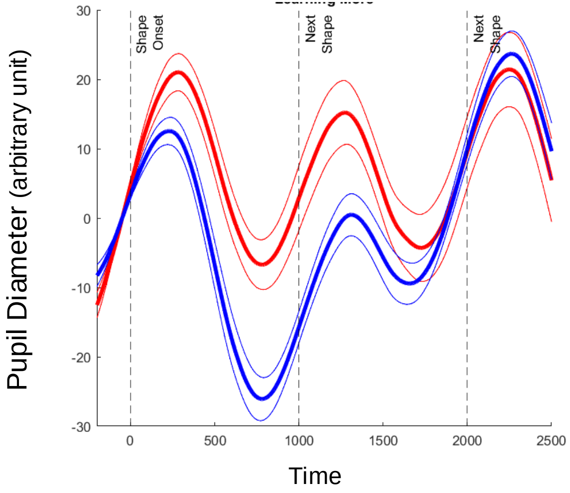
PUPIL DIAMETER

Pupil size dilates following surprising events (Alamia et. all, 2019)

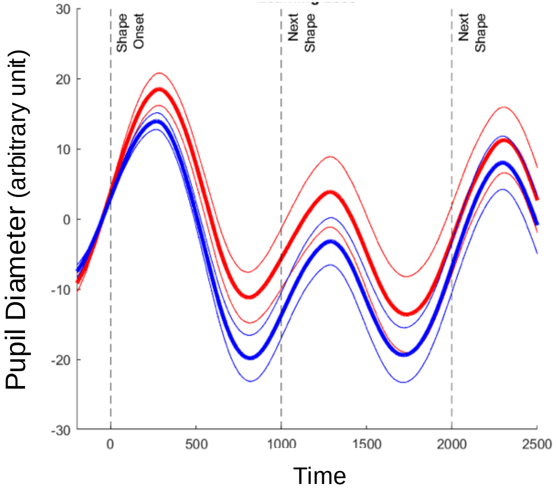
Expected
Rare

PUPIL DIAMETER AFTER RARE AND EXPECTED SHAPES

MORE

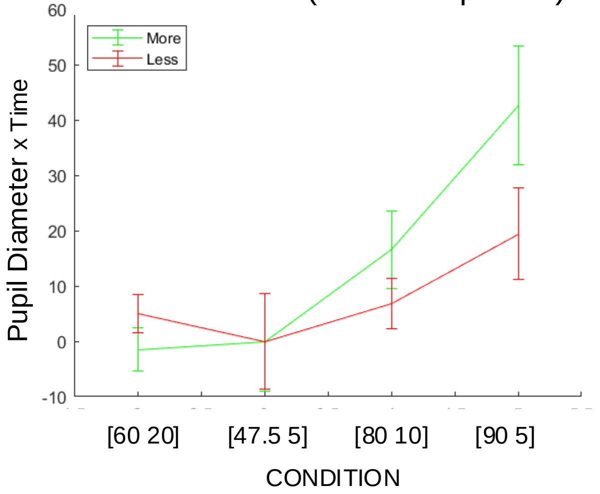


LESS



Bayesian Repeated Measure ANOVA
MORE = BF10 = 271 *
LESS = BF10 = 0.48

AREA UNDER THE CURVE OF DIFFERENCE (Rare – Expected)

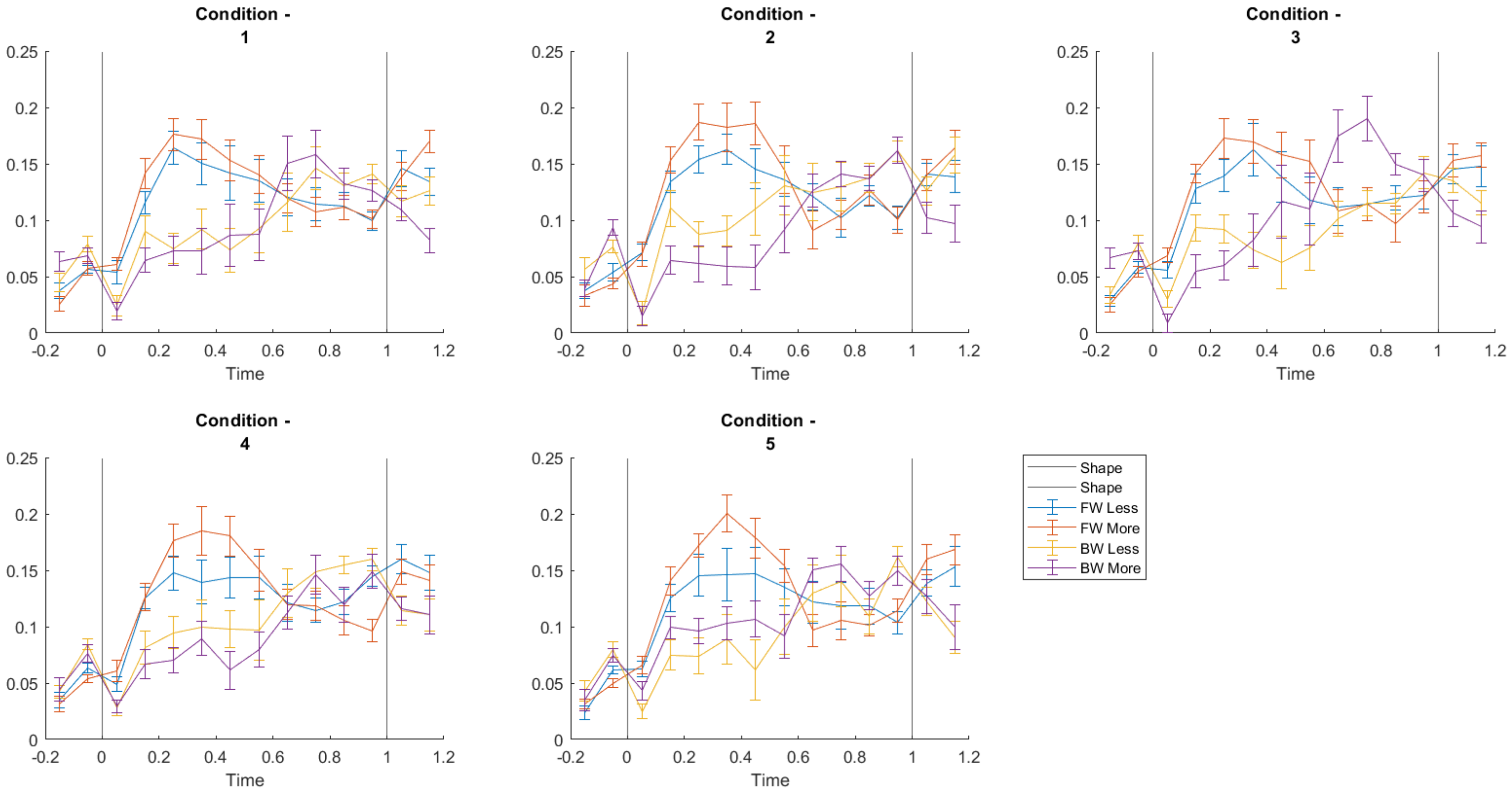


DECREASED SEQUENCE RELIABILITY

INCREASED SEQUENCE RELIABILITY

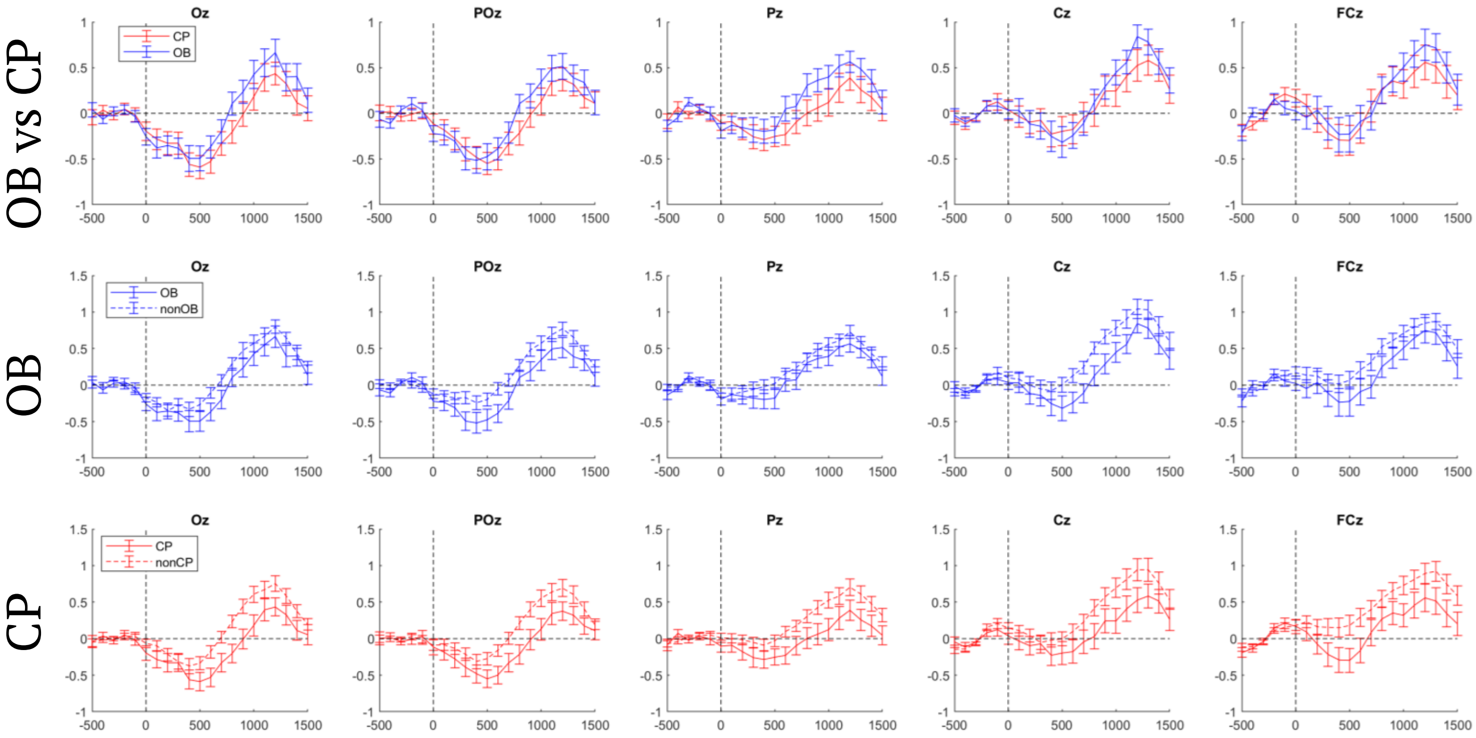
N = 31

TW DURING STATISTICAL LEARNING

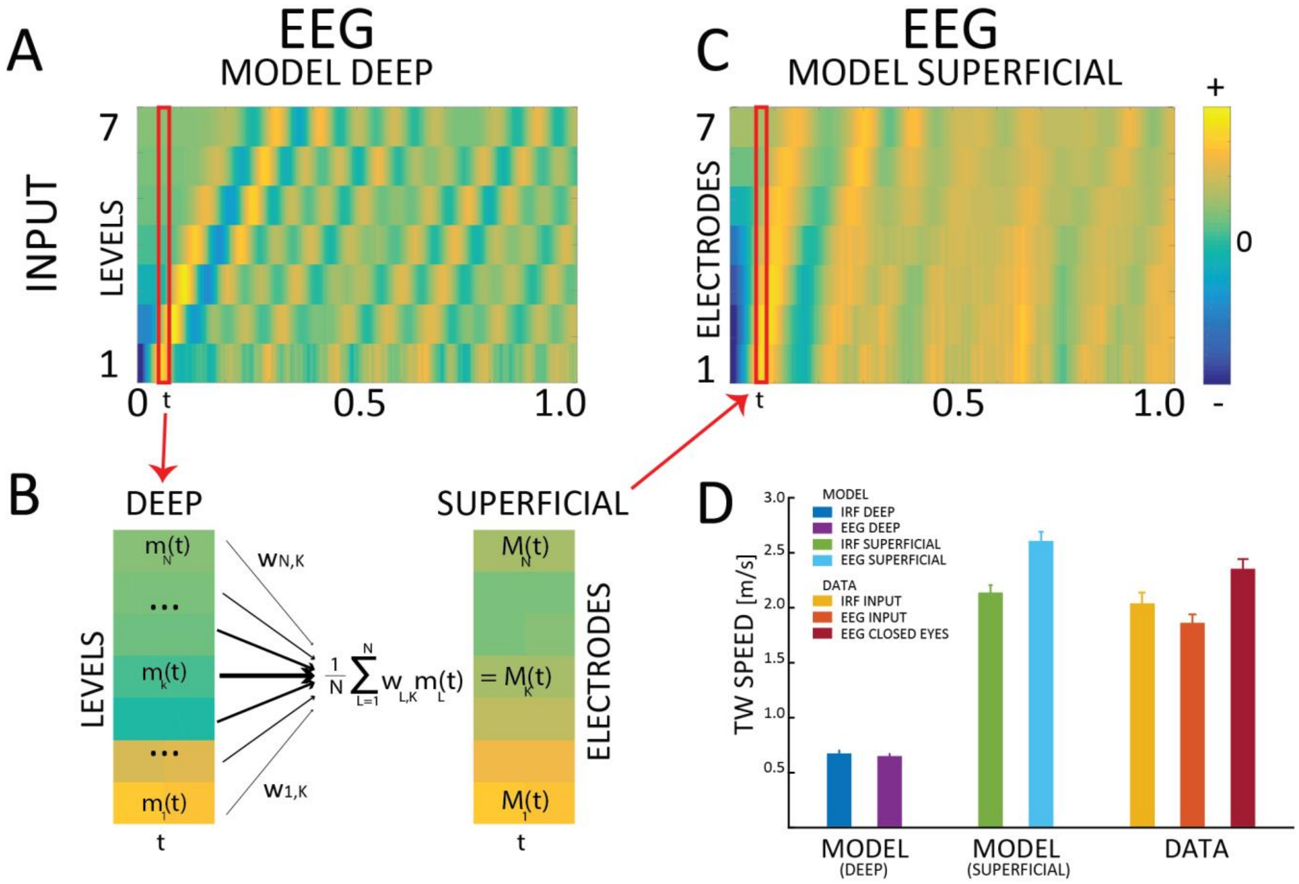


TW AND THE CANNONBALL

Alpha Power (1D-FFT)

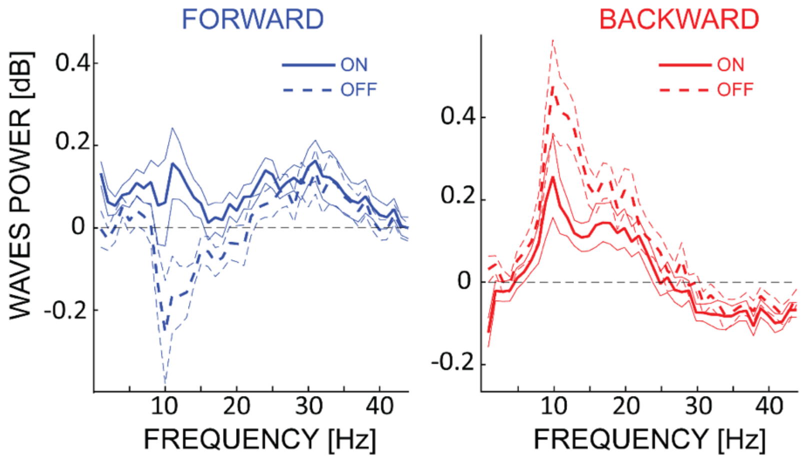


SPEED OF TW

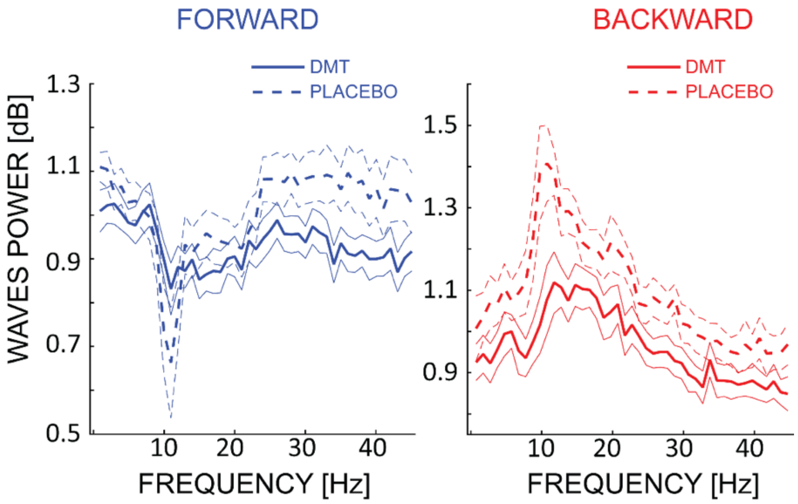

A
EEG
MODEL DEEP
INPUT
LEVELS
7
1
0
t
0.5
1.0
C
EEG
MODEL SUPERFICIAL
ELECTRODES
+
0
-
B
DEEP
SUPERFICIAL
LEVELS
ELECTRODES
$m_N(t)$
$m_k(t)$
$m_1(t)$
$w_{N,K}$
$w_{1,K}$
$\frac{1}{N}\sum_{L=1}^{N} w_{L,K}\, m_L(t) = M_K(t)$
$M_N(t)$
$M_1(t)$
D
MODEL
IRF DEEP
EEG DEEP
IRF SUPERFICIAL
EEG SUPERFICIAL
DATA
IRF INPUT
EEG INPUT
EEG CLOSED EYES
TW SPEED [m/s]
3.0
2.5
2.0
1.5
1.0
0.5
MODEL (DEEP)
MODEL (SUPERFICIAL)
DATA

SPECTRA OF TW

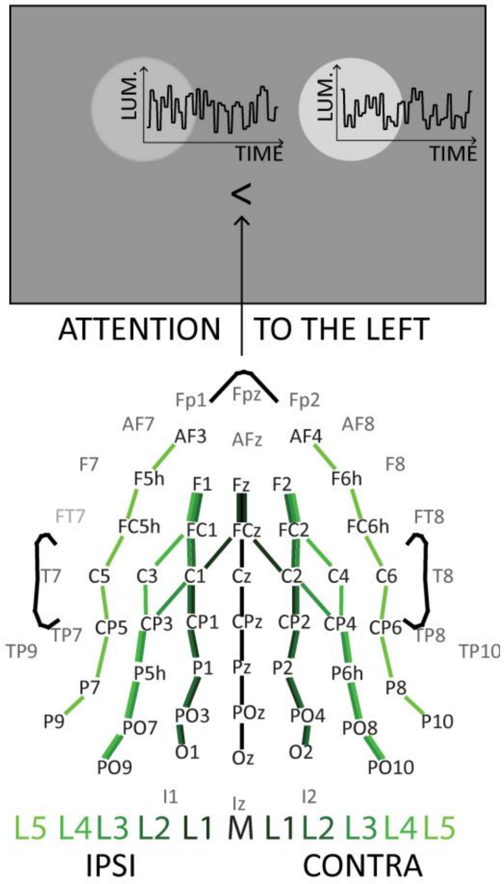
- PANG et al. data (OPEN EYES)

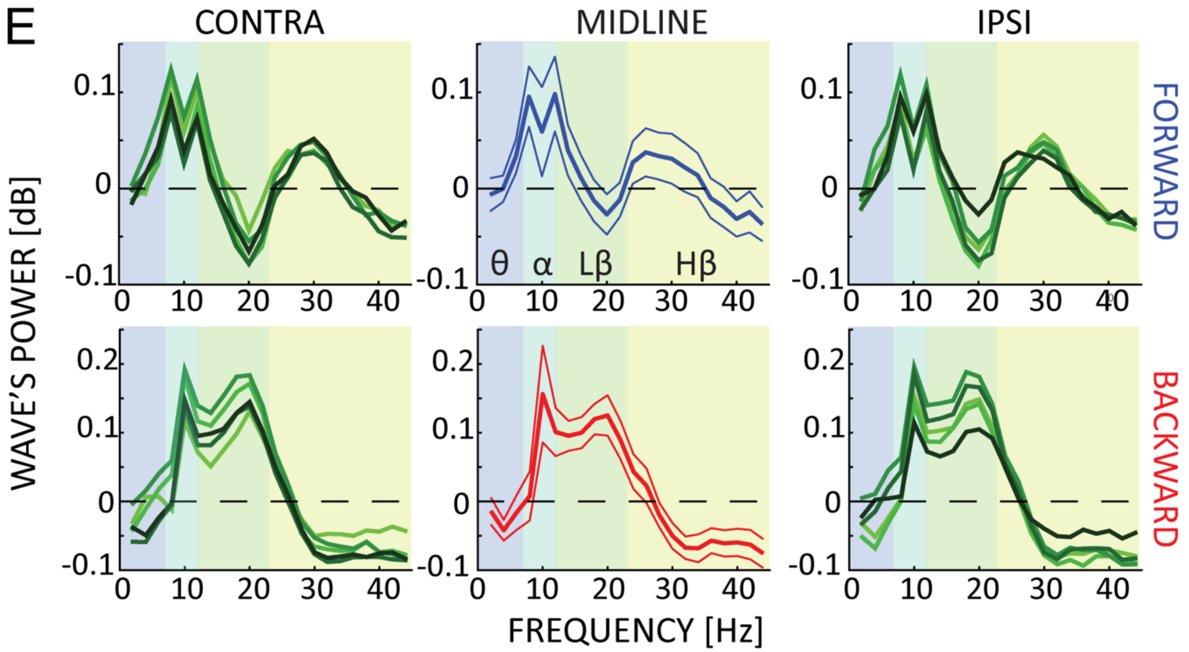


- DMT data (CLOSED EYES)



WAVES' SPECTRAL PROFILE

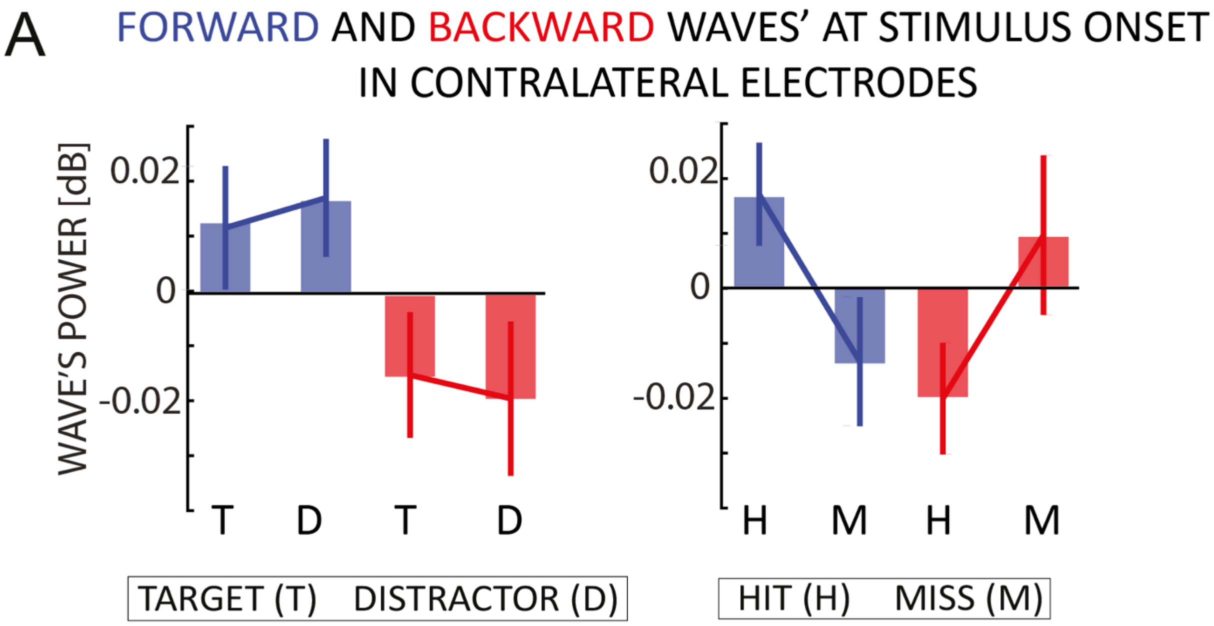




CORRELATING WAVES WITH POWER

Pearson r (BF_{10})		FW		BW	
		CONTRA	IPSI	CONTRA	IPSI
OCC.	CONTRA	-0.297 (0.549)	-0.350 (0.697)	**0.720 (28.519)**	**0.698 (19.503)**
	IPSI	-0.305 (0.566)	-0.342 (0.669)	**0.786 (116.990)**	**0.746 (47.512)**
FRONT.	CONTRA	-0.222 (0.422)	-0.252 (0.465)	**0.772 (84.225)**	**0.712 (24.645)**
	IPSI	-0.327 (0.625)	-0.354 (0.710)	**0.747 (48.448)**	**0.705 (21.841)**

RESULTS – EVENT ANALYSIS I



TW AND THE CANNONBALL

Summary:

- Alpha-band FW waves seem to increase during model update
- FW and BW TW correlate with *model update* and *prediction-error, but interpretation may not be in line with our hypothesis.*

To explore:

- Confirm results with another method to compute waves (e.g., phase plane fitting);
- Replicate in other datasets with similar tasks:
  - Do TW encode the ‘variability’ of the model? (the spread of the cannonball target area).
  - What if in the same block we have OD and CP?