# Analysis of EEG-based Depression Biomarkers

USING MACHINE LEARNING

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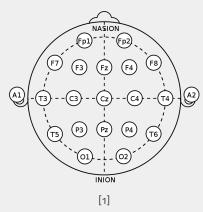


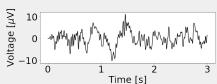


## PROBLEM STATEMENT AND APPROACH

■ MDD

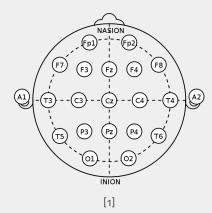
■ EEG

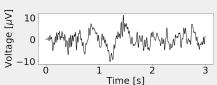




- MDD
  - ➤ 300 million suffering worldwide [2, 3]

■ EEG

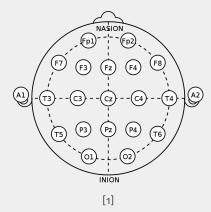


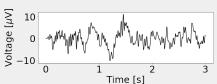


#### MDD

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

#### ■ EEG



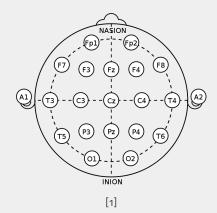


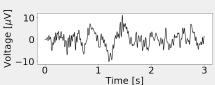
#### MDD

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

#### ■ EEG

accessible diagnosis-aid tool [4]?





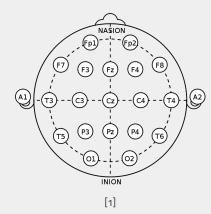
#### MDD

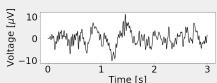
- ► 300 million suffering worldwide [2, 3]
- diagnosis requires time of trained professionals [3]

#### ■ FEG

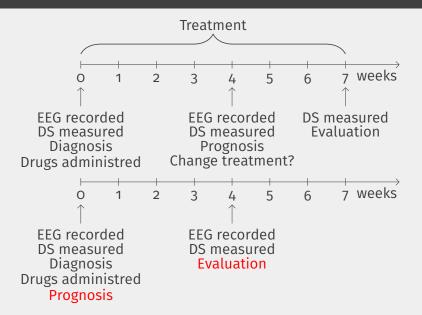
- accessible diagnosis-aid tool [4]?
- also effective at prognosis? studied very little!

Research into effective analysis techniques is ongoing...

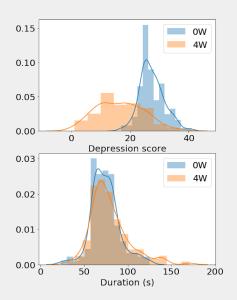




#### **OUR GOALS**

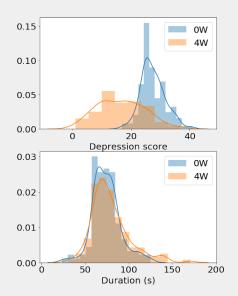


Relatively large:



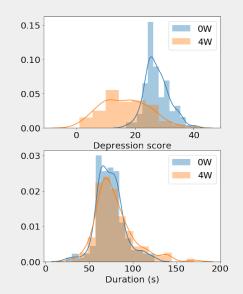
#### Relatively large:

■ 133 patients



#### Relatively large:

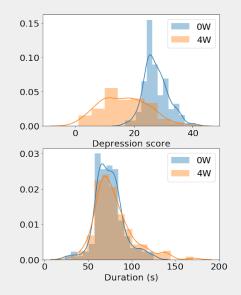
- 133 patients
- EEG recordings
  - ▶ 19 channels
  - ▶ 250 Hz or 1000 Hz
  - ▶ Various duration



3 | 15

#### Relatively large:

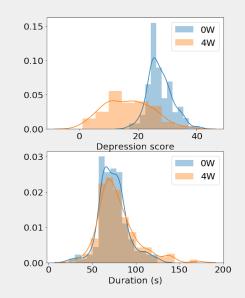
- 133 patients
- EEG recordings
  - ▶ 19 channels
  - ▶ 250 Hz or 1000 Hz
  - ▶ Various duration
- Metadata
  - ► Depression scores
    - Week o
    - Week 4
  - ► Age, gender, drugs



#### Relatively large:

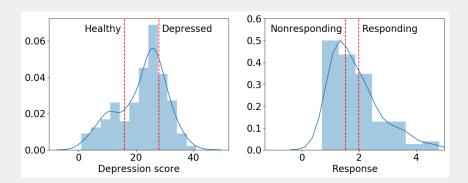
- 133 patients
- EEG recordings
  - ▶ 19 channels
  - ▶ 250 Hz or 1000 Hz
  - Various duration
- Metadata
  - ► Depression scores
    - Week o
    - Week 4
  - ► Age, gender, drugs

Obtained from Czech National Institute of Mental Health



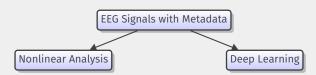
3 | 15

#### **LABELS**

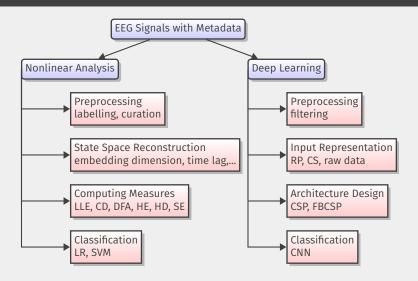


$$Response = \frac{Depression \ score_{Week \ 4}}{Depression \ score_{Week \ 0}}$$

#### OUR APPROACH



#### OUR APPROACH



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# NONLINEAR ANALYSIS APPROACH

#### NONLINEAR MEASURES

```
LLE Largest Lyapunov exponent
"stability"

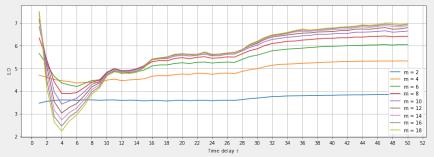
SE Sample entropy
"stability"

CD Correlation dimension
"complexity"

HD Higuchi fractal dimension
LRTC

DFA Detrended fluctuation analysis
LRTC
```

#### **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

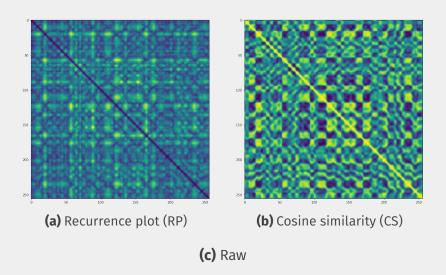
(	a)	Current	DS
- 1	α,	Current	$\nu_{\mathcal{I}}$

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

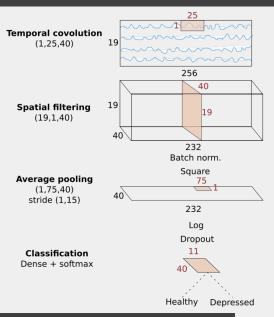
(b) Response prediction

# DEEP LEARNING APPROACH

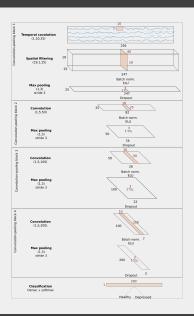
#### INPUT REPRESENTATION



#### **ARCHITECTURE DESIGN - SHALLOW**



#### **ARCHITECTURE DESIGN - DEEP**



#### **RESULTS**

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

Lab.	Freq.	Arch.	Accuracy	
			Mean	Std
DEP	$o-f_{fin}$	RP	0.63	0.02
	4 – f <sub>fin</sub>	RP	0.61	0.01
	$o-f_{fin}$	CS	0.59	0.02
	4 – f <sub>fin</sub>	CS	0.58	0.01
RES	$o-f_{fin}$	RP	0.61	0.03
	4 – f <sub>fin</sub>	RP	0.65	0.02
	$o-f_{fin}$	CS	0.55	0.02
	4 – f <sub>fin</sub>	CS	0.63	0.01

(a) Raw data

(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)
- 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



#### REFERENCES I



ASANGI.

**ELECTRODE LOCATIONS OF INTERNATIONAL 10-20 SYSTEM FOR EEG** (ELECTROENCEPHALOGRAPHY) RECORDING.

https://commons.wikimedia.org/wiki/File: 21 electrodes of International 10-20 system for EEG.svg, 2010.

[Online; accessed 18-March-2019].



SEBASTIAN OLBRICH AND MARTIJN ARNS.

**EEG BIOMARKERS IN MAJOR DEPRESSIVE DISORDER: DISCRIMINATIVE** POWER AND PREDICTION OF TREATMENT RESPONSE.

International Review of Psychiatry, 25(5):604–618, 2013.



WORLD HEATLH ORGANIZATION.

#### DEPRESSION.

http://www.who.int/en/news-room/fact-sheets/ detail/depression, 2018.

[Online; accessed 18-August-2018].

#### REFERENCES II



TEAL L SCHULTZ.

**TECHNICAL TIPS: MRI COMPATIBLE EEG ELECTRODES: ADVANTAGES, DISADVANTAGES, AND FINANCIAL FEASIBILITY IN A CLINICAL SETTING.** *The Neurodiagnostic Journal*, 52(1):69–81, 2012.

#### BACKUP SLIDES