Comparative Analysis of Functional Connectivity Metrics in EEG Datasets

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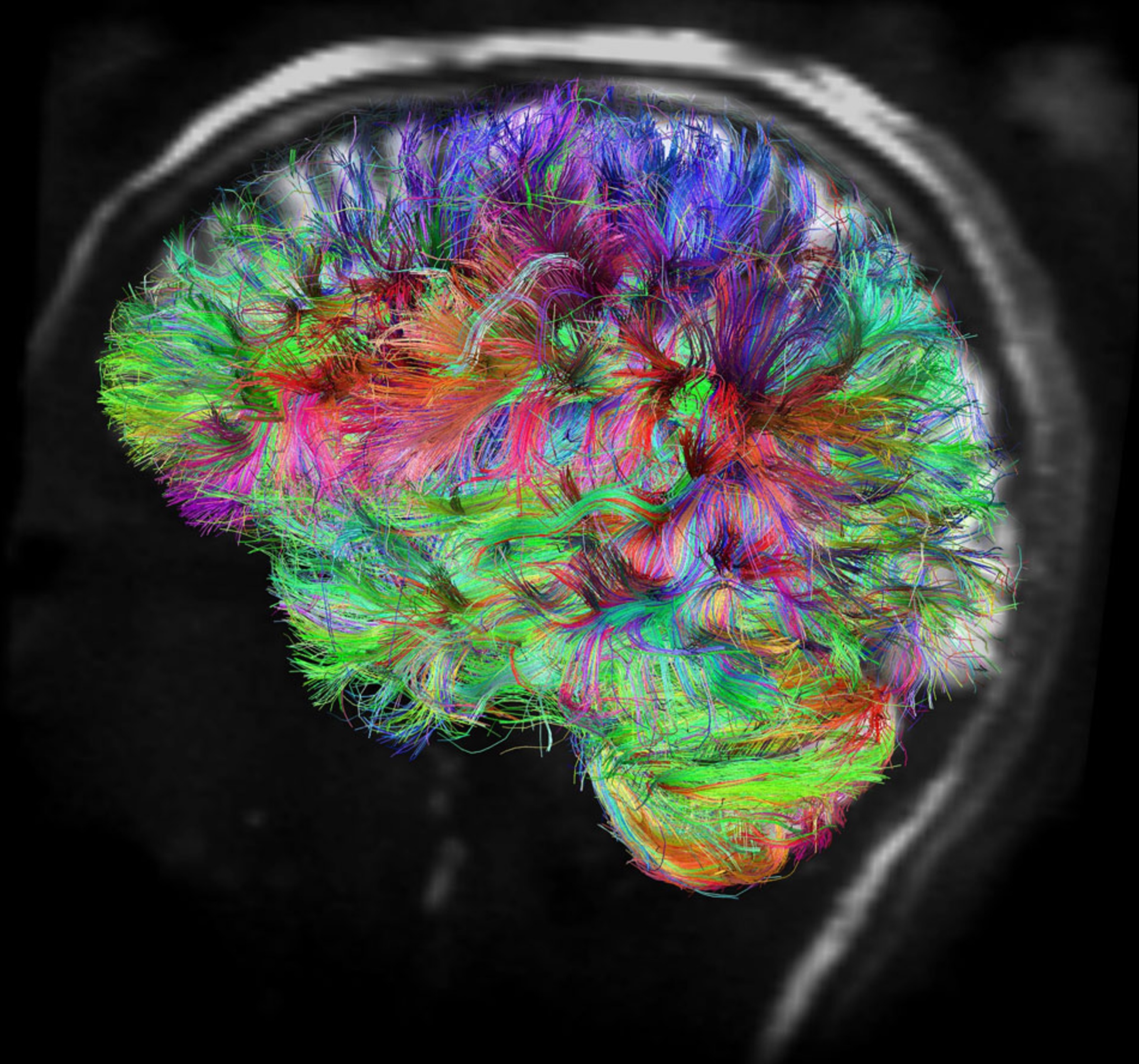
Introduction



Results on Functional Brain Connectivity Research

nature neuroscience

Published: 12 October 2015

Functional connectome fingerprinting: identifying individuals using patterns of brain connectivity

Emily S Finn, Xilin Shen, Dustin Scheinost, Monica D Rosenberg, Jessica Huang, Marvin M Chun, Xenophon Papademetris & R Todd Constable

Nature Neuroscience **18**, 1664–1671 (2015) | Cite this article

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Neuropsychologia

Volume 70, April 2015, Pages 177-184

Functional connectivity patterns reflect individual differences in conflict adaptation

Xiangpeng Wang [a], Ting Wang [a, b], Zhencai Chen [c], Glenn Hitchman [a], Yijun Liu [a], Antao Chen [a]

International Conference on Neural Information Processing

↳ ICONIP 2019: **Neural Information Processing** pp 441–449 | Cite as

Identifying EEG Responses Modulated by Working Memory Loads from Weighted Phase Lag Index Based Functional Connectivity Microstates

Li Zhang, Bo Shi, Mingna Cao, Sai Zhang, Yiming Dai & Yanmei Zhu

Conference paper | First Online: 05 December 2019

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Neurobiology of Aging

Volume 41, May 2016, Pages 122-129

Regular article

EEG-directed connectivity from posterior brain regions is decreased in dementia with Lewy bodies: a comparison with Alzheimer's disease and controls

Meenakshi Dauwan [a, b], Edwin van Dellen [a, b, c], Lotte van Boxtel [a], Elisabeth C.W. van Straaten [a], Hanneke de Waal [c], Afina W. Lemstra [c], Alida A. Gouw [a, c], Wiesje M. van der Flier [c, d], Philip Scheltens [c], Iris E. Sommer [b], Cornelis J. Stam [a]

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Intelligence

Volume 37, Issue 2, March–April 2009, Pages 223-229

Intelligence and neural efficiency: Measures of brain activation versus measures of functional connectivity in the brain

Aljoscha C. Neubauer, Andreas Fink

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NeuroImage

Volume 134, 1 July 2016, Pages 645-657

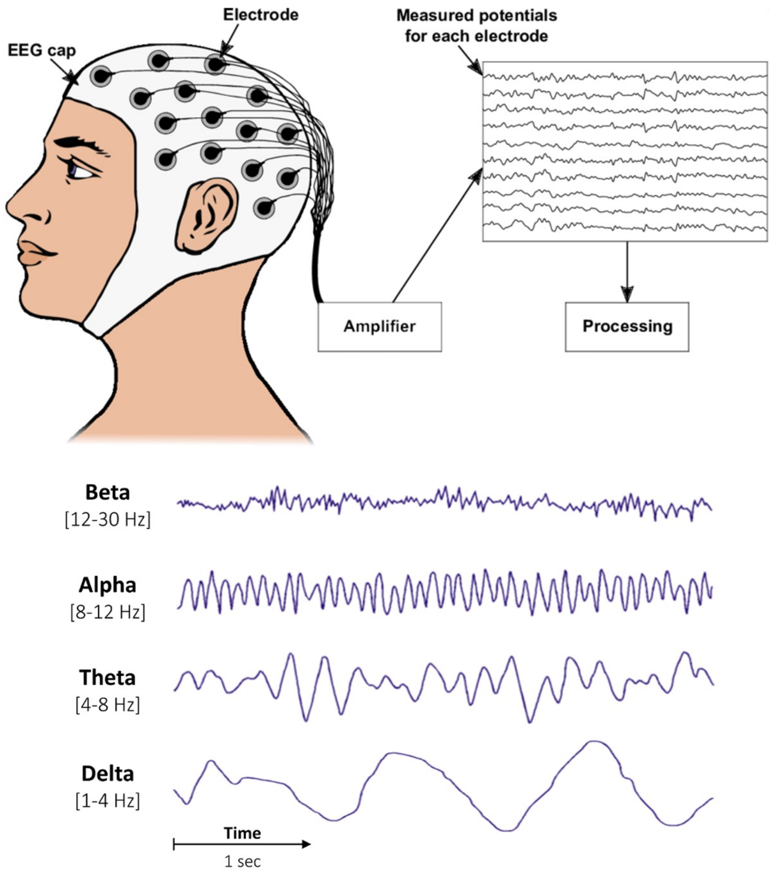
Classification of schizophrenia and bipolar patients using static and dynamic resting-state fMRI brain connectivity

Barnaly Rashid [a, b], Mohammad R. Arbabshirani [a, g], Eswar Damaraju [a, b], Mustafa S. Cetin [a, f], Robyn Miller [b], Godfrey D. Pearlson [c, d, e], Vince D. Calhoun [a, b, d, f]

Theory and background

EEG Data and Functional Connectivity Networks

EEG data



Advantages and disadvantages

+ well-spread and relatively cheap technology
+ high-frequency, millisecond-level data

- not possible to identify the exact source of the signal
- very sensitive to external factors that may spoil the data

Spurious connections

There are several factors that can distort functional connectivity patterns:

- artifacts in EEG data from eye blinking or hand/leg movements
- improper placement of electrodes

On the Analysis of Functional Connectivity Networks

Statistical measures

Purpose: quantify linear or non-linear relationships between signals.

Time-domain measures
- Correlation
- Mutual information

Frequency domain measures
- Phase Lag Index
- Directed transfer function

Graph theory

Purpose: topological analysis of connectivity graphs.

Graph integrity measures
- Global efficiency of the network

Graph segregation measures
- The clustering coefficient of the network

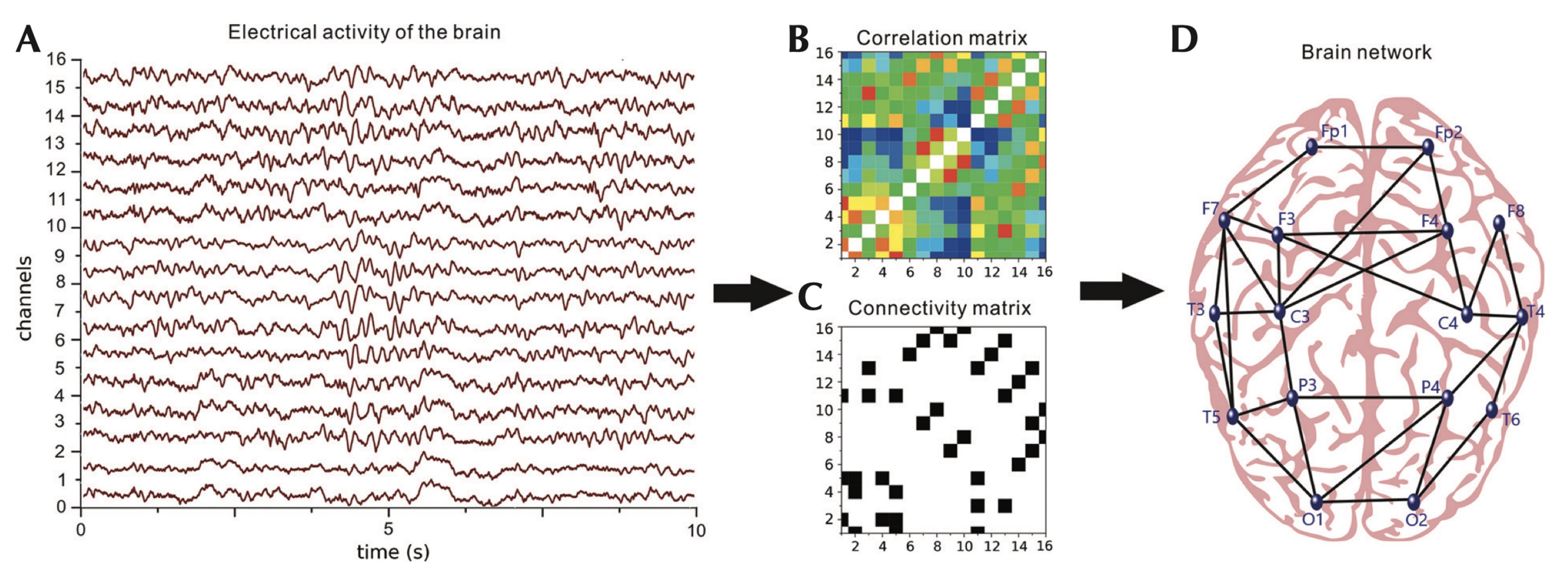
Machine learning

Purpose: analysing connectivity pattens.

Clustering analysis
- Hierarchical clustering

Classification models
- ML algorithms applied to embedded graph data
- Deep learning models
- Graph neural networks

Extracting Functional Connectivity Networks from EEG Data – Illustration



Review > Epileptic Disord. 2020 Oct 1;22(5):519-530. doi: 10.1684/epd.2020.1203.

The brain as a complex network: assessment of EEG-based functional connectivity patterns in patients with childhood absence epilepsy

Eva Paradiž Leitgeb [1], Marko Šterk [1], Timotej Petrijan [2], Peter Gradišnik [3], Marko Gosak [4]

Related Research Topics and Areas

Properties of functional connectivity networks

Analysing connectivity patterns in relation to different diseases.

Individual-level and group-level analyses.

Diagnosis automation

Supporting medical doctors in diagnosing brain-related diseases.

Understanding disease development.

Predictive modelling and explainability

Developing methods and tools for extracting meaningful information and insights from functional connectivity patterns.

- Machine learning
- Deep learning

Data and methodology

Temple University Hospital – TUH EEG Epilepsy Corpus

EEG data

- Data were gathered from 100 epileptic patients and 100 healthy persons.
- Several EEG recordings per subject stored in .edf files.
- Total of 1648 .edf files, filenames contain metadata.
- 23 GB of data in the dataset.

Data preparation

- Choose one .edf file per subject, 200 files in total.
- Select 19 EEG channels present in all the .edf files.
- For modelling, split each recording into non-overlapping 60-second intervals. Max. 10 intervals per subject.
- Account for memory constraints, model training time

Analysis goals

- Find differences in functional connectivity patterns between the healthy and epileptic subjects.
- Confirm if the differences are statistically significant on the group level.
- Build deep learning models for classification between epileptic and healthy subjects.

Analysis Stages and Methods

Functional connectivity measures

- Correlation: linear relationship between EEG signal data
- Mutual information: non-linear relationship between EEG signal data

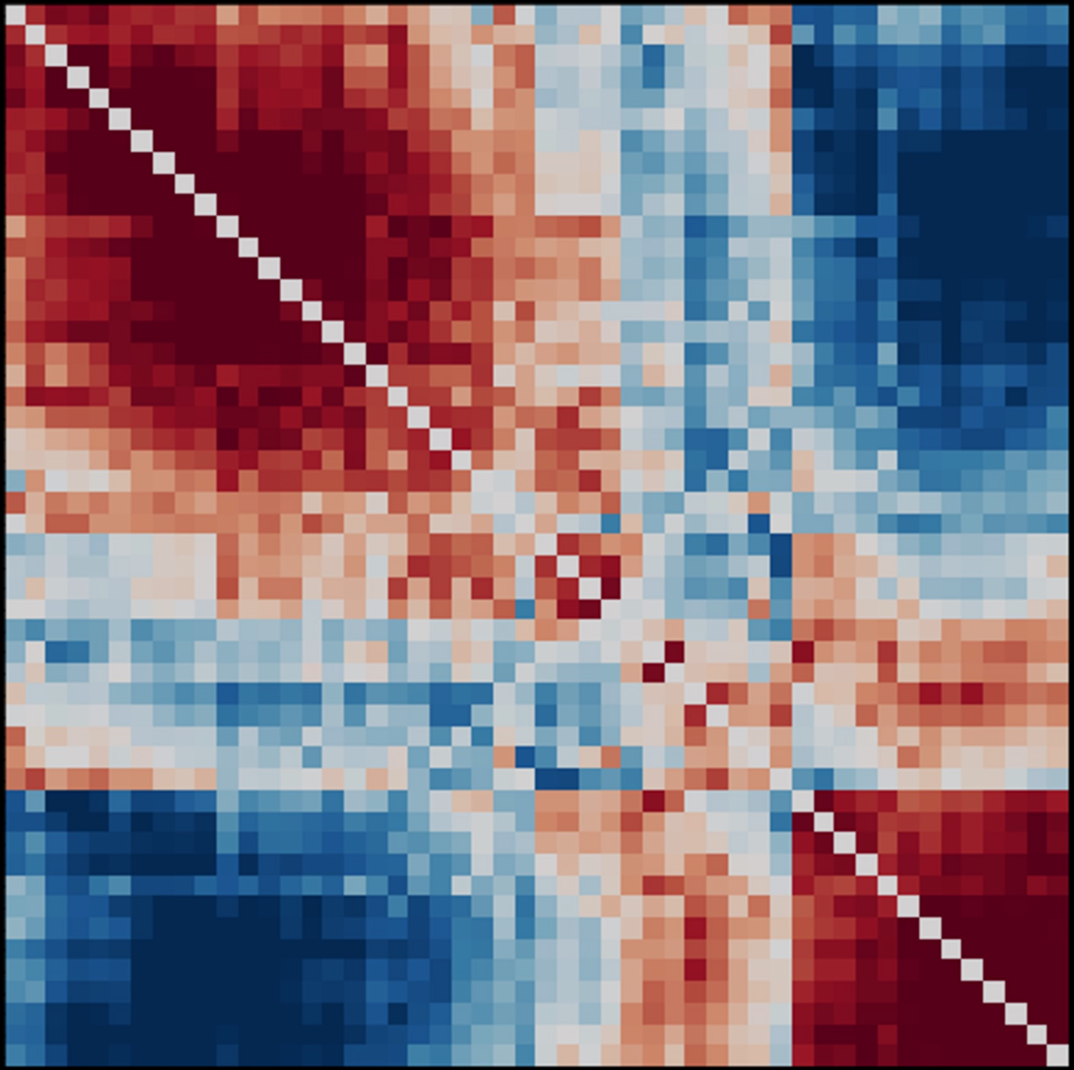
Individual-level analysis and experiments

- Heatmaps of functional connectivity matrices
- Proportional thresholding
- Hierarchical clustering and dendrograms
- Graph representation
- Maximum spanning tree

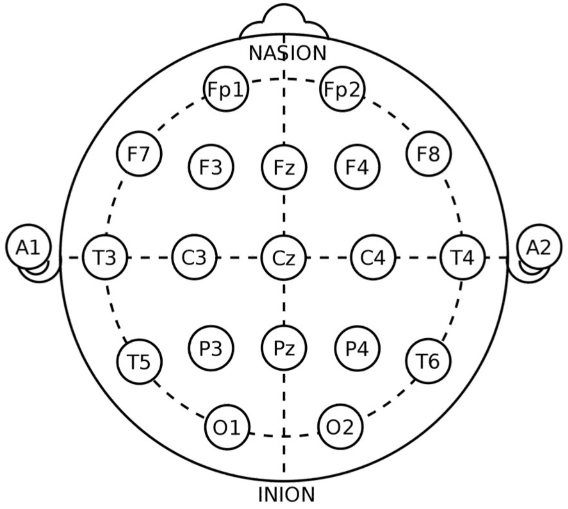
Group level analysis and experiments

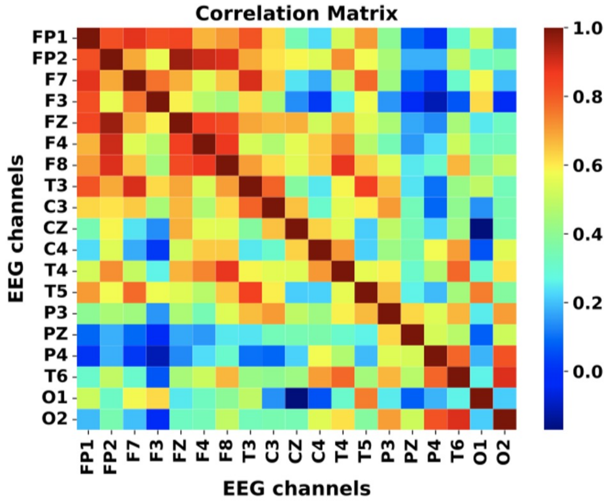
- Student’s t-test on node degrees of maximum spanning trees
- Convolutional neural network model for classification
- Graph neural network model for classification

Experiments

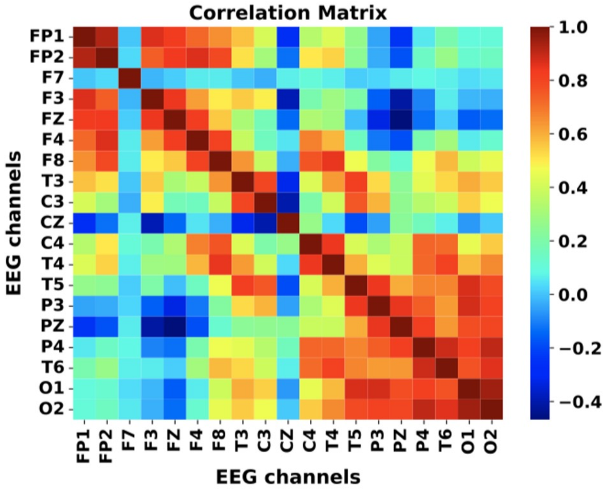


Functional Connectivity Heatmaps

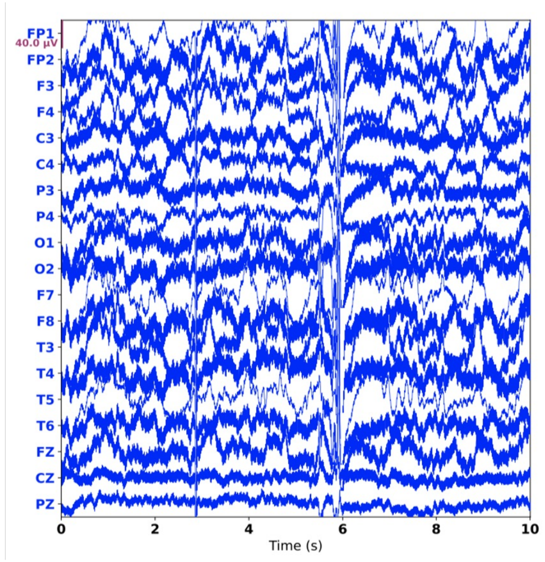




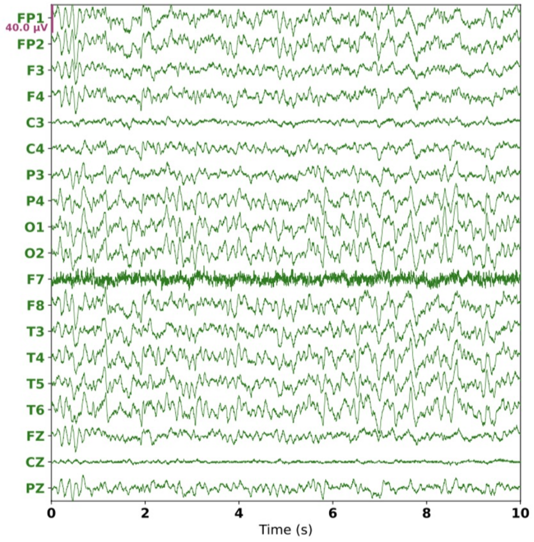
epilepsy



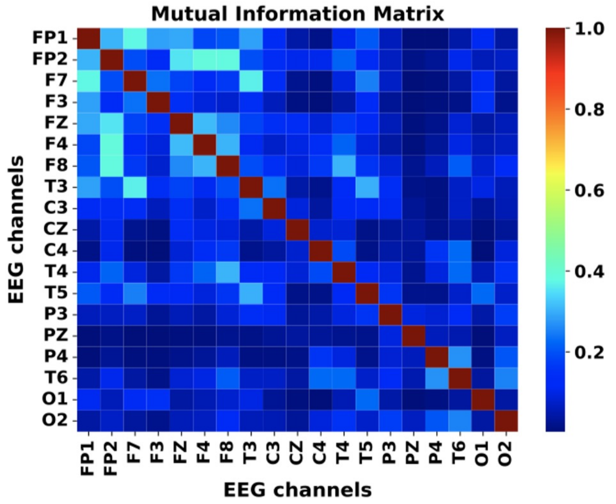
no epilepsy



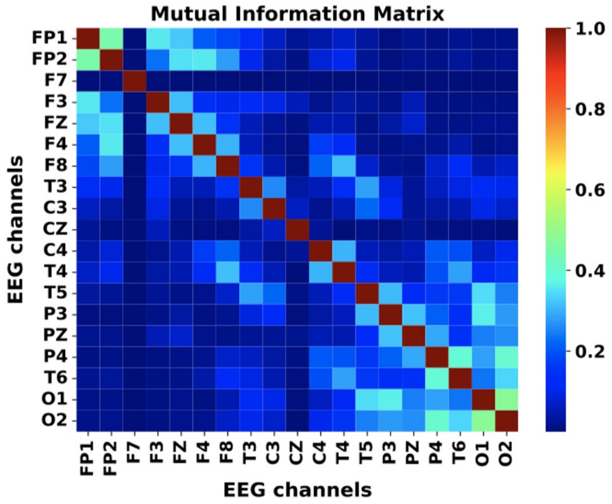
epilepsy



no epilepsy



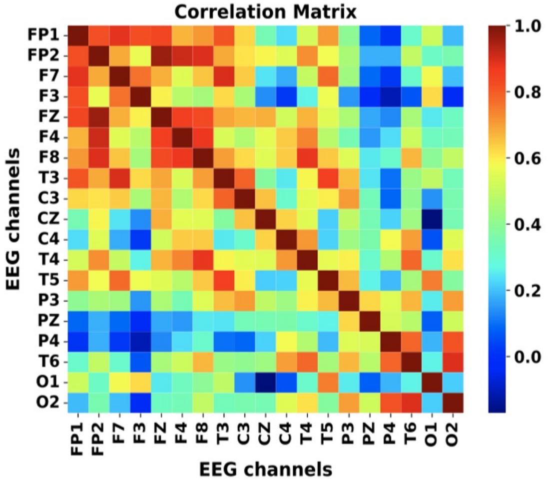
epilepsy



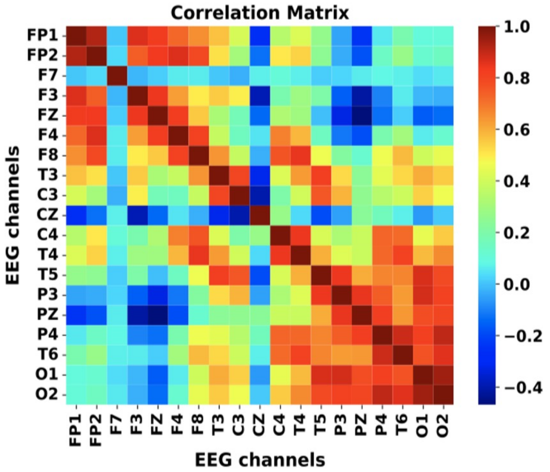
no epilepsy

Functional Connectivity Heatmaps

Original data



epilepsy



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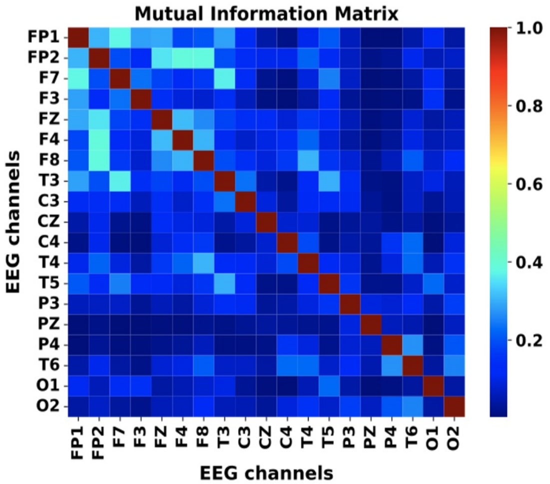
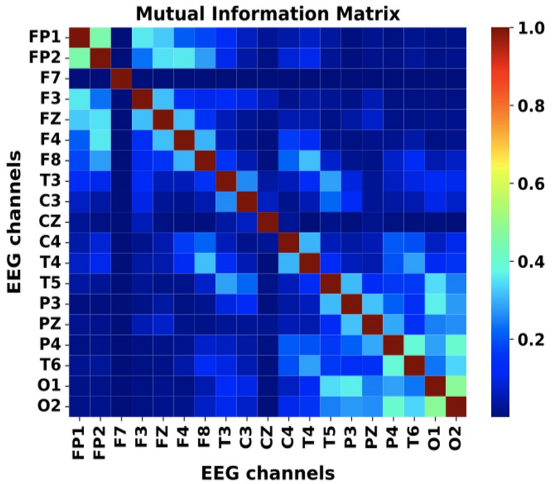
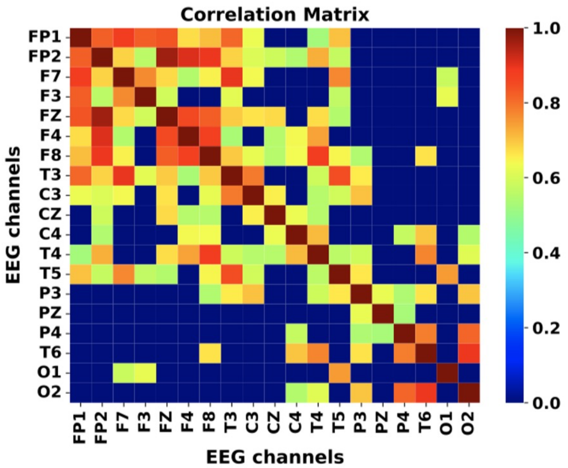


epilepsy

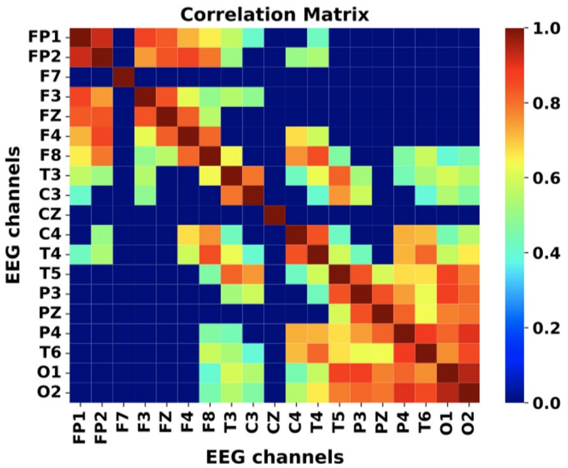


no epilepsy

After application of 50% proportional thresholding



epilepsy



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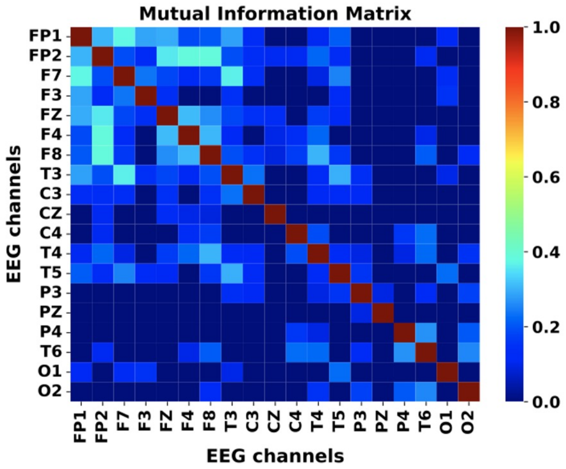
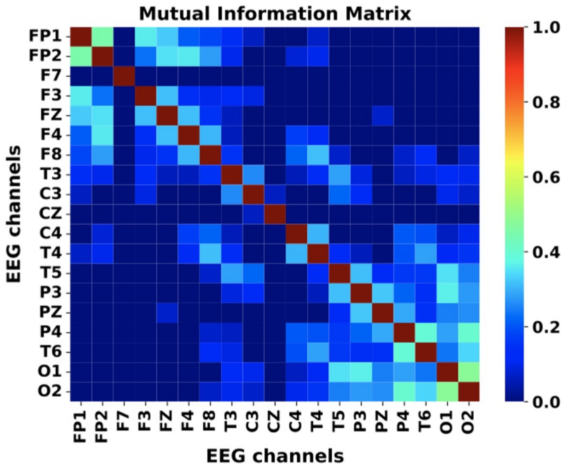
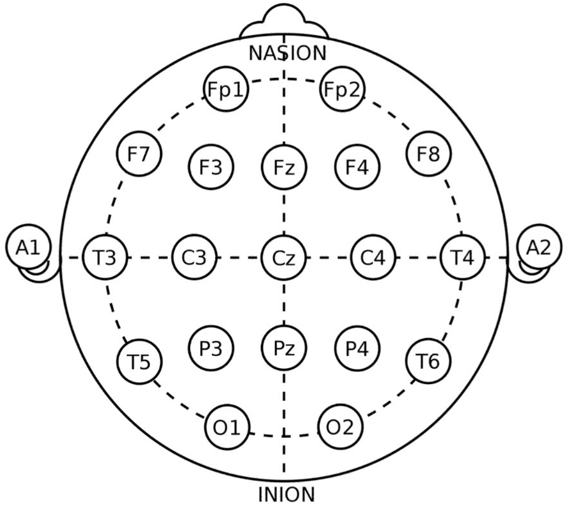


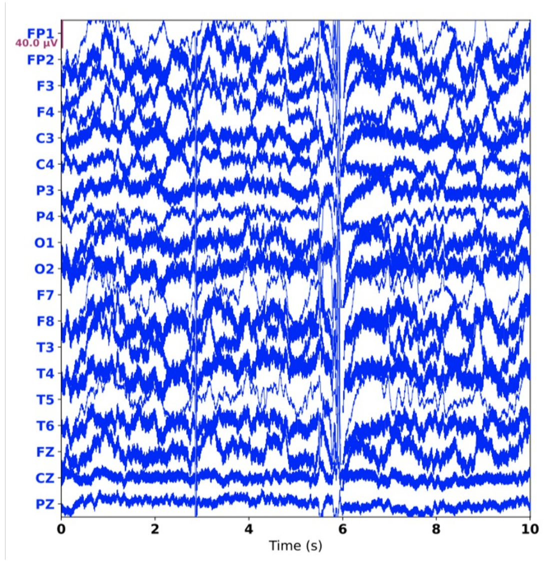
epilepsy



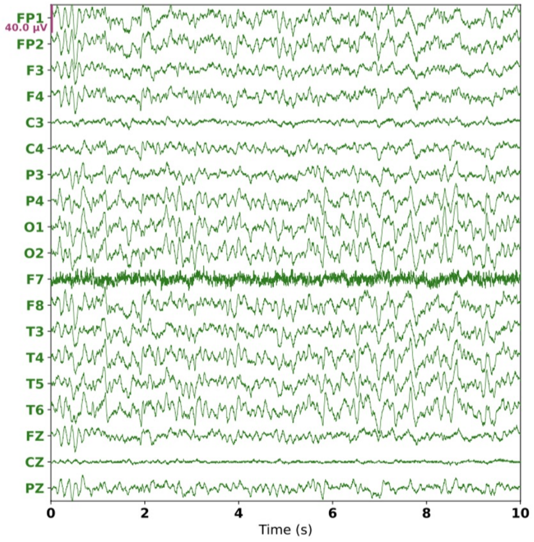
no epilepsy

Hierarchical Clustering Analysis - Dendrograms

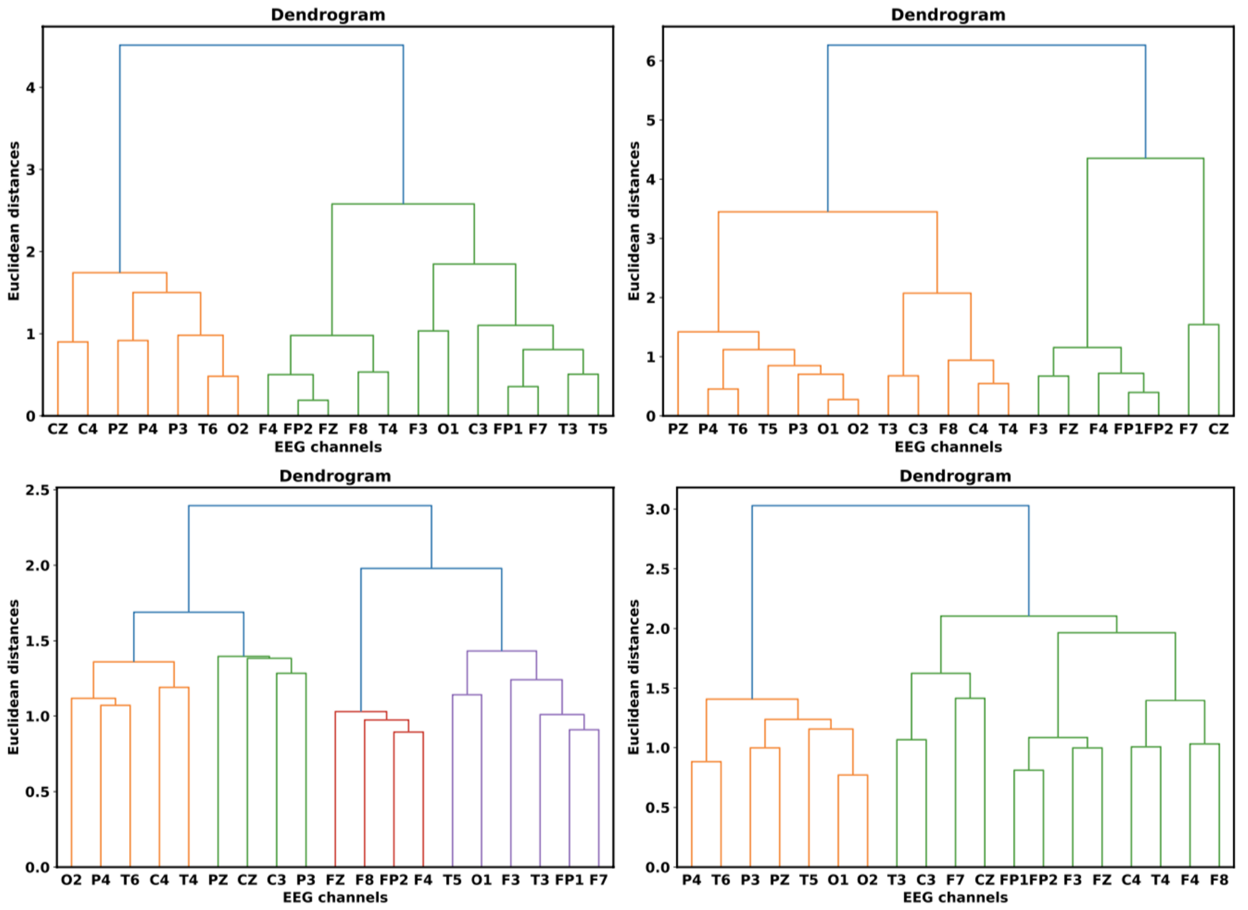




epilepsy



no epilepsy



Mutual Information

Correlation

epilepsy

no epilepsy

Proportional Thresholding – Selecting the Threshold Level

Find a threshold that is enough to make a significant difference in global efficiencies between the functional connectivity graphs of the two groups.

Global efficiency	Epilepsy		No Epilepsy		T-test	
	mean	std	mean	std	T-score	p-value
Mutual Information	0.732	0.032	0.744	0.043	2.145	0.033
Correlation	0.721	0.066	0.74	0.069	1.91	0.057

T-test for global efficiency between the FC graphs proportionally thresholded at 50%.

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NeuroImage
Volume 118, September 2015, Pages 651-661

The (in)stability of functional brain network measures across thresholds

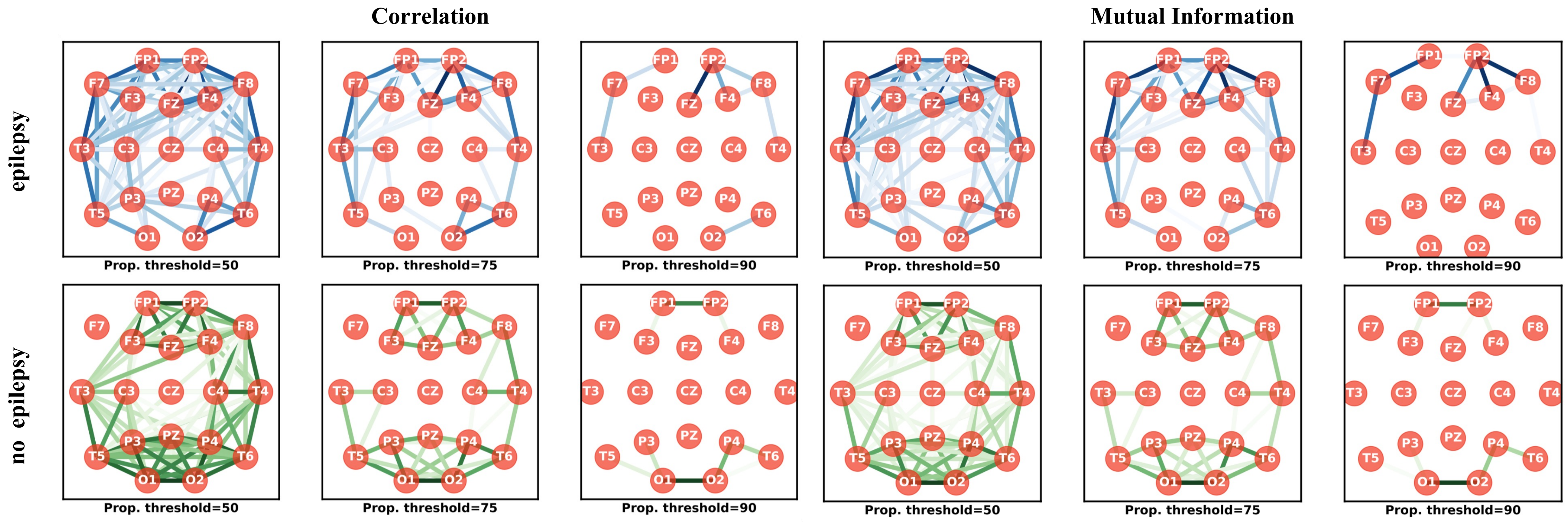
Kathleen A. Garrison [a], Dustin Scheinost [b], Emily S. Finn [c], Xilin Shen [b], R. Todd Constable [b, d]

Comparing Brain Networks of Different Size and Connectivity Density Using Graph Theory

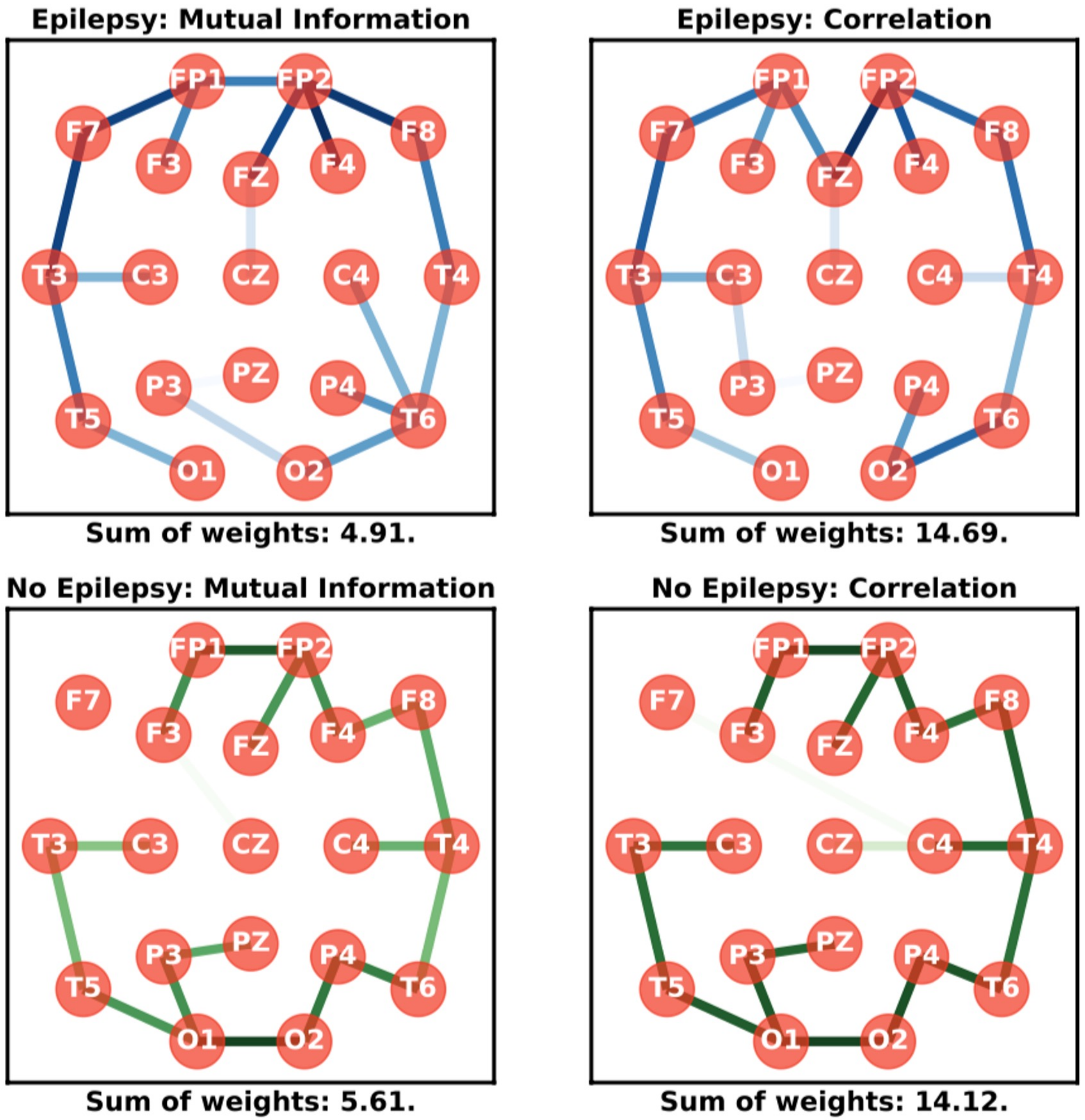
Bernadette C. M. van Wijk, Cornelis J. Stam, Andreas Daffertshofer

Published: October 28, 2010 • https://doi.org/10.1371/journal.pone.0013701

Proportional Thresholding – Effect on Functional Connectivity Graphs



Analysis of Maximum Spanning Trees



T-test results (p-value < 0.1) comparing Epilepsy and No Epilepsy groups: differences in node degrees of the Maximum spanning trees.

Correlation

Freq. bands	EEG channels	t-statistic	p-value
All [1-40 Hz]	FP2	1.821	0.070
All [1-40 Hz]	O2	-1.695	0.092
Alpha [8-12 Hz]	FZ	2.212	0.028
Beta [12-30 Hz]	F7	-2.372	0.019
Beta [12-30 Hz]	P4	1.896	0.059
Delta [1-4 Hz]	F7	1.676	0.095
Delta [1-4 Hz]	F8	1.810	0.072
Delta [1-4 Hz]	O2	-2.122	0.035

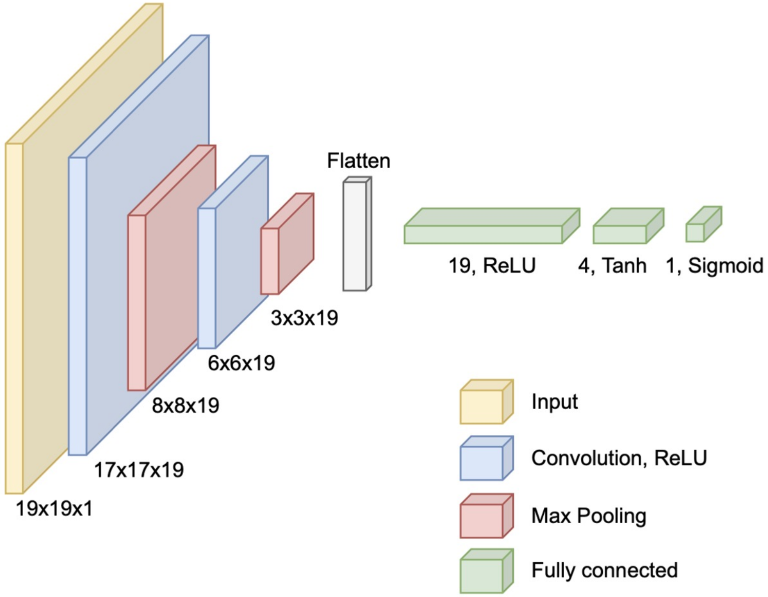
Mutual information

Freq. bands	EEG channels	t-statistic	p-value
All [1-40 Hz]	C4	1.661	0.098
Alpha [8-12 Hz]	T6	2.008	0.046
Beta [12-30 Hz]	P3	2.916	0.004
Beta [12-30 Hz]	P4	3.212	0.002
Delta [1-4 Hz]	F8	1.870	0.063
Theta [4-8 Hz]	CZ	1.922	0.056
Theta [4-8 Hz]	FP2	-1.689	0.093
Theta [4-8 Hz]	P4	2.022	0.045

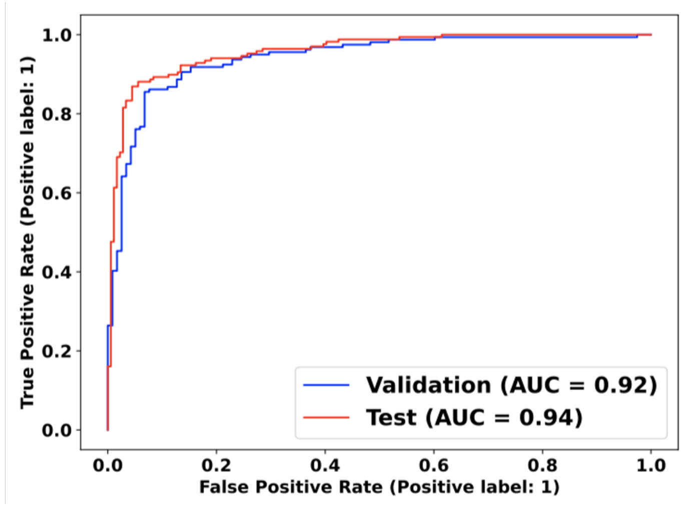
Convolutional Neural Network Model

The data

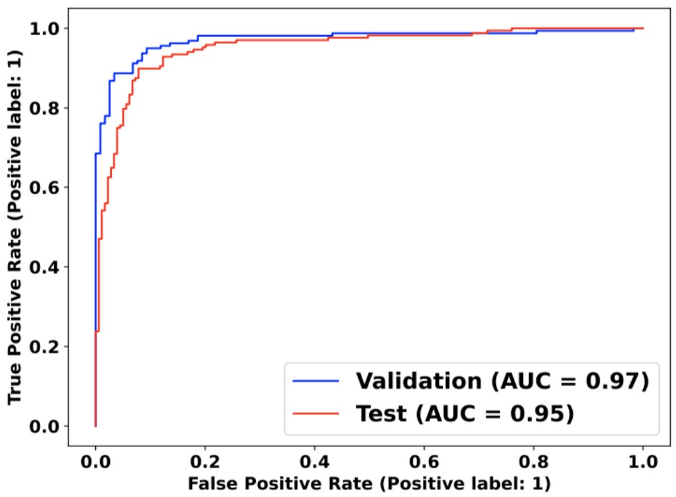
- 100 epileptic and 100 healthy subjects
- 60-second intervals, 1738 samples
- Correlation or Mutual information FC matrices
- Binary target = ‘epilepsy’ or ‘no epilepsy’



Correlation



Mutual Information



Metric on test set	Accuracy	ROC-AUC
Correlation	89%	94%
Mutual Information	89%	95%

		Predicted label			
		healthy	epileptic	healthy	epileptic
True label	healthy	157	22	151	28
	epileptic	17	151	11	157
		Correlation		Mutual Information	

Discussion and future work

Results and Future Work

Epileptic vs. healthy connectivity patterns

- Analyzing FC patterns can help to distinguish between epileptic and healthy persons.
- For healthy subject, clusters reflect geometric locations.
- Nodes in frontal and occipital brain regions are important to identify epilepsy.
- Analyzing FC networks across frequency bands is important.

Classification models based on functional graphs

- Functional connectivity matrices can be used in CNN-based models for classifying between epileptic and healthy subjects.
- Using non-overlapping windows of EEG signals helps to increase data volume for training neural network models.

Future work

- Analyse effective functional connectivity, e.g. Granger causality.
- Experiment with graph neural networks and extract graph representations.
- Work with model explainability methods.

Thank you!