Analysis of EEG-based Depression Biomarkers

Using Machine Learning & Nonlinear Analysis

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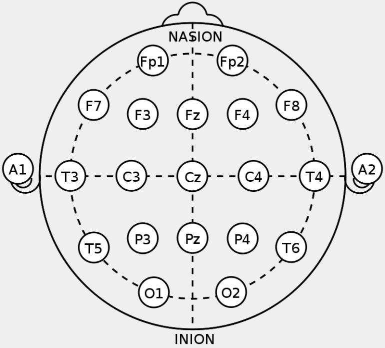
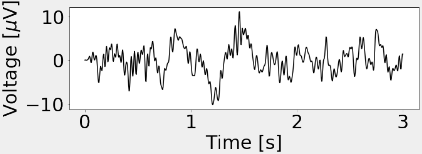
May 17, 2019

Problem Statement and Approach

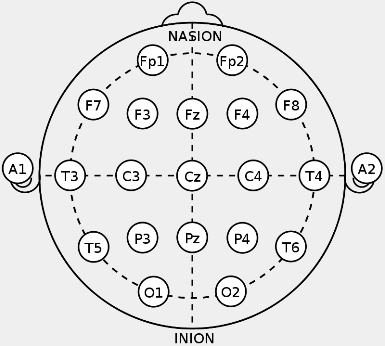
- MDD
- EEG

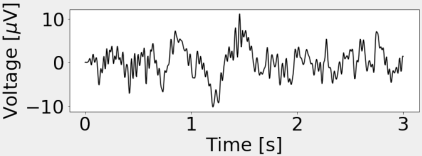

NASION
Fp1
Fp2
F7
F3
Fz
F4
F8
A1
T3
C3
Cz
C4
T4
A2
T5
P3
Pz
P4
T6
O1
O2
INION


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

Depression Treatment is Expensive

- MDD
  - 300 million suffering worldwide
- EEG





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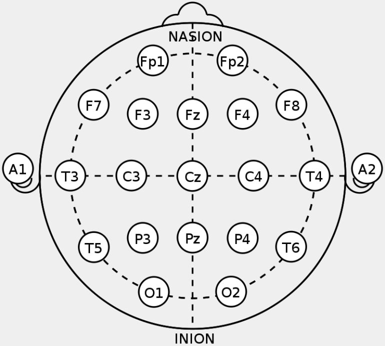
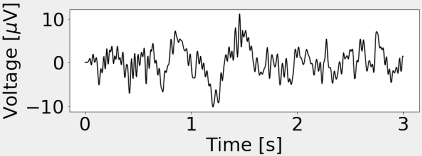
  - 300 million suffering worldwide
  - diagnosis requires time of trained professionals
- EEG





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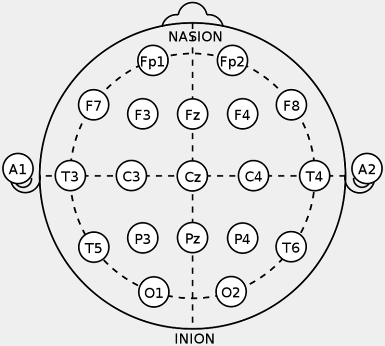
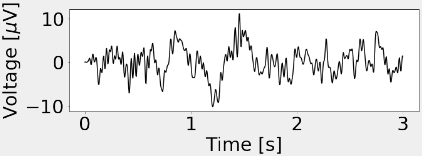
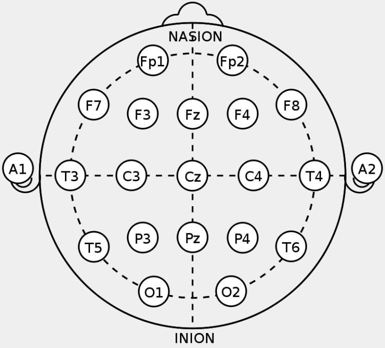


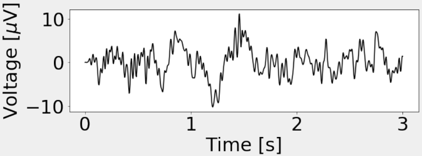


Depression Treatment is Expensive

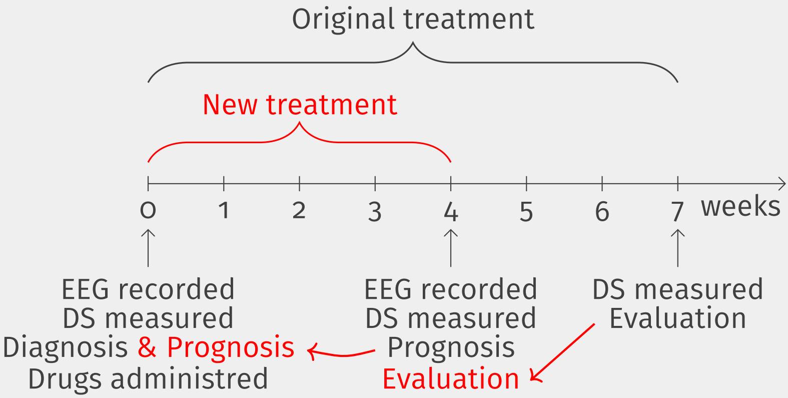
- MDD
  - 300 million suffering worldwide
  - diagnosis requires time of trained professionals
- EEG
  - accessible diagnosis-aid tool
  - still not reliable enough!

Research into effective analysis techniques is ongoing...





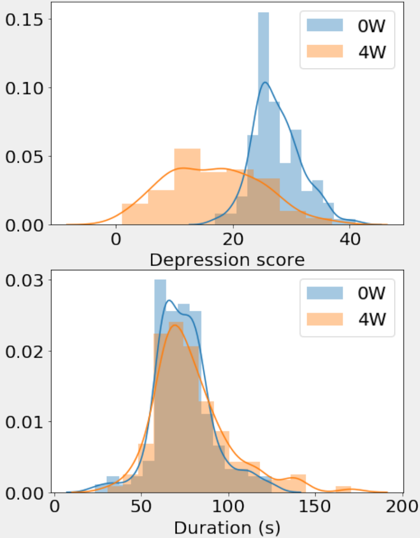
Our Goals



Original treatment
New treatment
0
1
2
3
4
5
6
7
weeks
EEG recorded
DS measured
Diagnosis & Prognosis
Drugs administred
EEG recorded
DS measured
Prognosis
Evaluation
DS measured
Evaluation

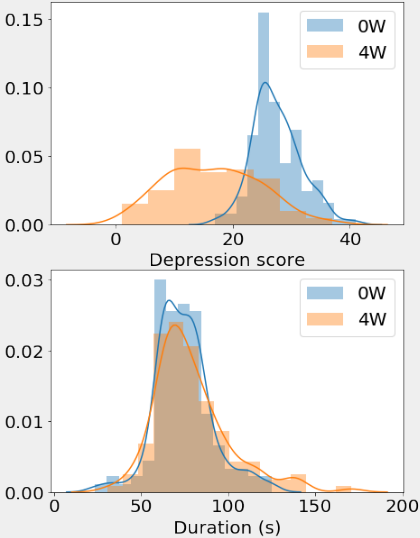
Our Dataset

- Czech National Institute of Mental Health



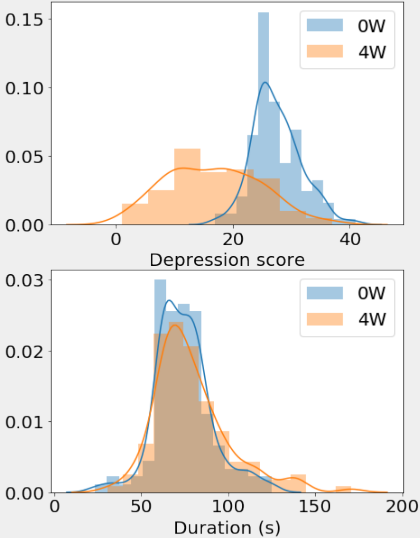
Our Dataset

- Czech National Institute of Mental Health
- 133 patients



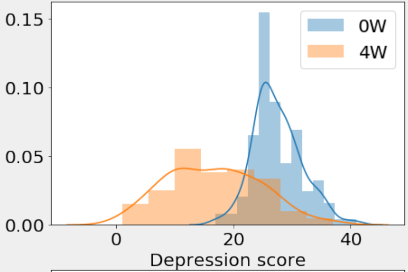
Our Dataset

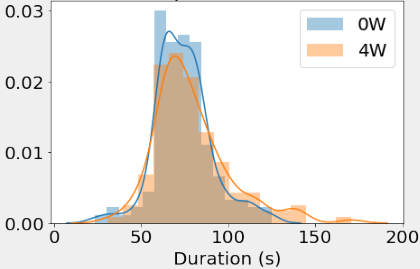
- Czech National Institute of Mental Health
- 133 patients
- EEG recordings
  - 250 Hz or 1000 Hz
  - Various duration
  - 19 channels



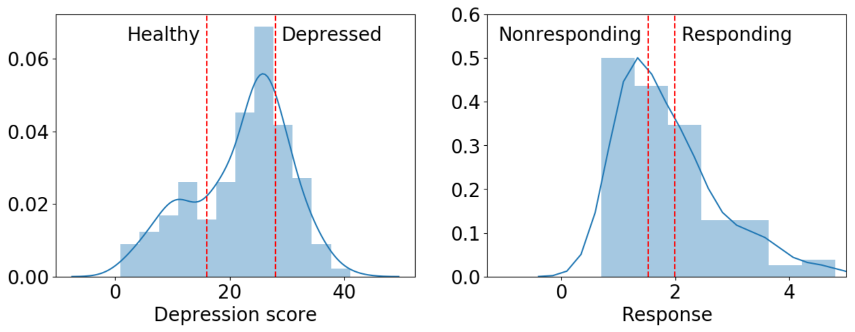
Our Dataset

- 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



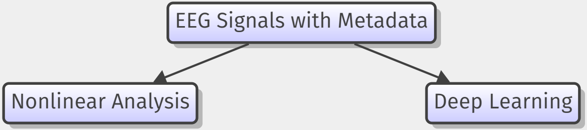


Labels



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

Our Approach



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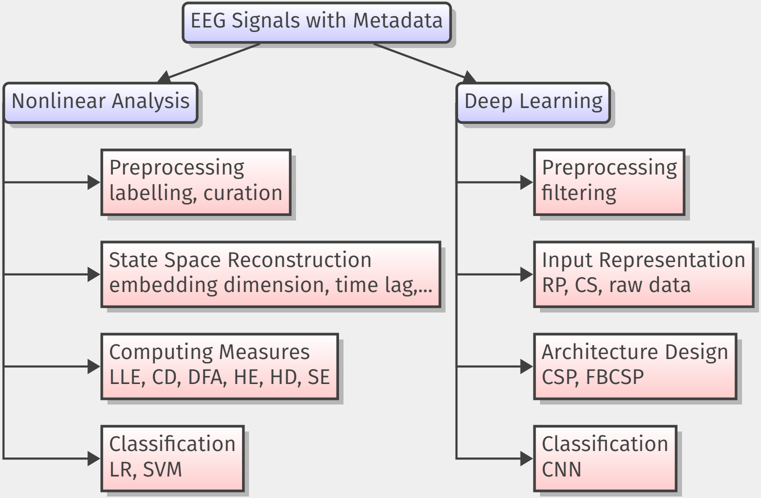
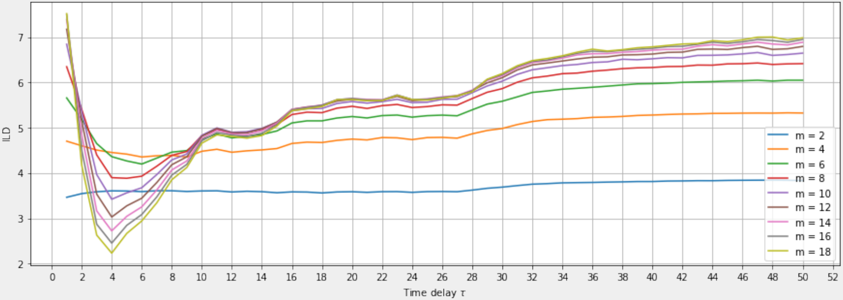


Nonlinear Analysis Approach

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

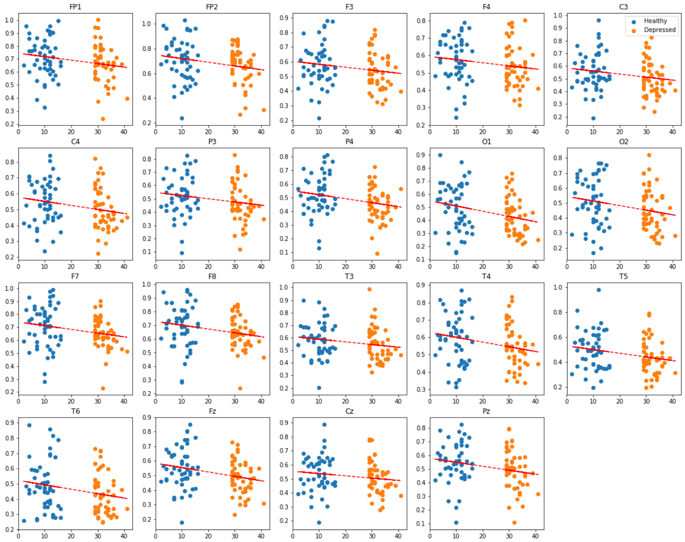
- Embedding dimension
- Time delay
- Scaling regions
- ...

Methods

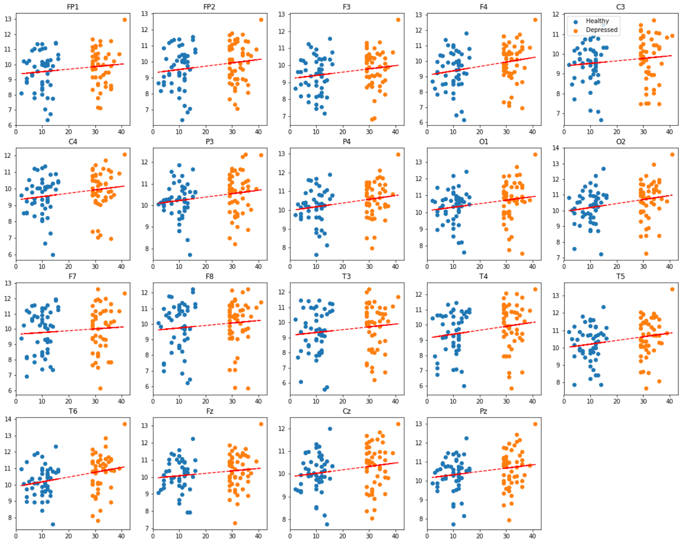
- Literature review
- Estimation algorithms (FNN, AFN, ADFD, ILD, ...)
- Result analysis

-> automated procedure

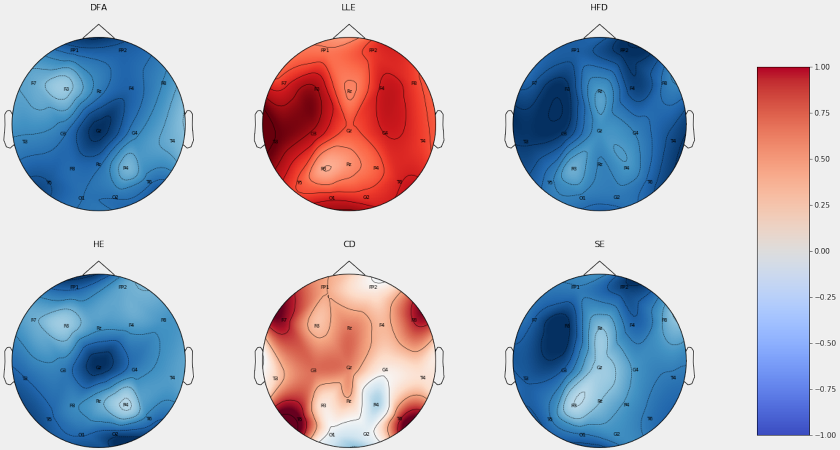
Correlation of DFA with DS



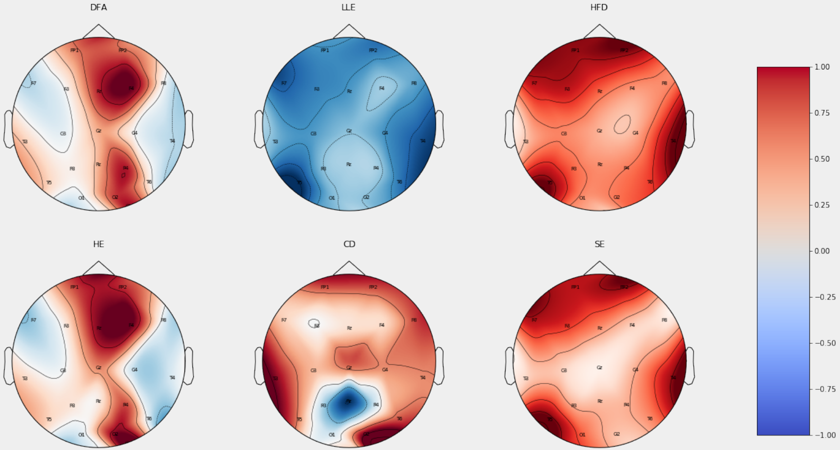
Correlation of LLE with DS



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

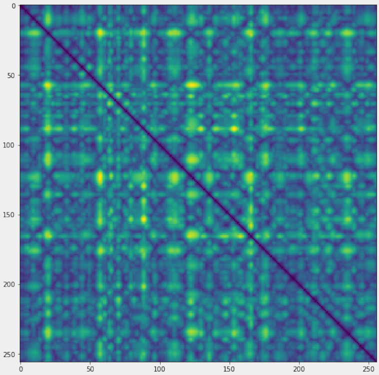
(a) Current DS

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

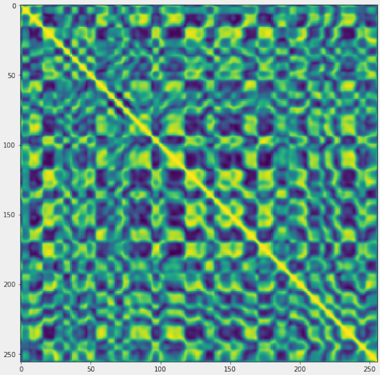
(b) Response prediction

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

Deep Learning Approach



(a) Recurrence plot (RP)

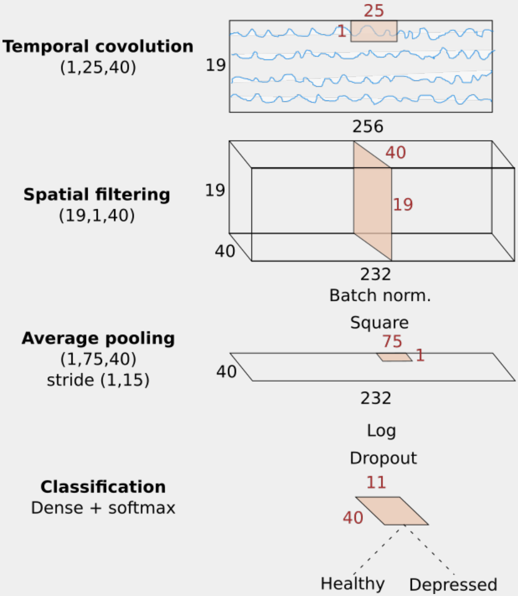


(b) Cosine similarity (CS)

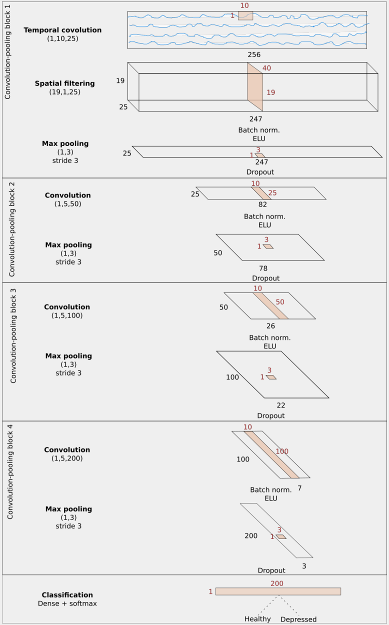
Multivariate GAFs?

(c) Raw data

Architecture Design - Shallow



Architecture Design - Deep



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.
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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

- 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

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Thank you for attention