# Determining causality in auditory pathways with TRENTool

## Causality in source space: a FEM-aided MEG study

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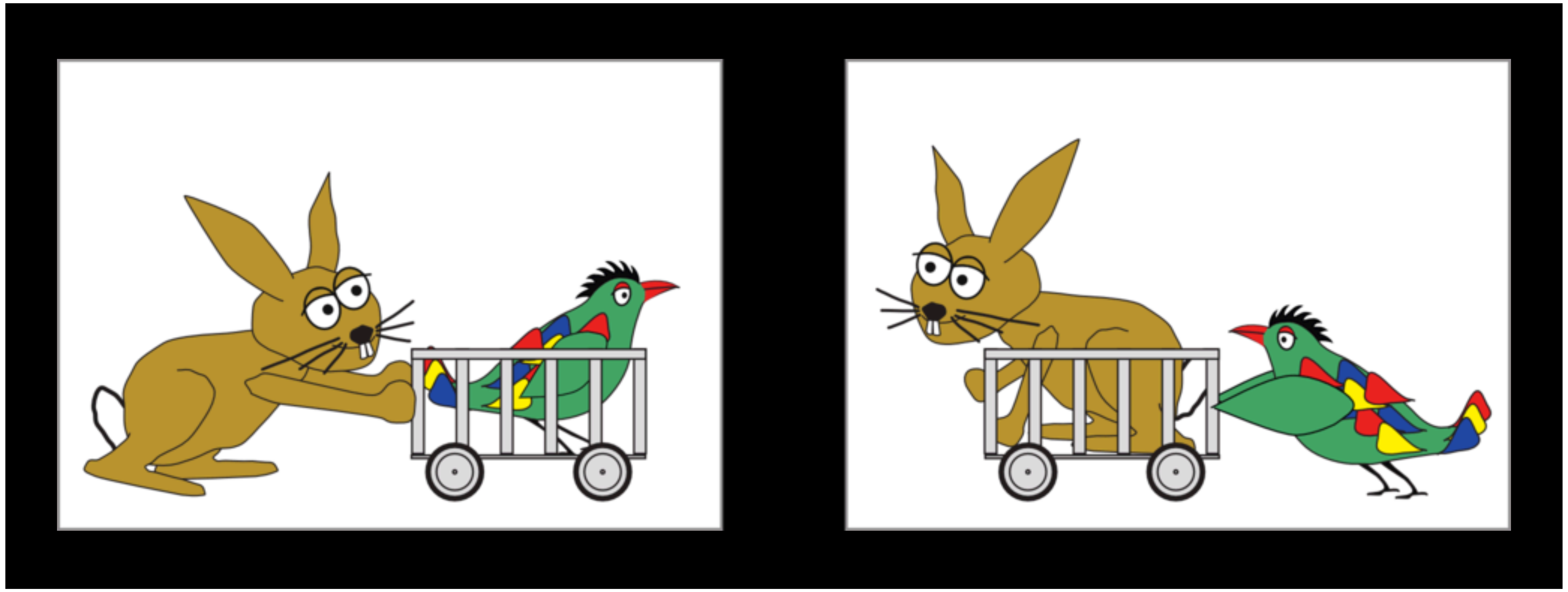
# Overview

- Task paradigm
- Cognitive background
- Data analysis
- Modeling Causality
- Transfer Entropy
- Properties of TRENTool

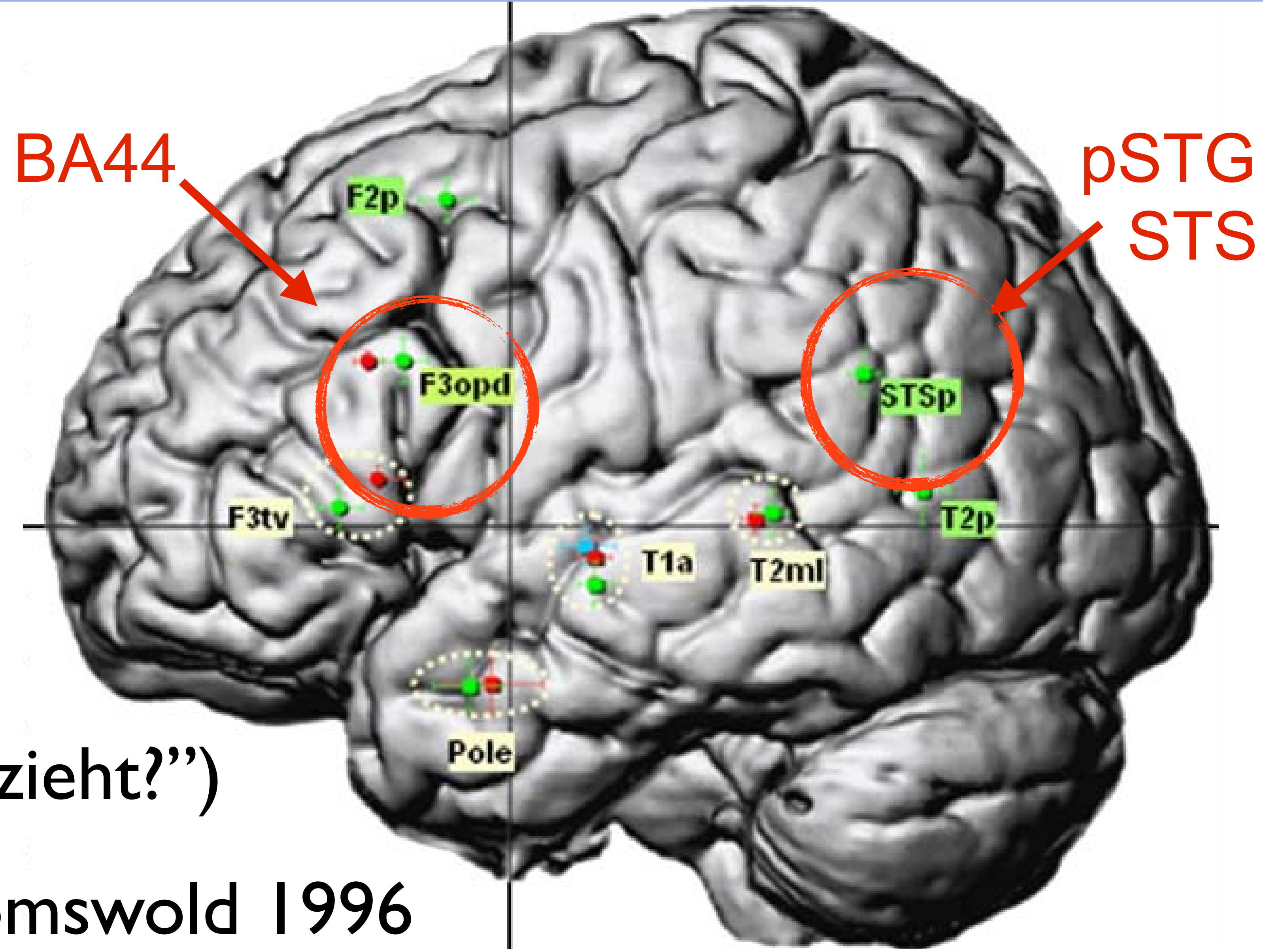
# Task

- Picture-Selection task
- 216 trials (Pilot, 18min)
  304 trials (MEG, 25min)
- Tutorial: random trials until 90% correct
- Feedback:
  - immediate: Correct response
  - delayed: Accuracy, Speed



"Wo ist das Tier, das der Vogel schiebt?"
"Wo ist das Tier, das den Vogel schiebt?"

# Paradigm

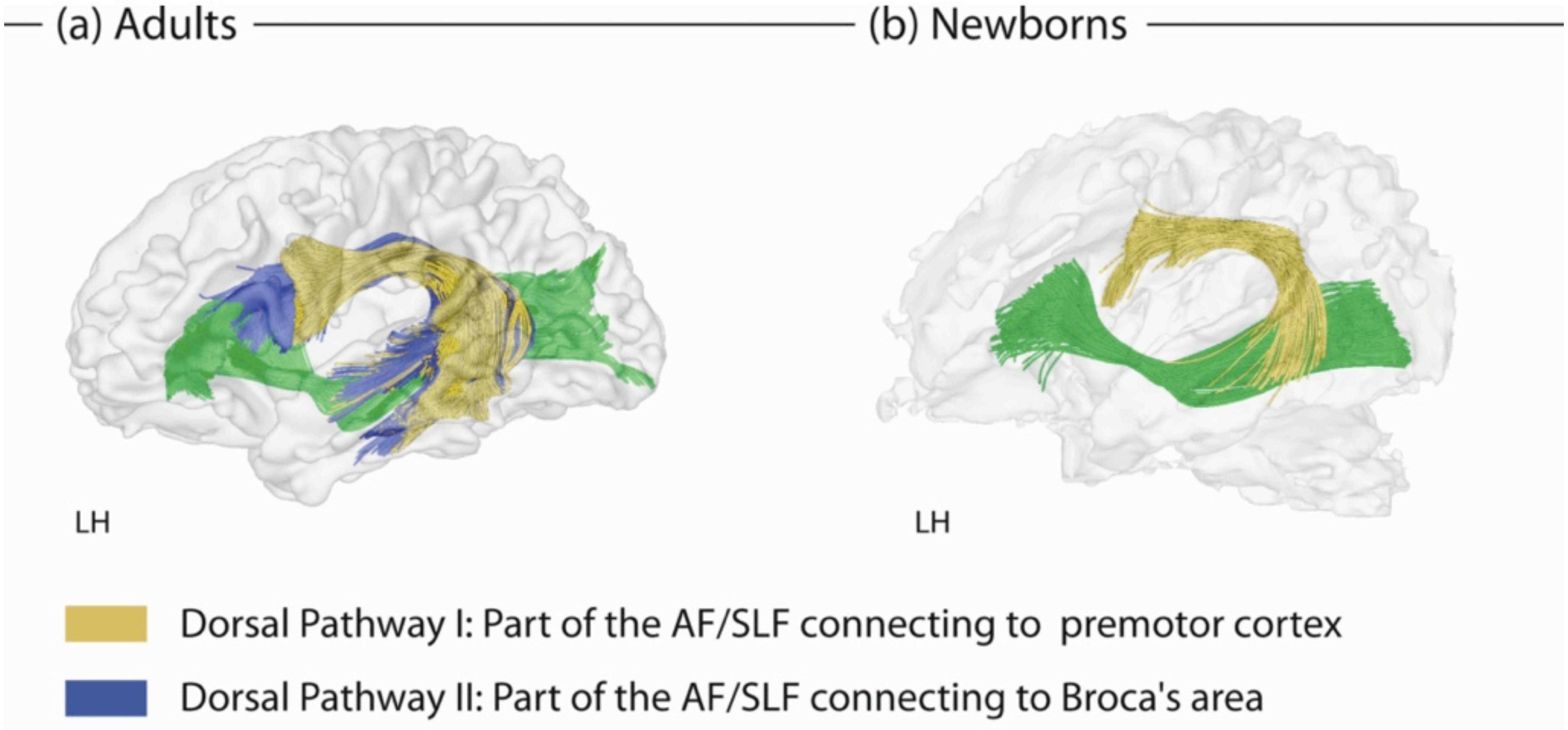


Vigneau 2006, NeuroImage

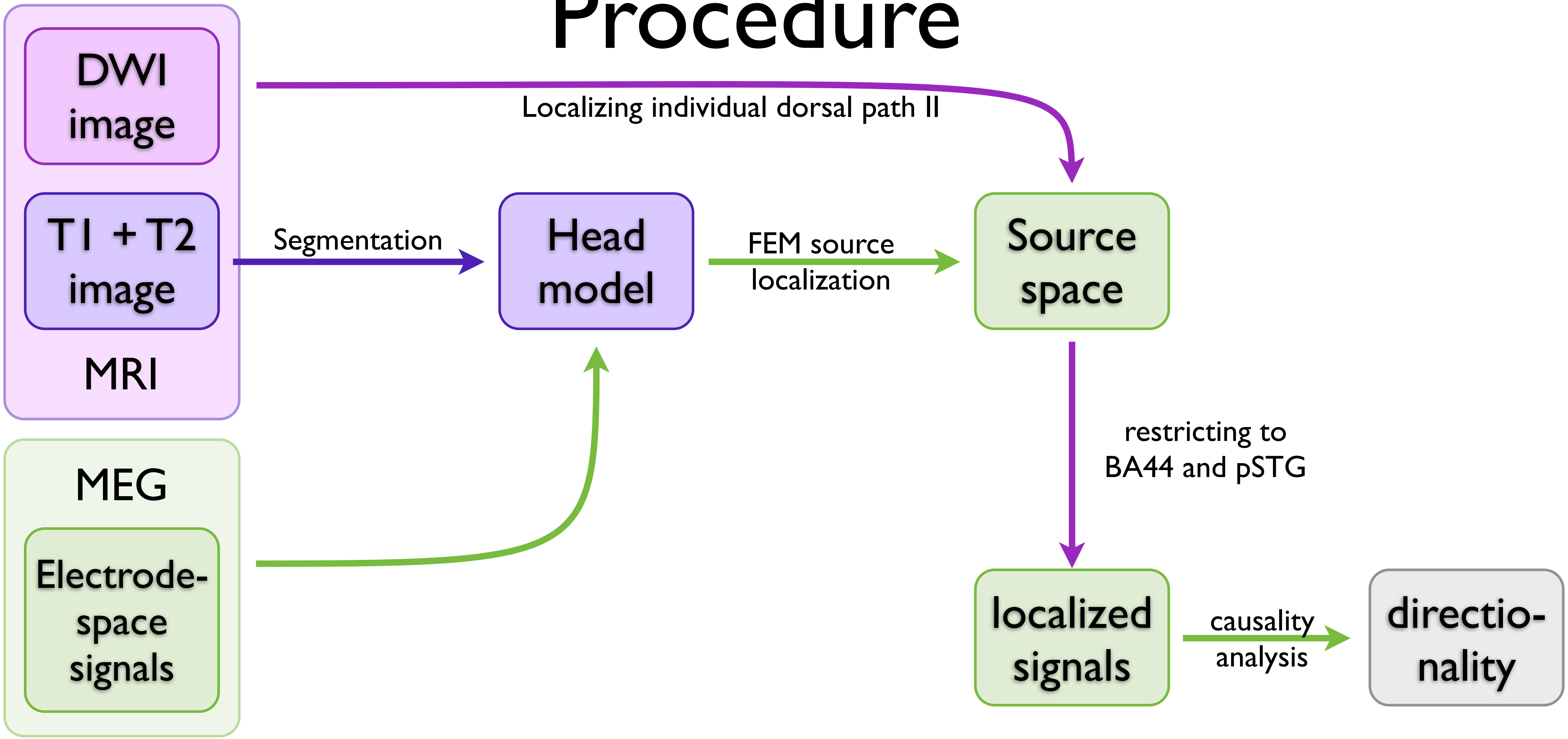
- "Subject-object" paradigm
  ("Wo ist der Affe, den der Tiger zieht?")
- fMRI evidence: Cooke 2002, Stromswold 1996
  - Activation in pSTG/STS during syntactic comprehension
  - Contrast in BA44 between subject/object-first conditions

# Age influence

Perani et al., PNAS 2011

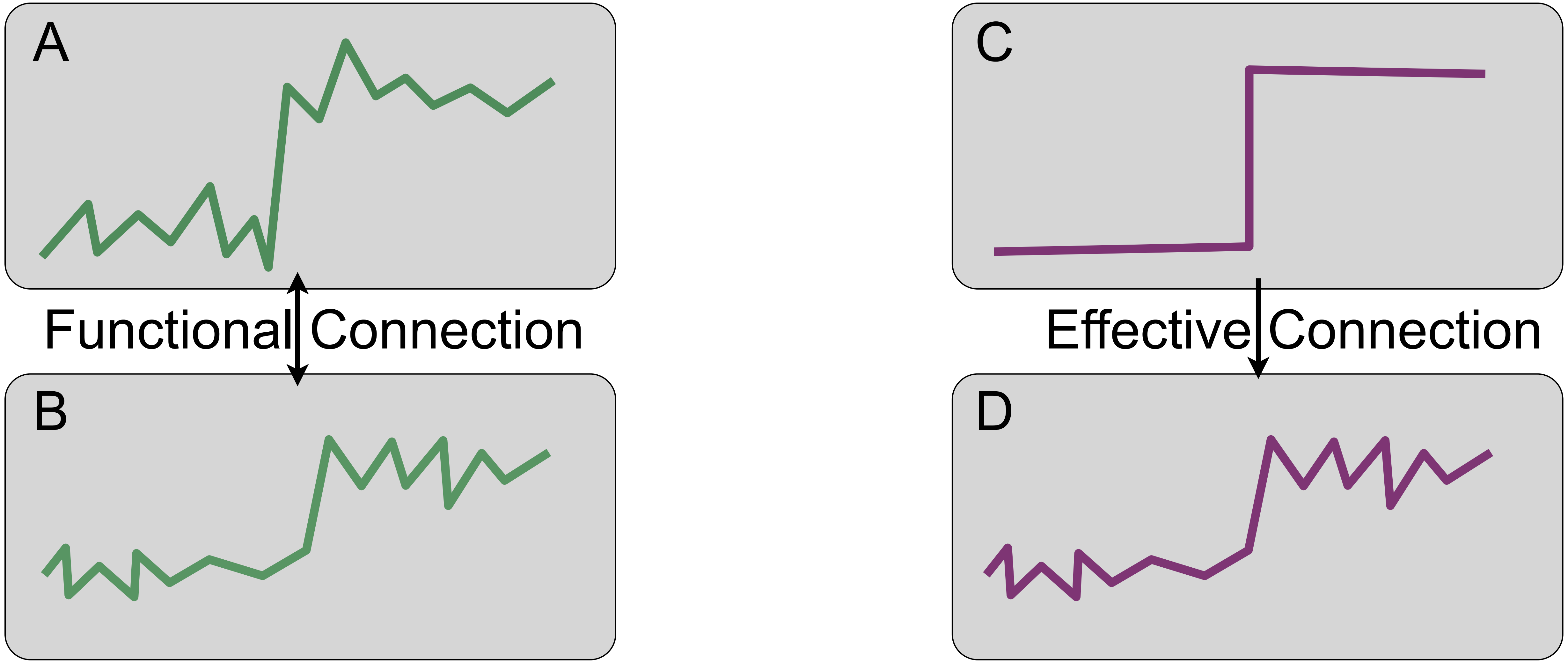


# Procedure


DWI
image
T1 + T2
image
MRI
MEG
Electrode-
space
signals
Localizing individual dorsal path II
Segmentation
Head
model
FEM source
localization
Source
space
restricting to
BA44 and pSTG
localized
signals
causality
analysis
directio-
nality

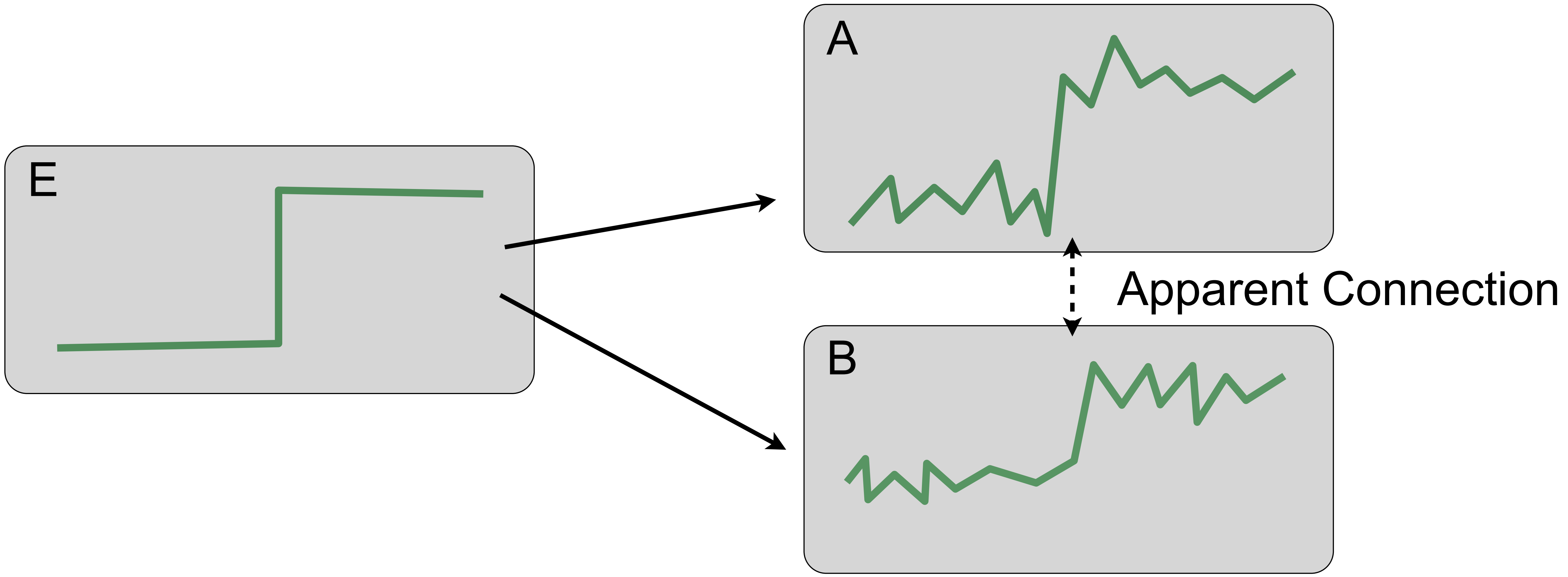
# Functional vs. effective causality

Discriminating cause and effect



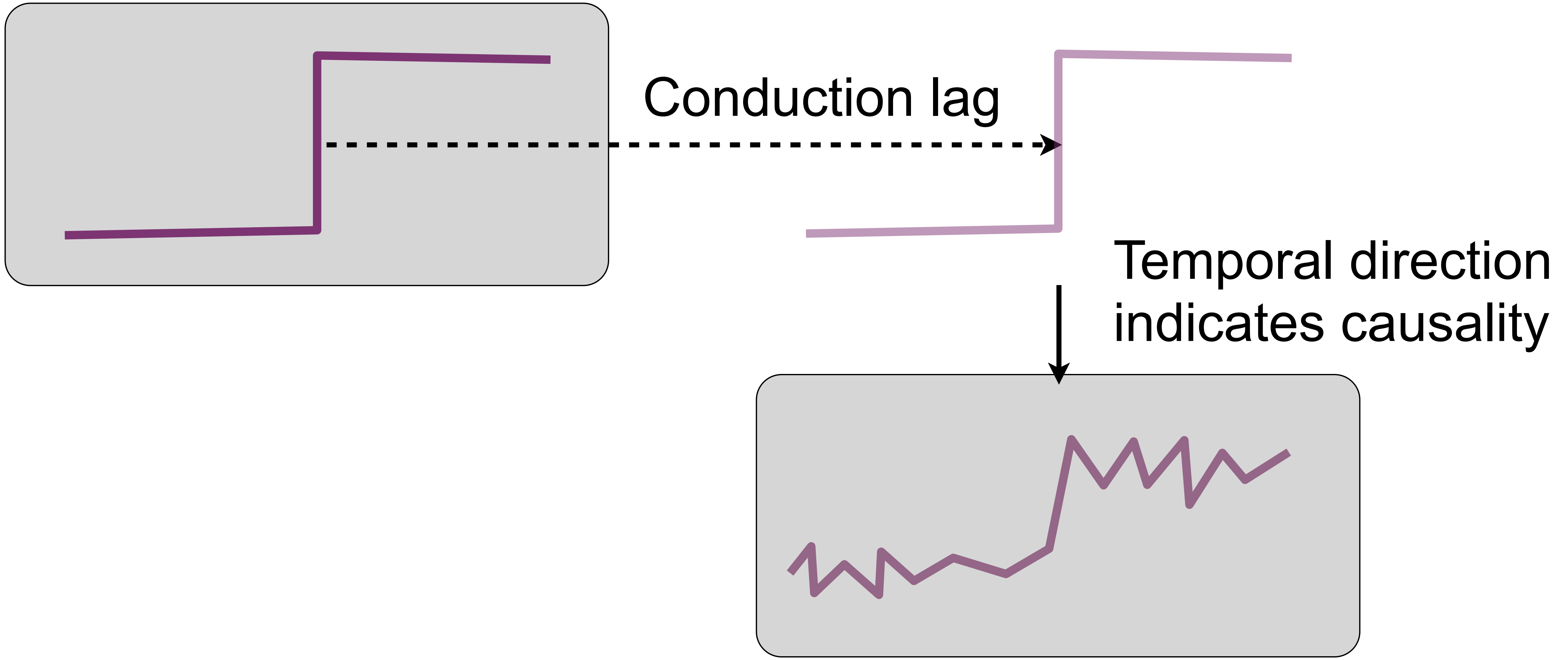
# Functional vs. effective causality

The pitfalls of functional causality



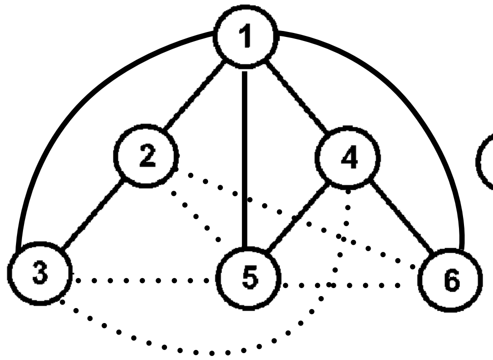
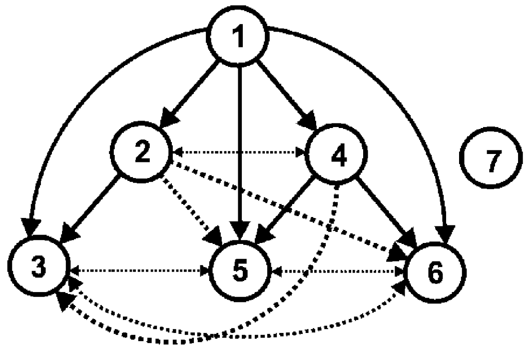
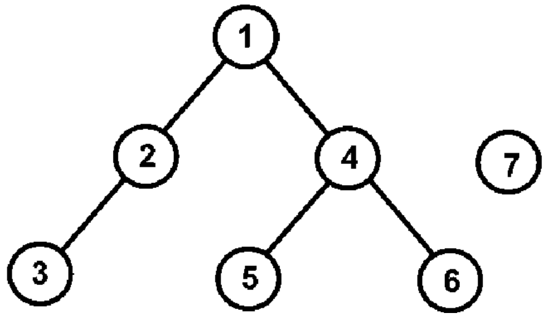
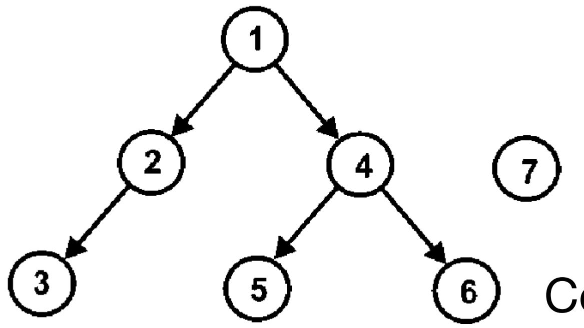
# Functional vs. effective causality

Effective Causality in cognitive Science



# Functional vs. effective causality

Causality methods

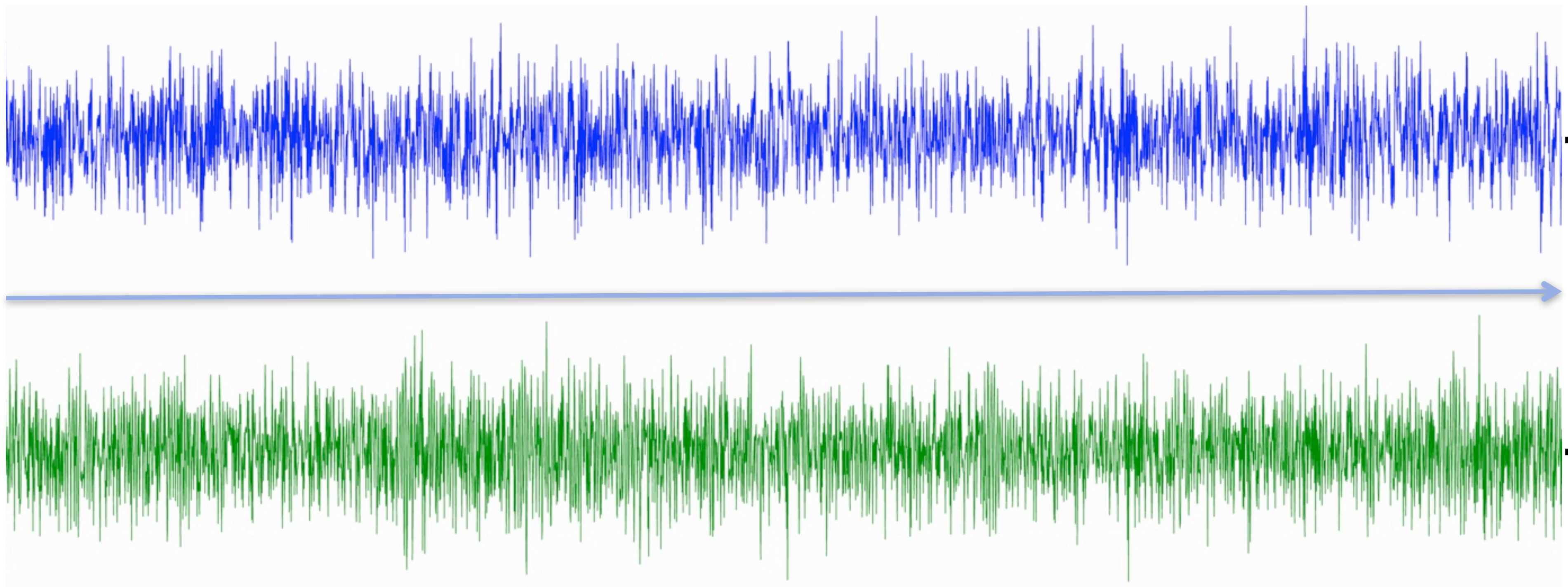
| Causal modeling | Functional models | Effective models |
|---|---|---|
| Bivariate |  Coherence |  Granger-Geweke Causality |
| Multivariate |  Partial Coherence |  Partial Directed Coherence |

# Transfer Entropy

Entropy components

Signal X

Signal Y



→ Entropy H(X)

→ Entropy H(Y)

$$H(X) + H(Y) = H(X_{t+1}|X_t) + H(Y_{t+1}|Y_t) + I(X,Y)$$

Entropy

Conditional Entropy

Mutual Information

Schreiber 2000

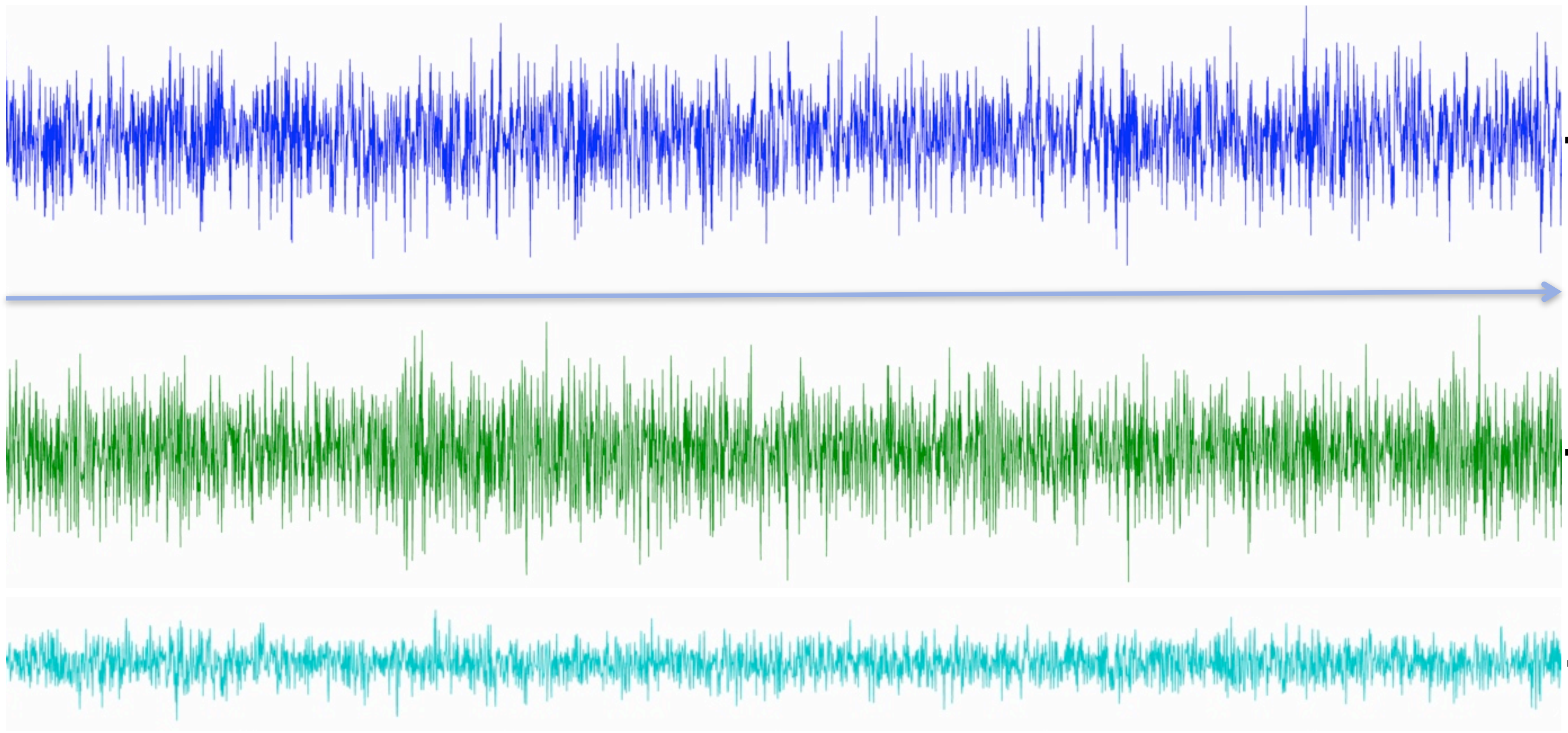
# Transfer Entropy

Mutual Information

Signal X → H(X)

Signal Y → H(Y)

X | Y → H(X | Y)



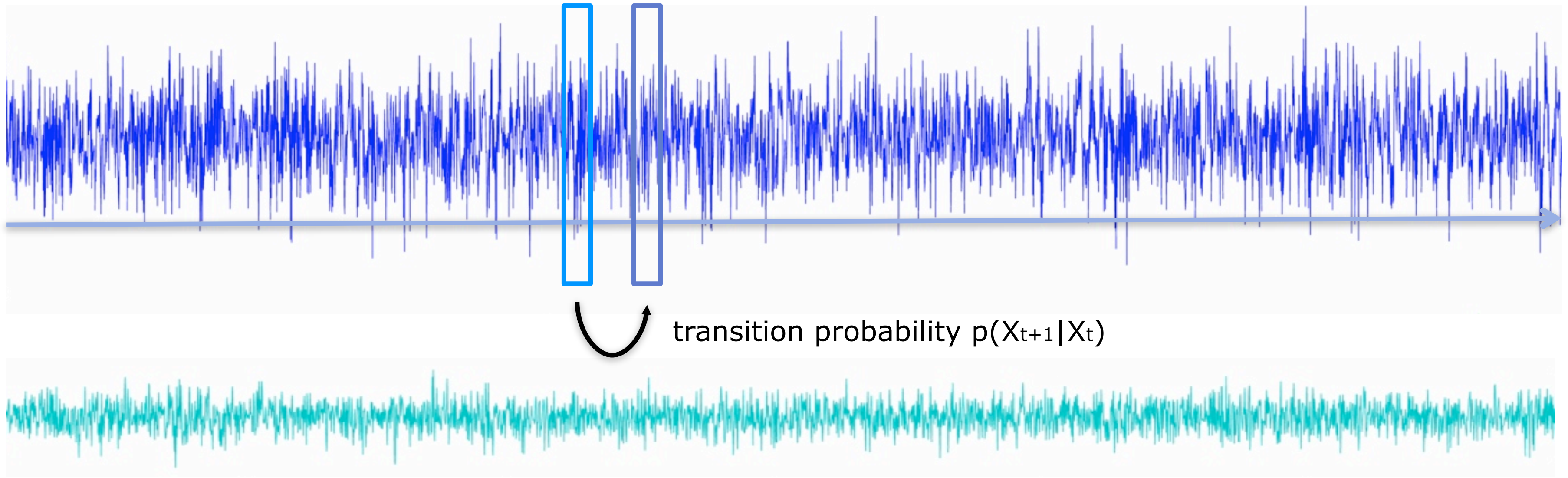
$I(X,Y) = H(X) + H(Y) - H(X|Y)$

"Mutual information"

# Transfer Entropy

## Conditional Entropy

Conditional Entropy: $H(X_{t+1}|X_t)$




Mutual information: $I(X,Y)$

“Apparent Transfer entropy”

Conditional mutual information: $I(X,Y_{t+1}|Y_t)$

“Conditional transfer entropy”

predictive information: $H(X_{t+1})$ - $H(X_{t+1}|X_t)$

total uncertainty about the future

uncertainty about the future, given the past

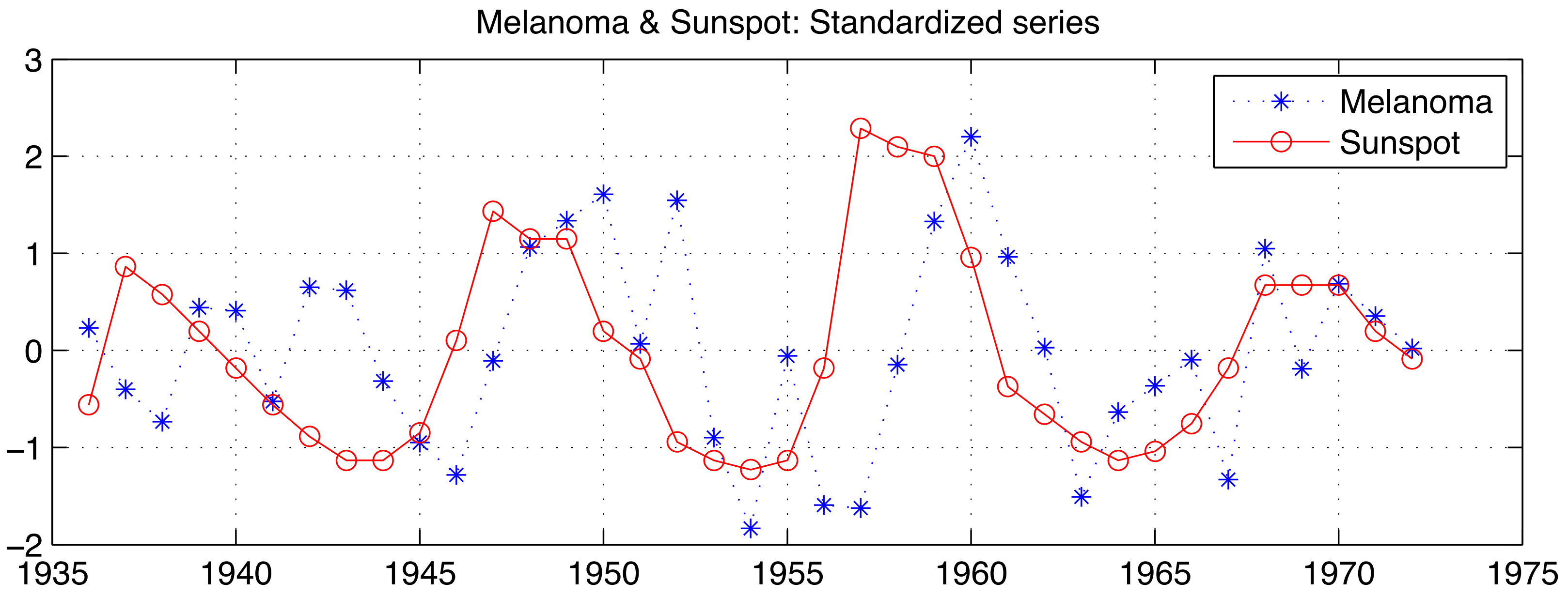
Full length implementation formulas:

$$T_{J\to I} = \sum_{x_{n+1},x_n,y_n} p(x_{n+1},x_n,y_n)\log\left(\frac{p(x_{n+1},x_n,y_n)\cdot p(x_n)}{p(x_n,y_n)\cdot p(x_{n+1},x_n)}\right)$$

$$T_{I\to J} = \sum_{y_{n+1},x_n,y_n} p(y_{n+1},x_n,y_n)\log\left(\frac{p(y_{n+1},x_n,y_n)\cdot p(y_n)}{p(x_n,y_n)\cdot p(y_{n+1},y_n)}\right)$$

# Properties of Transfer Entropy

## Advantages

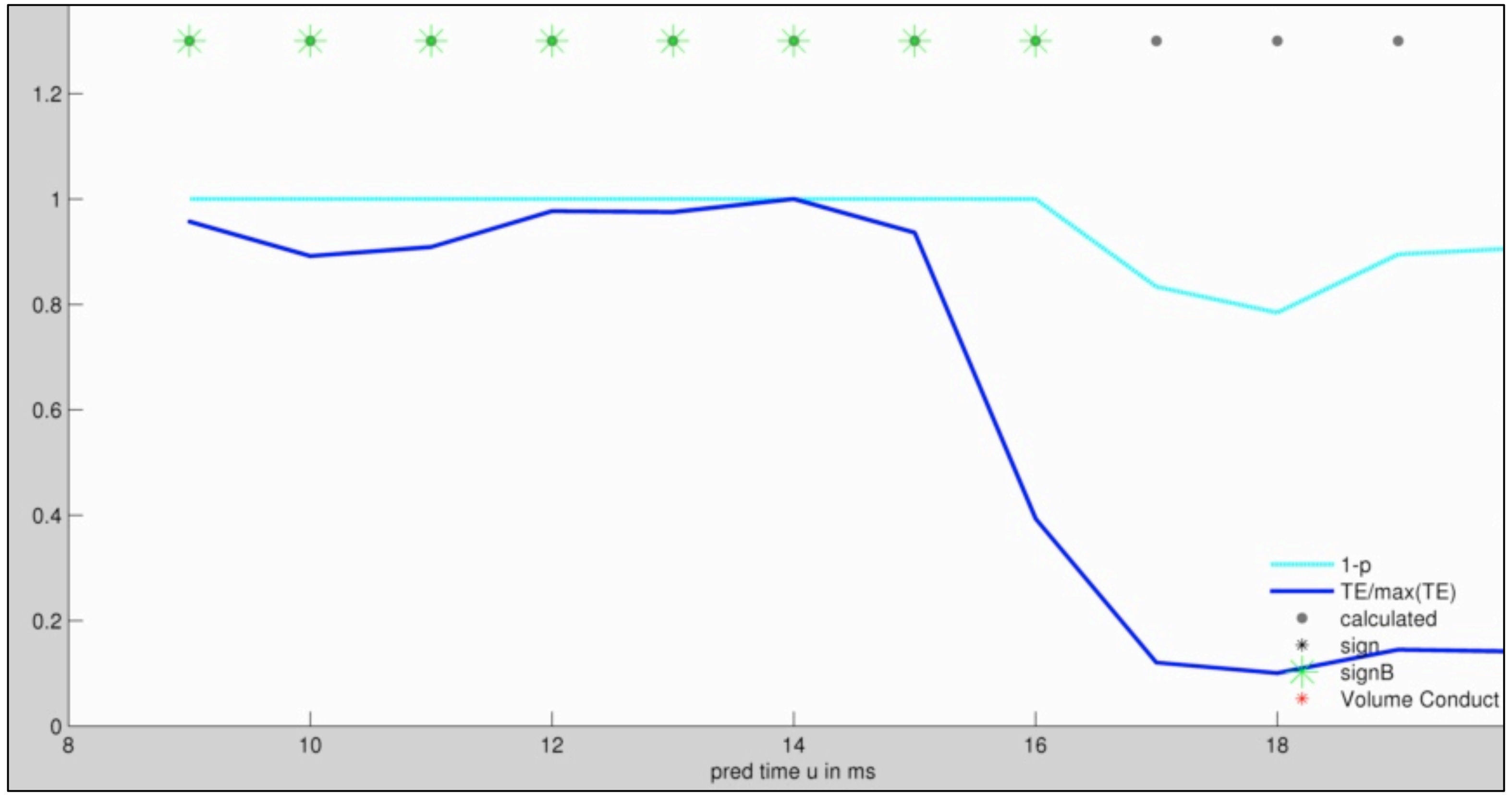



- model-free
- robust to noise
- inherently non-linear
  - but works fast with linear data
- weaker coupling -> better results!
- copes well with multivariate effects: ○ → △ → ▯ ≠ ○ → ▯

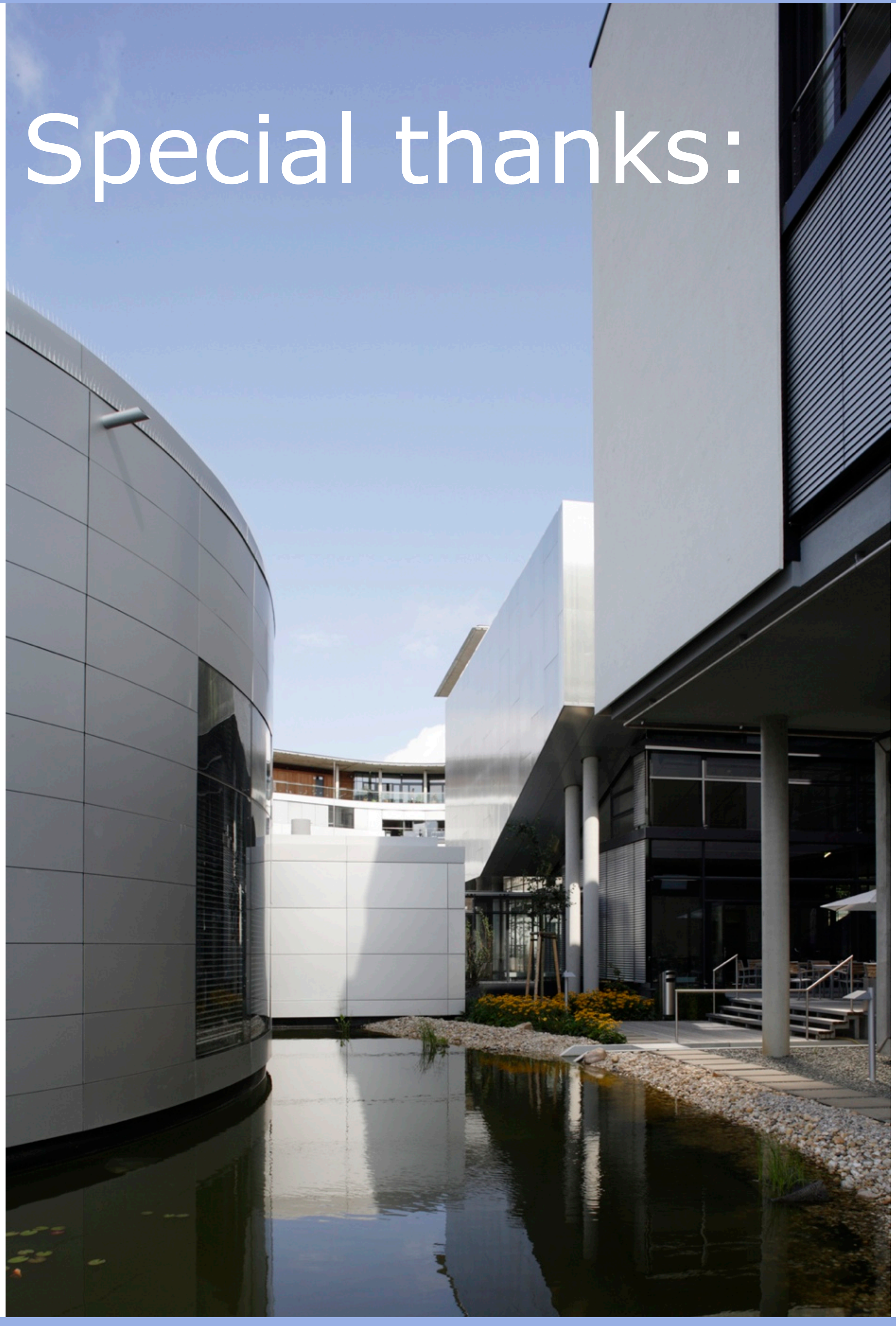
# Properties of Transfer Entropy

Application in Neuroscience

- causal interactions occur at a fine temporal scale (<10ms)
- (predictable) estimation bias for non-infinite data sequences
- Noise influence:
  - good detection rate for SNR above 15db
  - breaks down to 50% at 10db
- Issues with complex networks
- difficult to test for significance
- vulnerable to volume conduction



# Special thanks:



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- Burkhard Maess
- Alfred Anwander
- Michael Skeide