# Analysis of EEG-based Depression Biomarkers

## Using Machine Learning & Nonlinear Analysis

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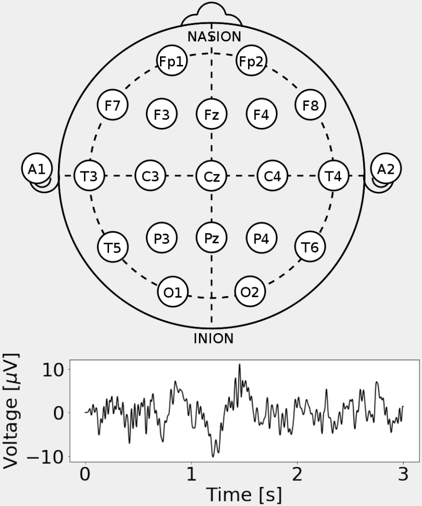
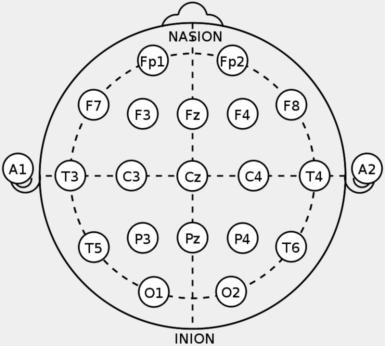
# Problem Statement and Approach

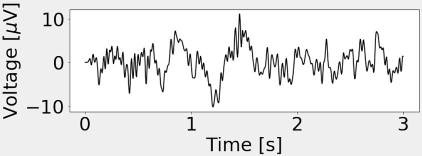
# Depression Treatment is Expensive

- MDD
- EEG



- MDD
  - 300 million suffering worldwide
- EEG



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  - diagnosis requires time of trained professionals
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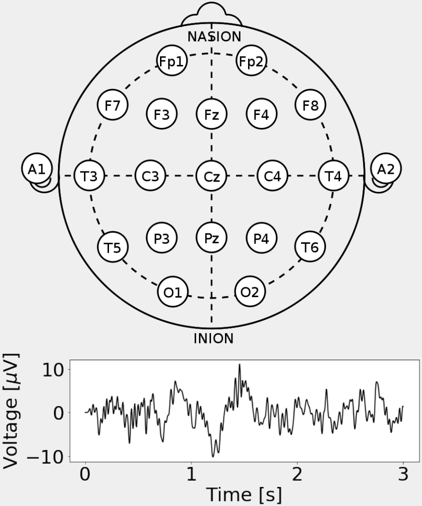

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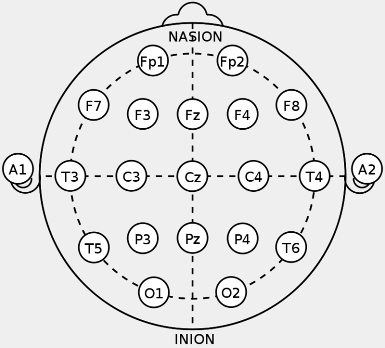
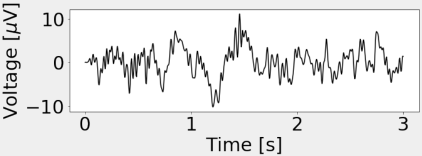
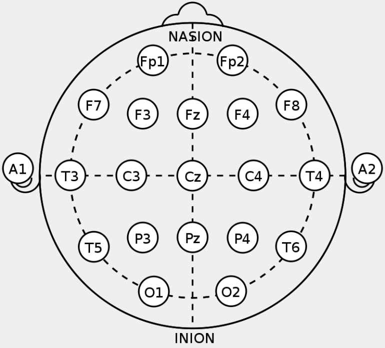


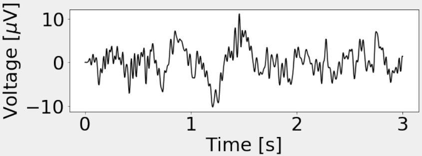



# Depression Treatment is Expensive

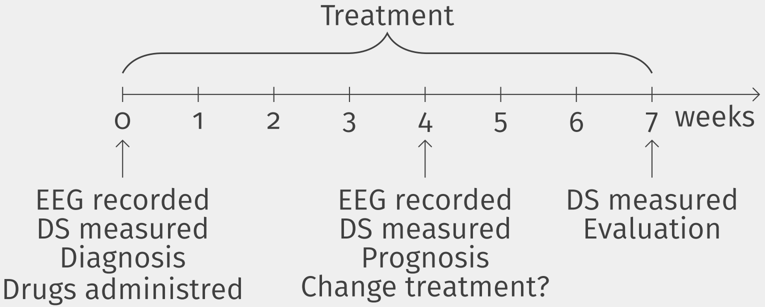
- MDD
  - 300 million suffering worldwide
  - diagnosis requires time of trained professionals
- EEG
  - accessible diagnosis-aid tool
  - still not reliable enough!

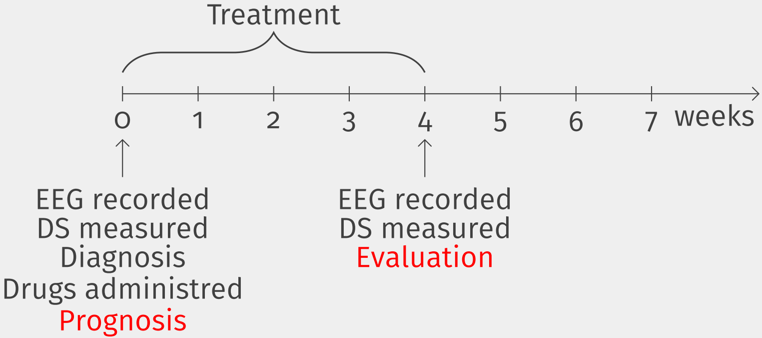
Research into effective analysis techniques is ongoing...



# Our Goals


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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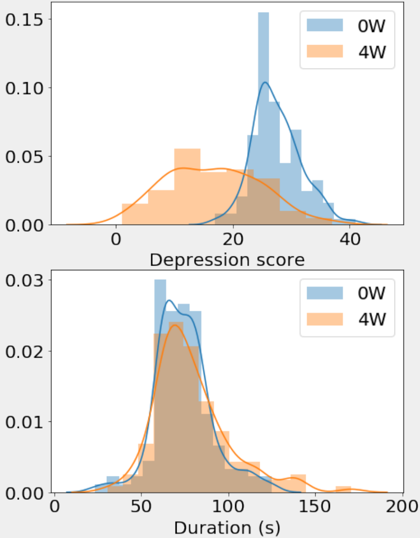
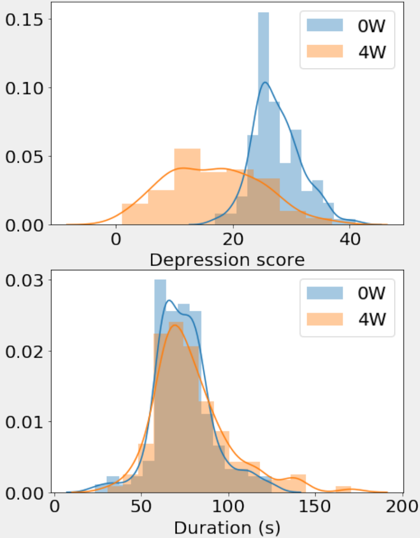
- Czech National Institute of Mental Health



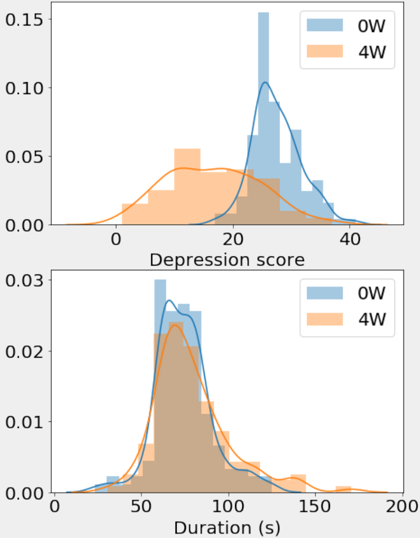
# Our Dataset

- Czech National Institute of Mental Health
- 133 patients



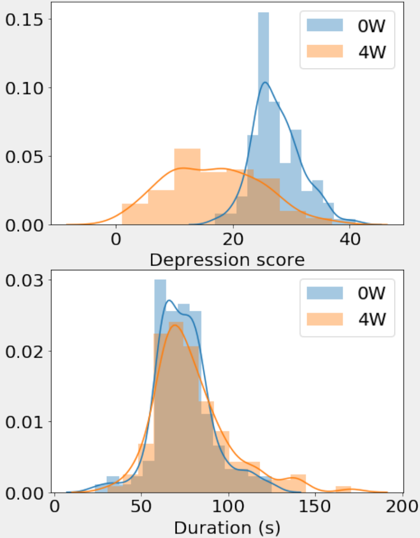
# Our Dataset

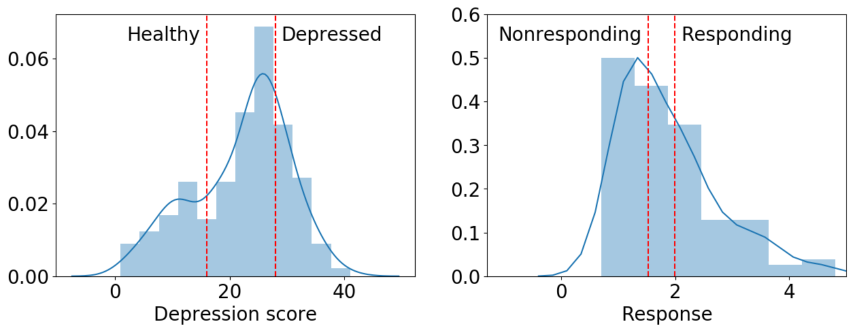
- Czech National Institute of Mental Health
- 133 patients
- EEG recordings
  - 19 channels
  - 250 Hz or 1000 Hz
  - Various duration



# Our Dataset

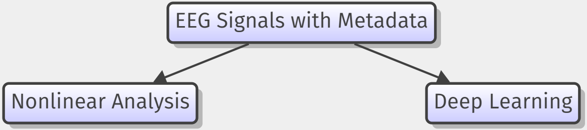
- Czech National Institute of Mental Health
- 133 patients
- EEG recordings
  - 19 channels
  - 250 Hz or 1000 Hz
  - Various duration
- Metadata
  - Depression scores
    - Week 0
    - Week 4
  - Age, gender, drugs






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

# Our Approach



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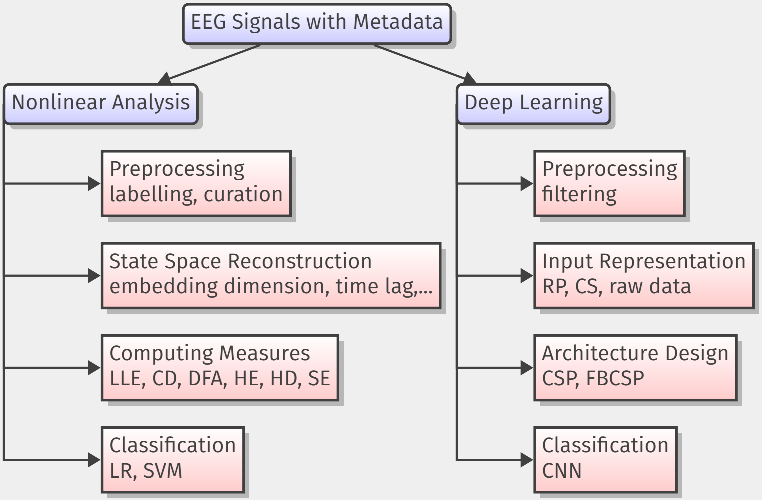
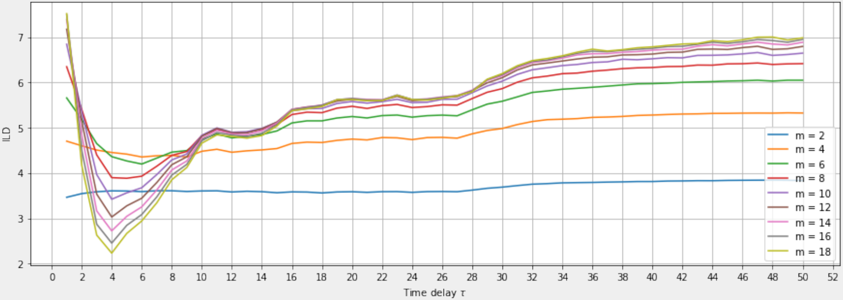


# Nonlinear Analysis Approach

# 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

| 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 |

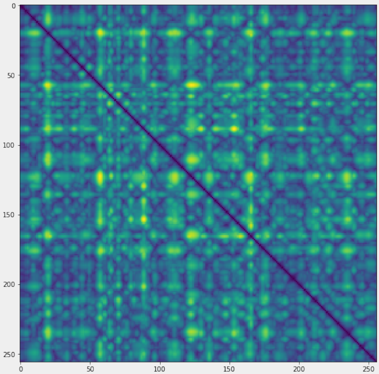
**(a)** Current DS

| 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 |

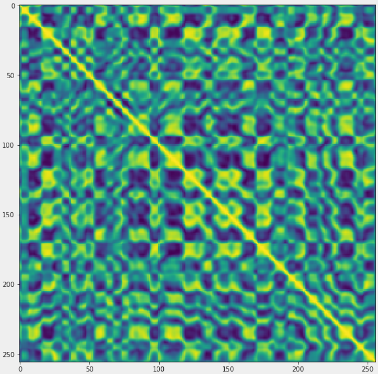
**(b)** Response prediction

# Deep Learning Approach

# Input Representation



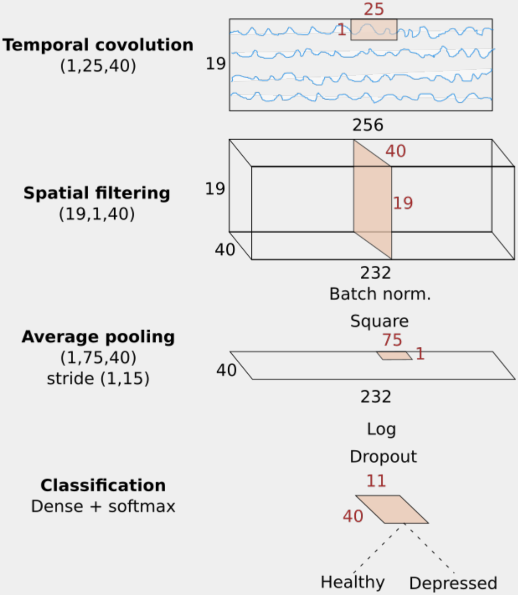

**(a)** Recurrence plot (RP)



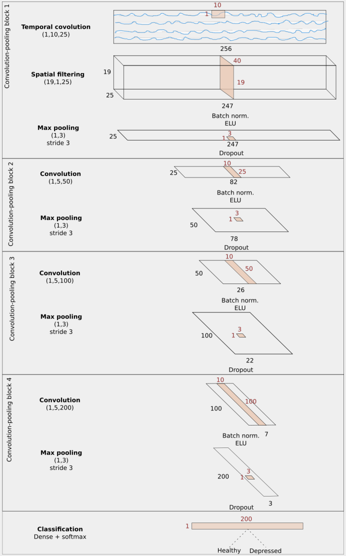

**(b)** Cosine similarity (CS)

**(c)** Raw

# Architecture Design - Shallow



# Architecture Design - Deep



| 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. 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

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# Questions