

ANALYSIS OF EEG-BASED DEPRESSION BIOMARKERS

USING MACHINE LEARNING

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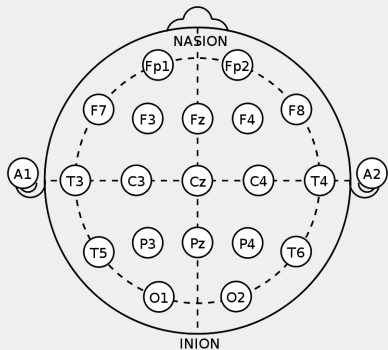


PROBLEM STATEMENT AND APPROACH

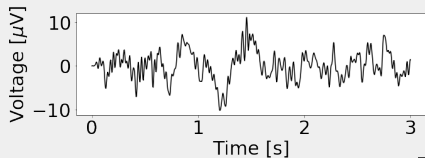
DEPRESSION TREATMENT IS EXPENSIVE

■ MDD

■ EEG



[1]

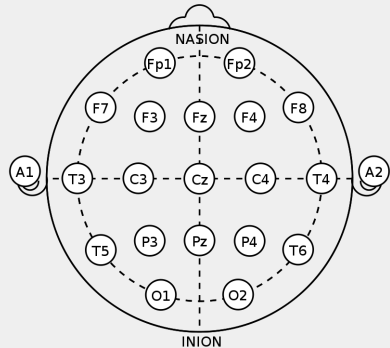


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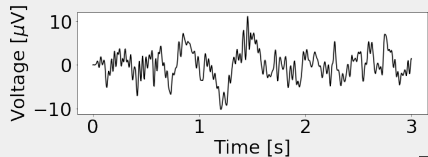
■ MDD

- ▶ 300 million suffering worldwide [2, 3]

■ EEG



[1]

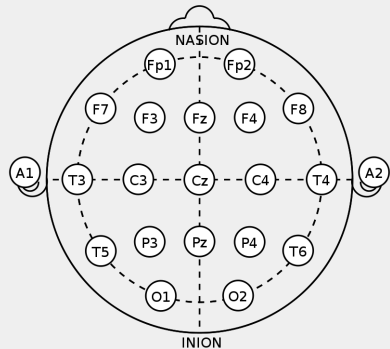


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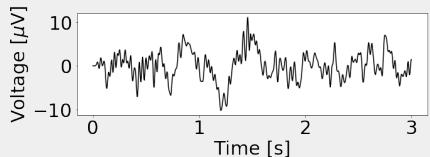
■ MDD

- ▶ 300 million suffering worldwide [2, 3]
- ▶ diagnosis requires time of trained professionals [3]

■ EEG



[1]



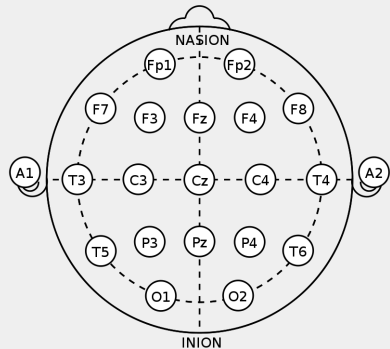
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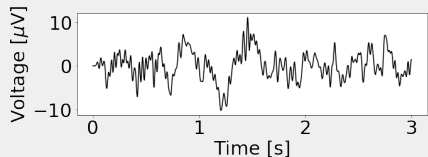
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■ EEG

- ▶ accessible diagnosis-aid tool [4]?



[1]



DEPRESSION TREATMENT IS EXPENSIVE

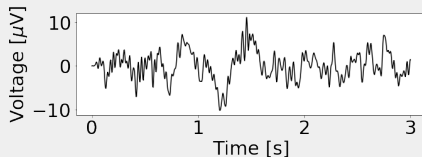
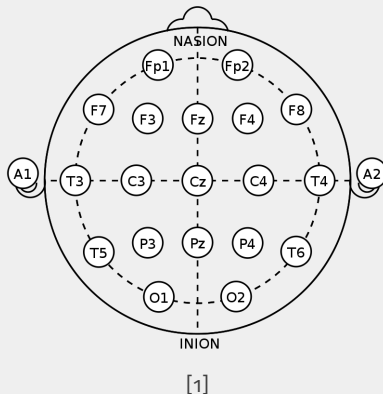
■ MDD

- ▶ 300 million suffering worldwide [2, 3]
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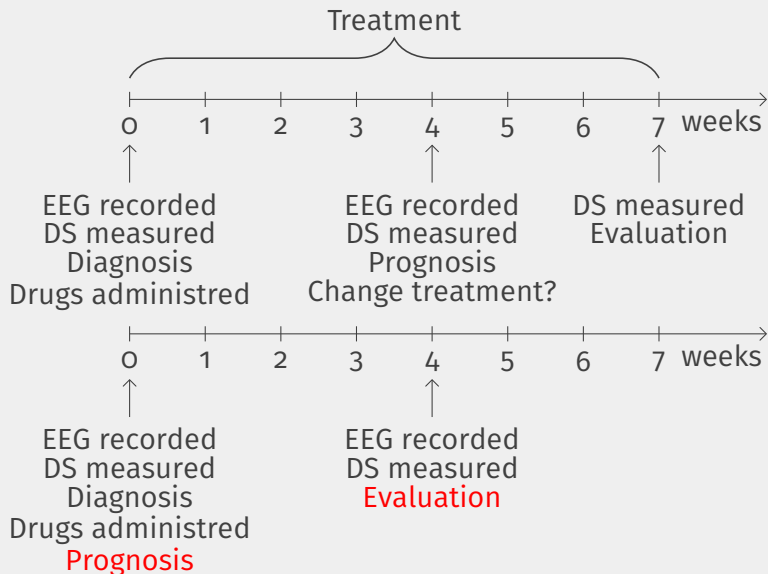
■ EEG

- ▶ accessible diagnosis-aid tool [4]?
- ▶ also effective at prognosis? studied very little!

Research into effective analysis techniques is ongoing...

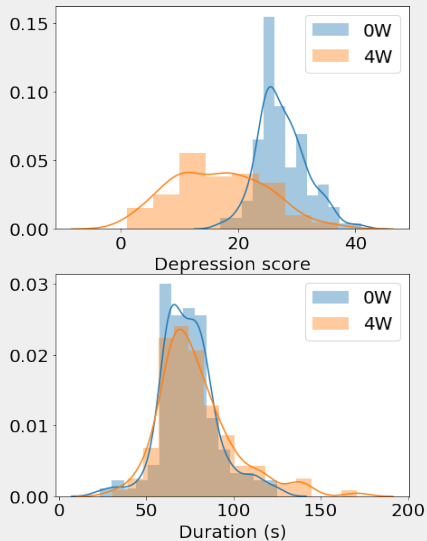


OUR GOALS



OUR DATASET

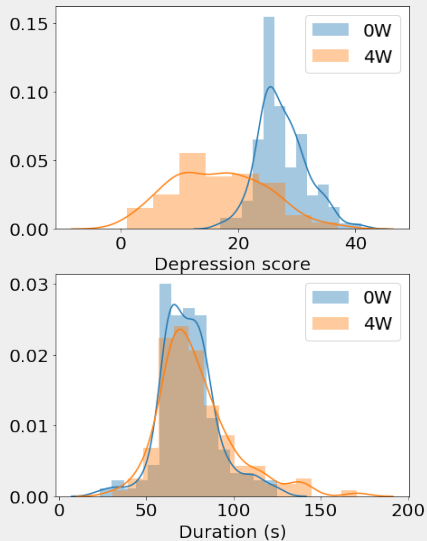
Relatively large:



OUR DATASET

Relatively large:

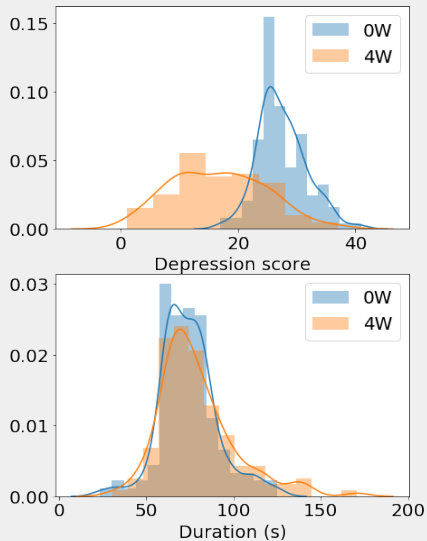
■ 133 patients



OUR DATASET

Relatively large:

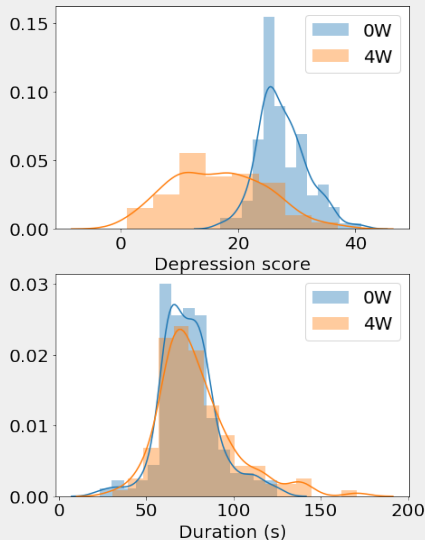
- 133 patients
- EEG recordings
 - ▶ 19 channels
 - ▶ 250 Hz or 1000 Hz
 - ▶ Various duration



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

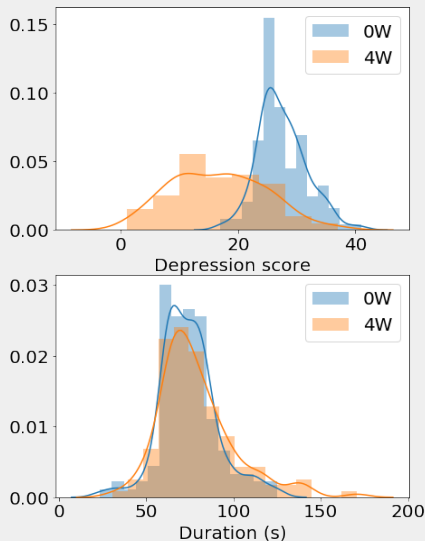


OUR DATASET

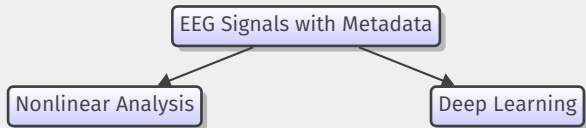
Relatively large:

- 133 patients
- EEG recordings
 - ▶ 19 channels
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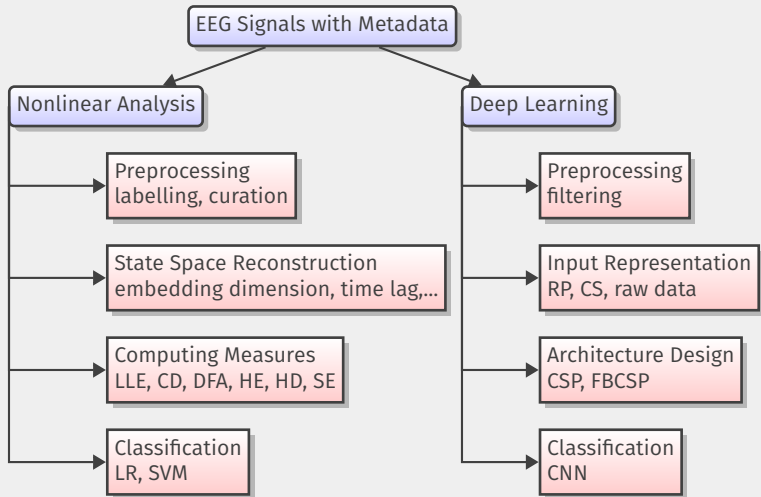
Obtained from Czech National
Institute of Mental Health



OUR APPROACH



OUR APPROACH

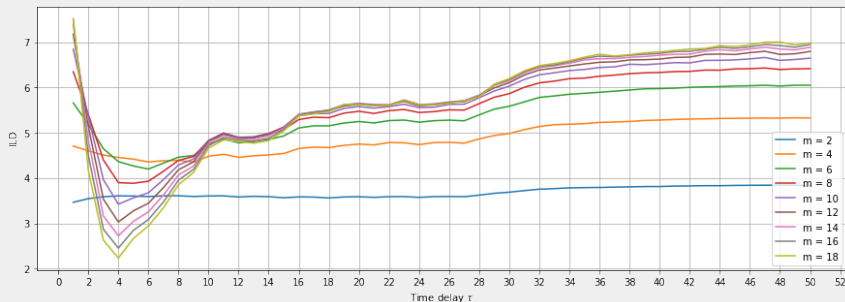


NONLINEAR ANALYSIS APPROACH

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		

EMBEDDING PARAMETER ESTIMATION



Parameters

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

Methods

- Literature review
- Estimation algorithms (FNN, AFN, ADFD, ILD, ...)
- Statistical tests

-> 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

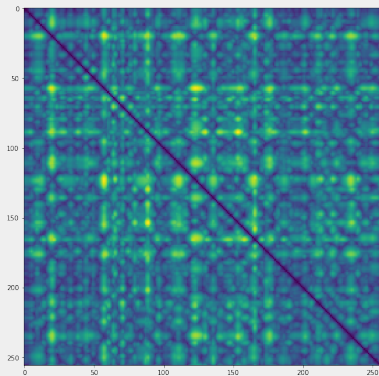
(a) Depression

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

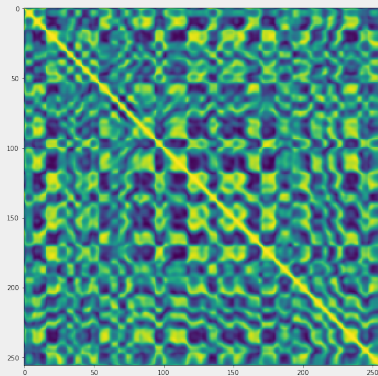
(b) Remission

DEEP LEARNING APPROACH

INPUT REPRESENTATION



(a) Recurrence plot

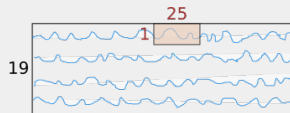


(b) Cosine similarity

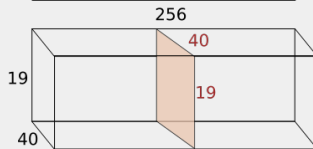
(c) Raw

ARCHITECTURE DESIGN - SHALLOW

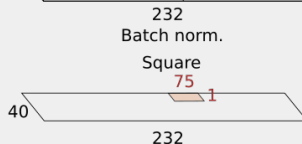
Temporal covolution
(1,25,40)



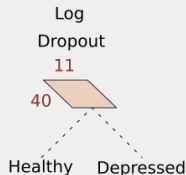
Spatial filtering
(19,1,40)



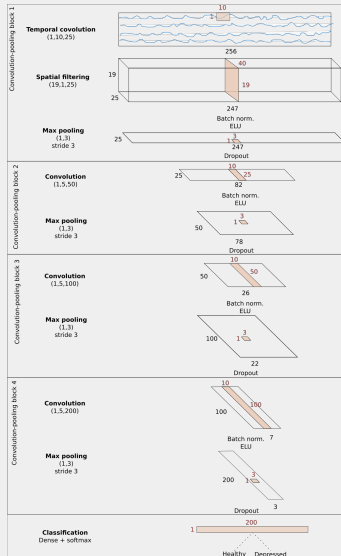
Average pooling
(1,75,40)
stride (1,15)



Classification
Dense + softmax



ARCHITECTURE DESIGN - DEEP



RESULTS

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

(a) Raw data

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

(b) Image-encoded data

CONCLUSION

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

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

QUESTIONS

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BACKUP SLIDES