An Information Theoretical Approach to EEG Source-Reconstructed Connectivity

Axel Faes
KU Leuven

EEG Source-Reconstructed Connectivity

In Short

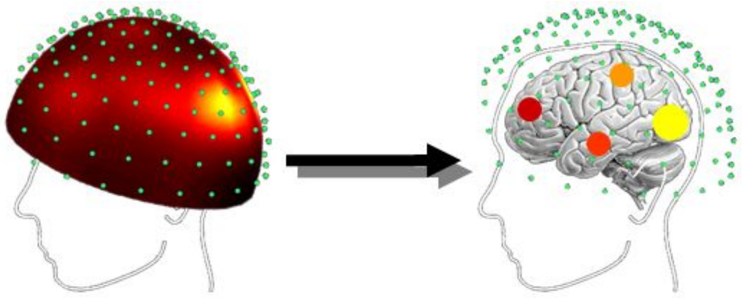
EEG data

Electrical activity on scalp

Source-reconstructed

Localisation of activity

Reverse problem



In Short

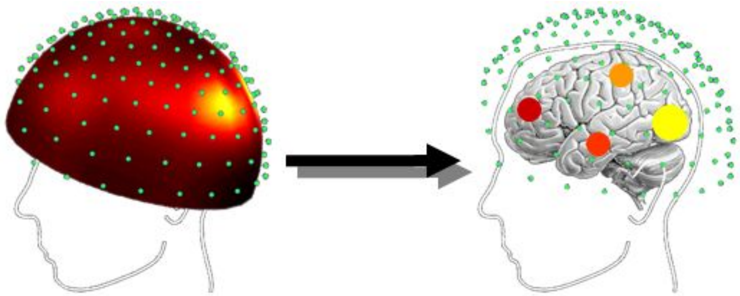
EEG data

Electrical activity on scalp

Source-reconstructed

Localisation of activity

Reverse problem



Context? Why?

Semantic Word Processing

Representation of semantic categories

Grounded cognition model

Semantic Word Processing

Representation of semantic categories

Grounded cognition model

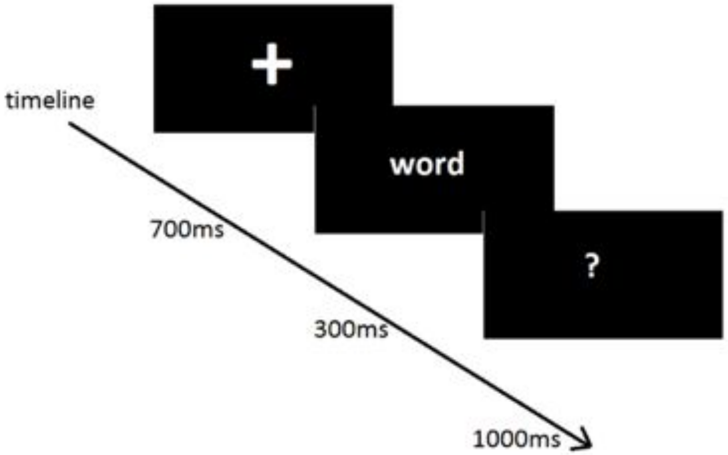
Dual coding

Context availability

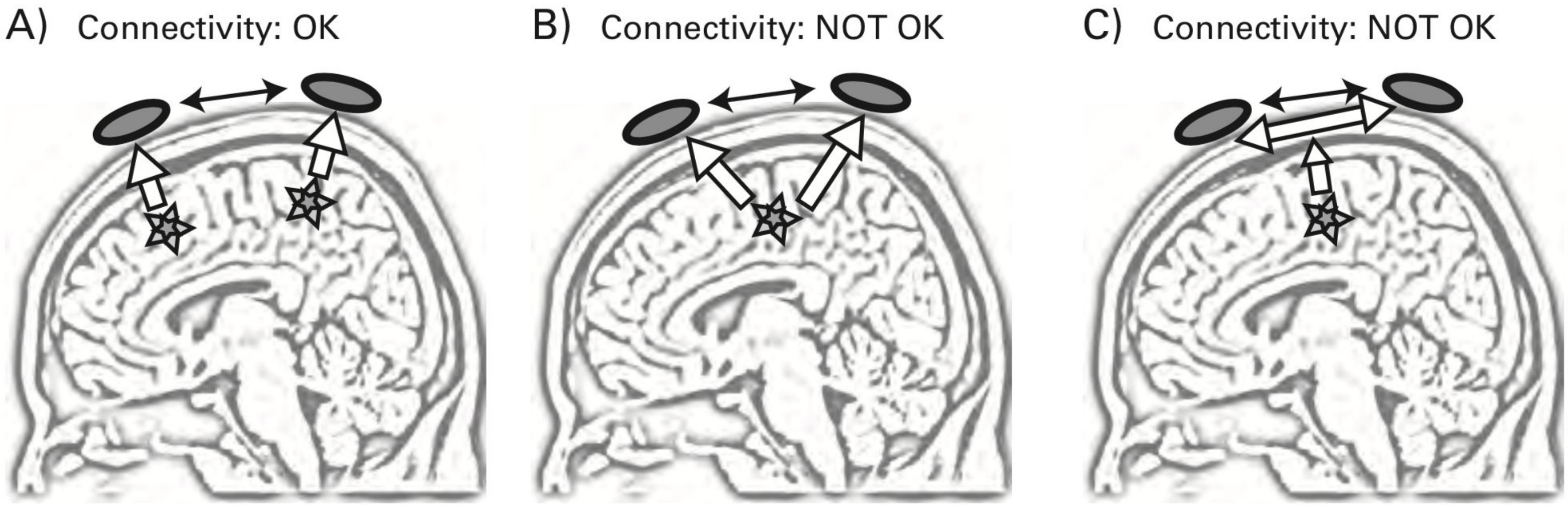
Experiment

Two groups

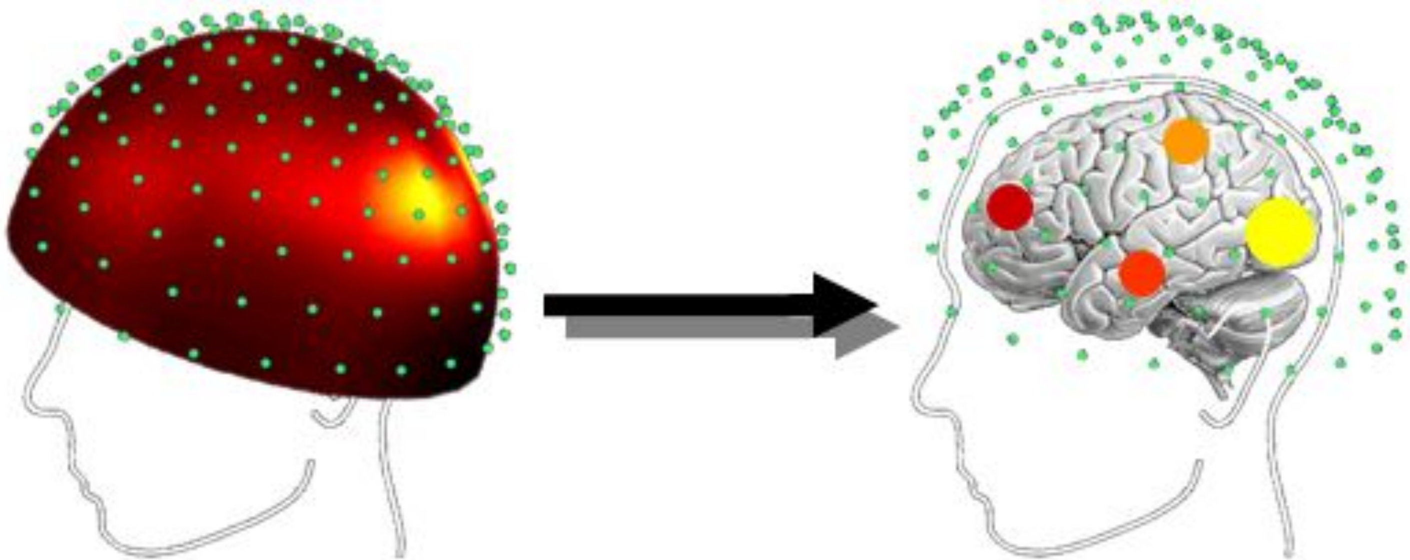
- Abstract
- Concrete



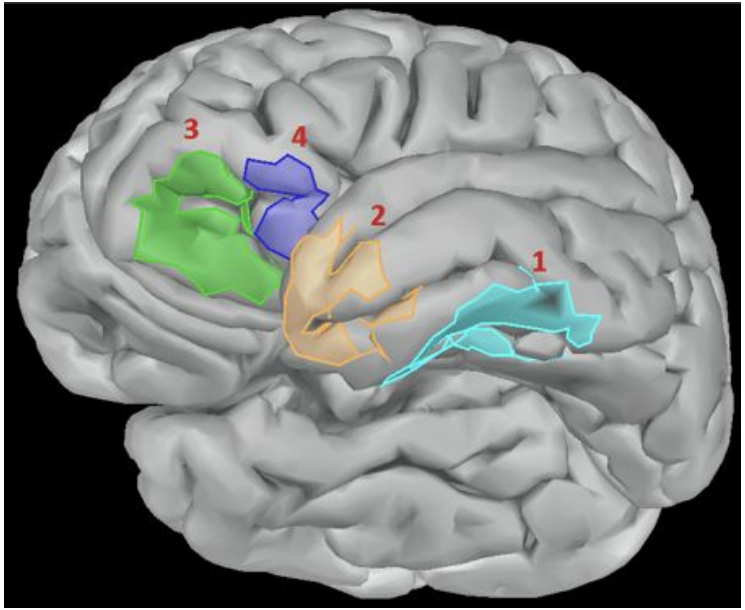
Volume Conduction



Source reconstruction



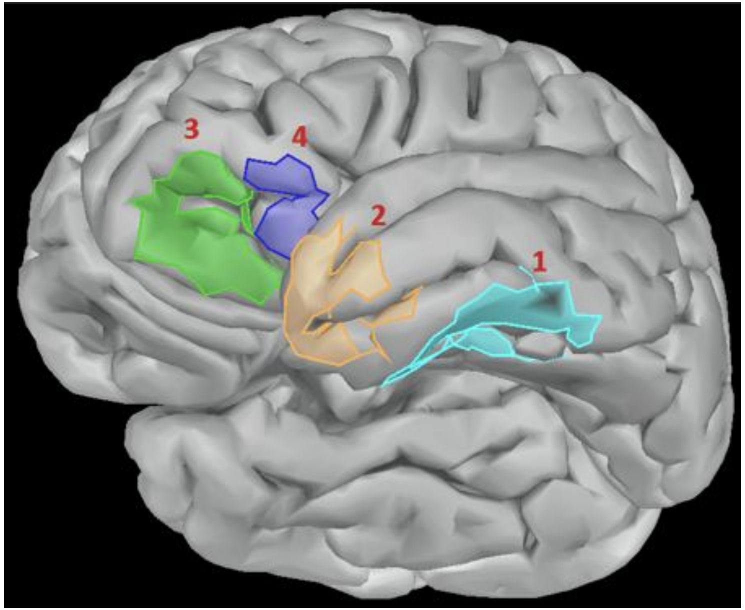
Region of interest selection



Most active regions

$3cm^2$

Region of interest selection



Inferior Temporal Gyrus

Temporal Pole

Inferior Frontal

Anterior Orbital Gyrus

Connectivity Measures

Phase-Based Connectivity

Power-Based Connectivity

Cross-Frequency Coupling

Graph Theory

Granger Causality

Information Theory

Connectivity Measures

Phase-Based Connectivity

Power-Based Connectivity

Cross-Frequency Coupling

Graph Theory

Granger Causality

Information Theory

Why Information Theory

Relatively new

Detect relationships

Information Theoretical Approach

Entropy

Measure of uncertainty

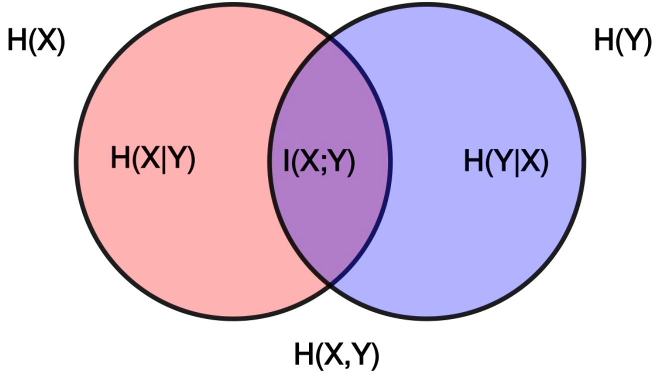
Quantified in bits

$$H(X) = -\sum_{i=1}^{n} P(x_i) log_2(P(x_i))$$

Joint Entropy

Uncertainty of multiple variables

$$H(X,Y) = -\sum_{i=1}^{n}\sum_{j=1}^{m} P(x_i, y_j) log_2(P(x_i, y_j))$$

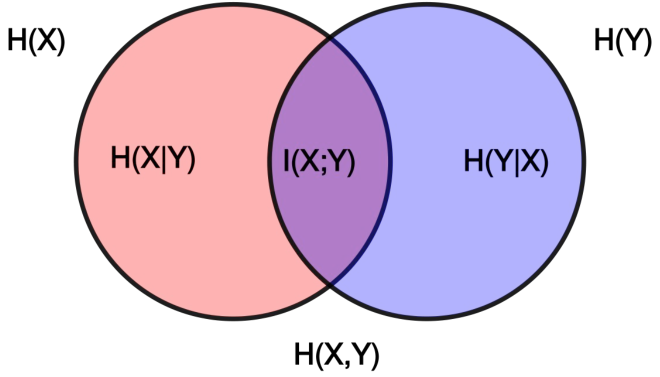


Mutual Information

Information that is common

Bivariate

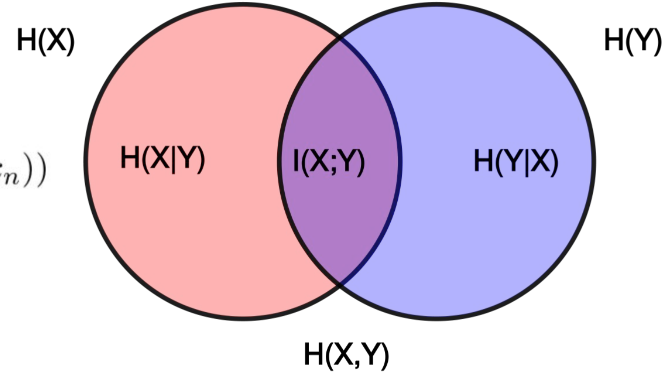
$$I(X,Y) = H(X) + H(Y) - H(X,Y)$$



Multivariate Information Theory

Generalisations

$$H(X_1, ..., X_n) = -\sum_{x_1} ... \sum_{x_n} P(x_1, ..., x_n) log_2(P(x_1, ..., x_n))$$

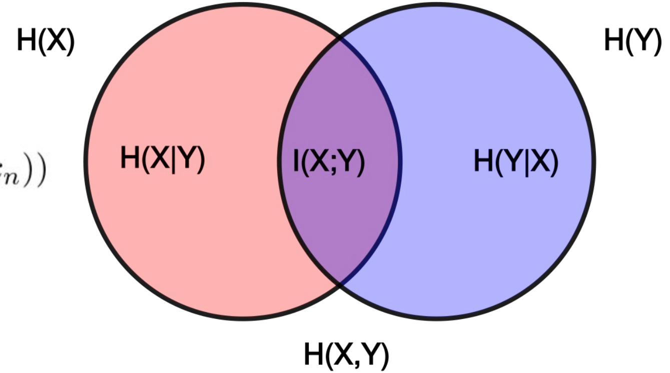


Multivariate Information Theory

Generalisations

$$H(X_1, ..., X_n) = -\sum_{x_1} ... \sum_{x_n} P(x_1, ..., x_n) log_2(P(x_1, ..., x_n))$$

Mutual Information?



Multivariate Mutual Information

Many different generalisations

Commonly used

Interaction Information

$$I(X_1, ..., X_n) = \sum_{T \subseteq \{1,...,n\}} (-1)^{|T|} H(T)$$

$$I(X_1, ..., X_n | Y) = \sum_{T \subseteq \{1,...,n\}} (-1)^{|T|} H(T|Y)$$

Continuous Data

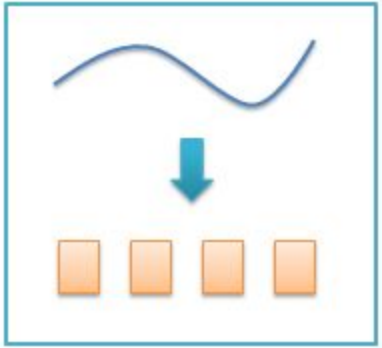
Information theory -> discrete

Our data -> continuous

$$H(X) = -\sum_{i=1}^{n} P(x_i) log_2(P(x_i))$$

Binning Data

Put continuous data into bins



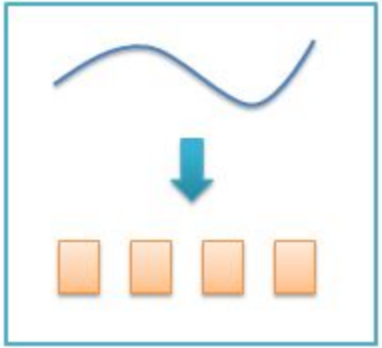
Binning Data

Put continuous data into bins

How many bins?

Freedman-Diaconis rule

$$nbins = \frac{max(x) - min(x)}{2Q_x n^{-1/3}}$$



Analysis

Data

13 subjects

3404 trials

Each trial -> 340 data points (1.7s with 200Hz)

4 regions

3 timeseries (concrete, abstract, rest)

Motivation

13 subjects

3404 trials

Each trial -> 340 data points (1.7s with 200Hz)

4 regions

3 timeseries (concrete, abstract, rest)

Motivation

Abstract vs Concrete

13 subjects

3404 trials

Each trial -> 340 data points (1.7s with 200Hz)

4 regions

3 timeseries (concrete, abstract, rest)

Motivation

Abstract vs Concrete

Per subject

Amount of trials

13 subjects

3404 trials

Each trial -> 340 data points (1.7s with 200Hz)

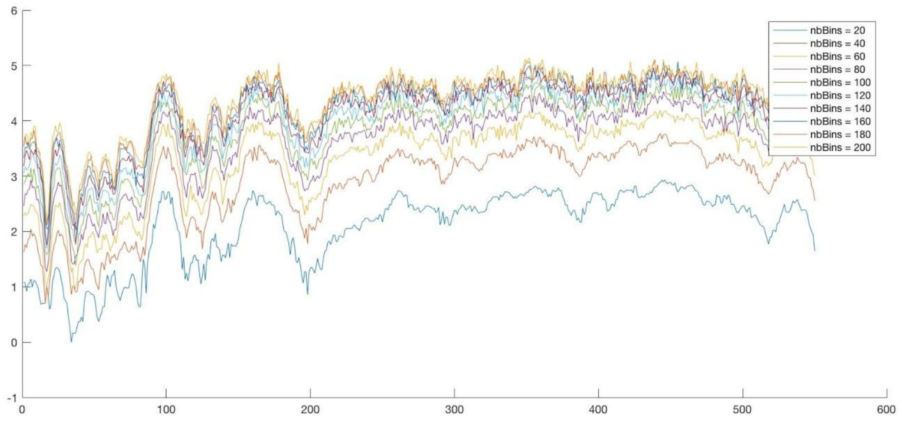
4 regions

3 timeseries (concrete, abstract, rest)

Bin Sizes

$$nbins = \frac{max(x) - min(x)}{2Q_x n^{-1/3}}$$

Bin size = 93

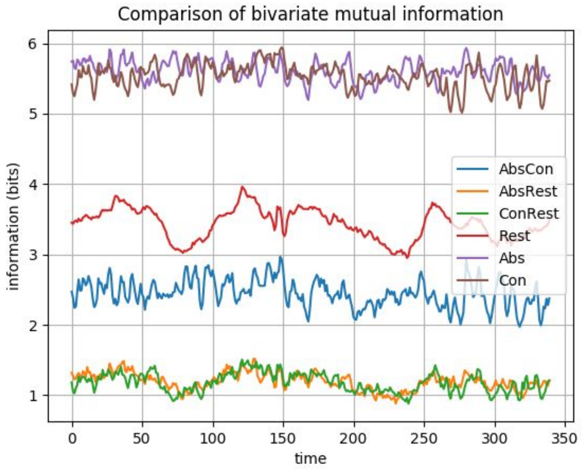


Cortical Regions

Con and Abs are equal

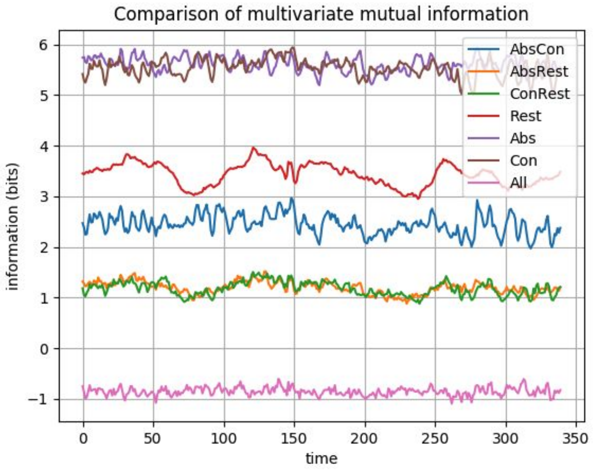
AbsRest and ConRest are equal

AbsCon is slightly lower than Rest

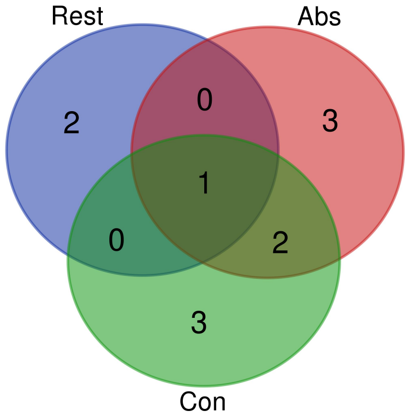


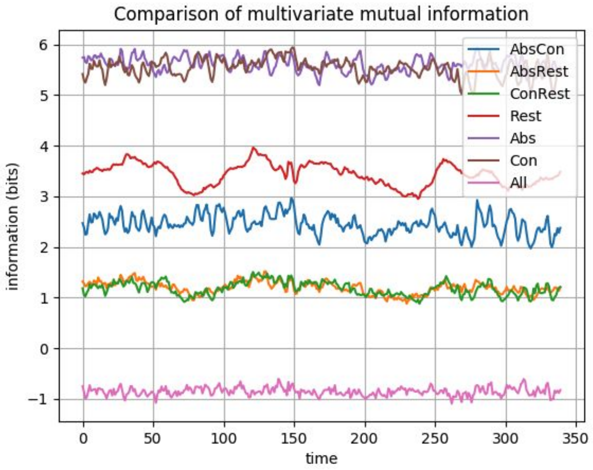
Multivariate Analysis

Negative information?



Multivariate Analysis

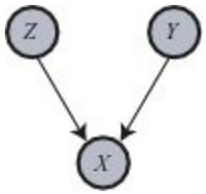


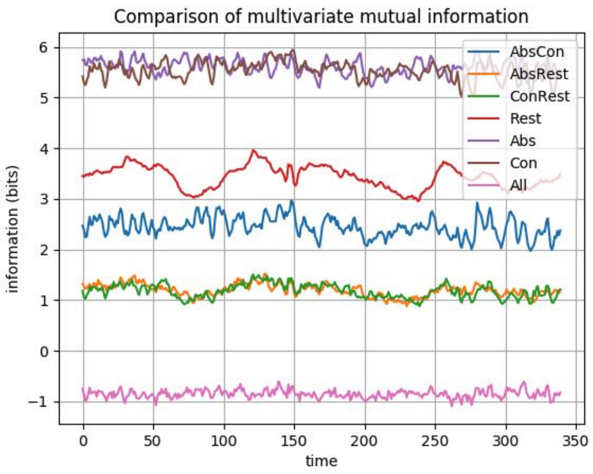


Multivariate Analysis

Negative information?

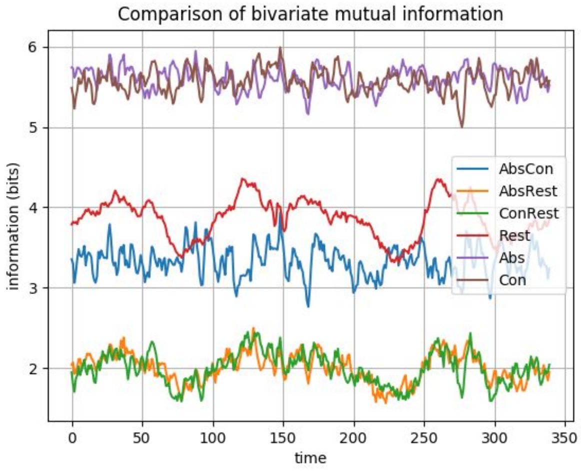
I(Abs, Con, Rest) = I(Abs, Con) - I(Abs, Con|Rest)





Per Subject

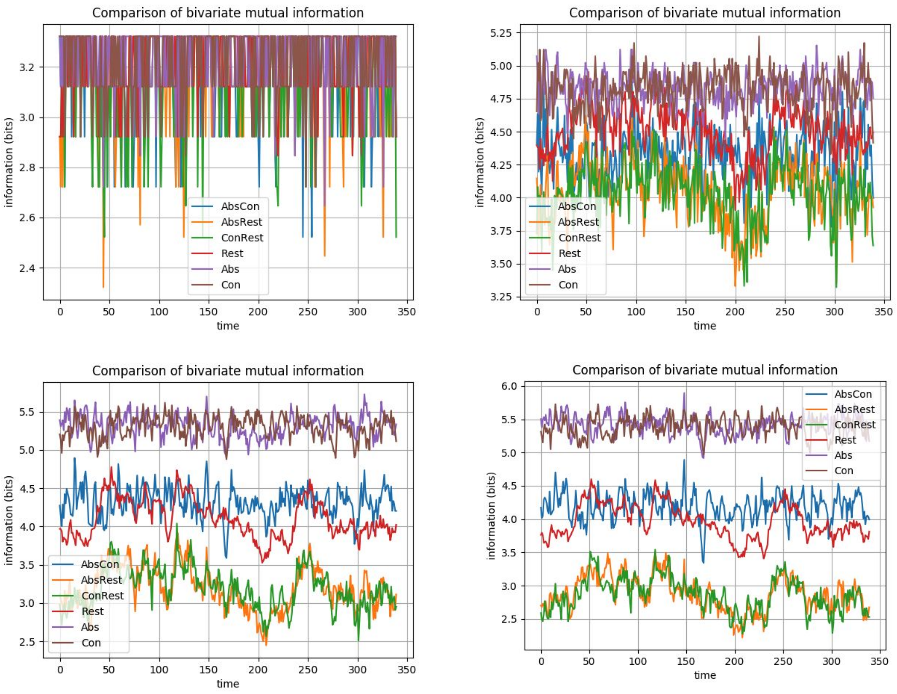
Similar observations



Per Subject

Per subject -> ~260 trials

Comparison between using 10, 40, 80 and 100 trials



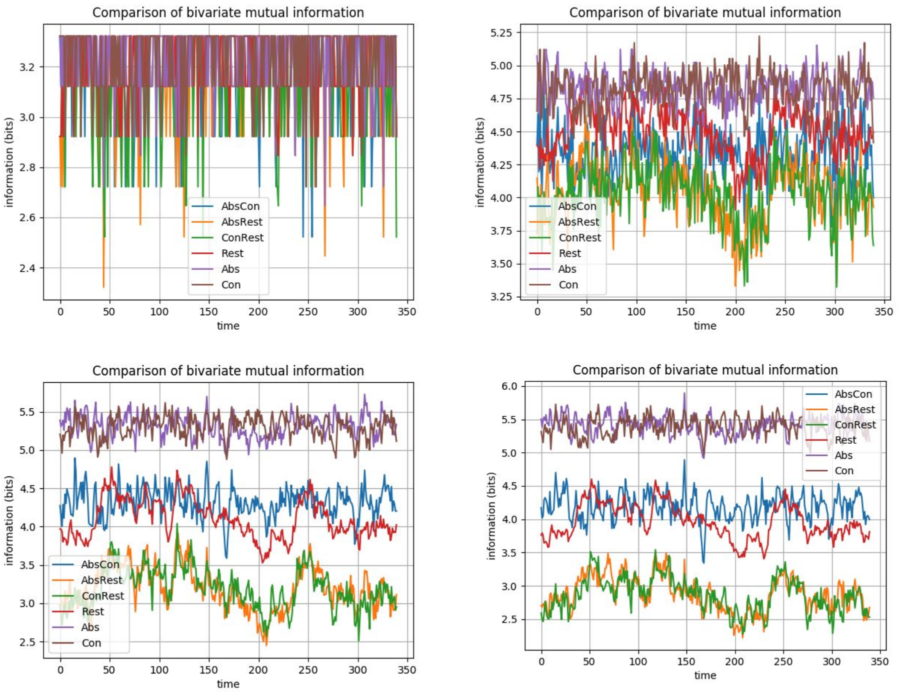
Per Subject

Per subject -> ~260 trials

Comparison between using 10, 40, 80 and 100 trials

Even with less trials than bins

Still reasonable results



Implementation

Reproducibility

Open Science

Implementation

Reproducibility

Open Science

Python

- Equal footing with Matlab
- Very popular with open-source community

Implementation

Reproducibility

Open Science

Python

- Equal footing with Matlab
- Very popular with open-source community

Data conversion is lossless

Equations are easily converted into python code

Implementation

Reproducibility

Open Science

Python

- Equal footing with Matlab
- Very popular with open-source community

Data conversion is lossless

Equations are easily converted into python code

$$I(X_1, \ldots, X_n) = \sum_{T \subseteq \{1, \ldots, n\}} (-1)^{|T|} H(T)$$

```
def mutualInformationMulti(bins, *X):
    subsets = get_subsets(*X)
    entr = 0
    for sub in subsets:
        entr += (-1)**(len(sub)) * entropy(bins, sub)
    return entr
```

Future Work

Directed Information

$$I(X^n \to Y^n) = \sum_{i=1}^{n} I(X^i, Y_i | Y^{i-1})$$

Open Source Connectivity Package

Future Work

Multivariate Mutual Information Alternatives

Total correlation

divergence of joint entropy to independent entropies

$$C(X^1, ..., X^n) = [\sum_{i=1}^{n} H(X^i)] - H(X^1, ..., X^n)$$

Dual total correlation

$$D(X^1, ..., X^n) = H(X^1, ..., X^n) - \sum_{i=1}^{n} H(X^i | X^1, ..., X^{i-1}, X^{i+1}, ..., X^n)$$

Apply Information Theory to Real Source-Reconstructed Data for Connectivity

Questions?