Causal Interpretation Rules for Encoding and Decoding Models in Neuroimaging

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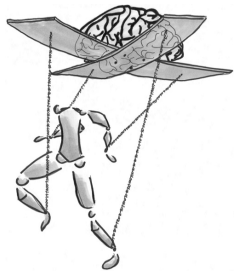

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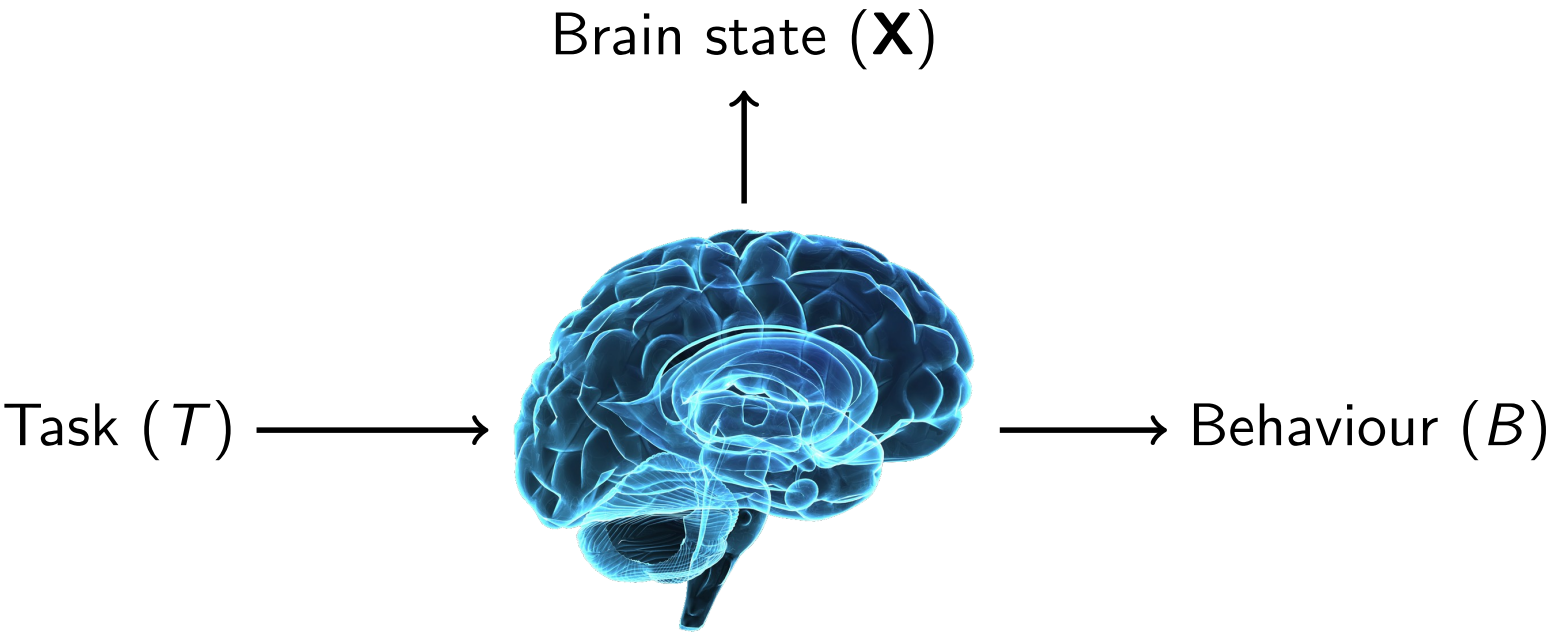
→ Which causal statements are warranted and which ones are not supported by empirical evidence?

Causal Modelling in Neuroimaging



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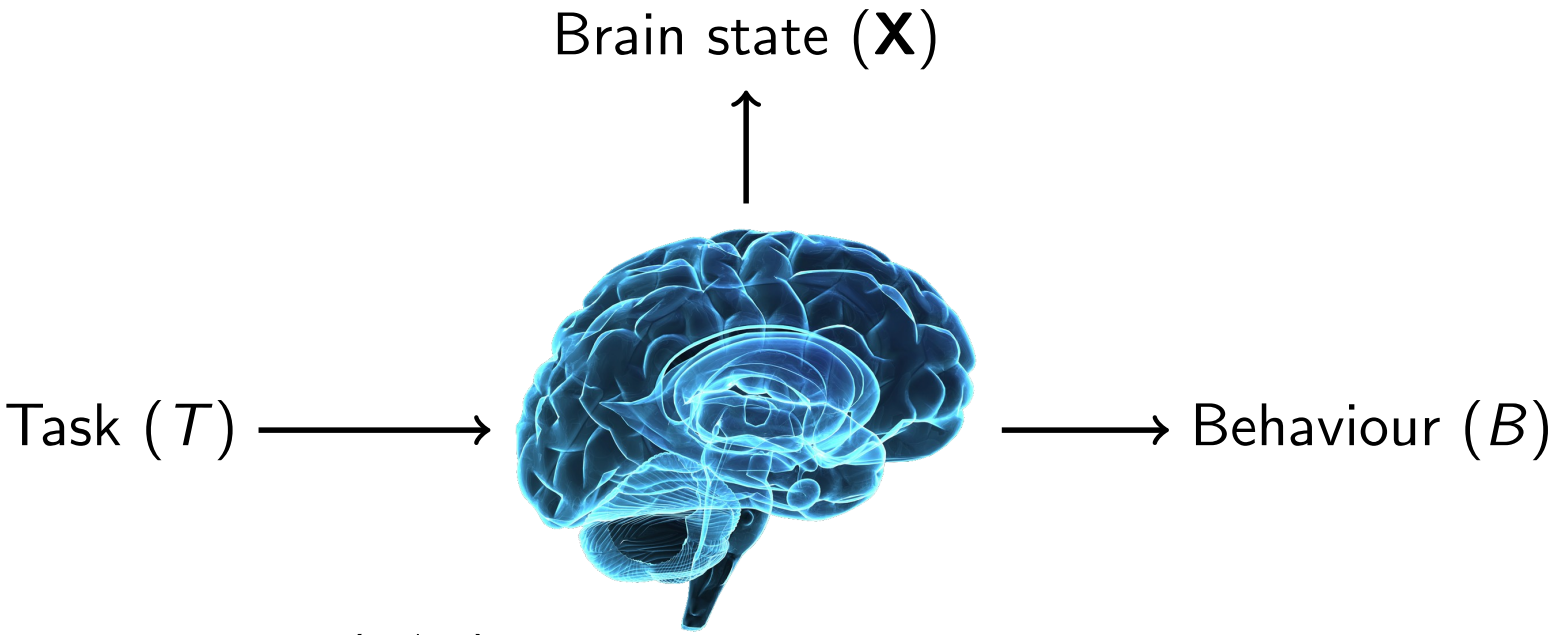
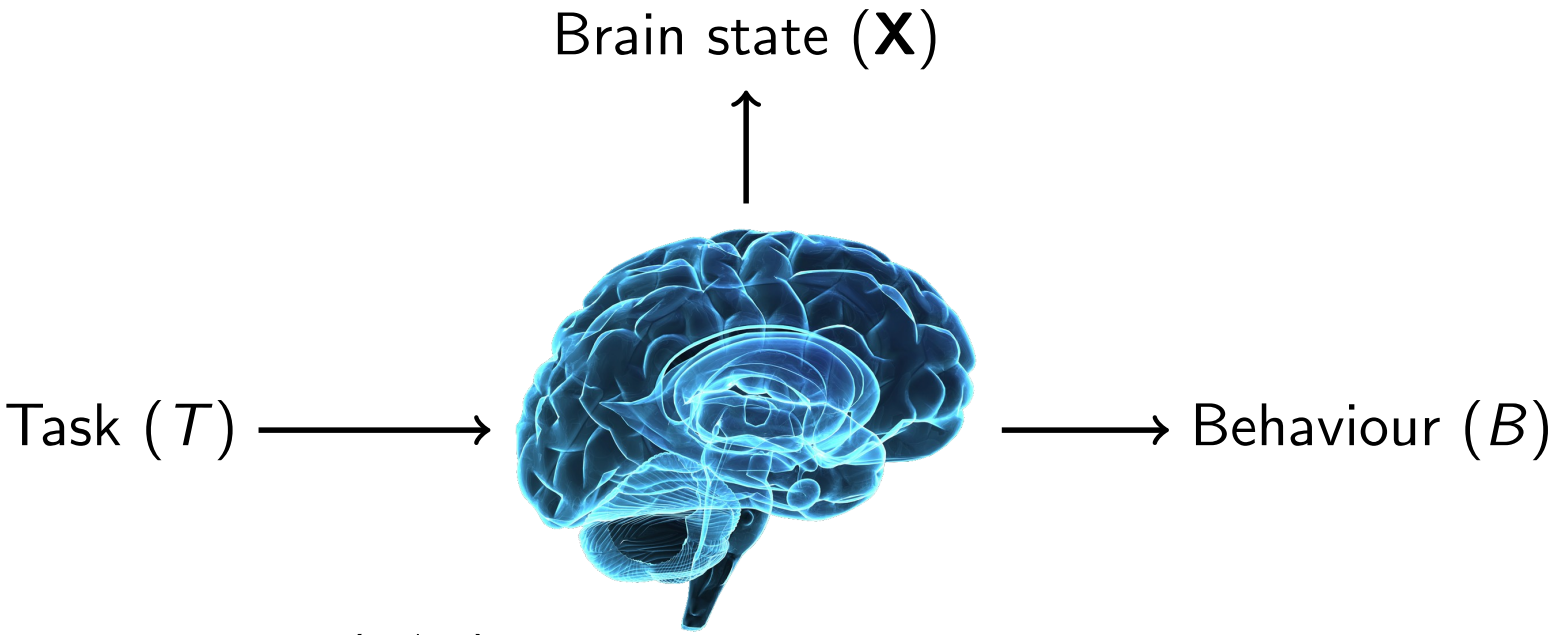


Encoding models: $p(\mathbf{X}|C)$

Causal Modelling in Neuroimaging



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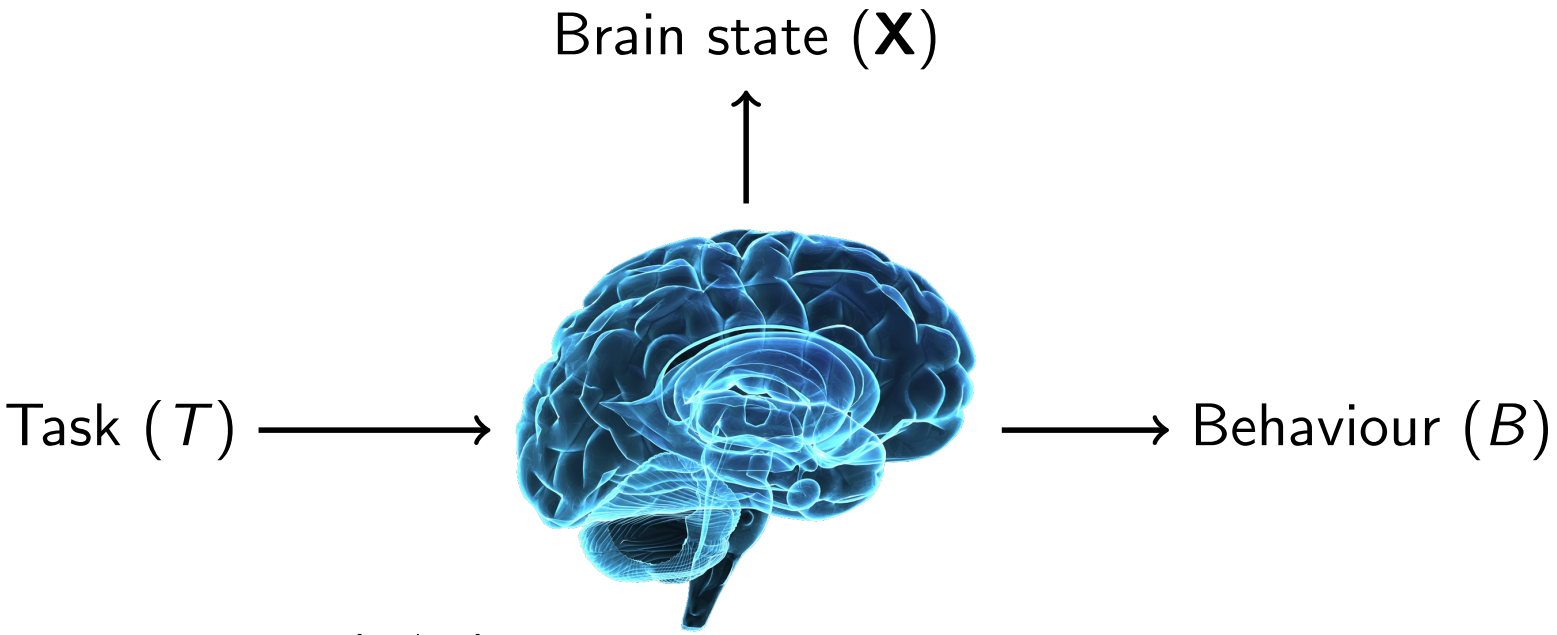

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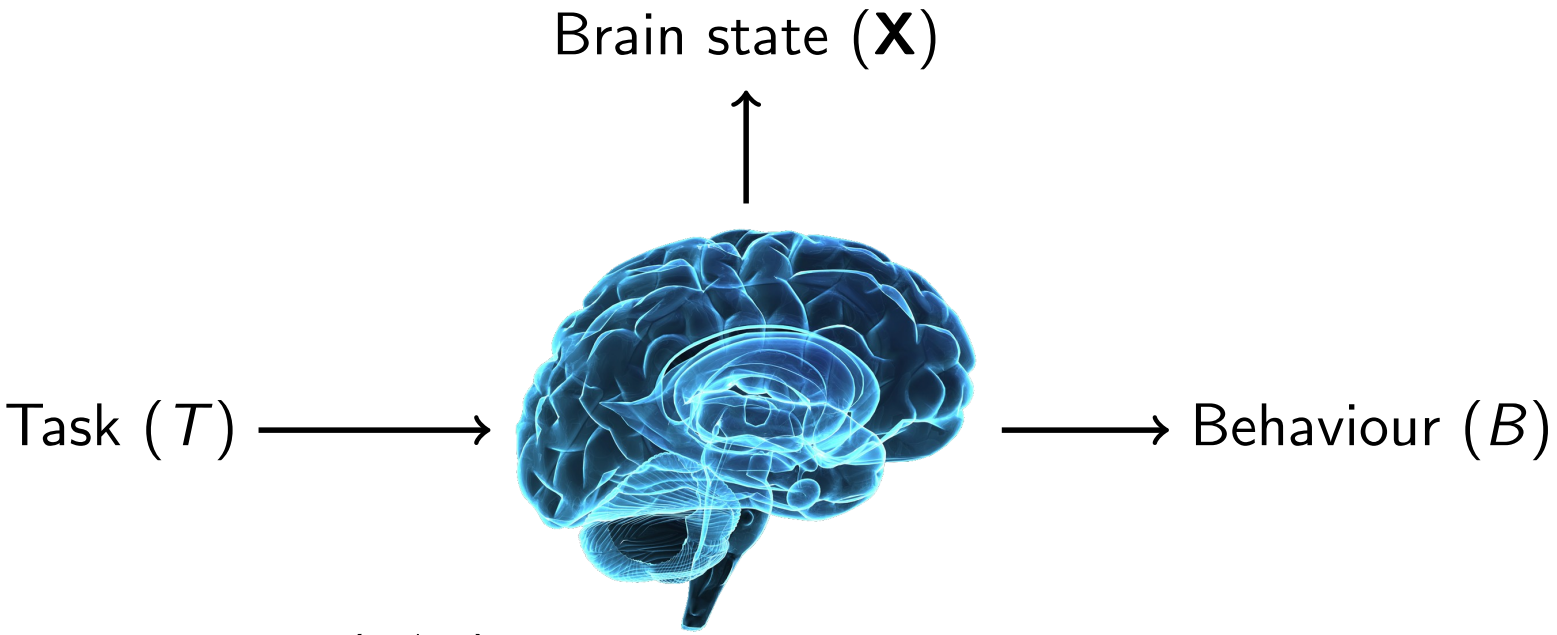

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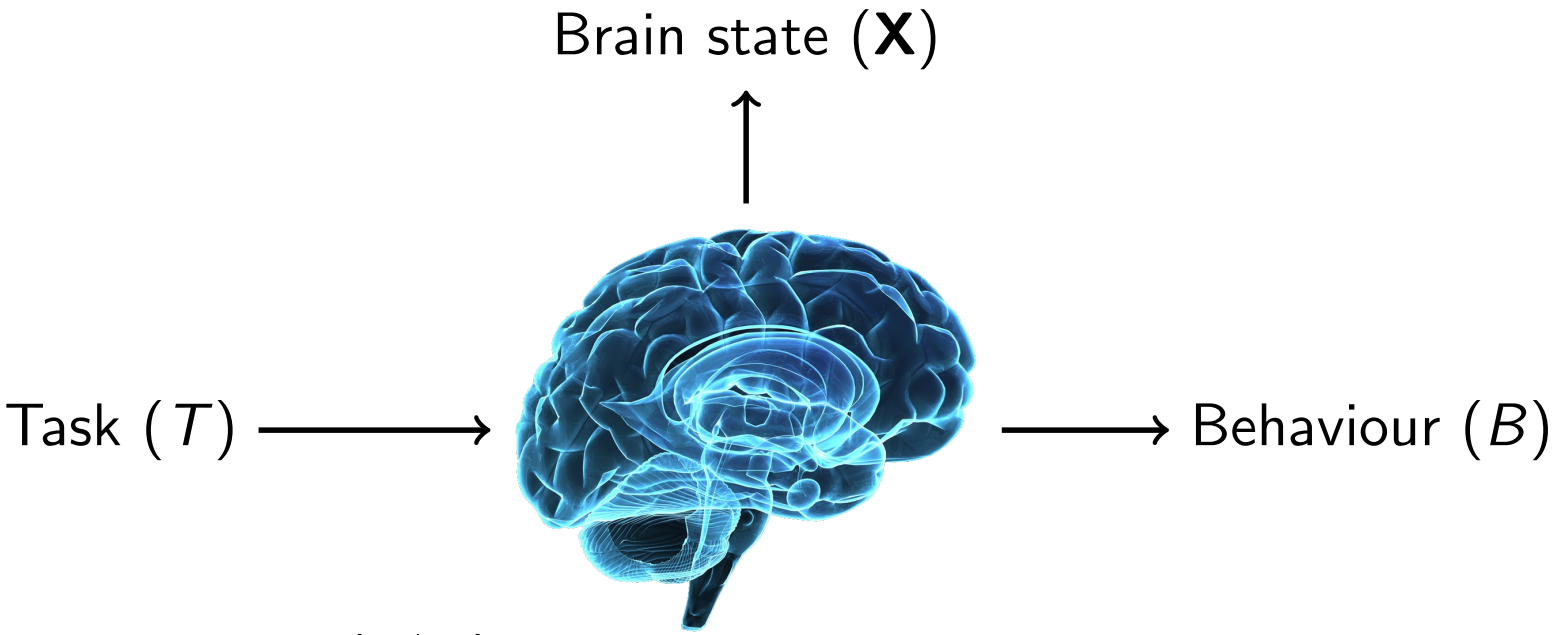

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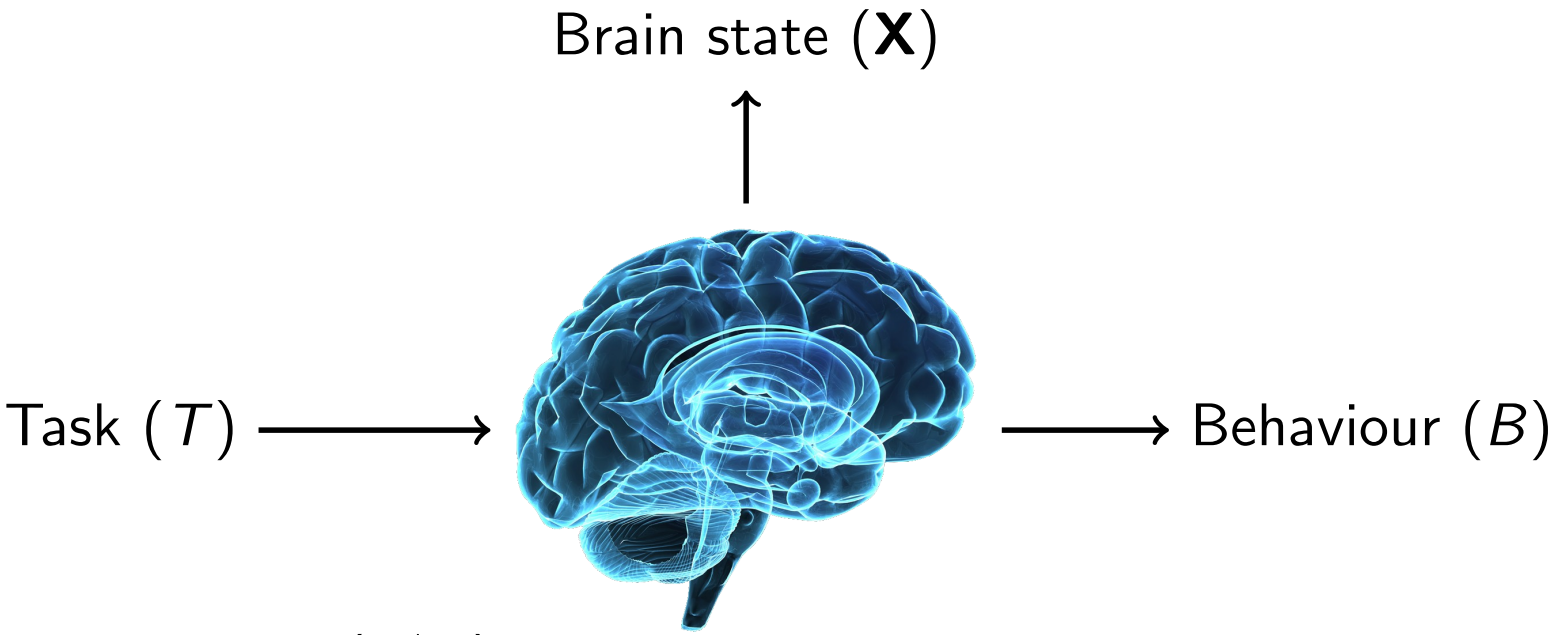

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  - Conditional statistical independence:
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The chain

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- Faithfulness: $p(\mathbf{X})$ contains no additional independence relations beyond those implied by its generating DAG.

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$$H0: \; C \perp\!\!\!\perp X_i|\mathbf{X}\backslash X_i$$

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$$\text{Feature relevance} \Rightarrow C \not\perp\!\!\!\perp X_i \; / \; C \not\perp\!\!\!\perp X_i|\mathbf{X}\backslash X_i \Rightarrow \text{causal structure}$$

Outline

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Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		$\times$		
		$\surd$		
			$\times$	
			$\surd$	
Behaviour		$\times$		
		$\surd$		
			$\times$	
			$\surd$	

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Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i$
Task		√		
Task			×	
Task			√	
Behaviour		×		
Behaviour		√		
Behaviour			×	
Behaviour			√	

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		√		
Task			×	
Task			√	
Behaviour		×		
Behaviour		√		
Behaviour			×	
Behaviour			√	

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Task		$\times$		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		$\surd$		
Task			$\times$	$T \perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i$
Task			$\surd$	
Behaviour		$\times$		
Behaviour		$\surd$		
Behaviour			$\times$	
Behaviour			$\surd$	

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		√		
Task			×	$T \perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i$
Task			√	
Behaviour		×		
Behaviour		√		
Behaviour			×	
Behaviour			√	

T X_i vs. $T \rightarrow X_j \rightarrow X_i$

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		√		
Task			×	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Task			√	
Behaviour		×		
Behaviour		√		
Behaviour			×	
Behaviour			√	

T X_i vs. $T \rightarrow X_j \rightarrow X_i$

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		√		$T \not\perp\!\!\!\perp X_i$
Task			×	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Task			√	
Behaviour		×		
Behaviour		√		
Behaviour			×	
Behaviour			√	

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		√		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
Task			×	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Task			√	
Behaviour		×		
Behaviour		√		
Behaviour			×	
Behaviour			√	

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		√		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
Task			×	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Task			√	$T \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i$
Behaviour		×		
Behaviour		√		
Behaviour			×	
Behaviour			√	

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		√		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
Task			×	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Task			√	$T \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i$
Behaviour		×		
Behaviour		√		
Behaviour			×	
Behaviour			√	

$$T \rightarrow X_i \text{ or } T \rightarrow X_j \leftarrow X_i$$

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		$\times$		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		$\surd$		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
Task			$\times$	$T \perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i \Rightarrow$ inconclusive
Task			$\surd$	$T \not\perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i \Rightarrow$ inconclusive
Behaviour		$\times$		
Behaviour		$\surd$		
Behaviour			$\times$	
Behaviour			$\surd$	

$$T \rightarrow X_i \text{ or } T \rightarrow X_j \leftarrow X_i$$

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		$\times$		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		$\surd$		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
Task			$\times$	$T \perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i \Rightarrow$ inconclusive
Task			$\surd$	$T \not\perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i \Rightarrow$ inconclusive
Behaviour		$\times$		$B \perp\!\!\!\perp X_i$
Behaviour		$\surd$		
Behaviour			$\times$	
Behaviour			$\surd$	

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		√		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
Task			×	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Task			√	$T \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour		×		$B \perp\!\!\!\perp X_i \Rightarrow X_i$ is no cause of B
Behaviour		√		
Behaviour			×	
Behaviour			√	

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		√		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
Task			×	$T \perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i \Rightarrow$ inconclusive
Task			√	$T \not\perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i \Rightarrow$ inconclusive
Behaviour		×		$B \perp\!\!\!\perp X_i \Rightarrow X_i$ is no cause of B
Behaviour		√		
Behaviour			×	$B \perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i$
Behaviour			√	

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		√		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
Task			×	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Task			√	$T \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour		×		$B \perp\!\!\!\perp X_i \Rightarrow X_i$ is no cause of B
Behaviour		√		
Behaviour			×	$B \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i$
Behaviour			√	

X_i $\quad$ B vs. $X_i \rightarrow X_j \rightarrow B$

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		√		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
Task			×	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Task			√	$T \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour		×		$B \perp\!\!\!\perp X_i \Rightarrow X_i$ is no cause of B
Behaviour		√		
Behaviour			×	$B \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour			√	

X_i B vs. $X_i \rightarrow X_j \rightarrow B$

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		√		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
Task			×	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Task			√	$T \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour		×		$B \perp\!\!\!\perp X_i \Rightarrow X_i$ is no cause of B
Behaviour		√		$B \not\perp\!\!\!\perp X_i$
Behaviour			×	$B \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour			√	

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		√		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
Task			×	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Task			√	$T \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour		×		$B \perp\!\!\!\perp X_i \Rightarrow X_i$ is no cause of B
Behaviour		√		$B \not\perp\!\!\!\perp X_i$
Behaviour			×	$B \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour			√	

$$X_i \rightarrow B \text{ or } X_i \leftarrow X_j \rightarrow B$$

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
	Task	×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
		√		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
			×	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
			√	$T \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
	Behaviour	×		$B \perp\!\!\!\perp X_i \Rightarrow X_i$ is no cause of B
		√		$B \not\perp\!\!\!\perp X_i \Rightarrow$ inconclusive
			×	$B \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
			√	

$$X_i \rightarrow B \text{ or } X_i \leftarrow X_j \rightarrow B$$

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		$\times$		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
		$\surd$		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
			$\times$	$T \perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i \Rightarrow$ inconclusive
			$\surd$	$T \not\perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i \Rightarrow$ inconclusive
Behaviour		$\times$		$B \perp\!\!\!\perp X_i \Rightarrow X_i$ is no cause of B
		$\surd$		$B \not\perp\!\!\!\perp X_i \Rightarrow$ inconclusive
			$\times$	$B \perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i \Rightarrow$ inconclusive
			$\surd$	$B \not\perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i$

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		$\times$		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		$\surd$		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
Task			$\times$	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Task			$\surd$	$T \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour		$\times$		$B \perp\!\!\!\perp X_i \Rightarrow X_i$ is no cause of B
Behaviour		$\surd$		$B \not\perp\!\!\!\perp X_i \Rightarrow$ inconclusive
Behaviour			$\times$	$B \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour			$\surd$	$B \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i$

$$X_i \rightarrow B \text{ or } X_i \leftarrow H \rightarrow X_j$$
$$\downarrow$$
$$B$$

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		√		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
Task			×	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Task			√	$T \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour		×		$B \perp\!\!\!\perp X_i \Rightarrow X_i$ is no cause of B
Behaviour		√		$B \not\perp\!\!\!\perp X_i \Rightarrow$ inconclusive
Behaviour			×	$B \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour			√	$B \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive

$$X_i \rightarrow B \text{ or } X_i \leftarrow H \rightarrow X_j$$
$$\downarrow$$
$$B$$

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
		√		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
			×	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
			√	$T \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour		×		$B \perp\!\!\!\perp X_i \Rightarrow X_i$ is no cause of B
		√		$B \not\perp\!\!\!\perp X_i \Rightarrow$ inconclusive
			×	$B \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
			√	$B \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive

We tested [...] whether pre-stimulus alpha oscillations **measured** *with electroencephalography (EEG)* **influence** *the encoding of items into working memory.* (Anonymous authors, *Journal of Neuroscience*, 2014)

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
		√		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
			×	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
			√	$T \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour		×		$B \perp\!\!\!\perp X_i \Rightarrow X_i$ is no cause of B
		√		$B \not\perp\!\!\!\perp X_i \Rightarrow$ inconclusive
			×	$B \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
			√	$B \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive

We tested [...] whether pre-stimulus alpha oscillations **measured** *with electroencephalography (EEG)* **influence** *the encoding of items into working memory.* (Anonymous authors, *Journal of Neuroscience*, 2014)

$$\alpha \not\perp\!\!\!\perp \text{WM} \Rightarrow \alpha \rightarrow \text{WM}$$

Causal Interpretation Rules for Individual Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×		$T \perp\!\!\!\perp X_i \Rightarrow X_i$ is no effect of T
Task		√		$T \not\perp\!\!\!\perp X_i \Rightarrow X_i$ is an effect of T
Task			×	$T \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Task			√	$T \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour		×		$B \perp\!\!\!\perp X_i \Rightarrow X_i$ is no cause of B
Behaviour		√		$B \not\perp\!\!\!\perp X_i \Rightarrow$ inconclusive
Behaviour			×	$B \perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive
Behaviour			√	$B \not\perp\!\!\!\perp X_i \mid \mathbf{X} \setminus X_i \Rightarrow$ inconclusive

Outline

1 Causal Interpretation Rules for Individual Encoding/Decoding Models

2 Causal Interpretation Rules for Joint Encoding/Decoding Models

Causal Interpretation Rules for Joint Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		$\times$	$\times$	
Task		$\surd$	$\times$	
Task		$\times$	$\surd$	
Task		$\surd$	$\surd$	
Behaviour		$\times$	$\times$	
Behaviour		$\surd$	$\times$	
Behaviour		$\times$	$\surd$	
Behaviour		$\surd$	$\surd$	

Causal Interpretation Rules for Joint Models

Experimental setting		Feature X_i relevant? Encoding	Decoding	Causal interpretation
Task		$\times$	$\times$	
		$\surd$	$\times$	$T \not\perp\!\!\!\perp X_i \;\&\; T \perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i$
		$\times$	$\surd$	
		$\surd$	$\surd$	
Behaviour		$\times$	$\times$	
		$\surd$	$\times$	
		$\times$	$\surd$	
		$\surd$	$\surd$	

Causal Interpretation Rules for Joint Models

Experimental setting		Feature X_i relevant? Encoding	Decoding	Causal interpretation
Task		$\times$	$\times$	
		$\surd$	$\times$	$T \not\perp\!\!\!\perp X_i \;\&\; T \perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i$
		$\times$	$\surd$	
		$\surd$	$\surd$	
Behaviour		$\times$	$\times$	
		$\surd$	$\times$	
		$\times$	$\surd$	
		$\surd$	$\surd$	

$$T \rightarrow X_j \rightarrow X_i$$

Causal Interpretation Rules for Joint Models

Experimental setting		Feature X_i relevant? Encoding	Decoding	Causal interpretation
Task		$\times$	$\times$	
		$\surd$	$\times$	X_i is an indirect effect of T
		$\times$	$\surd$	
		$\surd$	$\surd$	
Behaviour		$\times$	$\times$	
		$\surd$	$\times$	
		$\times$	$\surd$	
		$\surd$	$\surd$	

$$T \rightarrow X_j \rightarrow X_i$$

Causal Interpretation Rules for Joint Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		$\times$	$\times$	
		$\surd$	$\times$	X_i is an indirect effect of T
		$\times$	$\surd$	$T \perp\!\!\!\perp X_i$ & $T \not\perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i$
		$\surd$	$\surd$	
Behaviour		$\times$	$\times$	
		$\surd$	$\times$	
		$\times$	$\surd$	
		$\surd$	$\surd$	

Causal Interpretation Rules for Joint Models

		Feature X_i relevant? Encoding	Decoding	Causal interpretation
Experimental setting	Task	×	×	
		√	×	X_i is an indirect effect of T
		×	√	$T \perp\!\!\!\perp X_i$ & $T \not\perp\!\!\!\perp X_i \vert \mathbf{X} \backslash X_i$
		√	√	
	Behaviour	×	×	
		√	×	
		×	√	
		√	√	

$$T \rightarrow X_j \leftarrow X_i \text{ or } T \rightarrow X_j \leftarrow H \rightarrow X_i$$

Causal Interpretation Rules for Joint Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		$\times$	$\times$	
		$\surd$	$\times$	X_i is an indirect effect of T
		$\times$	$\surd$	X_i provides context
		$\surd$	$\surd$	
Behaviour		$\times$	$\times$	
		$\surd$	$\times$	
		$\times$	$\surd$	
		$\surd$	$\surd$	

$$T \rightarrow X_j \leftarrow X_i \text{ or } T \rightarrow X_j \leftarrow H \rightarrow X_i$$

Causal Interpretation Rules for Joint Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		$\times$	$\times$	X_i is no effect of T
		$\surd$	$\times$	X_i is an indirect effect of T
		$\times$	$\surd$	X_i provides context
		$\surd$	$\surd$	X_i is an effect of T
Behaviour		$\times$	$\times$	X_i is no cause of B
		$\surd$	$\times$	X_i is no direct cause of B
		$\times$	$\surd$	X_i provides context
		$\surd$	$\surd$	inconclusive

Causal Interpretation Rules for Joint Models

Experimental setting		Feature X_i relevant? Encoding	Feature X_i relevant? Decoding	Causal interpretation
Task		×	×	X_i is no effect of T
		√	×	X_i is an indirect effect of T
		×	√	X_i provides context
		√	√	X_i is an effect of T
Behaviour		×	×	X_i is no cause of B
		√	×	X_i is no direct cause of B
		×	√	X_i provides context
		√	√	inconclusive

Causal Interpretation Rules for Joint Models

		Feature X_i relevant? Encoding	Decoding	Causal interpretation
Experimental setting	Task	×	×	X_i is no effect of T
		√	×	X_i is an indirect effect of T
		×	√	X_i provides context
		√	√	X_i is an effect of T
	Behaviour	×	×	X_i is no cause of B
		√	×	X_i is no direct cause of B
		×	√	X_i provides context
		√	√	inconclusive

Hippocampal activity in this study was **correlated** *with amygdala activity, supporting the view that the amygdala* **enhances** *explicit memory by* **modulating** *activity in the hippocampus. (Anonymous author, Trends in Cognitive Sciences, 2001)*

Causal Interpretation Rules for Joint Models

		Feature X_i relevant? Encoding	Decoding	Causal interpretation
Experimental setting	Task	×	×	X_i is no effect of T
		√	×	X_i is an indirect effect of T
		×	√	X_i provides context
		√	√	X_i is an effect of T
	Behaviour	×	×	X_i is no cause of B
		√	×	X_i is no direct cause of B
		×	√	X_i provides context
		√	√	inconclusive

Hippocampal activity in this study was **correlated** *with amygdala activity, supporting the view that the amygdala* **enhances** *explicit memory by* **modulating** *activity in the hippocampus. (Anonymous author, Trends in Cognitive Sciences, 2001)*

$$\text{HC} \not\perp\!\!\!\perp \text{AM} \Rightarrow \text{AM} \rightarrow \text{HC} \rightarrow \text{EM}$$

Causal Interpretation Rules for Joint Models

		Feature X_i relevant? Encoding	Decoding	Causal interpretation
Experimental setting	Task	×	×	X_i is no effect of T
		√	×	X_i is an indirect effect of T
		×	√	X_i provides context
		√	√	X_i is an effect of T
	Behaviour	×	×	X_i is no cause of B
		√	×	X_i is no direct cause of B
		×	√	X_i provides context
		√	√	inconclusive

Hippocampal activity in this study was **correlated** *with amygdala activity, supporting the view that the amygdala* **enhances** *explicit memory by* **modulating** *activity in the hippocampus. (Anonymous author, Trends in Cognitive Sciences, 2001)*

$$\mathrm{AM} \not\perp\!\!\!\perp \mathrm{EM} \;\&\; \mathrm{AM} \perp\!\!\!\perp \mathrm{EM} | \mathrm{HC} \Leftarrow \mathrm{AM} \rightarrow \mathrm{HC} \rightarrow \mathrm{EM}$$

Wrapping Up

Wrapping Up

Caveats:

Wrapping Up

Caveats:

- The probability of type II errors can not be quantified in the same manner as the probability of type I errors.

Wrapping Up

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- Permutation-based relevance tests in decoding models are biased towards dependence (Strobl et al., *BMC Bioinformatics*, 2008)

Wrapping Up

Caveats:

- The probability of type II errors can not be quantified in the same manner as the probability of type I errors.
- The assumption of faithfulness is presently untestable.
- Permutation-based relevance tests in decoding models are biased towards dependence (Strobl et al., *BMC Bioinformatics*, 2008)
- Unbiased conditional independence tests are hard (Zhang et al., *UAI*, 2011)

Wrapping Up

Caveats:

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Acknowledgements

People:

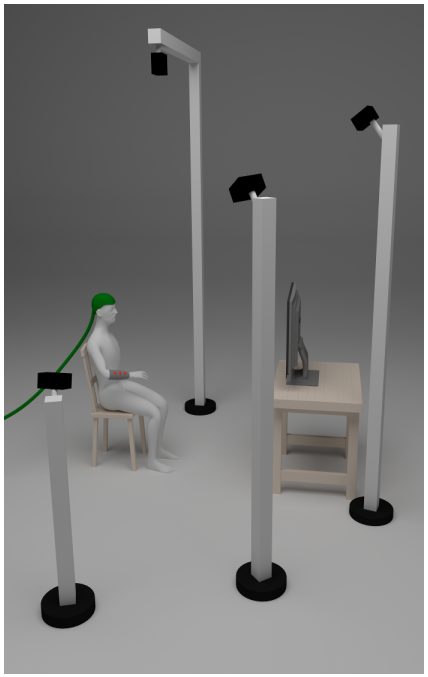
- Sebastian Weichwald (UCL)
- Timm Meyer (MPI-IS)
- Ozan Özdenizci (Sabanci University)
- Bernhard Schölkopf (MPI-IS)
- Tonio Ball (University of Freiburg)

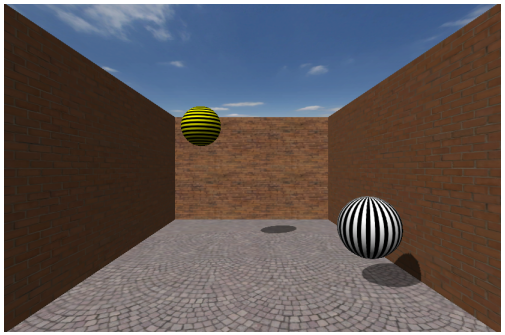
Publications:

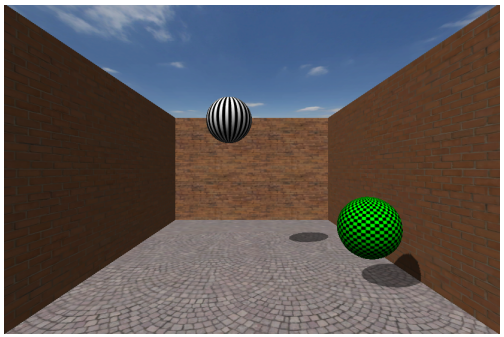
- Weichwald et al., Causal interpretation rules for encoding and decoding models in neuroimaging. *NeuroImage*, 2015.
- Weichwald et al., Causal and anti-causal learning in pattern recognition for neuroimaging. *PRNI*, 2014.

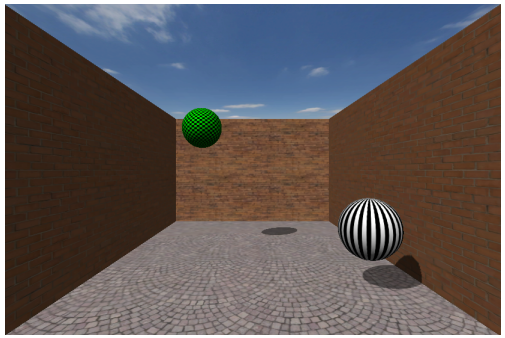
`http://brain-computer-interfaces.net`

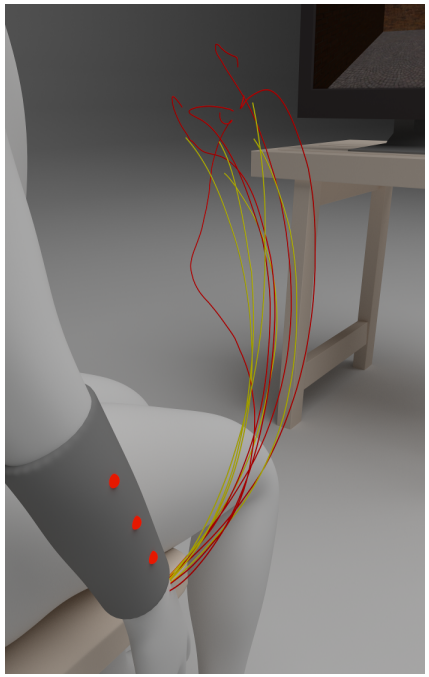
Experimental Setup











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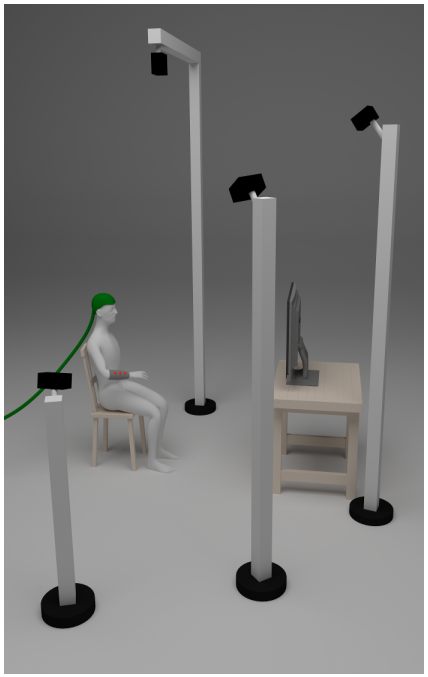

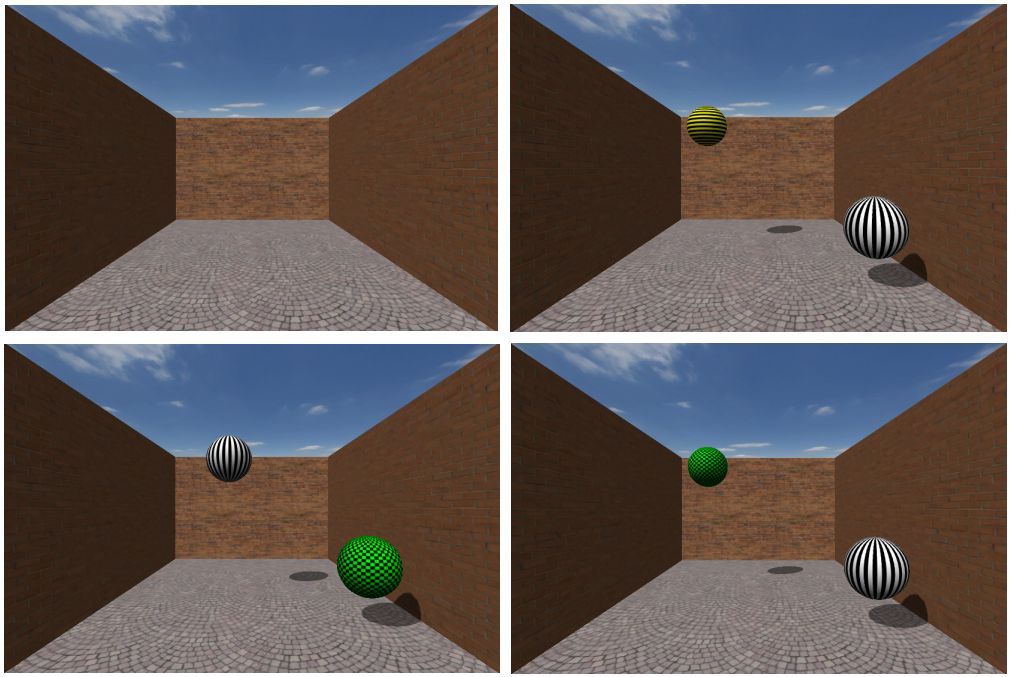

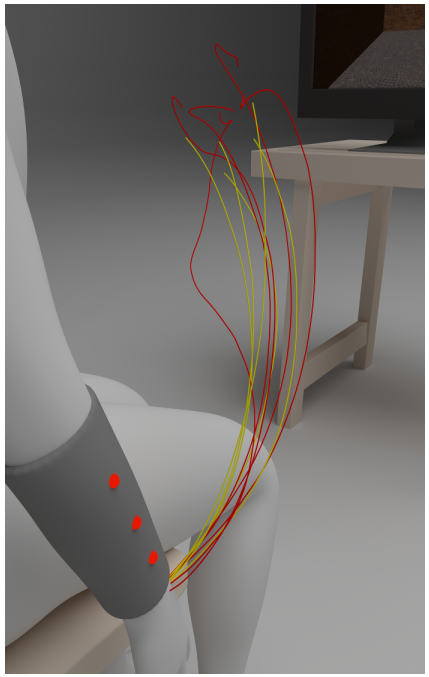

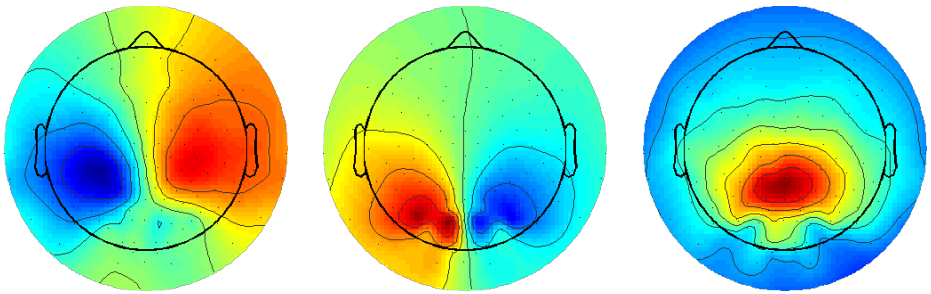

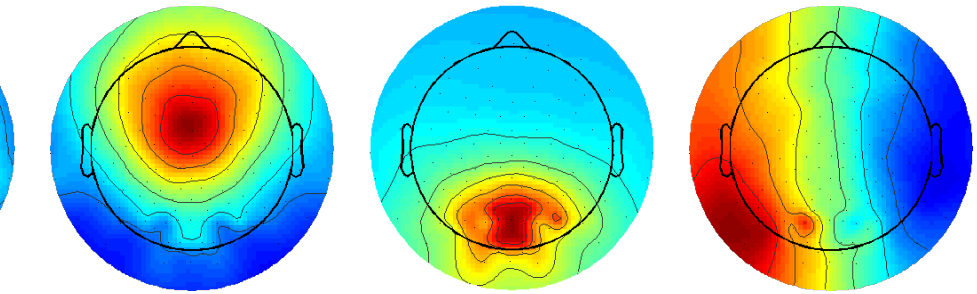

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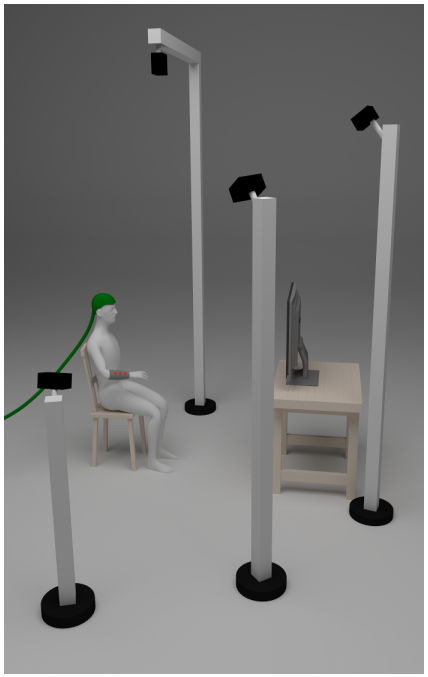

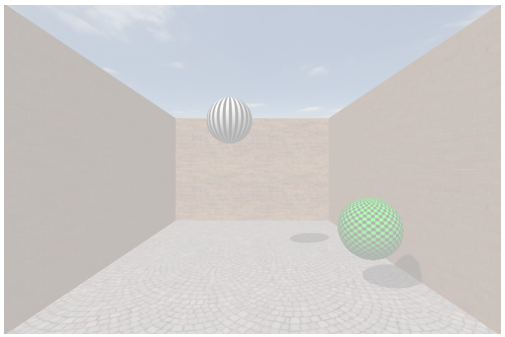

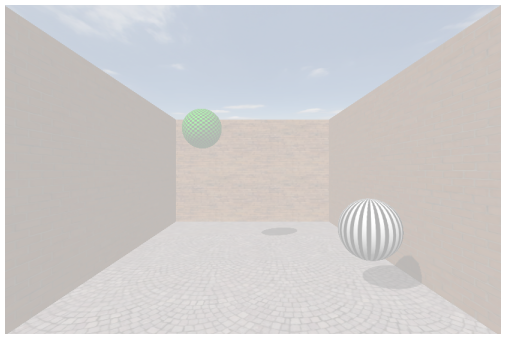

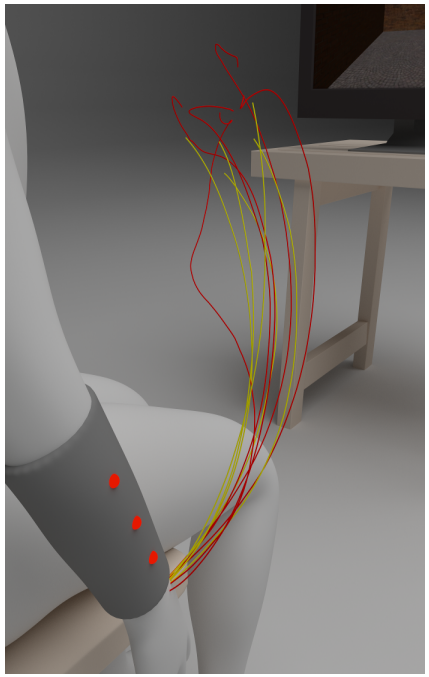

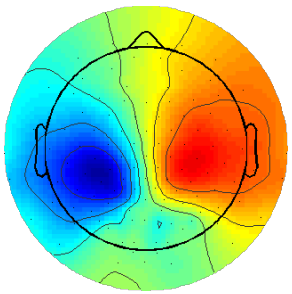

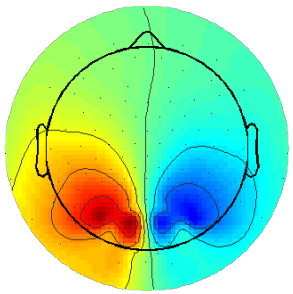

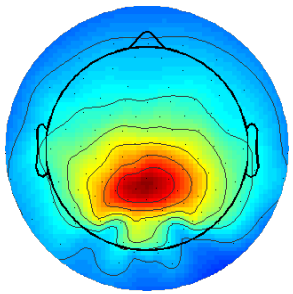

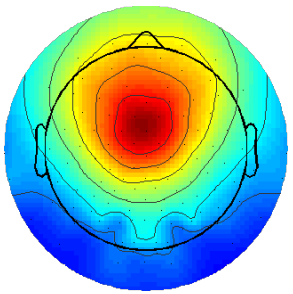

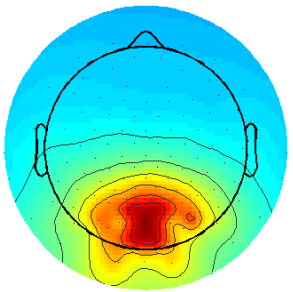

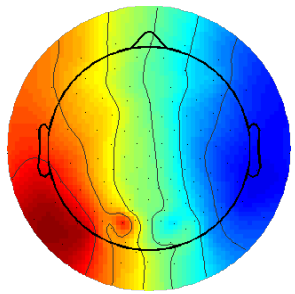

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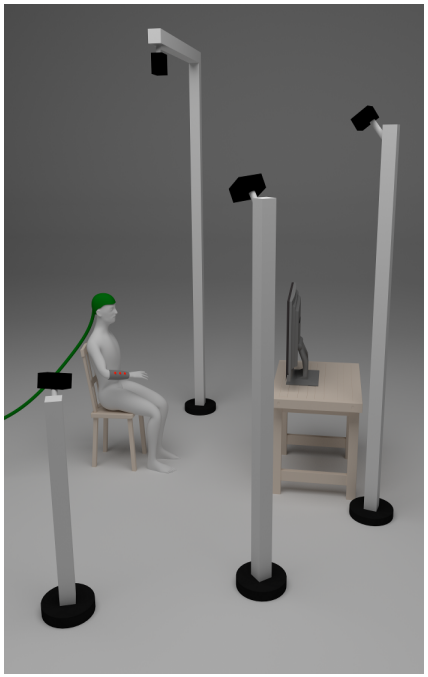

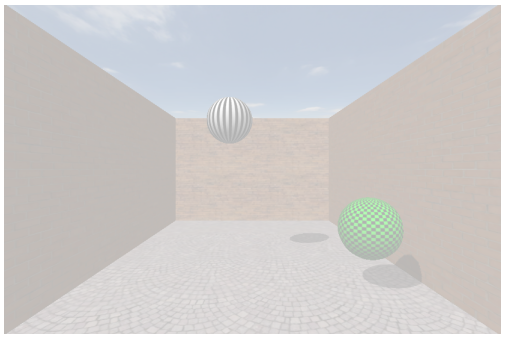

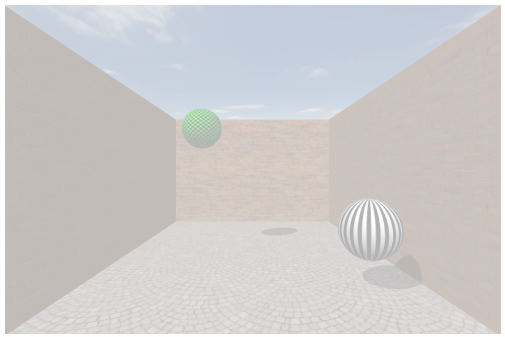

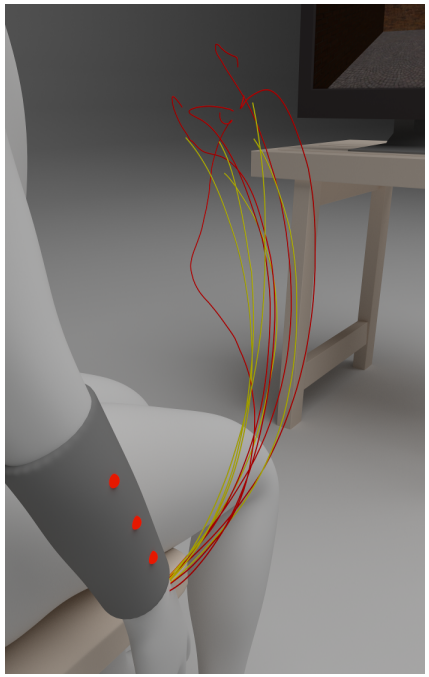

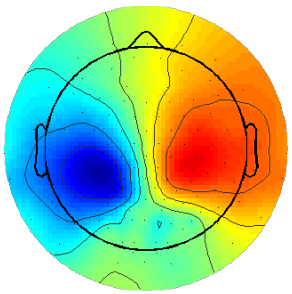

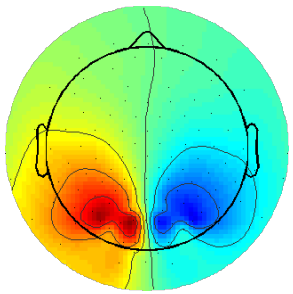

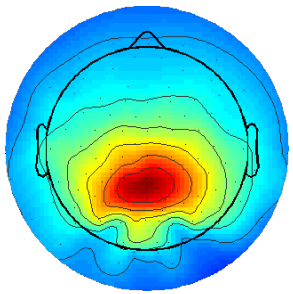

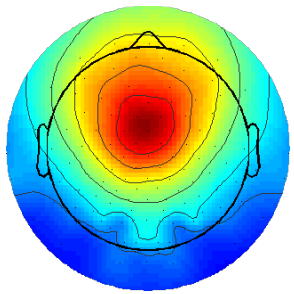

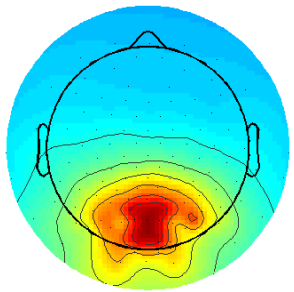

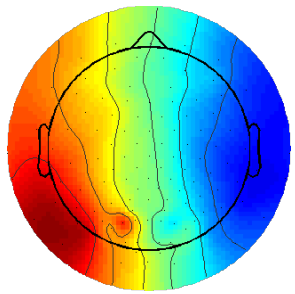

$$\{S, X_1, \ldots, X_6\} = \{\text{rest/plan}, |\alpha_{\text{IC}_1}|, \ldots, |\alpha_{\text{IC}_6}|\}$$

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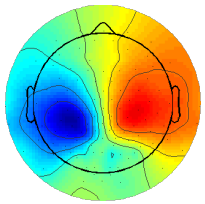
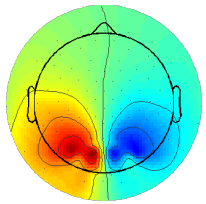
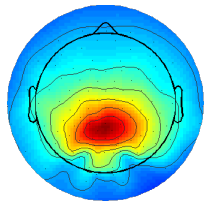
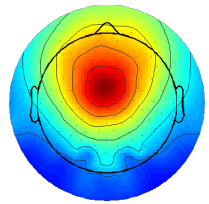
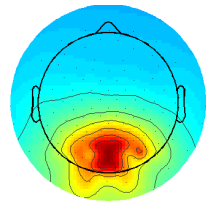
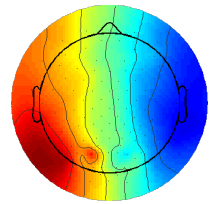
p-values						
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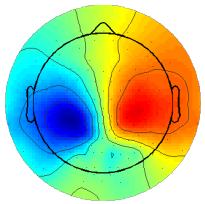
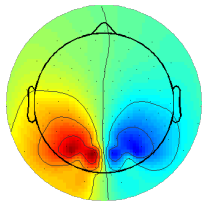
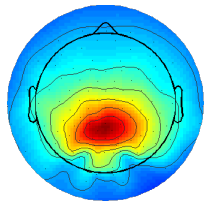
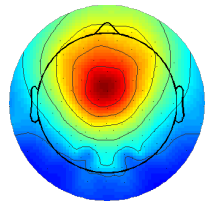
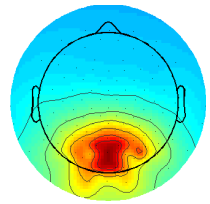
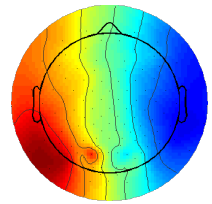
p-values						
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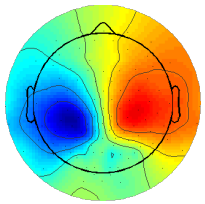
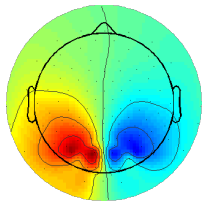
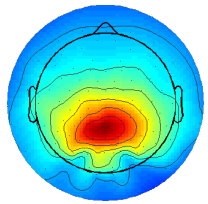
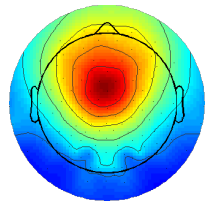
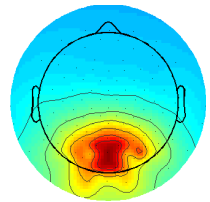
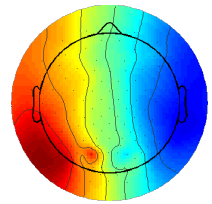
p-values						
Encoding	0	0	0	0	0	0
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→ The instruction to plan a reaching movement causes modulation of α-power at every IC: $S \rightarrow \{|\alpha_{\mathrm{IC}_i}|\},\ i = 1, \ldots, 6$

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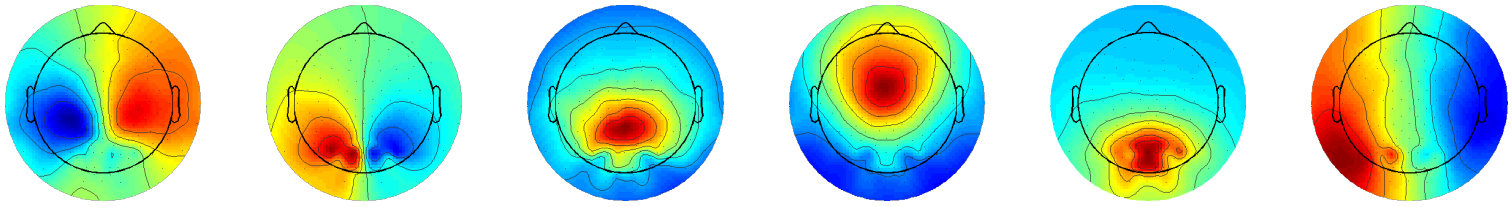

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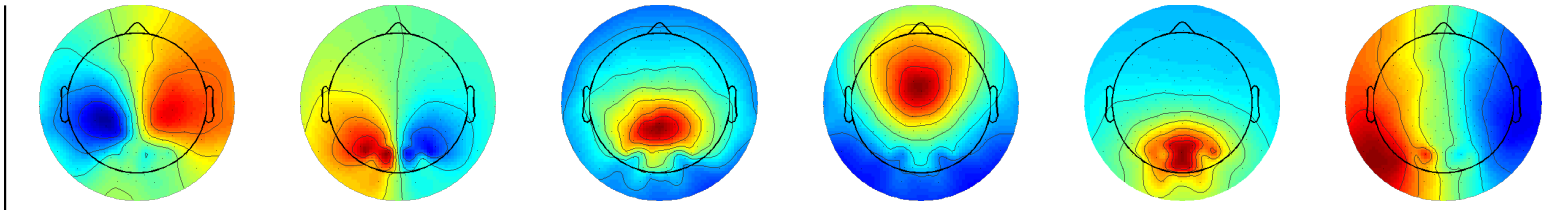
Encoding	0	0	0	0	0	0
Decoding	0	0	0.50	0.34	0.79	0.13

$\rightarrow$ The instruction to plan a reaching movement causes modulation of α-power at every IC: $S \rightarrow \{|\alpha_{\text{IC}_i}|\},\ i = 1, \ldots, 6$

Data Analysis & Experimental Results

- Experimental data: 17 subjects with 444 - 498 trials each
- Encoding model: $H0: S \perp\!\!\!\perp X_i$ [HSIC (Gretton et al., *NIPS*, 2008)]
- Decoding model: $H0: S \perp\!\!\!\perp X_i | \mathbf{X} \backslash X_i$ [Random forest (Breiman, *Machine Learning*, 2001)]



p-values						
Encoding	0	0	0	0	0	0
Decoding	0	0	0.50	0.34	0.79	0.13

→ The instruction to plan a reaching movement causes modulation of α-power at every IC: $S \rightarrow \{|\alpha_{\mathrm{IC}_i}|\},\ i = 1, \ldots, 6$

→ Modulation of α-power at ICs 3–6 is only an indirect effect relative to ICs 1 & 2: $S \rightarrow \{|\alpha_{\mathrm{IC}_1}|, |\alpha_{\mathrm{IC}_2}|\} \rightarrow \{|\alpha_{\mathrm{IC}_3}|, |\alpha_{\mathrm{IC}_4}|, |\alpha_{\mathrm{IC}_5}|, |\alpha_{\mathrm{IC}_6}|\}$