Analysis of EEG-based Depression Biomarkers

Using Machine Learning & Nonlinear Analysis

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FJFI

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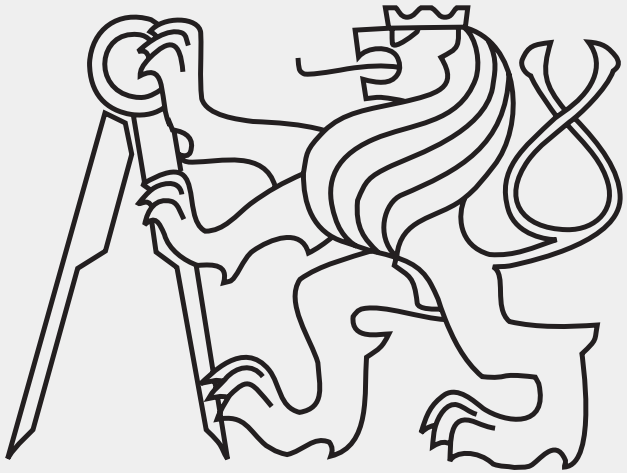
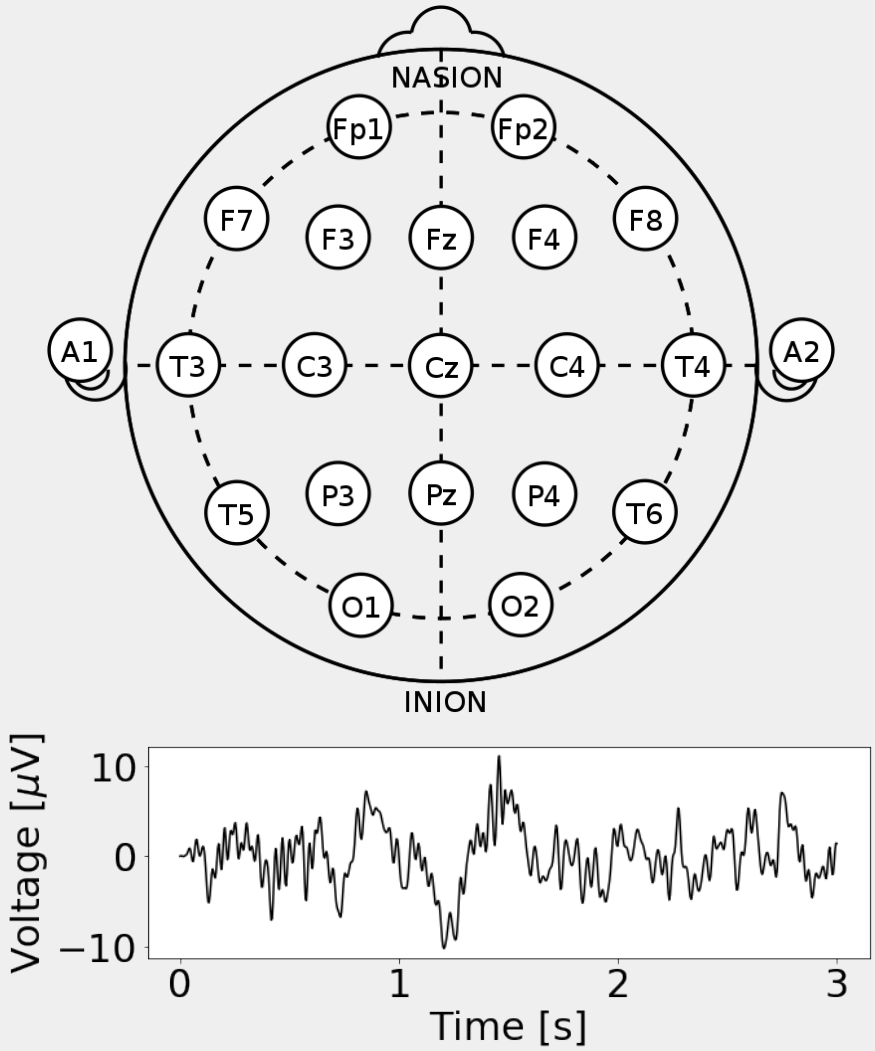


Problem Statement and Approach

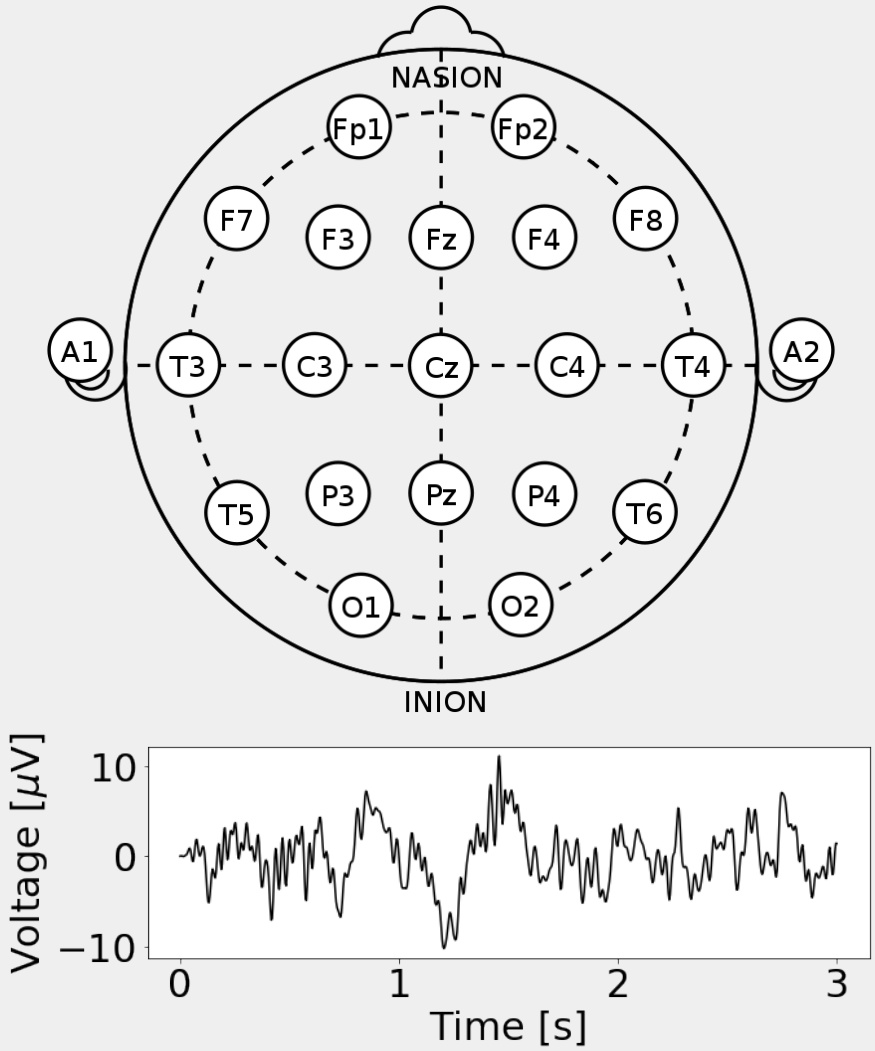
Depression Treatment is Expensive

- MDD
- EEG



Depression Treatment is Expensive

- MDD
  - 300 million suffering worldwide
- EEG



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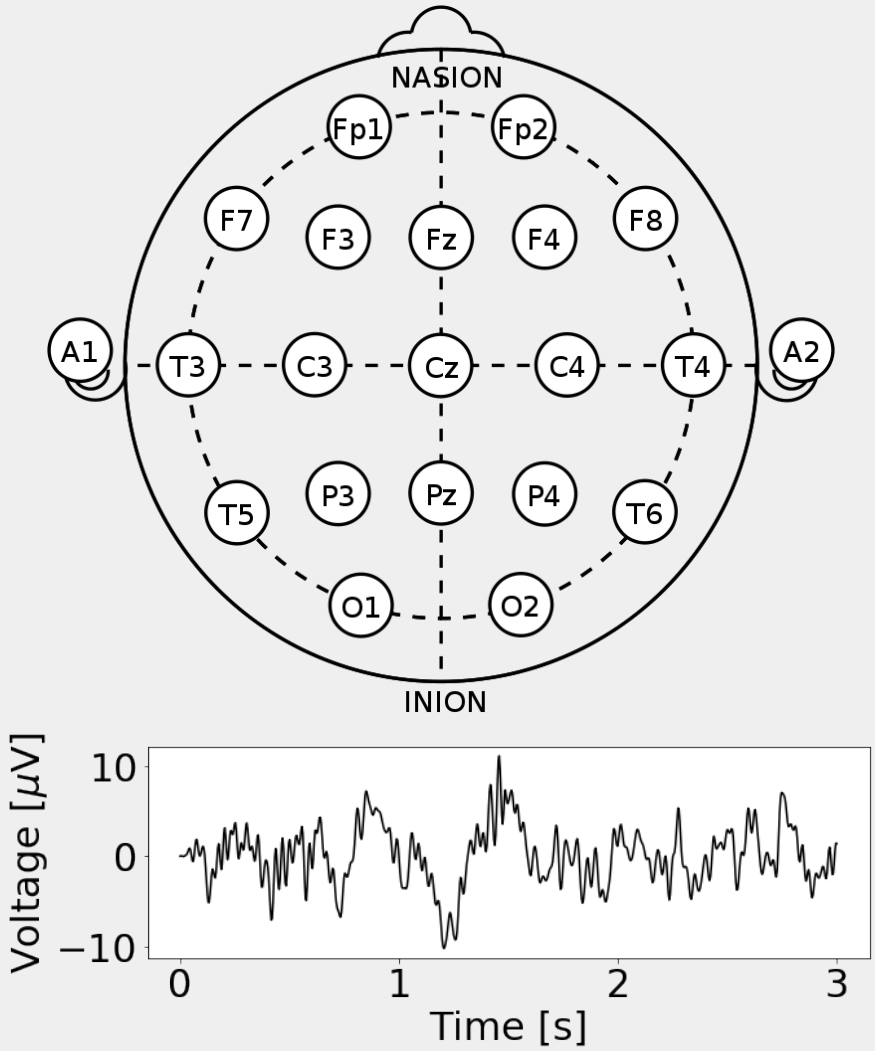

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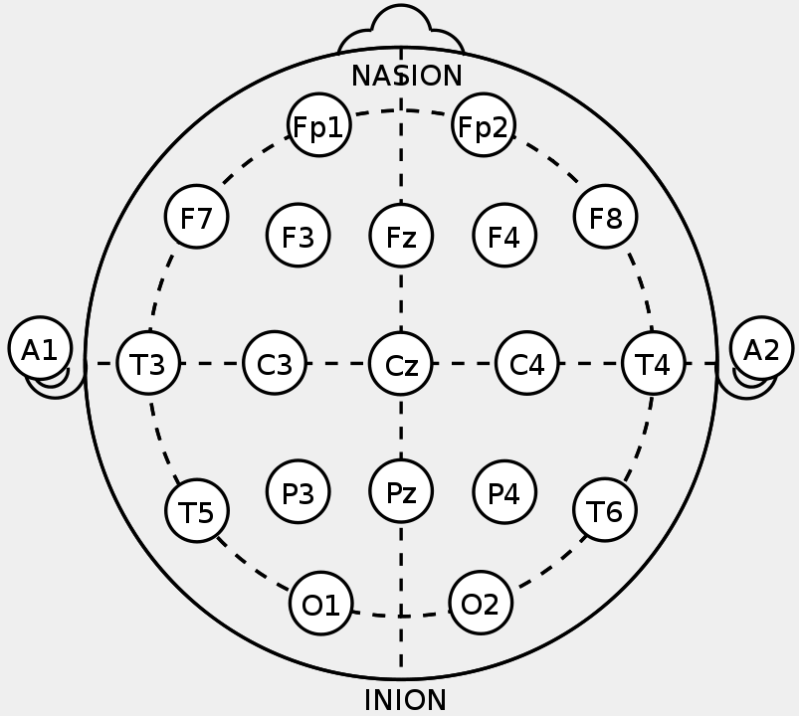
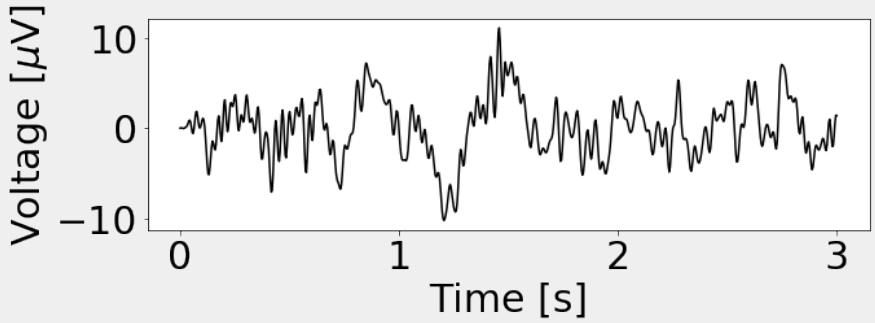
  - accessible diagnosis-aid tool

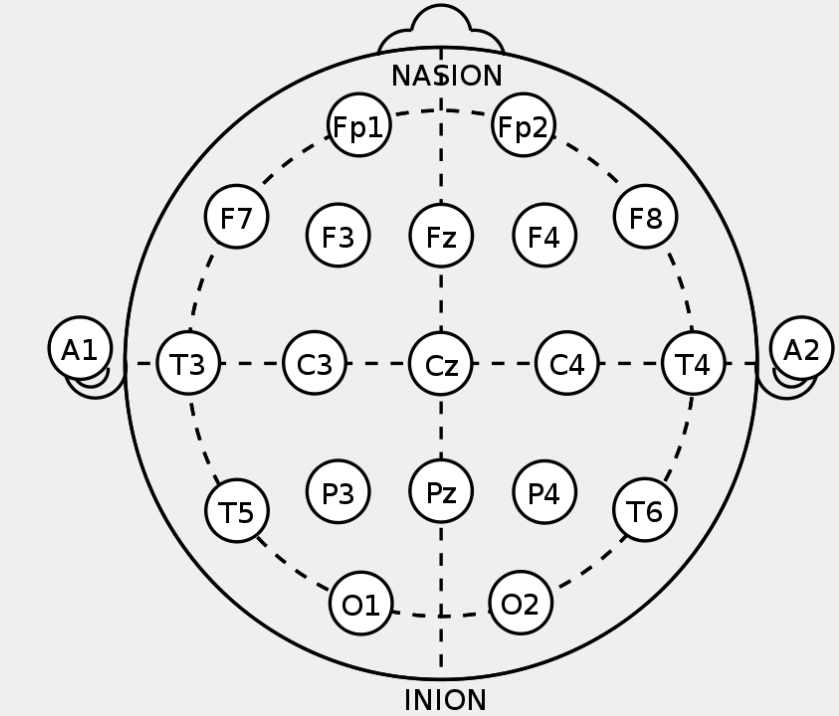




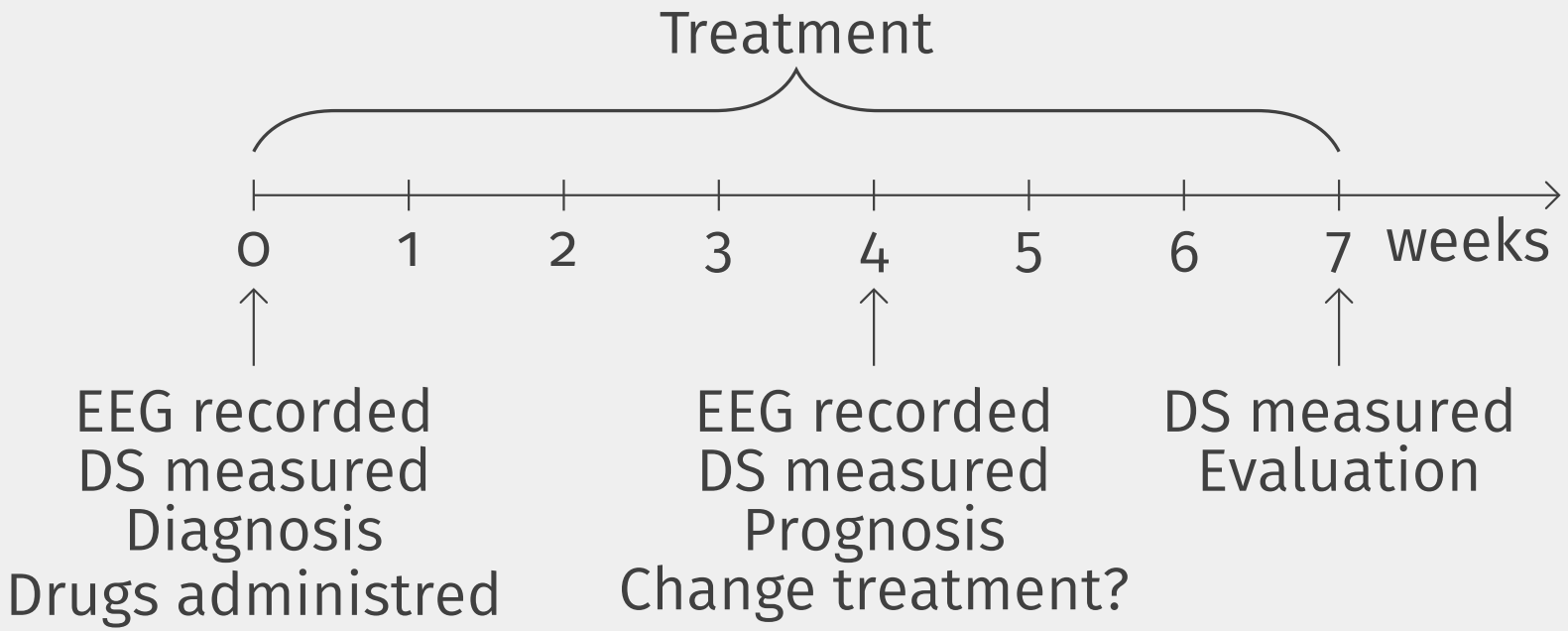
Depression Treatment is Expensive

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

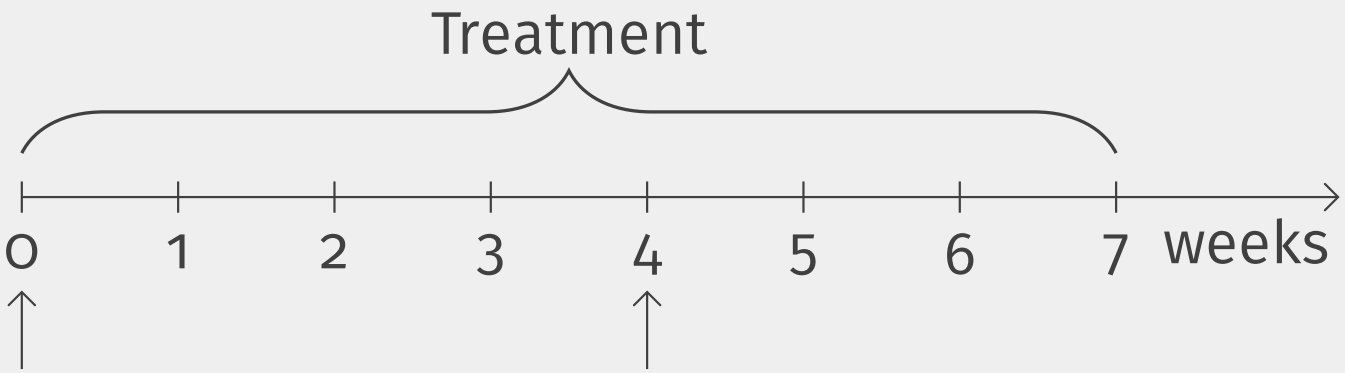
Research into effective analysis techniques is ongoing…



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

Our Goals

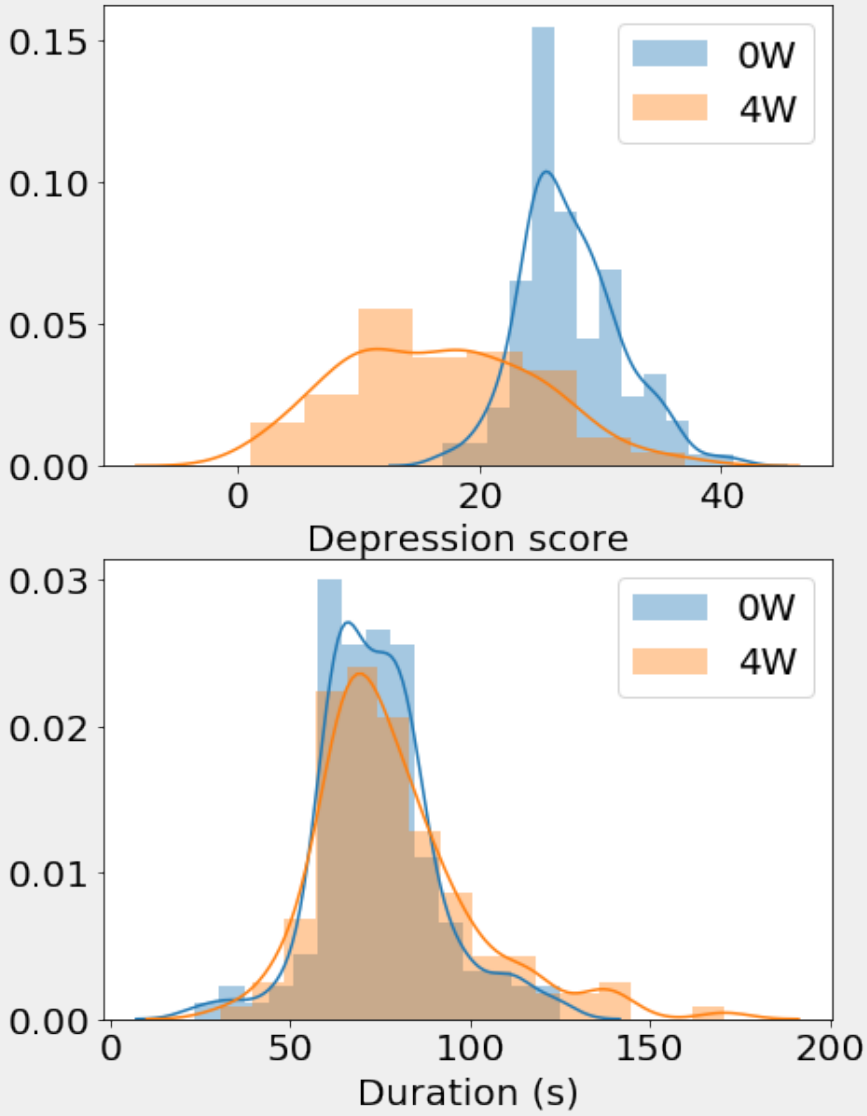


EEG recorded
DS measured
Diagnosis
Drugs administred
Prognosis

EEG recorded
DS measured
Evaluation

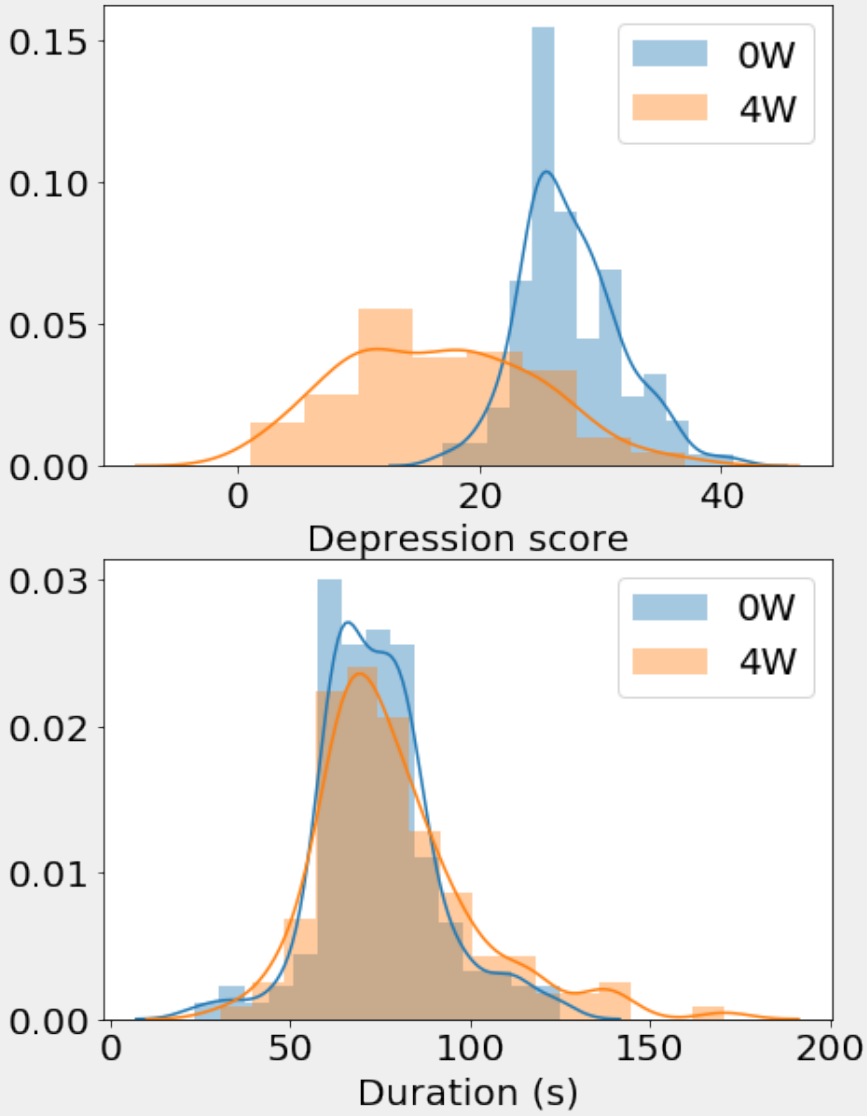
Our Dataset

- Czech National Institute of Mental Health



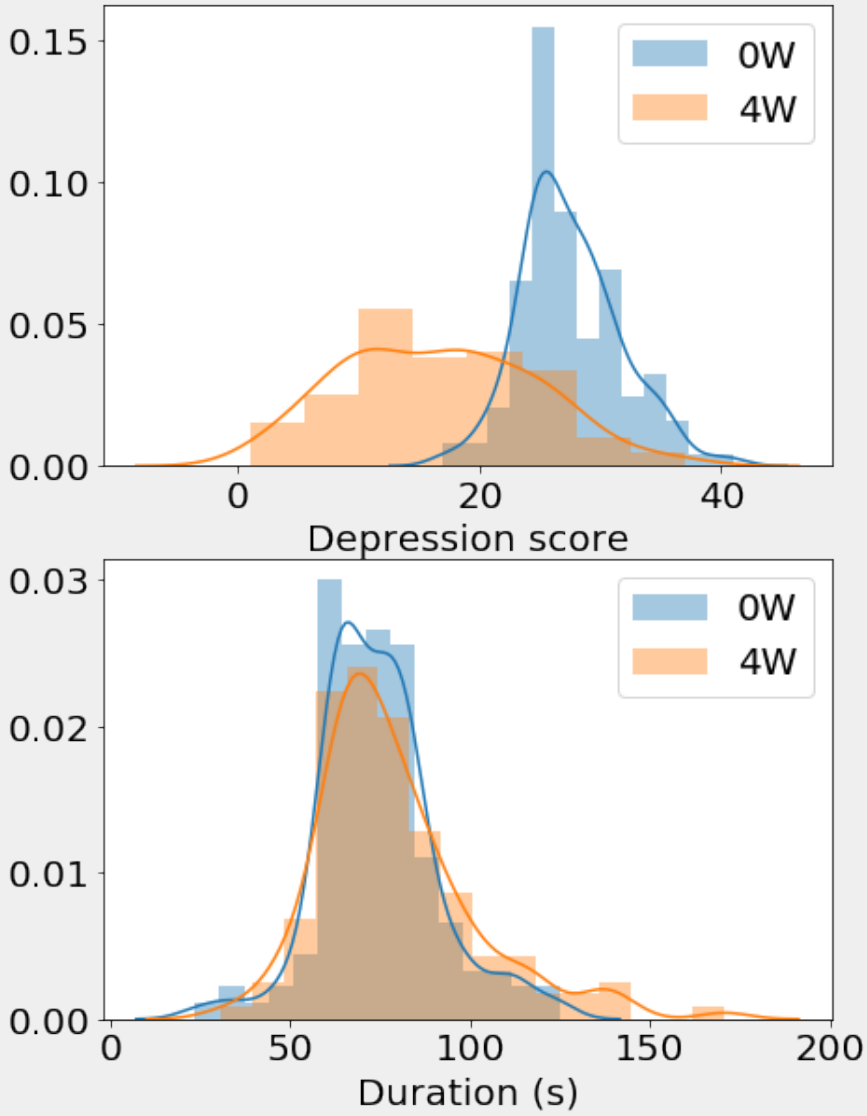
Our Dataset

- Czech National Institute of Mental Health
- 133 patients



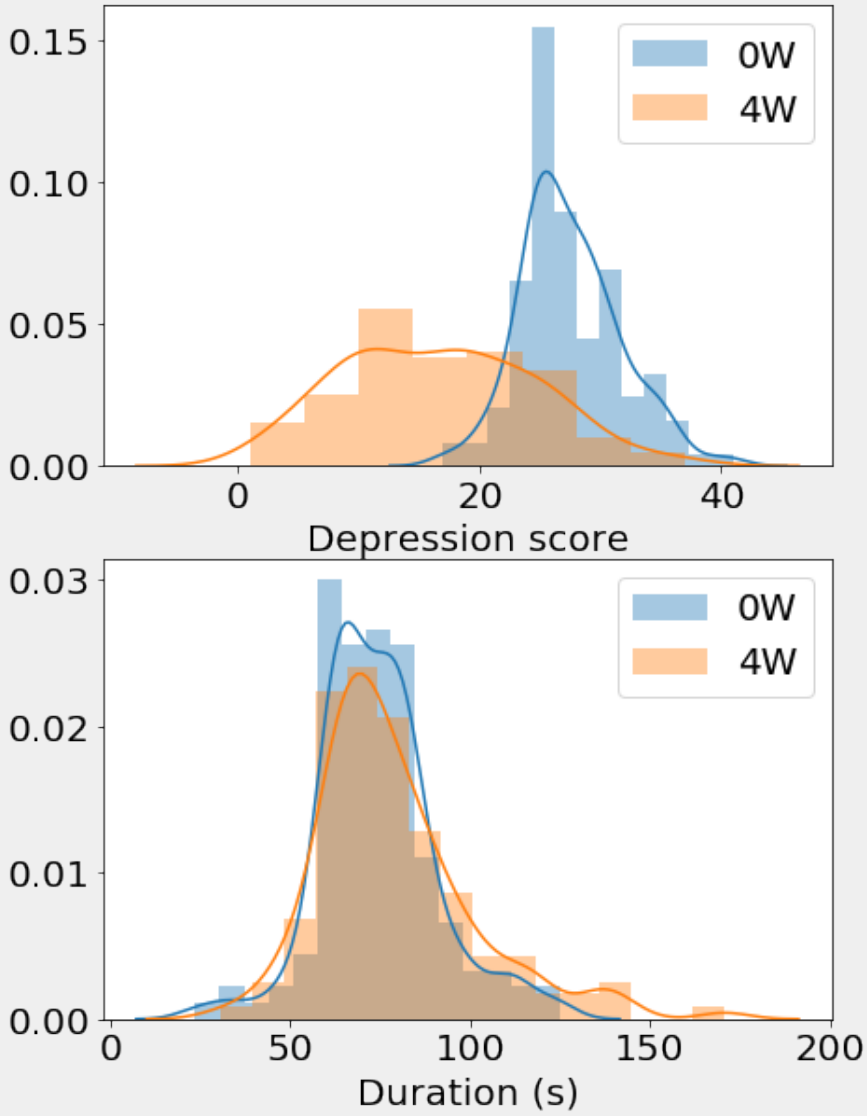
Our Dataset

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

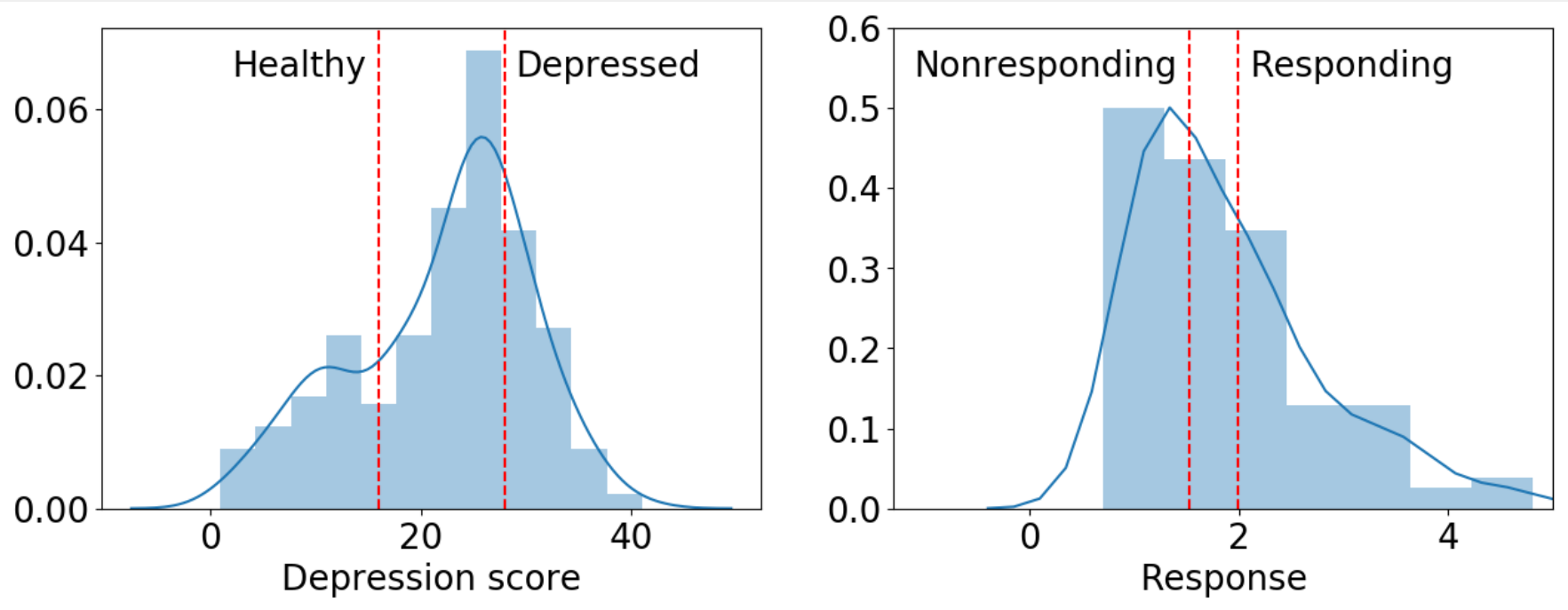


Our Dataset

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

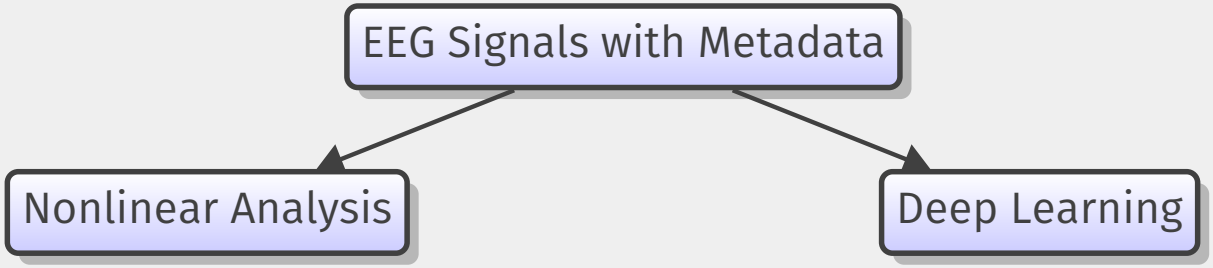


Labels



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

Our Approach



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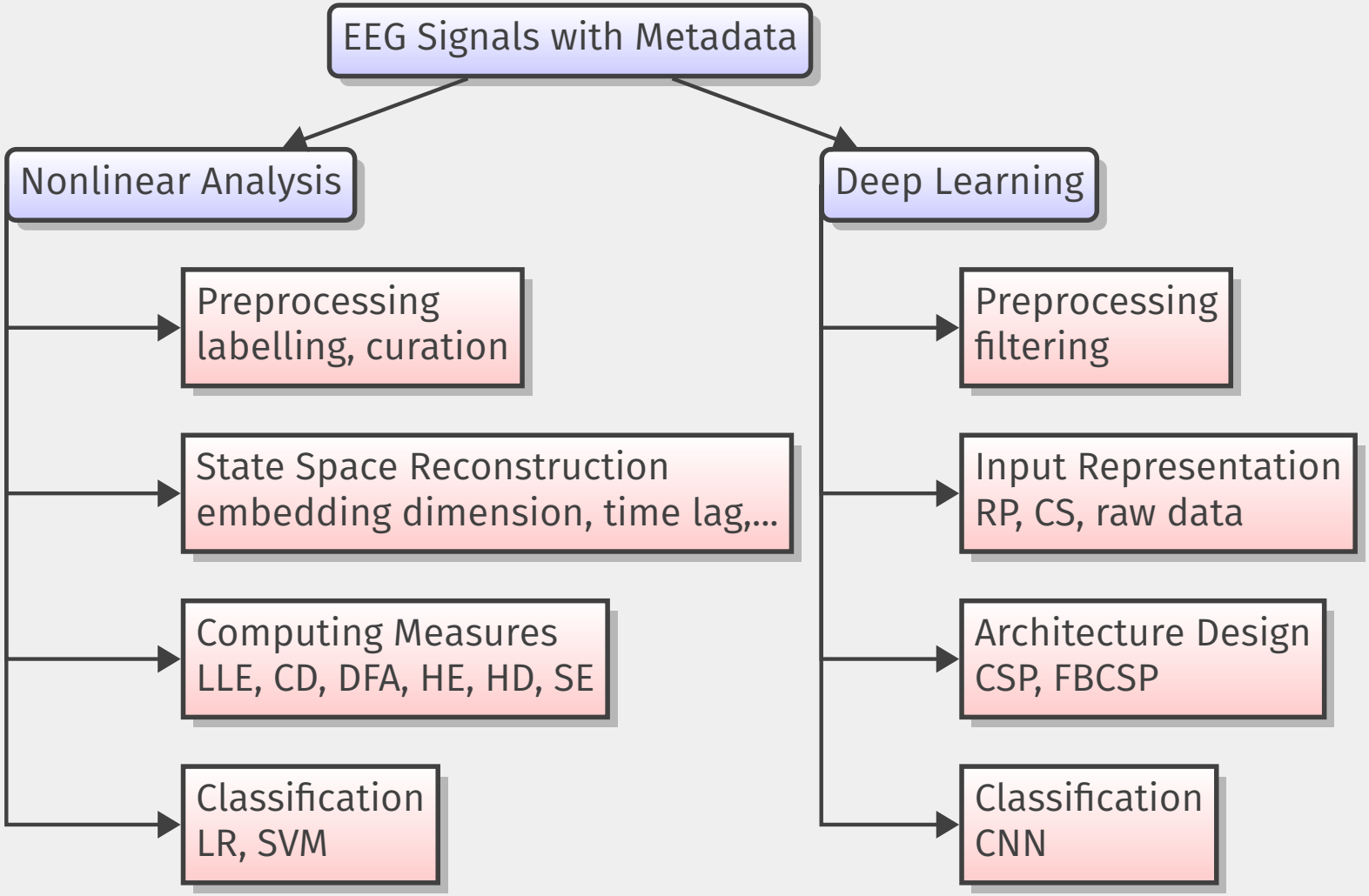
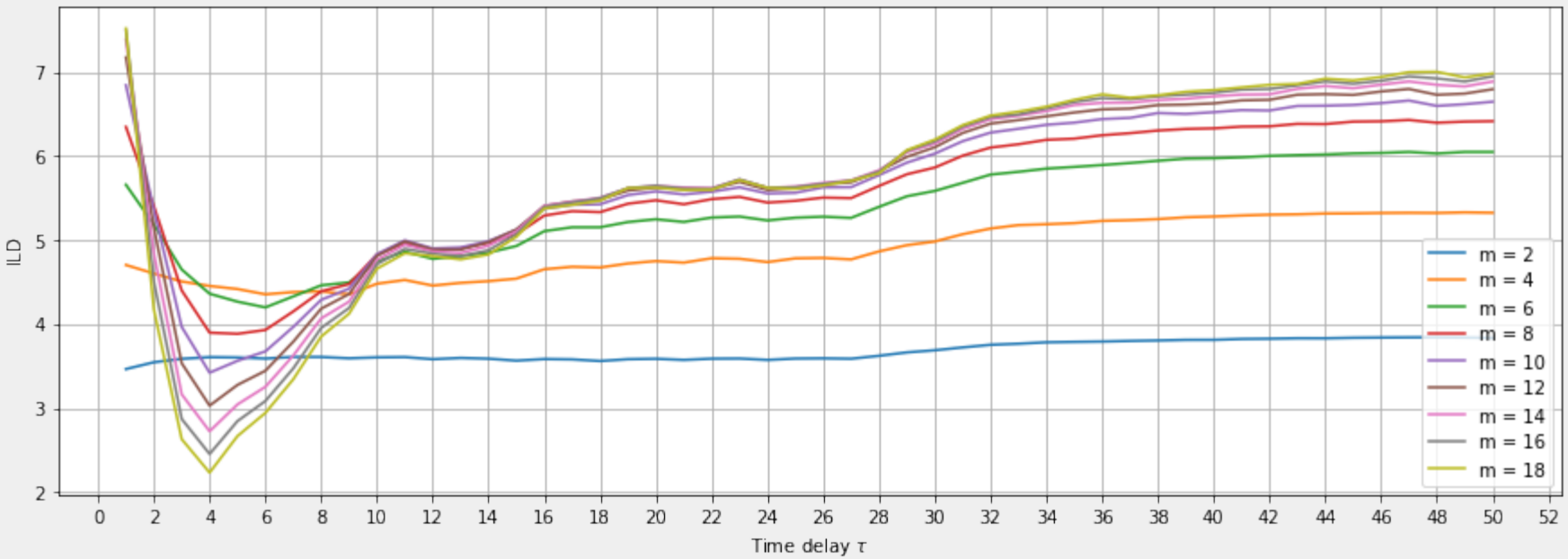


Nonlinear Analysis Approach

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	

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

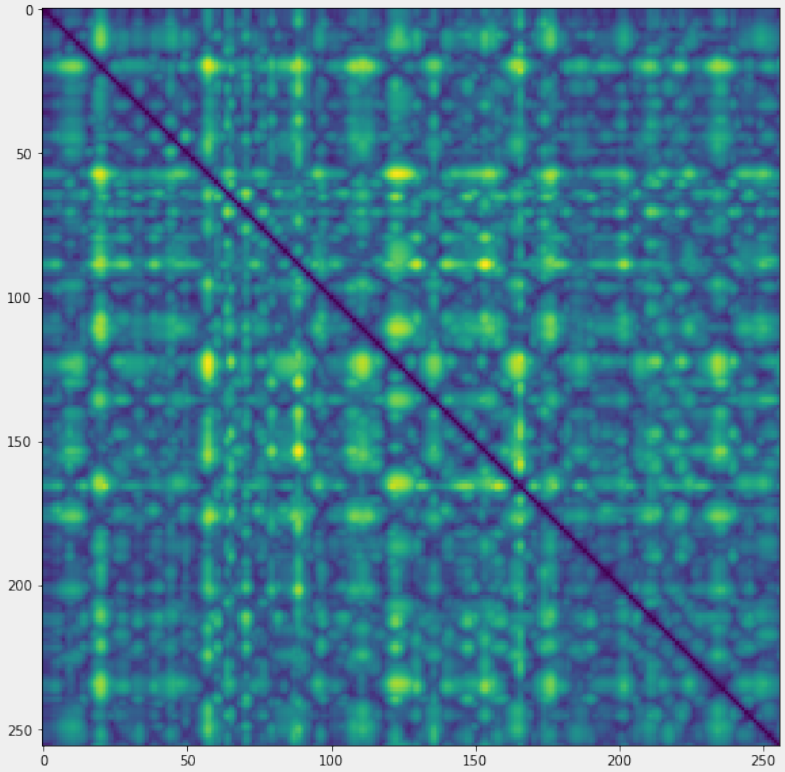
(a) Current DS

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

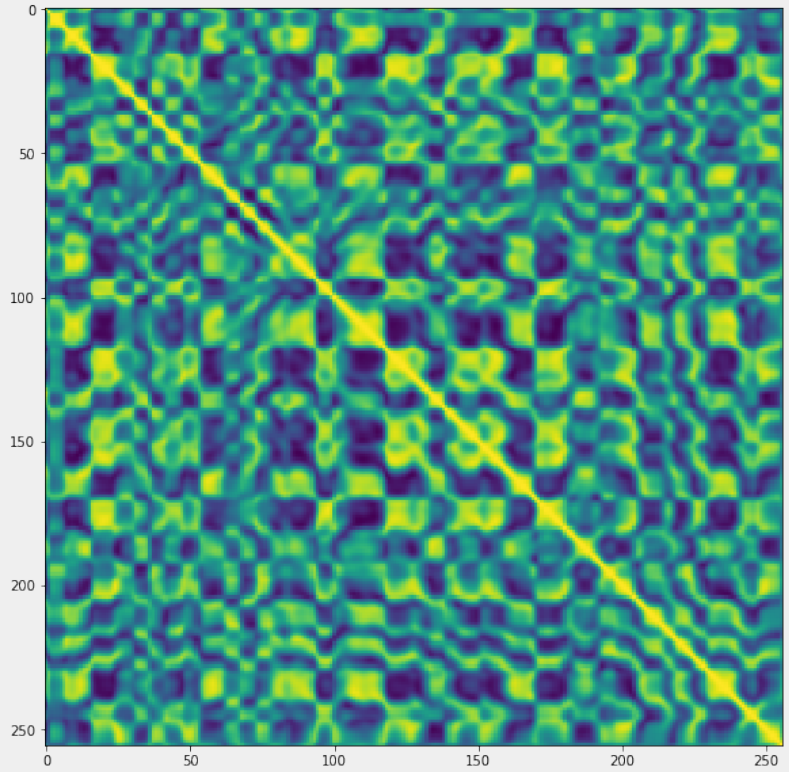
(b) Response prediction

Deep Learning Approach

Input Representation



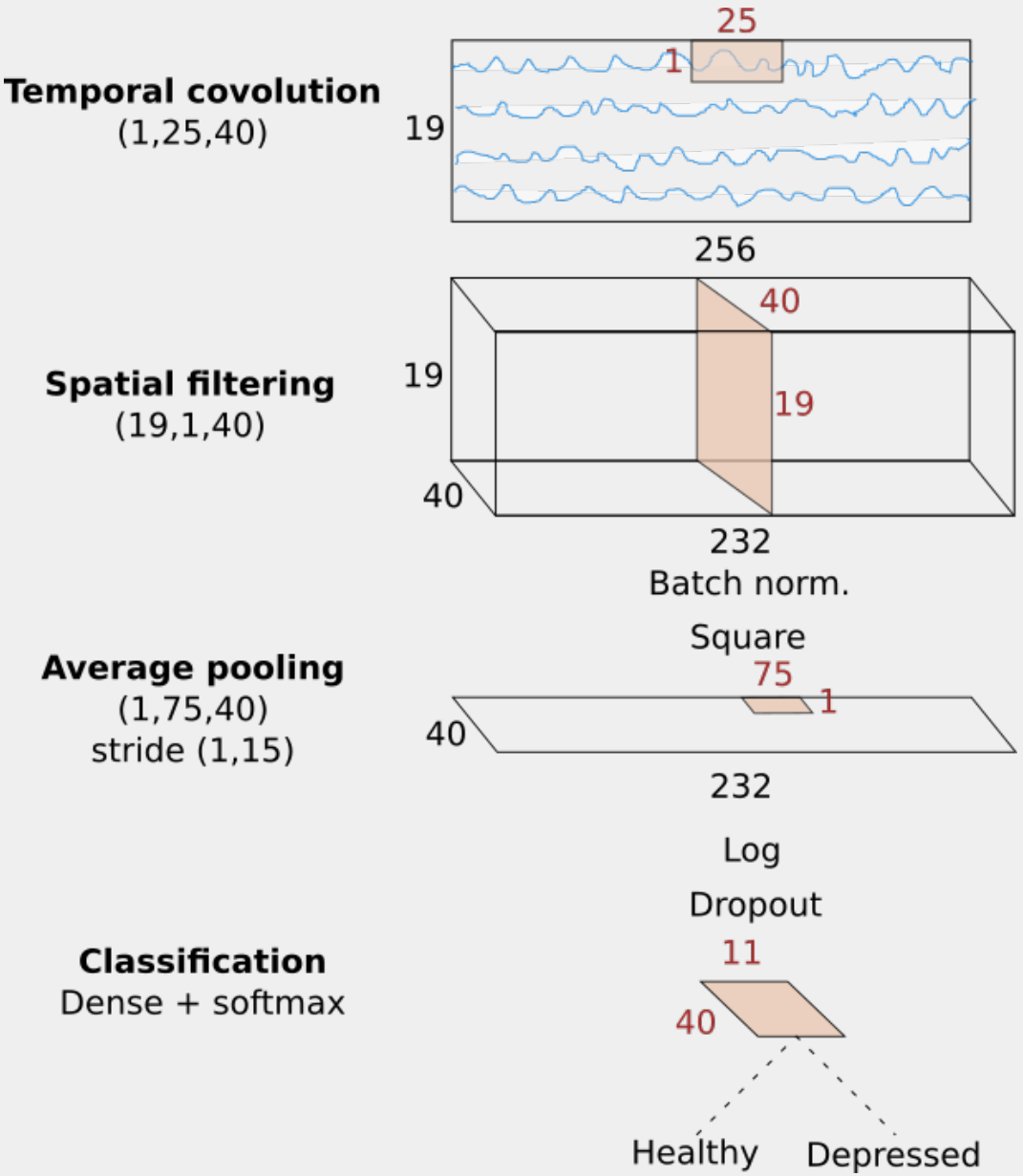
(a) Recurrence plot (RP)



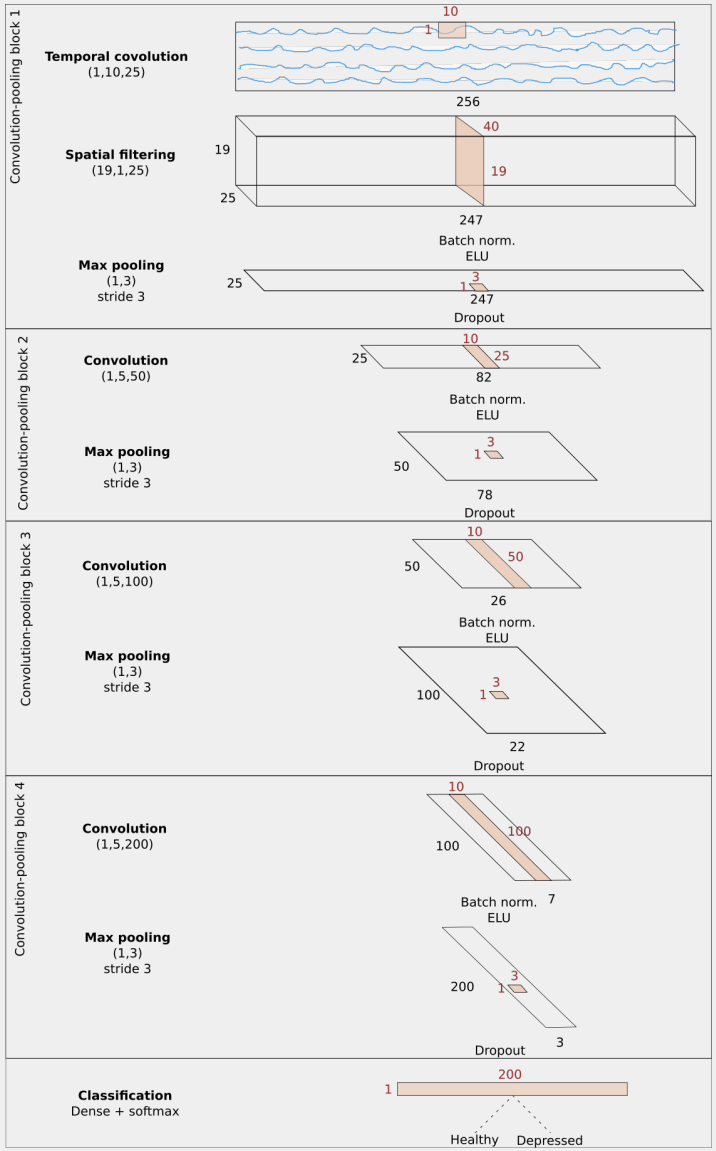
(b) Cosine similarity (CS)

(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

Conclusion

Summary

1. NL measures are potentially effective methods for depression diagnosis and prognosis (despite nonstationarity)

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1. NL measures are potentially effective methods for depression diagnosis and prognosis (despite nonstationarity)
2. LLE, CD and SE seem most discriminative (out of evaluated)
3. FBCSP-inspired CNN models seem effective
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

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

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Questions