# A novel transformer-based approach for estimating causal interaction in multichannel electroencephalographic data



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Master Thesis – M.Sc. in Artificial Intelligence and Robotics

Relatore: Prof.ssa Laura Astolfi

Correlatore: Prof. Nicola Toschi

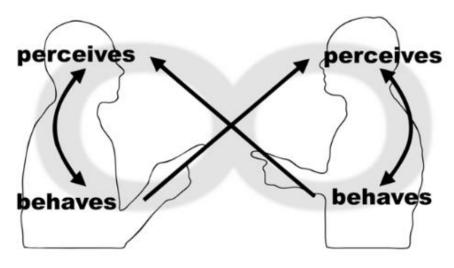
Controrelatore: Prof. Luca locchi



# Introduction – EEG Hyperscanning

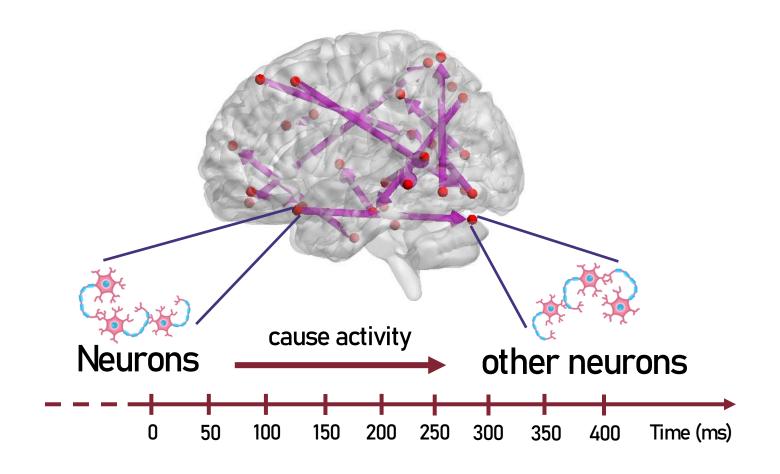
- Simultaneous acquisition of brain signals on two (or more) subjects during their interaction.
- Interdependencies between the two sets of brain signals can reveal brain processes that support the interaction.
- EEG hyperscanning allows more natural, face-to-face interaction and follows the brain dynamics with an excellent time resolution.

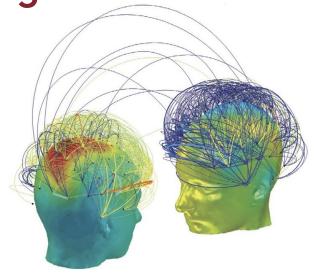


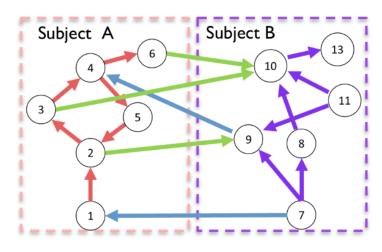




Introduction - Causality in hyperscanning

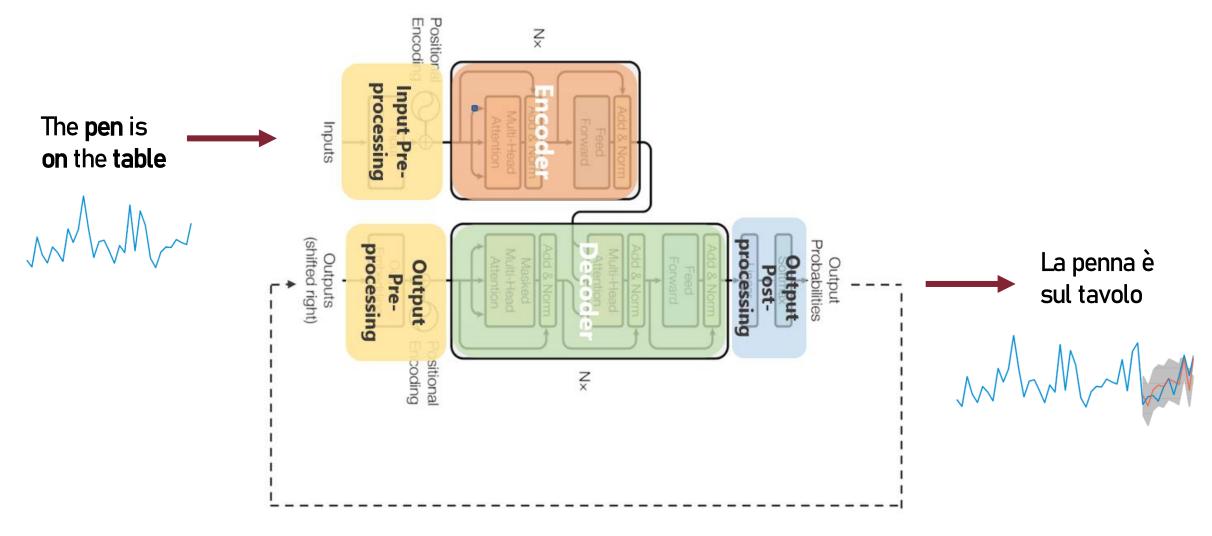








## Introduction – Basic of Transformers





## Propose two novel methods

**Method 1:** Conditioned Granger
Causality based on Spacetimeformer
residuals

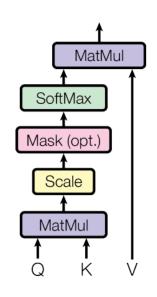
Assess feasibility of the novel approach, using synthetic EEG data as a benchmark, to compare results with a ground truth. **Method 2:** Attention matrices as measure of causality

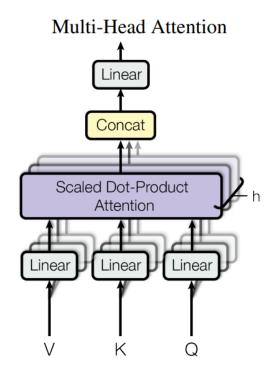
 Assess the plausibility of this novel method by applying it to real hyperscanning EEG data.



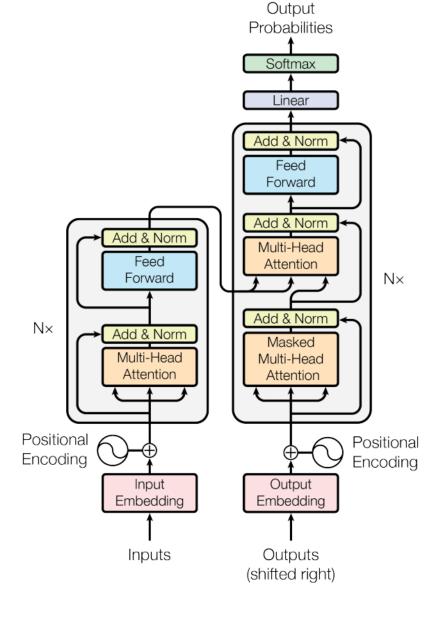
## Methods – Transformers

#### Scaled Dot-Product Attention





Attention(Q, K, V) = 
$$soft max \left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

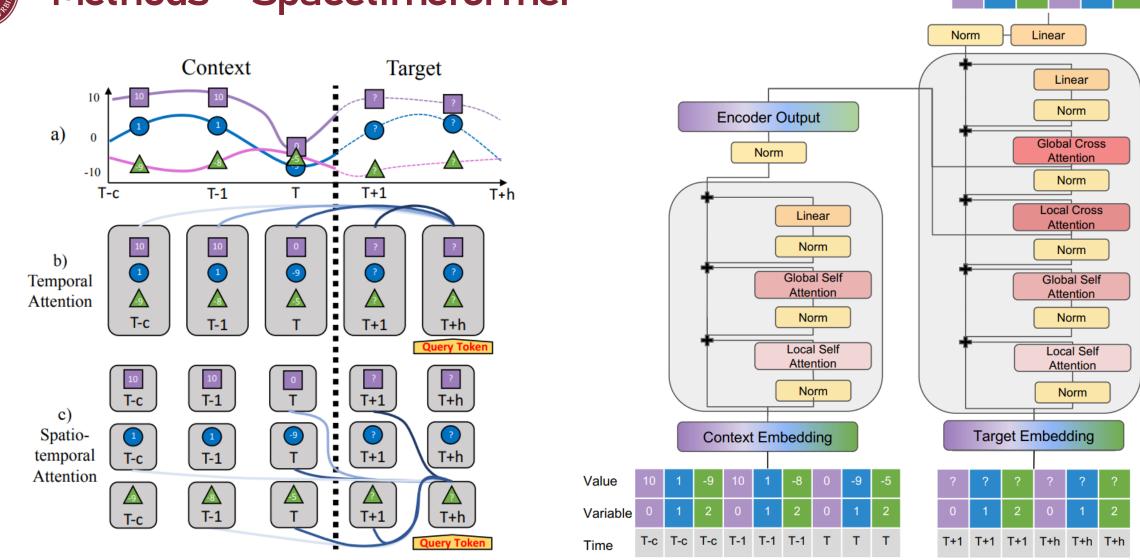




**Transformer** 

Spacetimeformer

# Methods - Spacetimeformer



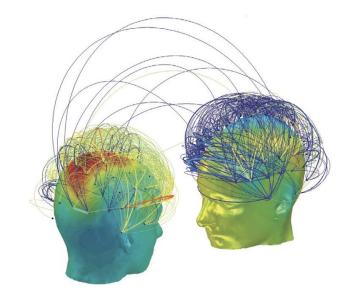
Predictions:

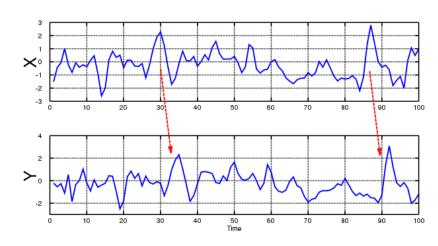


# Methods – Wiener-Granger causality

Granger causality is based on the improvement of the predicting capability of a model by incorporating the past of a second signal. This is measured by the reduction of the residuals.

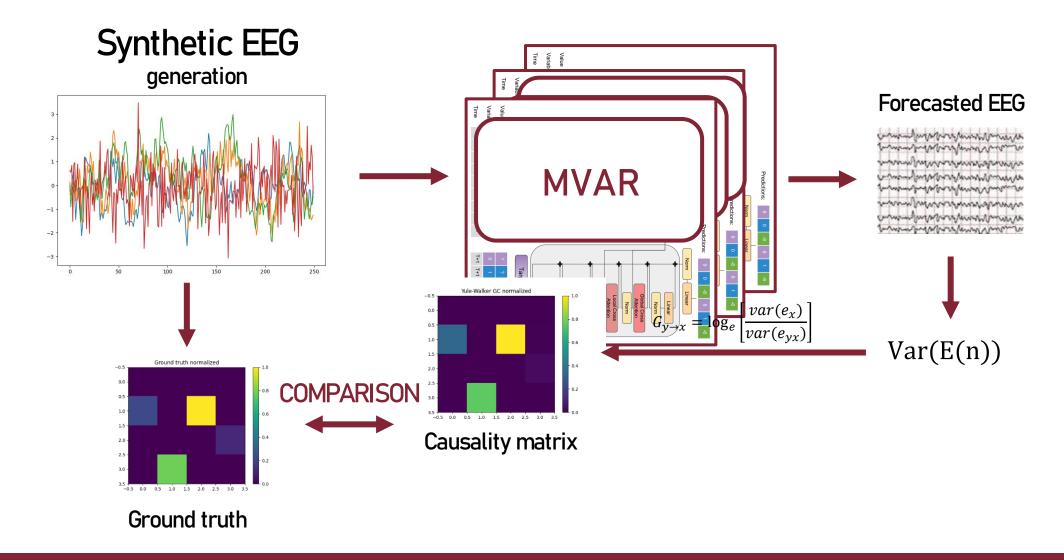
$$G_{y \to x} = \log_e \left[ \frac{var(e_x)}{var(e_{yx})} \right]$$





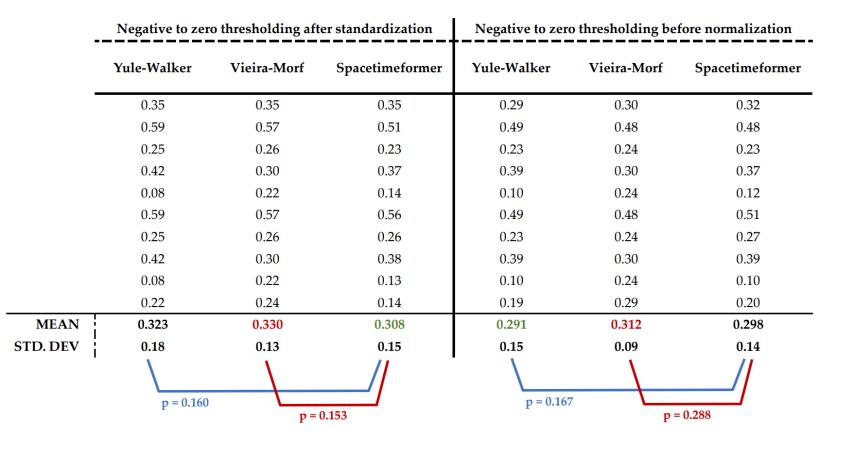


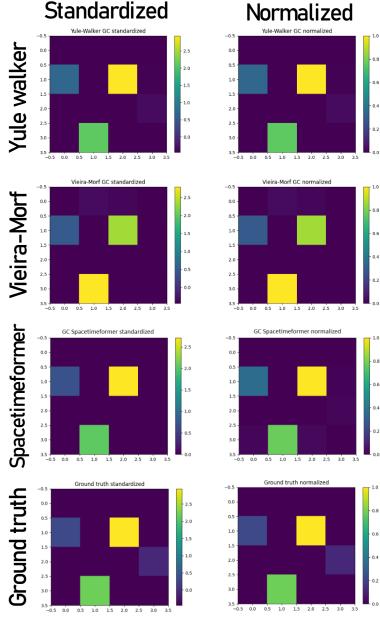
# Method 1: CGC with Spacetimeformer





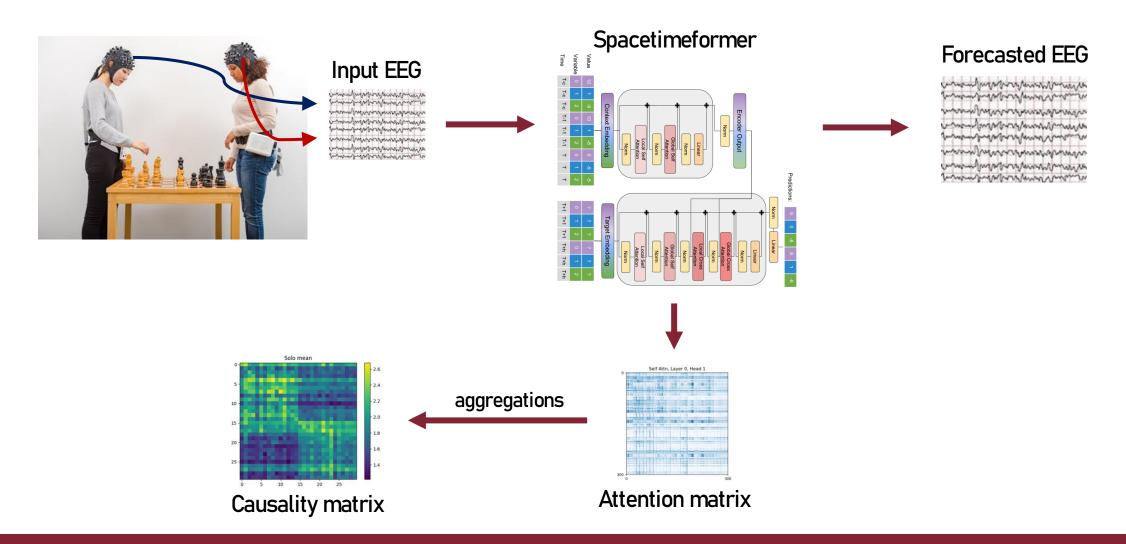
## Results of Method 1







## Method 2: Attention matrices as causality measure

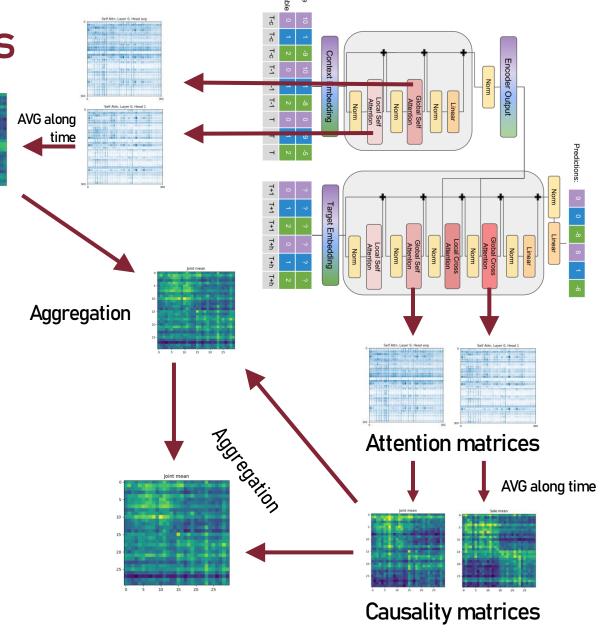




## Method 2: Attention matrices

## Types of aggregation considered

- 1. Cross-attention on Layer 0
- 2. Cross-attention on Layer 1
- 3. Average of cross-attentions
- 4. Element-wise product between cross-attentions
- 5. Self-attention on Layer 0
- Self-attention on Layer 1
- 7. Average of self-attentions.
- 8. Element-wise product between self-attentions
- 9. Average of all the attention on every layer
- 10. Element-wise product between all the attention on every layer
- 11. Element-wise product between the averages of cross and self-attention





# Method 2: Hyperscanning Joint experiment

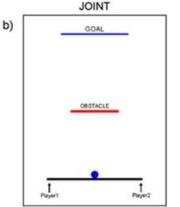
#### Two conditions considered:

- Solo experiment: each subject completed the task on their own, two fingers to control both sides of the virtual bar.
- Joint experiment: the dyad worked on the same task together. Each participant used one finger to press a button to control one side of the virtual bar.

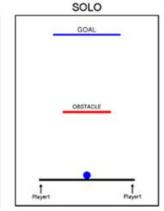
(Astolfi, et al., 2020)

The neuroelectrical hyperscanning recordings were performed with a 128-channel EEG acquisition system (64+64 channels) with a sampling frequency of 250 Hz







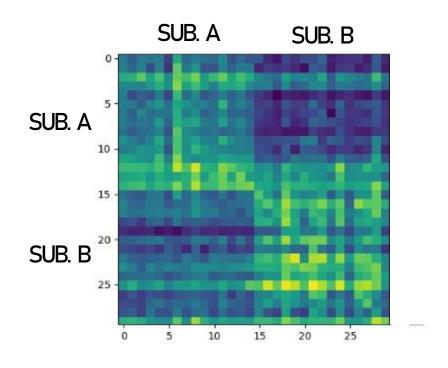




# Method 2: Graph's indices

## Six graph's indices

- 1. Sum of the intra-group connections
- **2. Sum** of the **inter**-group connections
- 3. Weighted density of the intra-group connections
- 4. Weighted density of the inter-group connections
- 5. Divisibility
- 6. Modularity

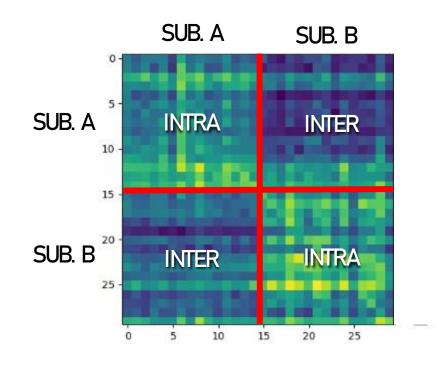




# Method 2: Graph's indices

## Six graph's indices

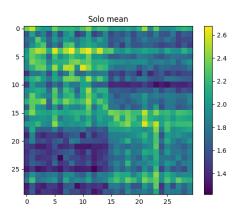
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## Results of Method 2 - Table of t-tests

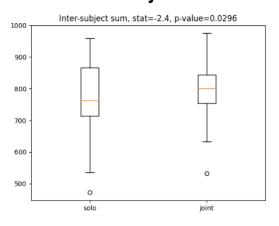
	Sum in	ıtra-sub.	Sum inter-sub.		Density	intra-sub.	Density	inter-sub.	Divisibility		Modularity	
Matrix type	Stat.	P-value	Stat.	P-value	Stat.	P-value	Stat.	P-value	Stat.	P-value	Stat.	P-value
1. Cross-attention on Layer 0	1.69	0.1119	-1.69	0.1119	1.47	0.1613	-1.47	0.1613	1.47	0.1613	0.34	0.7381
2. Cross-attention on Layer 1	-0.99	0.3366	0.99	0.3366	-0.90	0.3828	0.90	0.3828	-0.85	0.4089	-0.91	0.3752
3. Average of cross-attentions	1.14	0.2704	-1.14	0.2704	1.24	0.2340	-1.24	0.2340	1.27	0.2251	0.22	0.8262
4. Element-wise product between cross-attentions	-0.27	0.7902	0.27	0.7902	-0.35	0.7348	0.35	0.7348	-0.30	0.7705	-0.42	0.6771
5. Self-attention on Layer 0	1.05	0.3121	-1.05	0.3121	1.28	0.2191	-1.28	0.2191	1.30	0.2143	-0.47	0.6433
6. Self -attention on Layer 1	2.40	0.0296	-2.40	0.0296	2.59	0.0204	-2.59	0.0204	2.62	0.0192	1.64	0.1224
7. Average of self-attentions	2.04	0.0592	-2.04	0.0592	2.28	0.0377	-2.28	0.0377	2.31	0.0355	1.08	0.2953
8. Element-wise product between self-attentions	2.29	0.0369	-2.29	0.0369	2.61	0.0197	-2.61	0.0197	2.66	0.0180	1.28	0.2209
<ol><li>Average of all the attention on every layer</li></ol>	1.78	0.0950	-1.78	0.0950	1.82	0.0894	-1.82	0.0894	1.84	0.0854	0.49	0.6298
10. Element-wise product between all the attention on every layer	0.34	0.7364	-0.34	0.7364	0.15	0.8810	-0.15	0.8810	0.34	0.7356	-0.69	0.5007
11. Element-wise product between the averages of cross and self-attention	1.93	0.0725	-1.93	0.0725	1.91	0.0757	-1.91	0.0757	1.95	0.0702	0.14	0.8928



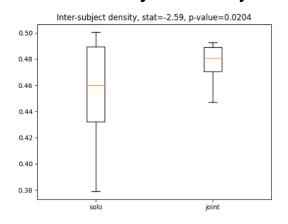


# Results of Method 2 – Self-attention on Layer 1

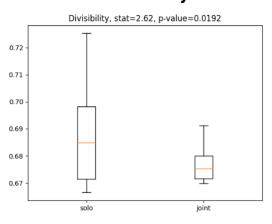
#### Inter-subject sum



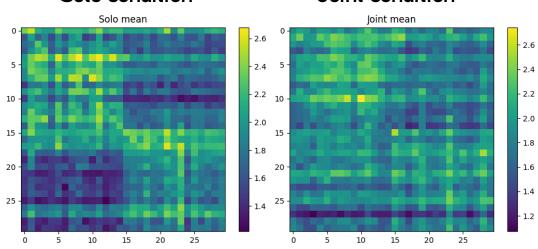
#### Inter-subject density



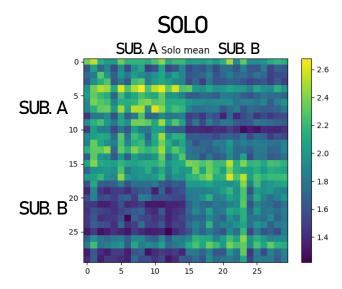
#### **Divisibility**



#### Solo condition



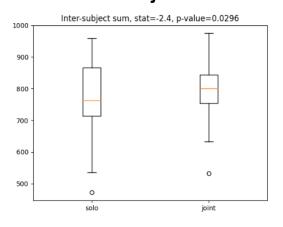
#### Joint condition



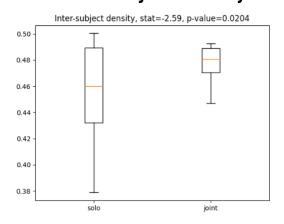


# Results of Method 2 – Self-attention on Layer 1

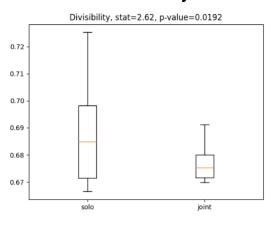
#### Inter-subject sum



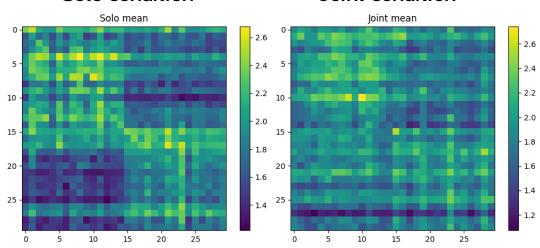
#### Inter-subject density



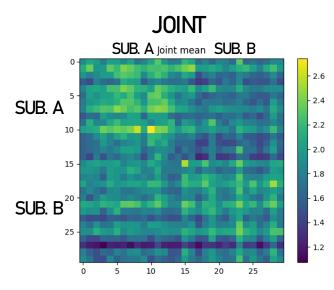
#### Divisibility



#### Solo condition



#### Joint condition





# Results of Method 2 – Significant types of aggregations

	Sum intra-sub. Sum inter-sub.		nter-sub.	Density intra-sub.		Density inter-sub.		Divisibility		Modularity			
Matrix type	Stat.	P-value	Stat.	P-value	Stat.	P-value	Stat.	P-value	Stat.	P-value	Stat.	P-value	
6. Self -attention on Layer 1	2.40	0.0296	-2.40	0.0296	2.59	0.0204	-2.59	0.0204	2.62	0.0192	1.64	0.1224	
7. Average of self-attentions	2.04	0.0592	-2.04	0.0592	2.28	0.0377	-2.28	0.0377	2.31	0.0355	1.08	0.2953	Predictions: 9 0 -8 8 1 -6
8. Element-wise product between self-attentions	2.29	0.0369	-2.29	0.0369	2.61	0.0197	-2.61	0.0197	2.66	0.0180	1.28	0.2209	Norm Linear
Pl	E RODU(	W CT				A	5	piot mean	<b>▼</b>	_ayer 1	Con. 1 -9 1 2	Linear Norm  Global Self Attention Norm  Local Self Attention Norm  text Embedding	Clobal Cross Attention Norm  Local Cross Attention Norm  Clobal Self Attention Norm  Local Self Attention Norm  Target Embedding  -9 -5 ? ? ? ? ? ? ?  1 2 0 1 2 0 1 2  T T T T+1 T+1 T+1 T+1 T+1 T+1 T+1 T+1 T+



## Method 1

Modify Conditioned Granger Causality with Spacetimeformer

- The novel approach showed performances comparable to those of the Linear Conditioned Granger causality method.
- Long computational times, (around 600 min on a Tesla T4 on a hyperscanning dyad).

## Method 2

Use attention matrices as a causality measure

- The method provided physiologically meaningful and sound results, supported by statistical evidence.
- Computational times are sensibly lower (more then 30 times lower, 15-20 min on a Tesla T4 on a hyperscanning dyad).



# Novelty and Future works

## Novel aspects

I proposed two novel methods for the estimation of brain causality:

- Base Conditioned Granger causality on Spacetimeformer residuals
- 2. Attention matrices as a measure of causality

First application of a Deep Learning method to EEG hyperscanning data.

### Future research avenues

- Experimenting with different aggregation functions.
- Varying the number of decoder and encoder layers.
- Correlating computed indices with behavioural data.
- Using the same attention method for estimating temporal relationships.

# Thank you



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