Analysis of EEG-based Depression Biomarkers

Using Machine Learning & Nonlinear Analysis

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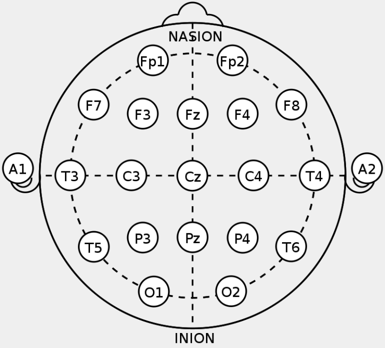
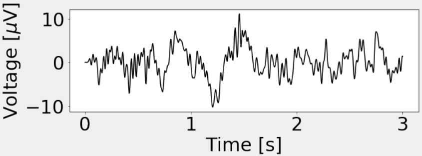
Problem Statement and Approach

Depression Treatment is Expensive

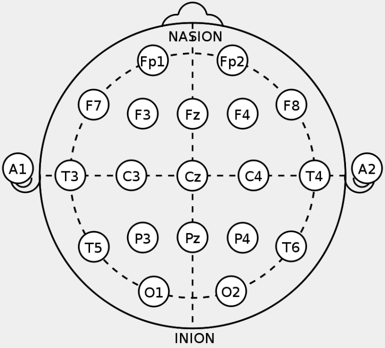
- MDD
- EEG



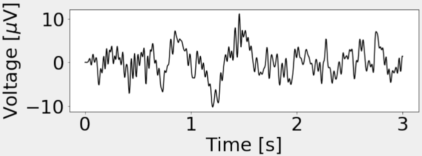


Depression Treatment is Expensive

- MDD
  - 300 million suffering worldwide



- EEG



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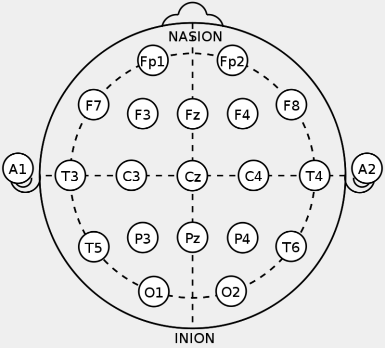
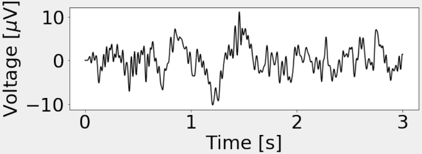
  - 300 million suffering worldwide
  - diagnosis requires time of trained professionals
- EEG





Depression Treatment is Expensive

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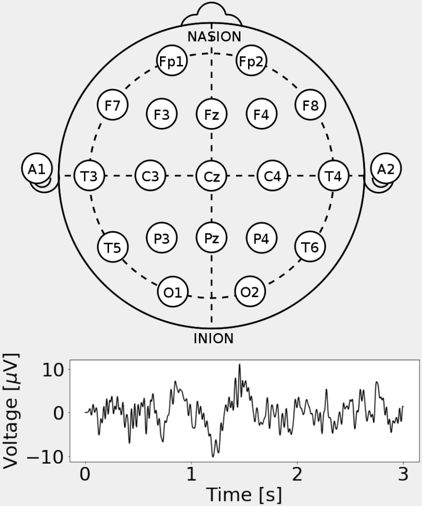
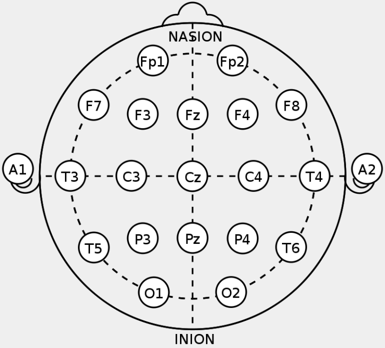
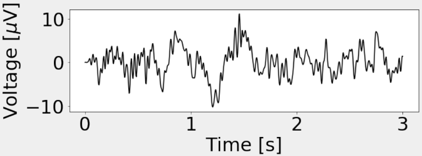
- EEG
    - accessible diagnosis-aid tool



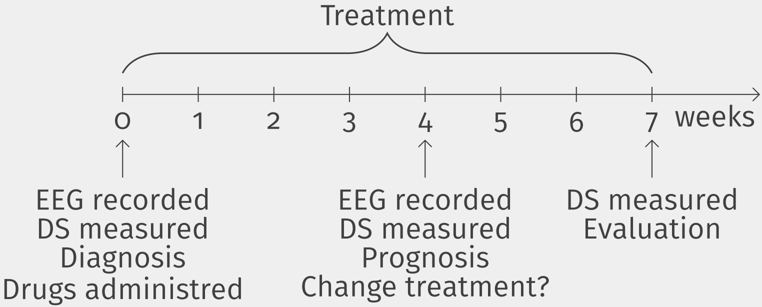
- MDD
    - 300 million suffering worldwide
    - diagnosis requires time of trained professionals
- EEG
    - accessible diagnosis-aid tool
    - still not reliable enough!

Research into effective analysis techniques is ongoing...





Our Goals


Treatment
0
1
2
3
4
5
6
7
weeks
EEG recorded
DS measured
Diagnosis
Drugs administred
EEG recorded
DS measured
Prognosis
Change treatment?
DS measured
Evaluation

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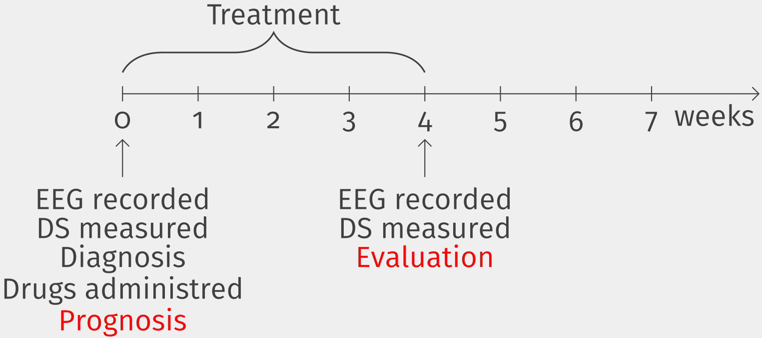
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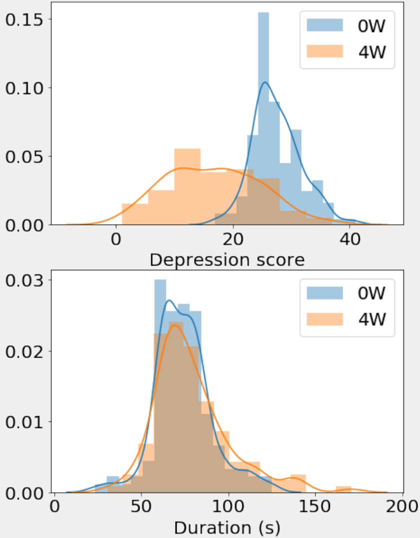
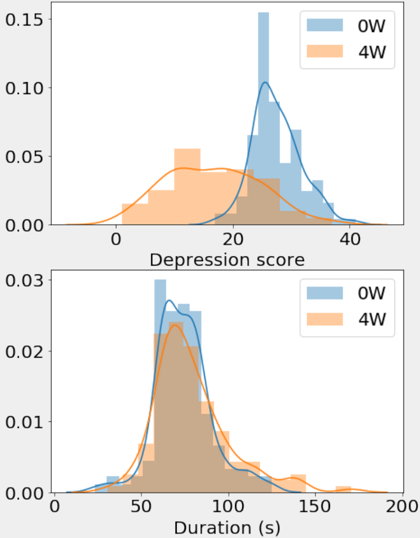
Our Dataset

- Czech National Institute of Mental Health



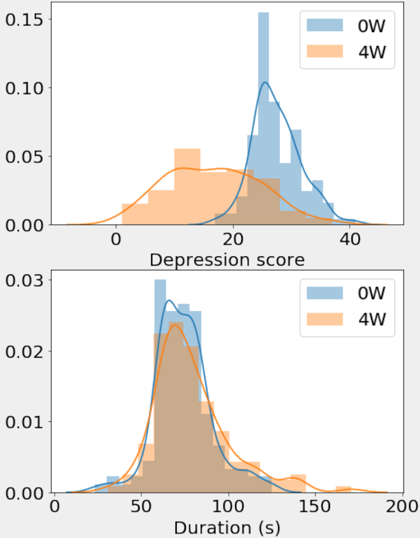
Our Dataset

- Czech National Institute of Mental Health
- 133 patients



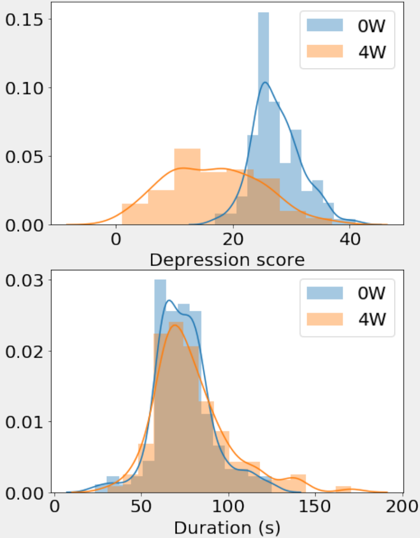
Our Dataset

- Czech National Institute of Mental Health
- 133 patients
- EEG recordings
  - 250 Hz or 1000 Hz
  - Various duration
  - 19 channels

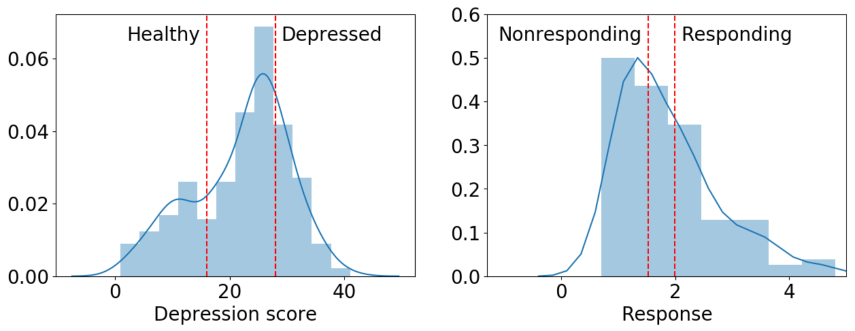


Our Dataset

- Czech National Institute of Mental Health
- 133 patients
- EEG recordings
  - 250 Hz or 1000 Hz
  - Various duration
  - 19 channels
- Metadata
  - Depression scores
    - Week 0
    - Week 4
  - Age, gender, drugs

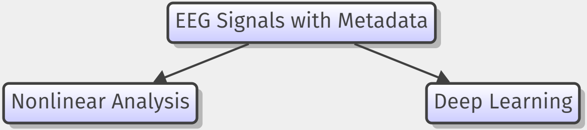


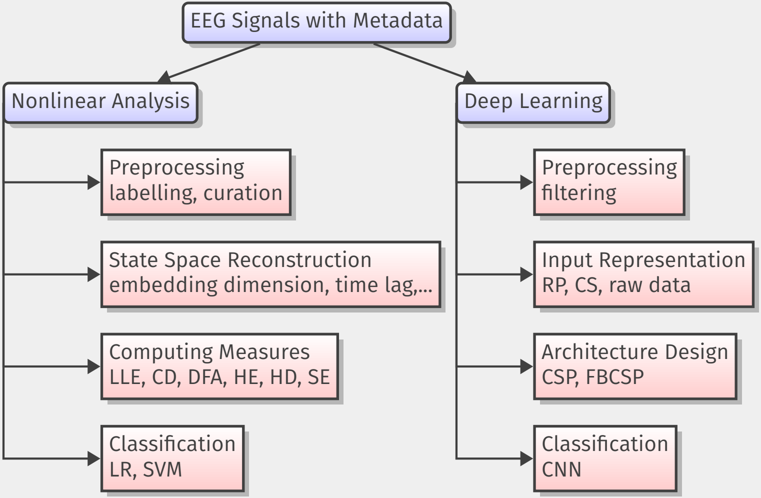
Labels



$$\text{Response} = \frac{\text{Depression score}_{\text{Week 4}}}{\text{Depression score}_{\text{Week 0}}}$$

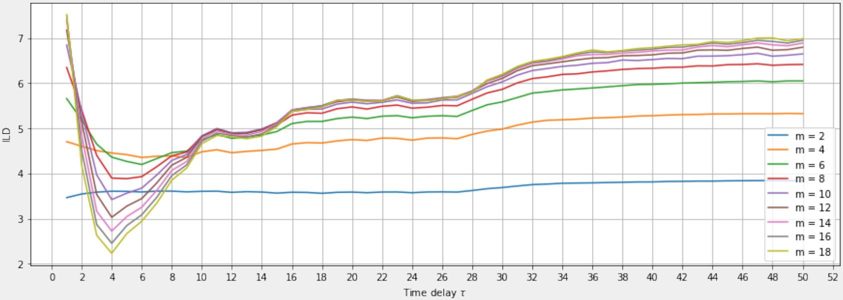
Our Approach




EEG Signals with Metadata
Nonlinear Analysis
Deep Learning
Preprocessing
labelling, curation
State Space Reconstruction
embedding dimension, time lag,...
Computing Measures
LLE, CD, DFA, HE, HD, SE
Classification
LR, SVM
Preprocessing
filtering
Input Representation
RP, CS, raw data
Architecture Design
CSP, FBCSP
Classification
CNN

Nonlinear Analysis Approach

LLE	Largest Lyapunov exponent	“stability”
SE	Sample entropy	
CD	Correlation dimension	“complexity”
HD	Higuchi fractal dimension	
DFA	Detrended fluctuation analysis	LRTC
HE	Hurst exponent	



Parameters

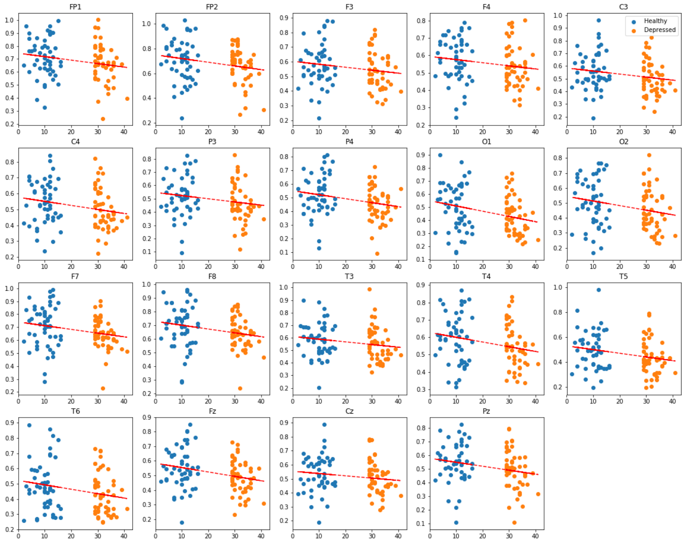
- Embedding dimension
- Time delay
- Scaling regions
- ...

Methods

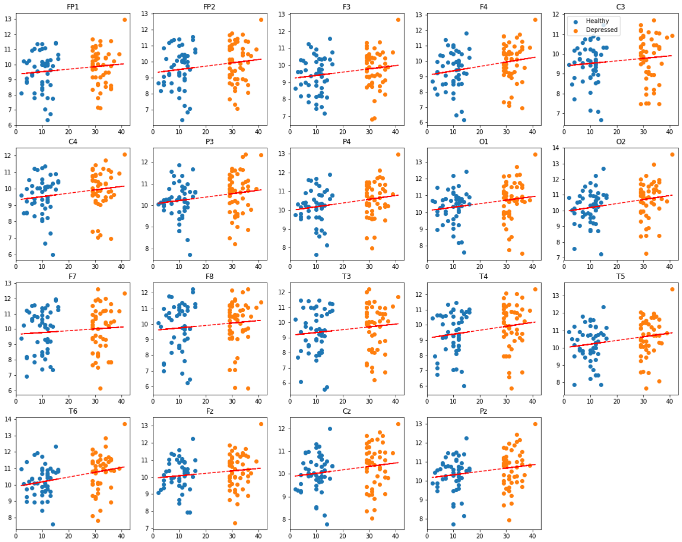
- Literature review
- Estimation algorithms (FNN, AFN, ADFD, ILD, ...)
- Result analysis

-> automated procedure

Correlation of DFA with DS



Correlation of LLE with DS



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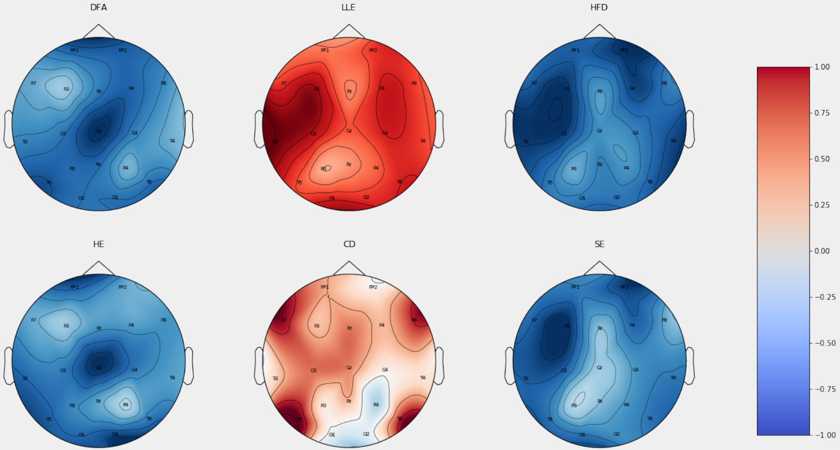
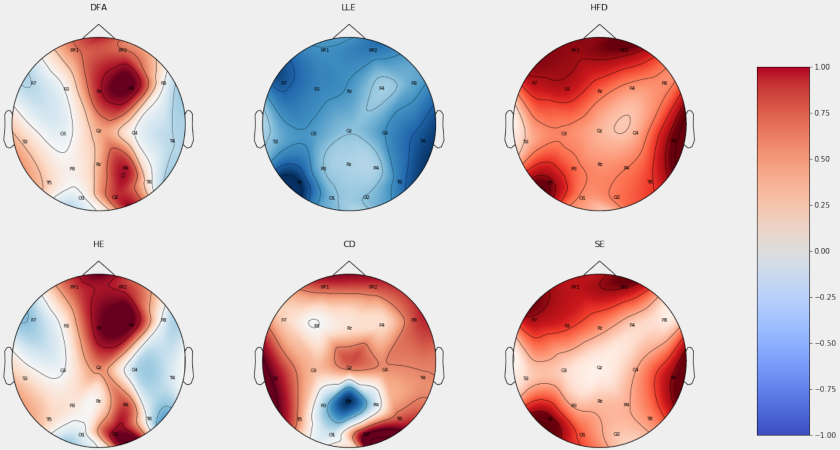


Correlations with response



Results

Measure	Classifier	Accuracy	
		Mean	Std
LLE, CD	SVM (lin.)	**0.74**	0.04
LLE, SE	SVM (lin.)	**0.75**	0.10
LLE, HE	SVM (lin.)	0.73	0.06
LLE, SE, DFA	SVM (lin.)	0.73	0.09
CD, HD	LR	0.73	0.10
LLE	SVM (lin.)	**0.72**	0.04
CD	SVM (lin.)	**0.71**	0.05
SE	LR	0.68	0.12
HD	SVM (rbf)	0.67	0.11
DFA	LR	0.67	0.16
HE	LR	0.67	0.17

(a) Current DS

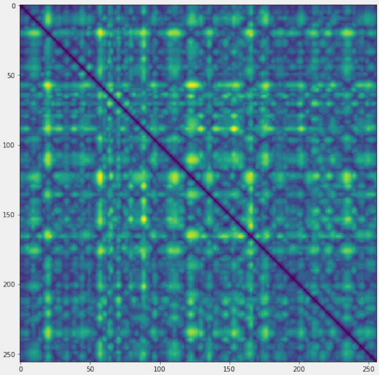
Measure	Classifier	Accuracy	
		Mean	Std
LLE, CD	SVM (lin.)	**0.75**	0.11
LLE, SE	SVM (lin.)	**0.75**	0.10
LLE	LR	**0.71**	0.08
CD	LR	**0.67**	0.09
HD	LR	0.66	0.05
SE	LR	0.66	0.09
DFA	SVM (lin.)	0.64	0.15
HE	SVM (rbf)	0.63	0.09

(b) Response prediction

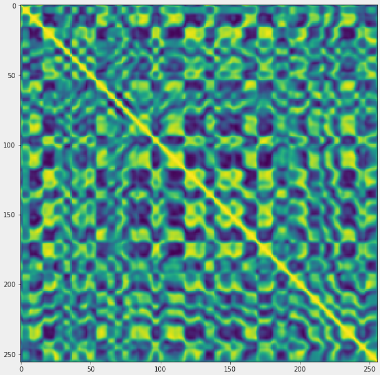
- 60 s samples
- 5f-CV on 100 recordings

Deep Learning Approach

Input Representation



(a) Recurrence plot (RP)

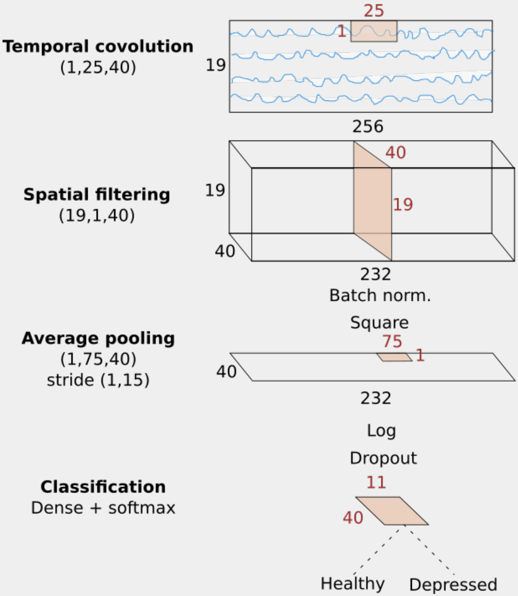


(b) Cosine similarity (CS)

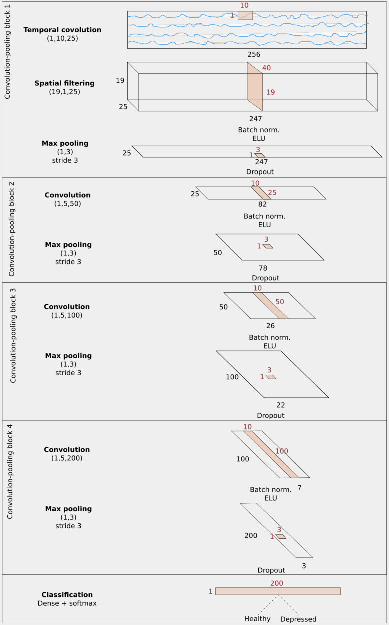
Multivariate GAFs?

(c) Raw data

Architecture Design - Shallow



Architecture Design - Deep



Results

Lab.	Freq.	Arch.	Accuracy	
			Mean	Std
DEP	$0 - f_{\text{fin}}$	SHAL	0.85	0.13
	$4 - f_{\text{fin}}$	SHAL	0.84	0.11
	$0 - f_{\text{fin}}$	DEEP	**0.86**	0.01
	$4 - f_{\text{fin}}$	DEEP	0.85	0.02
RES	$0 - f_{\text{fin}}$	SHAL	**0.94**	0.02
	$4 - f_{\text{fin}}$	SHAL	0.94	0.03
	$0 - f_{\text{fin}}$	DEEP	0.88	0.01
	$4 - f_{\text{fin}}$	DEEP	0.86	0.02

(a) Raw data

Lab.	Freq.	Arch.	Accuracy	
			Mean	Std
DEP	$0 - f_{\text{fin}}$	RP	**0.63**	0.02
	$4 - f_{\text{fin}}$	RP	0.61	0.01
	$0 - f_{\text{fin}}$	CS	0.59	0.02
	$4 - f_{\text{fin}}$	CS	0.58	0.01
RES	$0 - f_{\text{fin}}$	RP	0.61	0.03
	$4 - f_{\text{fin}}$	RP	**0.65**	0.02
	$0 - f_{\text{fin}}$	CS	0.55	0.02
	$4 - f_{\text{fin}}$	CS	0.63	0.01

(b) Image-encoded data

Dataset	DEP		RES	
	Neg.	Pos.	Neg.	Pos.
Training	3278	3230	2684	2705
Validation	826	802	686	662
Test	**1038**	**997**	**830**	**855**

1 s samples

Conclusion

Contributions

1. Largest Lyapunov exponent seem to be predictive of treatment response.

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4. Analysis of nonlinear measure and input parameter estimation algorithms and procedures for EEG analysis.

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1. Largest Lyapunov exponent seem to be predictive of treatment response.
2. Analysis of correlations between nonlinear measures and
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3. Analysis of spatial distribution across brain regions in depression.
4. Analysis of nonlinear measure and input parameter estimation algorithms and procedures for EEG analysis.
5. Evaluation of FBCSP-inspired neural network architectures for depression diagnosis and prognosis.

Limitations and Future Work

Limitations

- Binary output
- Most patients initially depressed and in remission

NL approach

- Nonstationarity (windowing?)
- Spatially local
- Temporally global
- Inconclusive surrogate tests
- "Theoretically too ambitious"

DL approach

- Short samples

Future Work

- Implement application to aid treatment
- Generalization to other datasets (sample bias)
- Output depression severity measure
- Ensemble of models combining (neuroimaging) modalities
- Incorporate information about treatment details (drugs,...)

NL approach

- Compare with spatial embedding
- New (spatiotemporal) measures

DL approach

- Model interpretation
- Compare with FBCSP
- Dimensionality reduction techniques

References I

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Thank you for attention