Analysis of EEG-based Depression Biomarkers

Using Machine Learning & Nonlinear Analysis

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FJFI

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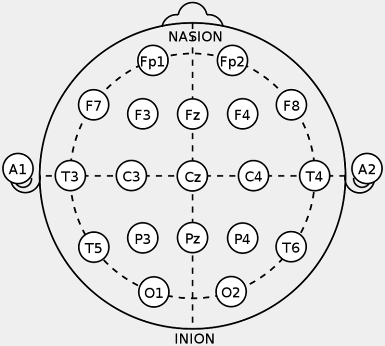
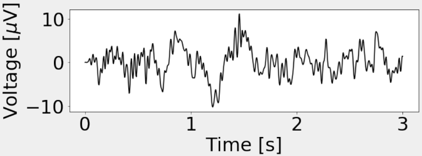
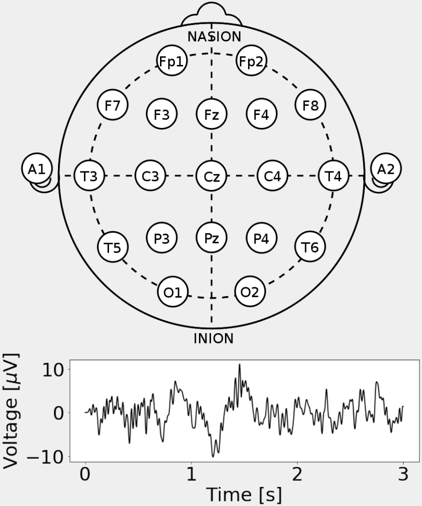
Problem Statement and Approach

- MDD
- EEG


NASION
Fp1
Fp2
F7
F3
Fz
F4
F8
A1
T3
C3
Cz
C4
T4
A2
T5
P3
Pz
P4
T6
O1
O2
INION

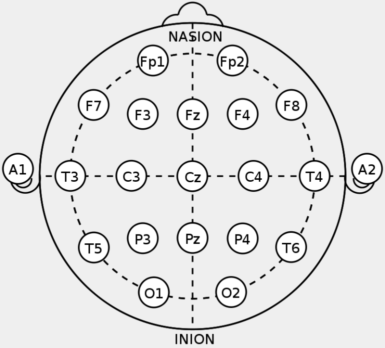

Voltage [μV]
10
0
−10
0
1
2
3
Time [s]

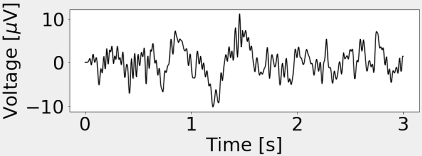
- MDD
  - 300 million suffering worldwide
- EEG



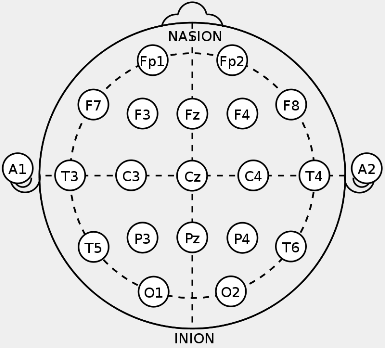
Depression Treatment is Expensive

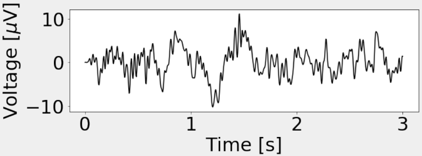
- MDD
  - 300 million suffering worldwide
  - diagnosis requires time of trained professionals
- EEG





- MDD
  - 300 million suffering worldwide
  - diagnosis requires time of trained professionals
- EEG
  - accessible diagnosis-aid tool

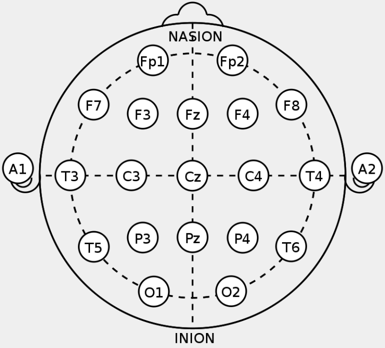


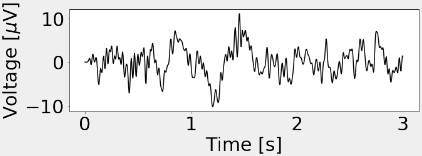


Depression Treatment is Expensive

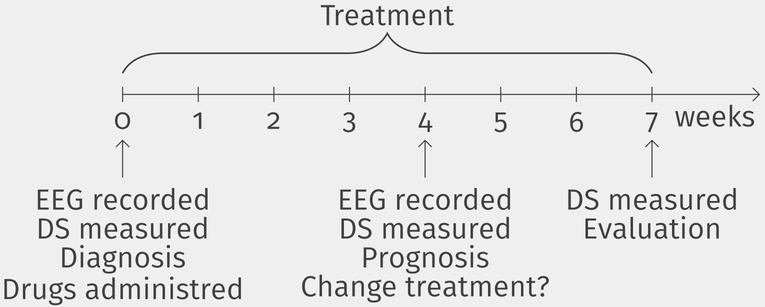
- MDD
  - 300 million suffering worldwide
  - diagnosis requires time of trained professionals
- EEG
  - accessible diagnosis-aid tool
  - still not reliable enough!

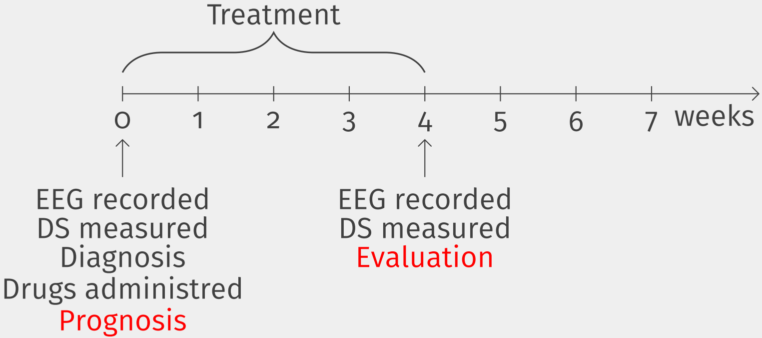
Research into effective analysis techniques is ongoing...





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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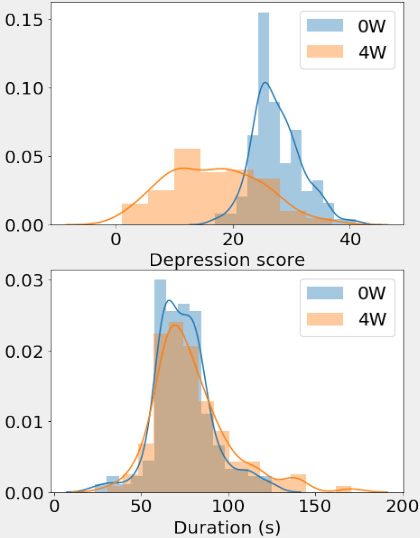
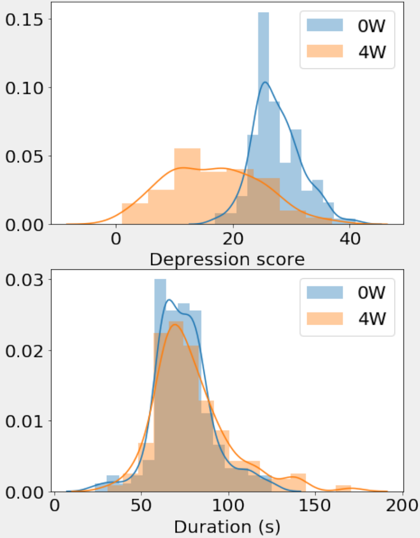
Our Dataset

- Czech National Institute of Mental Health



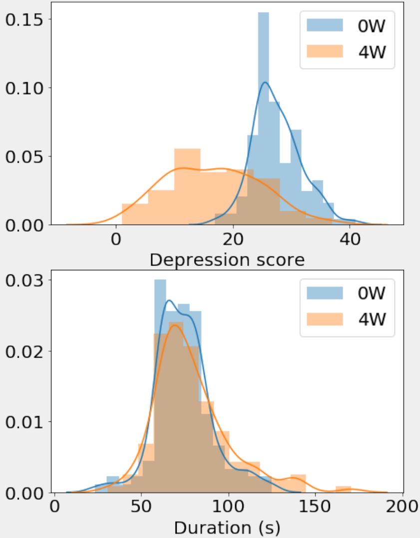
Our Dataset

- Czech National Institute of Mental Health
- 133 patients



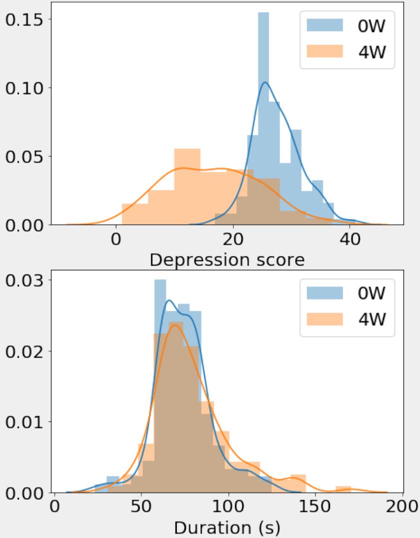
Our Dataset

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

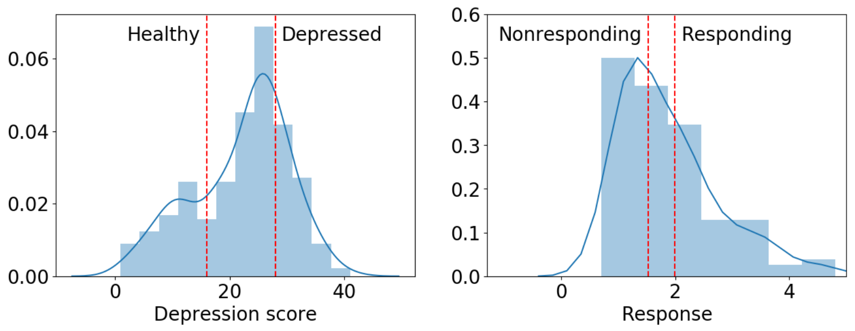


Our Dataset

- 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

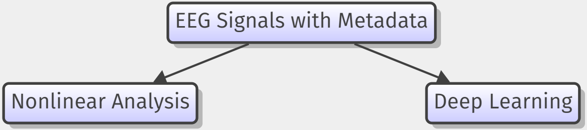


Labels

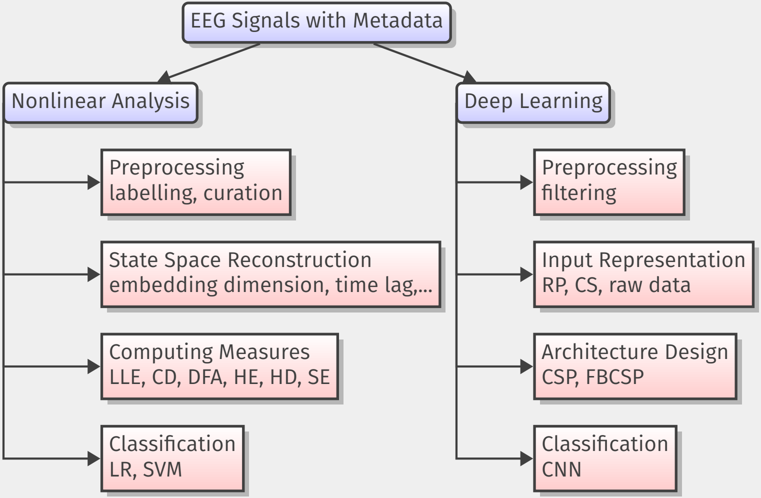


$$\text{Response} = \frac{\text{Depression score}_{\text{Week 4}}}{\text{Depression score}_{\text{Week 0}}}$$

Our Approach



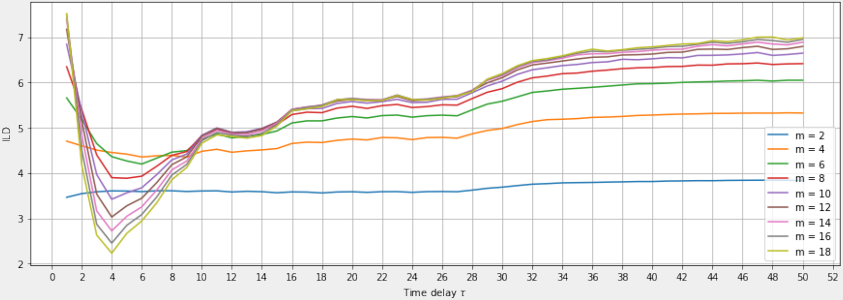
Our Approach



Nonlinear Analysis Approach

Nonlinear Measures

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

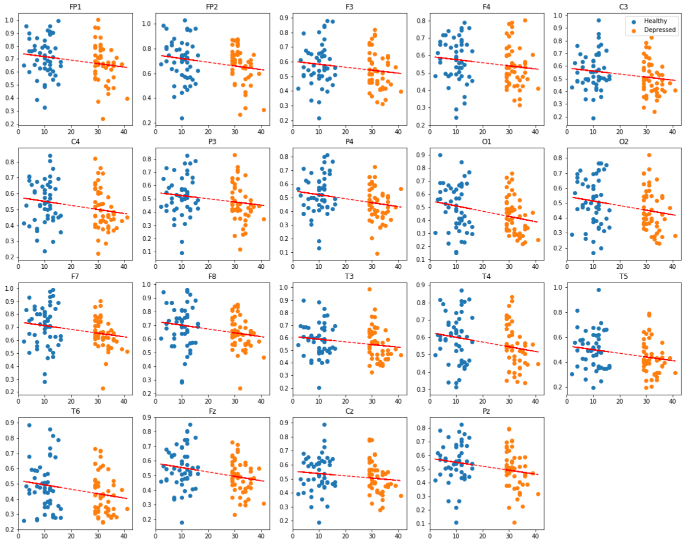
- Embedding dimension
- Time delay
- Scaling regions
- ...

Methods

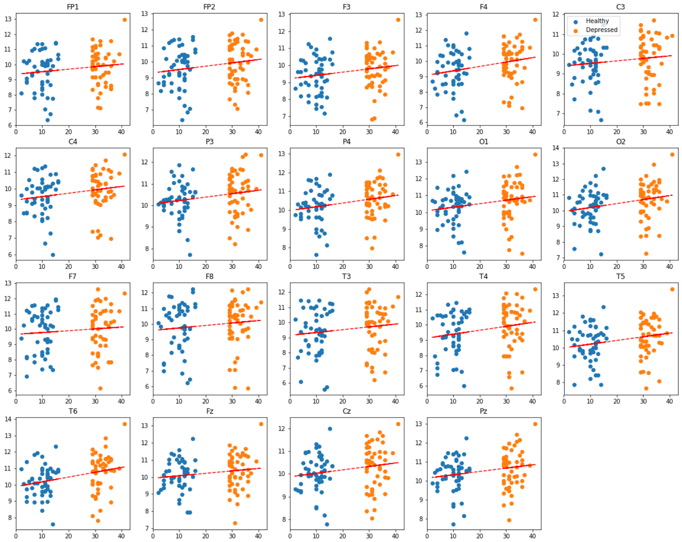
- Literature review
- Estimation algorithms (FNN, AFN, ADFD, ILD, ...)
- Result analysis

-> automated procedure

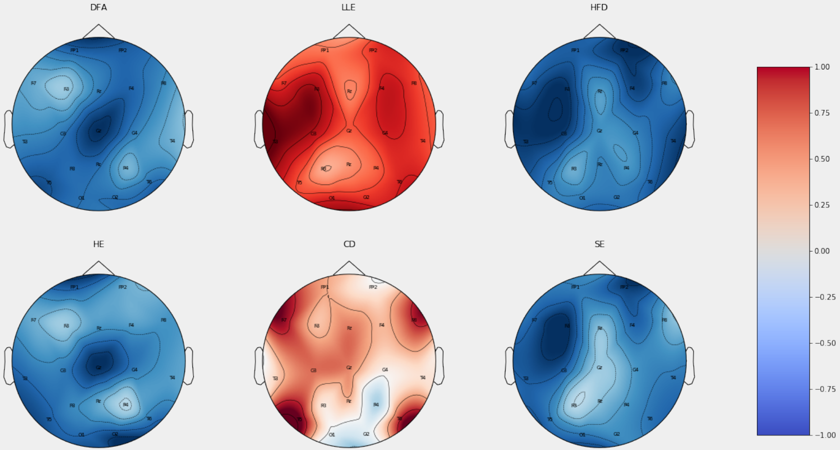
Correlation of DFA with DS



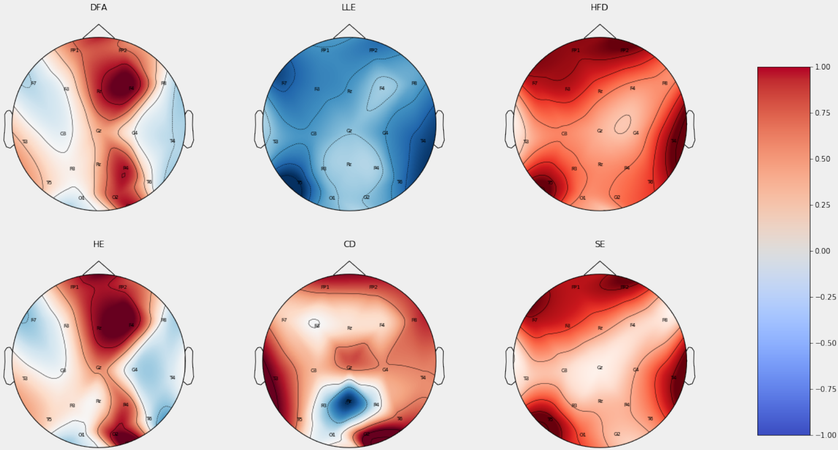
Correlation of LLE with DS



Correlations with DS



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

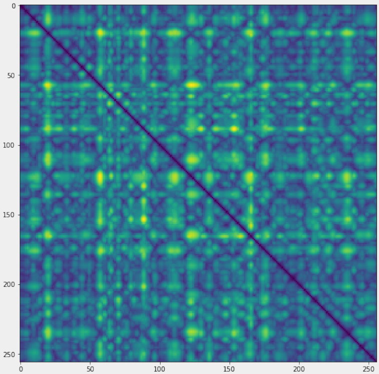
(a) Current DS

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

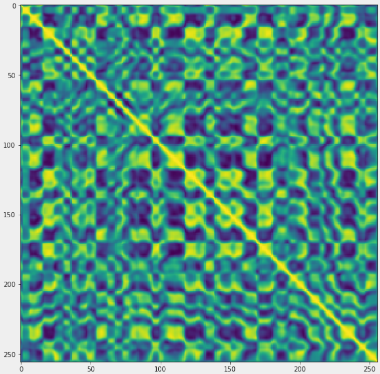
(b) Response prediction

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

Deep Learning Approach



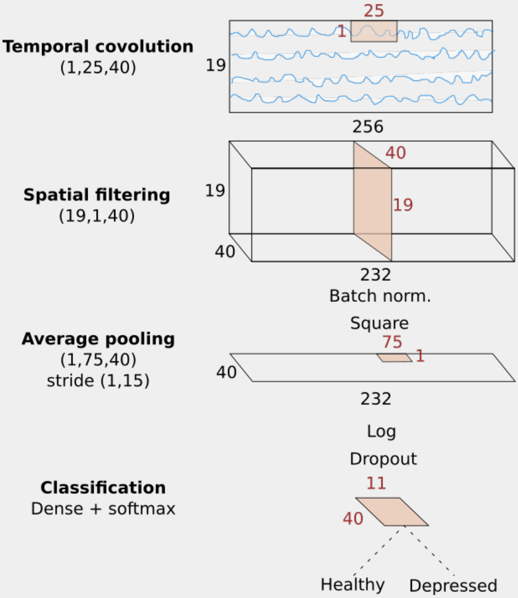
(a) Recurrence plot (RP)



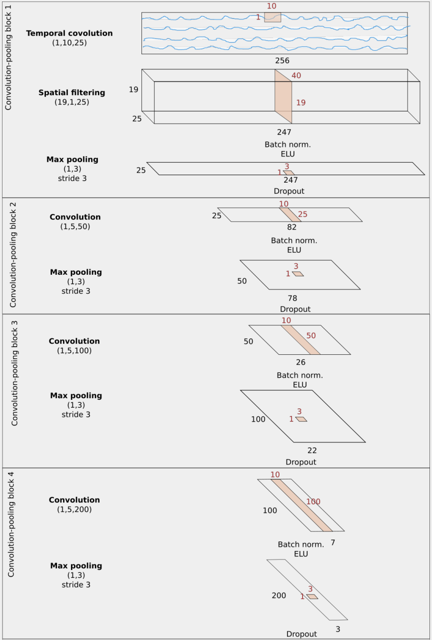
(b) Cosine similarity (CS)

(c) Raw

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

Summary

1. NL measures seem to be effective
   1.1 depression biomarkers (despite nonstationarity)
   1.2 predictors of treatment response

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    1.1 depression biomarkers (despite nonstationarity)
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2. LLE, CD and SE seem most discriminative (out of evaluated)
3. FBCSP-inspired CNN models seem highly effective for
    3.1 assesment of depression severity
    3.2 prediction of treatment response

Summary

1. NL measures seem to be effective
   1.1 depression biomarkers (despite nonstationarity)
   1.2 predictors of treatment response
2. LLE, CD and SE seem most discriminative (out of evaluated)
3. FBCSP-inspired CNN models seem highly effective for
   3.1 assesment of depression severity
   3.2 prediction of treatment response
4. RP and CS do not seem effective data encoding methods for EEG analysis
5. …

Summary

Limitations

- Binary output
- Most patients in remission

NL approach

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

DL approach

- Short samples
- Simple models

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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Questions