Analysis of EEG-based Depression Biomarkers

Using Machine Learning & Nonlinear Analysis

Miroslav Kovář

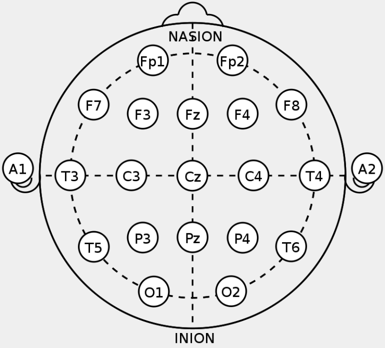
FJFI

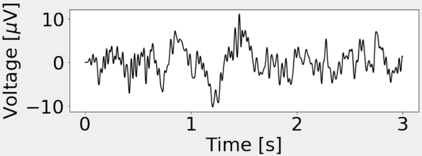
March 13, 2019

Problem Statement and Approach

Depression Treatment is Expensive

- MDD
- EEG

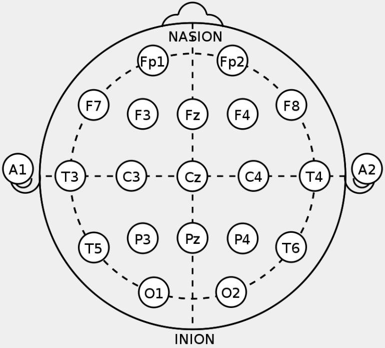


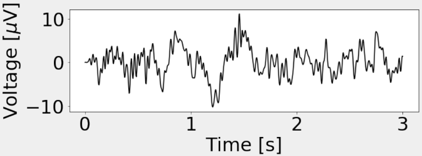


Depression Treatment is Expensive

- MDD
    - 300 million suffering worldwide

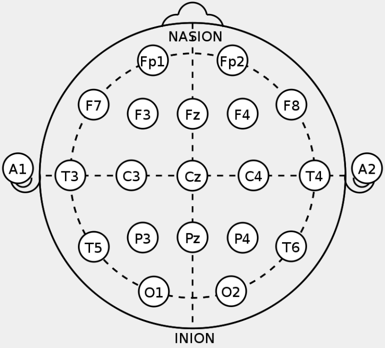
- EEG

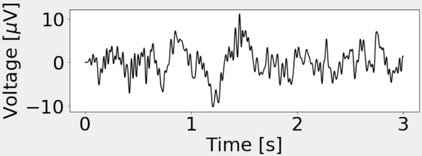




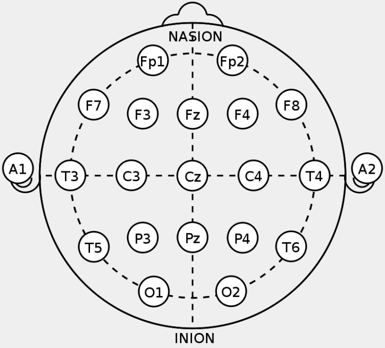
Depression Treatment is Expensive

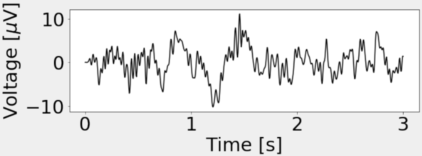
- MDD
  - 300 million suffering worldwide
  - diagnosis requires time of trained professionals
- EEG





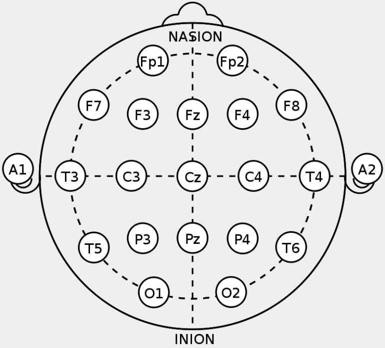
- MDD
  - 300 million suffering worldwide
  - diagnosis requires time of trained professionals
- EEG
  - accessible diagnosis-aid tool

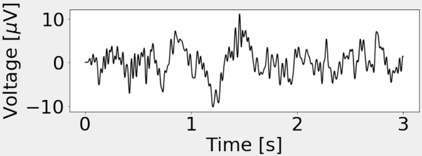




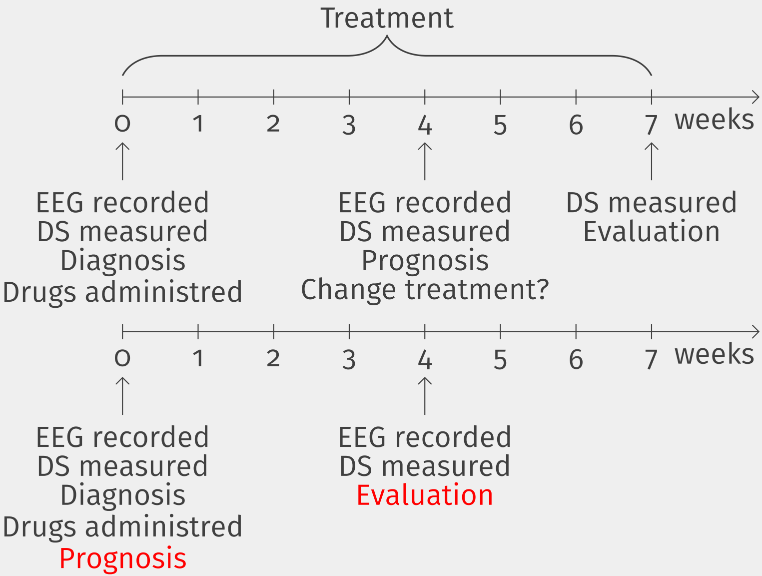
- MDD
  - 300 million suffering worldwide
  - diagnosis requires time of trained professionals
- EEG
  - accessible diagnosis-aid tool
  - also effective at prognosis? studied very little!

Research into effective analysis techniques is ongoing...

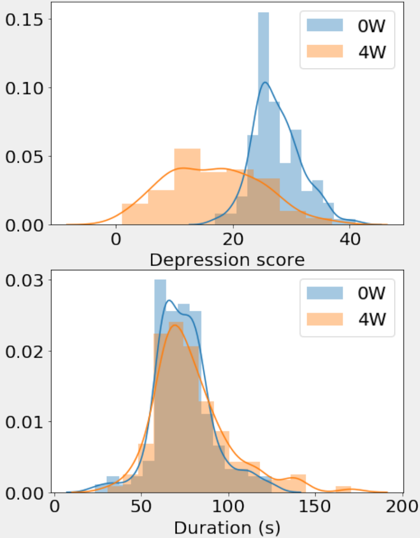




Our Goals

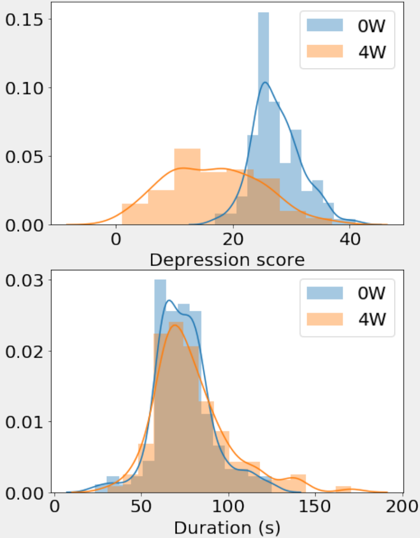

Treatment
0
1
2
3
4
5
6
7
weeks
EEG recorded
DS measured
Diagnosis
Drugs administred
EEG recorded
DS measured
Prognosis
Change treatment?
DS measured
Evaluation
0
1
2
3
4
5
6
7
weeks
EEG recorded
DS measured
Diagnosis
Drugs administred
Prognosis
EEG recorded
DS measured
Evaluation

Relatively large:



Relatively large:

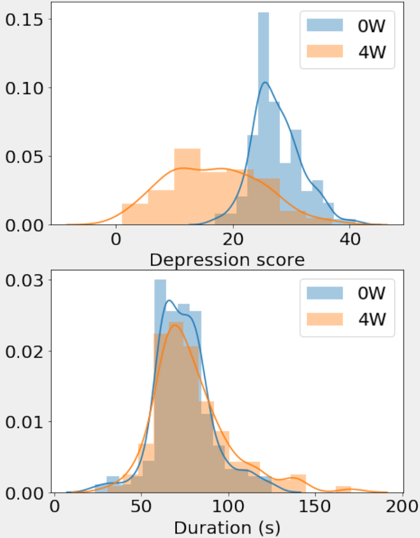
- 133 patients



Our Dataset

Relatively large:

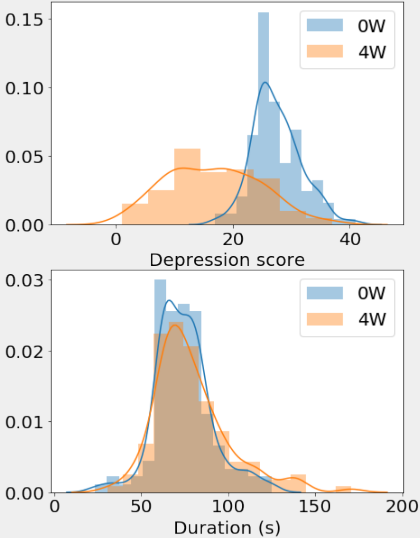
- 133 patients
- EEG recordings
  - 19 channels
  - 250 Hz or 1000 Hz
  - Various duration



Our Dataset

Relatively large:

- 133 patients
- EEG recordings
  - 19 channels
  - 250 Hz or 1000 Hz
  - Various duration
- Metadata
  - Depression scores
    - Week 0
    - Week 4
  - Age, gender, drugs

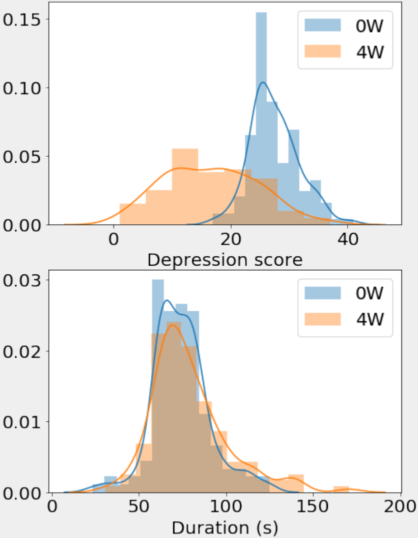


Our Dataset

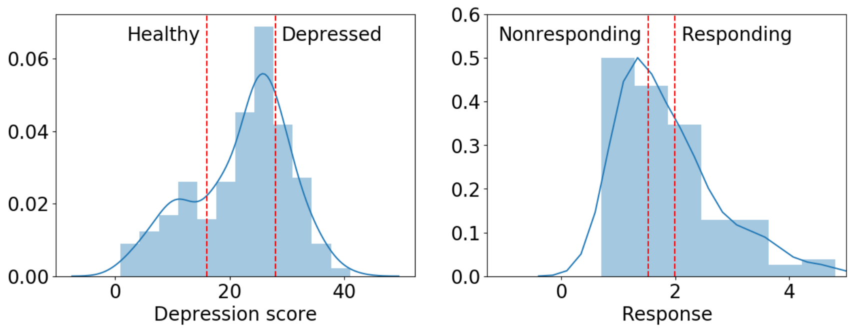
Relatively large:

- 133 patients
- EEG recordings
  - 19 channels
  - 250 Hz or 1000 Hz
  - Various duration
- Metadata
  - Depression scores
    - Week 0
    - Week 4
  - Age, gender, drugs

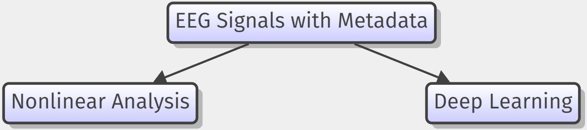
Obtained from Czech National Institute of Mental Health



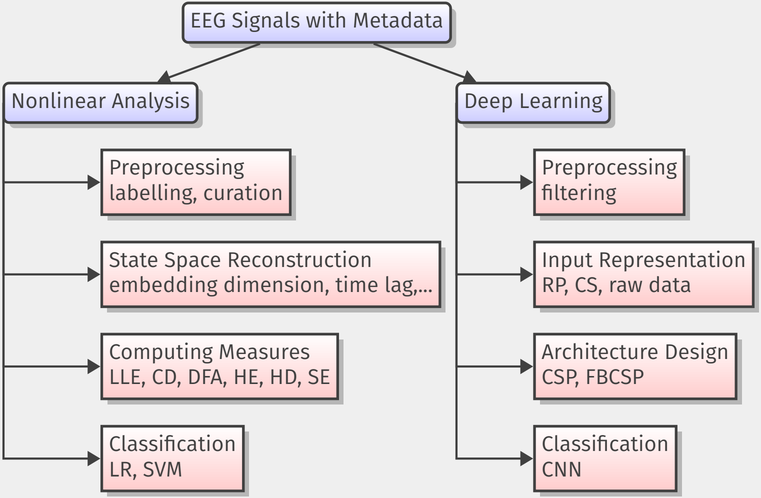
Labels



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


EEG Signals with Metadata
Nonlinear Analysis
Deep Learning

Our Approach



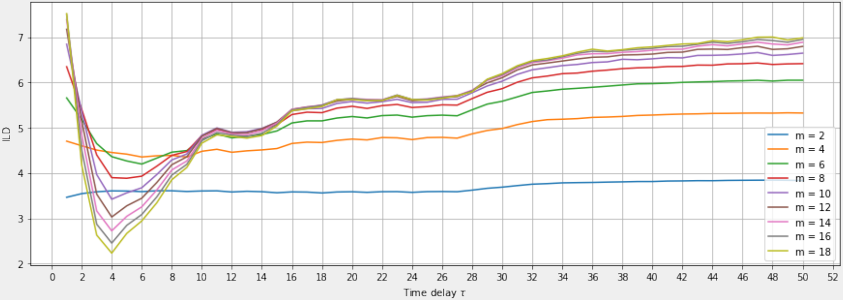
Nonlinear Analysis Approach

$$\left.\begin{array}{rl}\textbf{LLE} & \text{Largest Lyapunov exponent}\\ \textbf{SE} & \text{Sample entropy}\end{array}\right\}\text{"stability"}$$

$$\left.\begin{array}{rl}\textbf{CD} & \text{Correlation dimension}\\ \textbf{HD} & \text{Higuchi fractal dimension}\end{array}\right\}\text{"complexity"}$$

$$\left.\begin{array}{rl}\textbf{DFA} & \text{Detrended fluctuation analysis}\\ \textbf{HE} & \text{Hurst exponent}\end{array}\right\}\text{LRTC}$$

Embedding Parameter Estimation



Parameters

- Embedding dimension
- Time delay
- Scaling regions
- …

Methods

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

-> automated procedure

Results

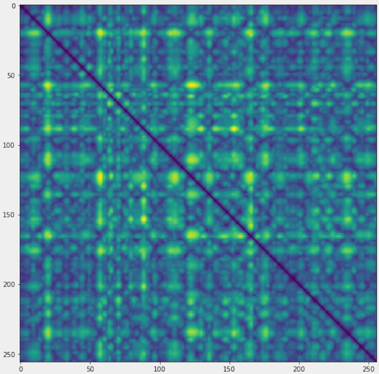
Measure	Classifier	Accuracy	
		Mean	Std
LLE, CD	SVM (lin.)	**0.74**	0.04
LLE, SE	SVM (lin.)	0.75	0.10
LLE, HE	SVM (lin.)	0.73	0.06
LLE, SE, DFA	SVM (lin.)	0.73	0.09
CD, HD	LR	0.73	0.10
LLE	SVM (lin.)	**0.72**	0.04
CD	SVM (lin.)	0.71	0.05
SE	LR	0.68	0.12
HD	SVM (rbf)	0.67	0.11
DFA	LR	0.67	0.16
HE	LR	0.67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

(a) Current DS

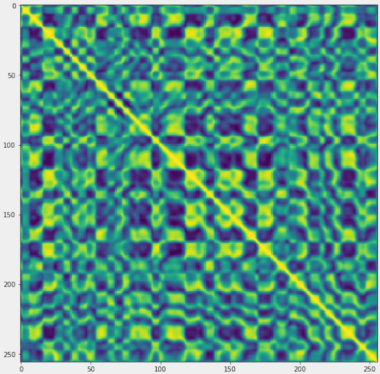
Measure	Classifier	Accuracy	
		Mean	Std
LLE, CD	SVM (lin.)	**0.75**	0.11
LLE, SE	SVM (lin.)	0.75	0.10
LLE	LR	**0.71**	0.08
CD	LR	0.67	0.09
HD	LR	0.66	0.05
SE	LR	0.66	0.09
DFA	SVM (lin.)	0.64	0.15
HE	SVM (rbf)	0.63	0.09

(b) Response prediction

Deep Learning Approach



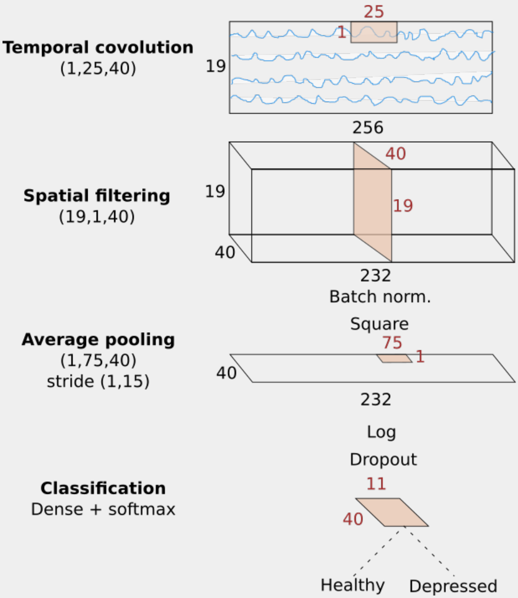
(a) Recurrence plot (RP)



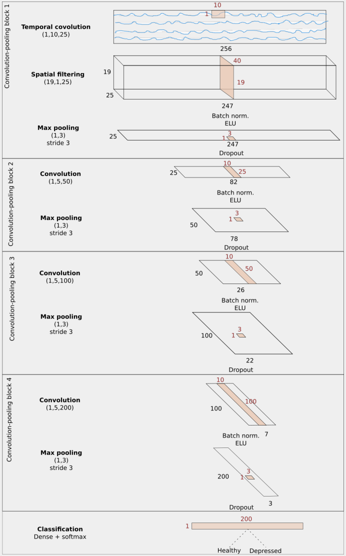
(b) Cosine similarity (CS)

(c) Raw

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

Conclusion

Summary

1. NL measures are potentially effective methods for depression diagnosis and prognosis (despite nonstationarity)
2. CD and LLE seem most discriminative (out of evaluated)
3. FBCSP-inspired CNN models seem more effective than common models
4. ILD seems most effective embedding parameters estimation algorithm (out of evaluated)
5. RP and CS do not seem effective data encoding methods for EEG analysis

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

Questions

References I

Backup Slides