Focal onset seizure prediction using convolutional networks

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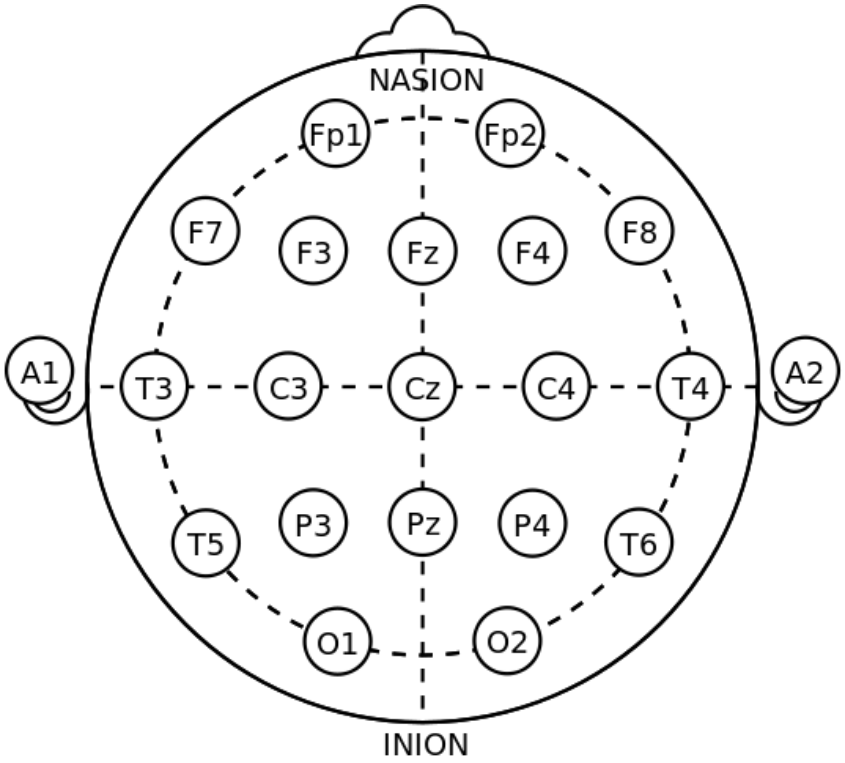
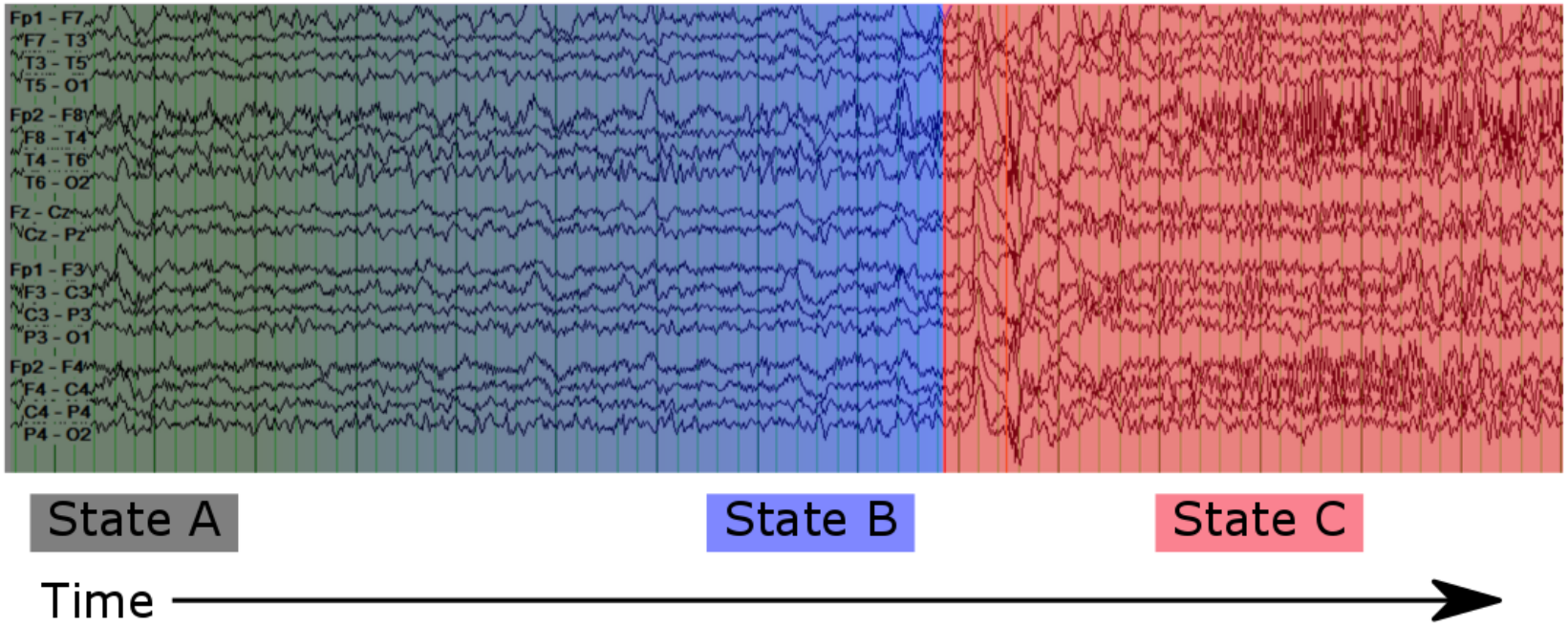
20 Feb 2019

About me

Epilepsy is a neurological disorder characterized by the unpredictable occurrence of seizures.
Affects 65M people in the world, 3.4M in the US
Symptoms of seizures: convulsions, auras, forgetfulness




Fp1 - F7
F7 - T3
T3 - T5
T5 - O1
Fp2 - F8
F8 - T4
T4 - T6
T6 - O2
Fz - Cz
Cz - Pz
Fp1 - F3
F3 - C3
C3 - P3
P3 - O1
Fp2 - F4
F4 - C4
C4 - P4
P4 - O2
State A
State B
State C
Time

Preseizure period

- Changes occur in the brain prior to seizure onset that make the seizure inevitable.
- Central question:
  - *When do the preseizure changes occur?*

Preseizure period

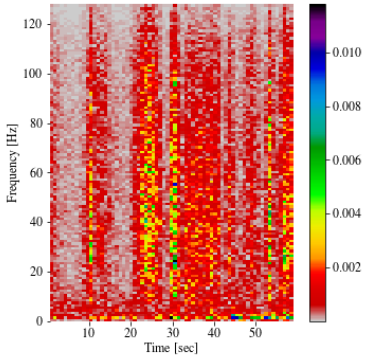
Previous studies assume values in the range 2-262.5 minutes (Mormann et al. 2007).

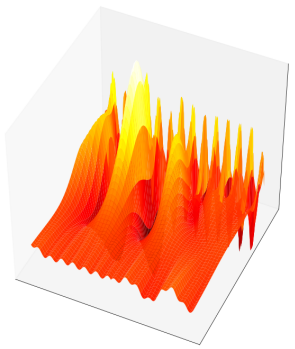
- Changes occur in the brain prior to seizure onset that make the seizure inevitable.
- Central question:
  - *When do the preseizure changes occur?*

Assumed pre-ictal period (min)	Sensitivity (%)	False-positive rate (FP/h)	Mean prediction time (min)	Statistical validation of performance
30	94	0	12	No
20	89	n.a.	3	No
20	83	n.a.	6	No
20	94	n.a.	4	No
n.s.	100	0	n.s.	No
60	100	0	n.s.	No
262.5	100	n.a.	52	No
60	96	n.a.	7	No
Variable	91	n.s.	49	No
180	90	0.12	19	No
n.s.	77	n.s.	Several min	No
n.s.	47	0	19	No
60	95	0	n.s.	No
3	100	n.a.	2	No
90	83	0.31[c]	8	No
Variable	100	n.s.	83	No
240	86	0	86/102[h]	Yes
240	81	0	4–221	No
60	0	n.a.	–	No
2	94	0.08[f]	5–80 s	No
90	n.s.	n.s.	>>30	No
60	88	0.02	35	No

Features for seizure prediction

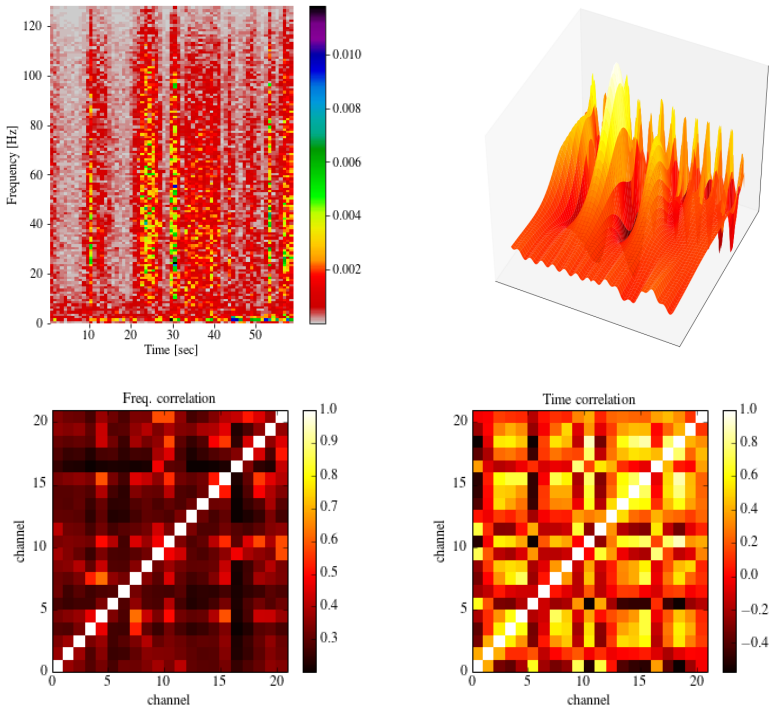
- Time/frequency domain features





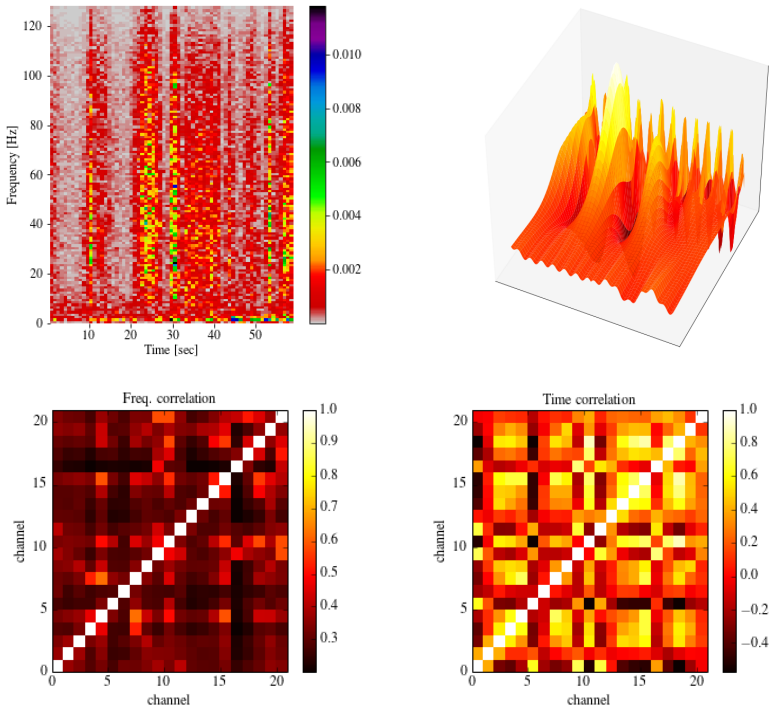
Features for seizure prediction

- Time/frequency domain features
- Multivariate features



Features for seizure prediction

- Time/frequency domain features
- Multivariate features
- Model based features



State of the art

- "Crowdsourcing reproducible seizure forecasting in human and canine epilepsy"[1]
  - Results of Kaggle competition on seizure prediction
  - Winning submissions used time/frequency domain features extracted from intracranial human and dog EEG

[1] Brinkmann et al. 2016.
[2] Cook et al. 2013.
[3] Bandarabadi et al. 2015.

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- "Prediction of seizure likelihood with a long-term, implanted seizure advisory system in patients with drug-resistant epilepsy: A first-in-man study"[2]
  - Implanted seizure prediction device
  - Three energy measures in filtered intracranial EEG as features

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- "On the proper selection of preictal period for seizure prediction"[3]
  - Measure common area between preictal and interictal feature histograms

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Virtual Classifiers (VC)

Definition

Time series of feature vectors $\{x_k\}_{k=1}^{T}$ with state space $\mathbb{X} = \mathbb{R}^d$.
Time t defines a split of the time series into disjoint sets:

$$A_t = \{x_1, x_2, ...x_t\}$$

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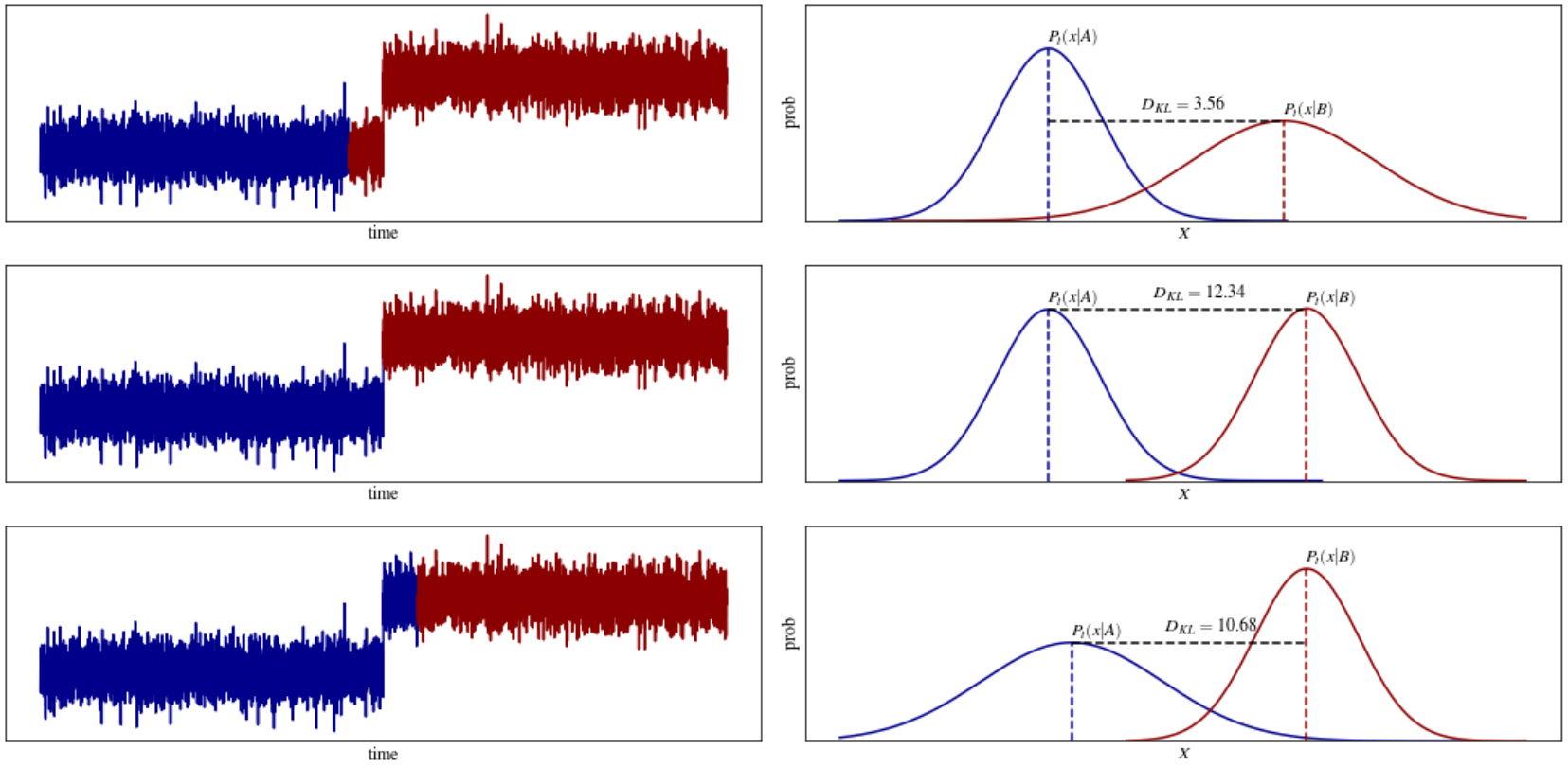
Consider change point detection as an optimization problem:

$$\max_t D(P(x|A_t), P(x|B_t))$$

Idea is to approximate $D(P(x|A_t), P(x|B_t))$ with classification accuracy.

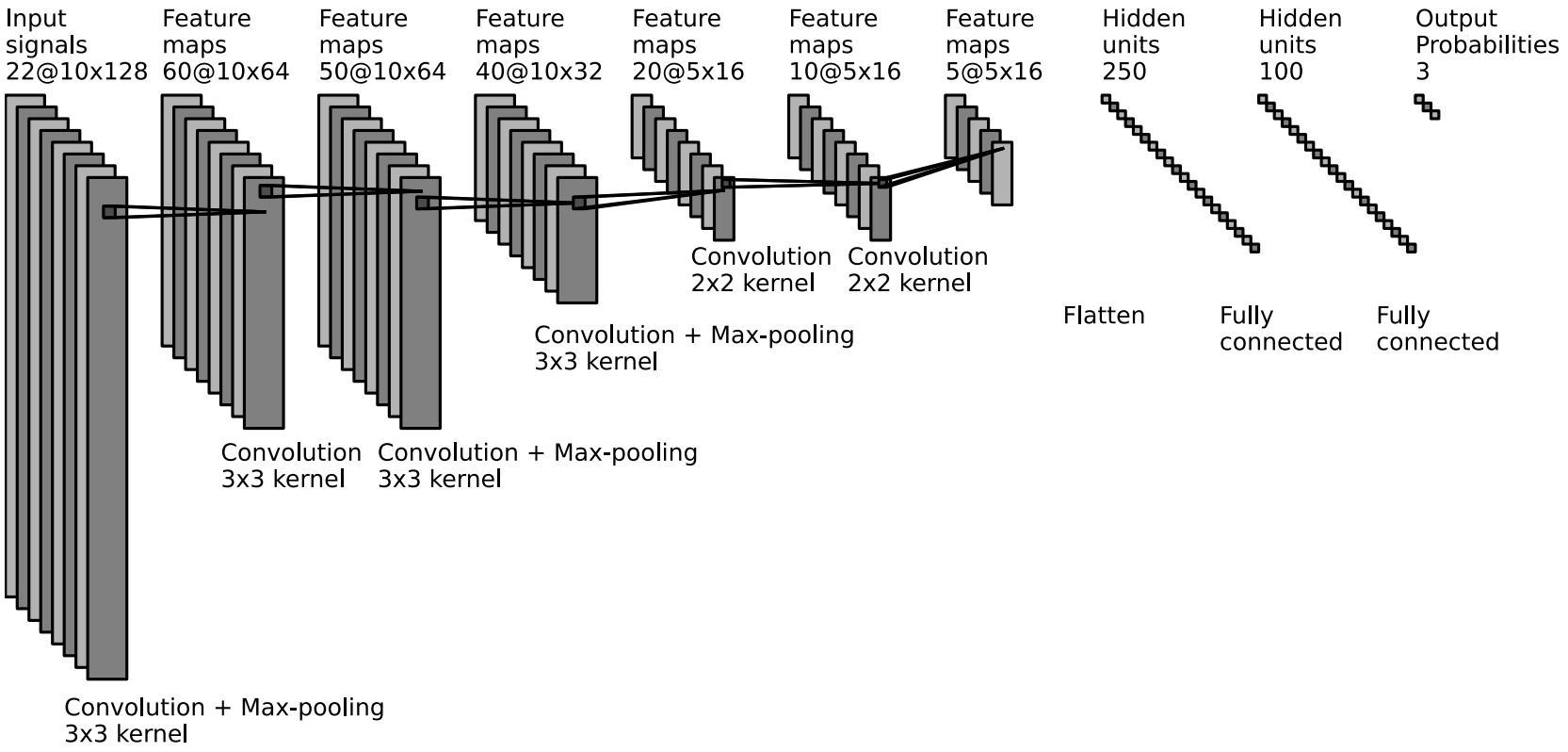


Example of a Gaussian noise signal undergoing a mean shift.

CNN for feature extraction

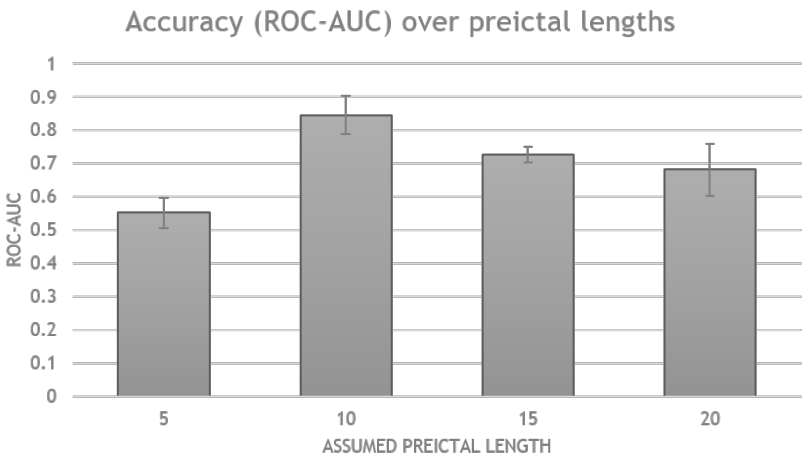
Use CNN to learn features from EEG

Convolutions over time and frequency using wavelets



VC for preseizure period length

Candidate preseizure lengths: 5, 10, 15, 20 minutes CNN trained for each labelling of the data



Results and comparison

Dataset of 500+ hours of 22-channel EEG
We compared our results to:

- 2 top performing algorithms from Kaggle[4]
- Algorithm from Cook et al.[5]

Method	**PH** (mins)	**Sensitivity**	**FPr** (FP/h)	**Random pred.** σ_{low}-σ_{high}
Kaggle1	60	72.7%	0.285	15.1% - 27.2%
Kaggle2	60	75.8%	0.230	12.1% - 24.2%
Cook et al.	PS	66.7%	0.186	12.1% - 21.2%
This work	10	**87.8%**	**0.142**	9.1% - 15.1%

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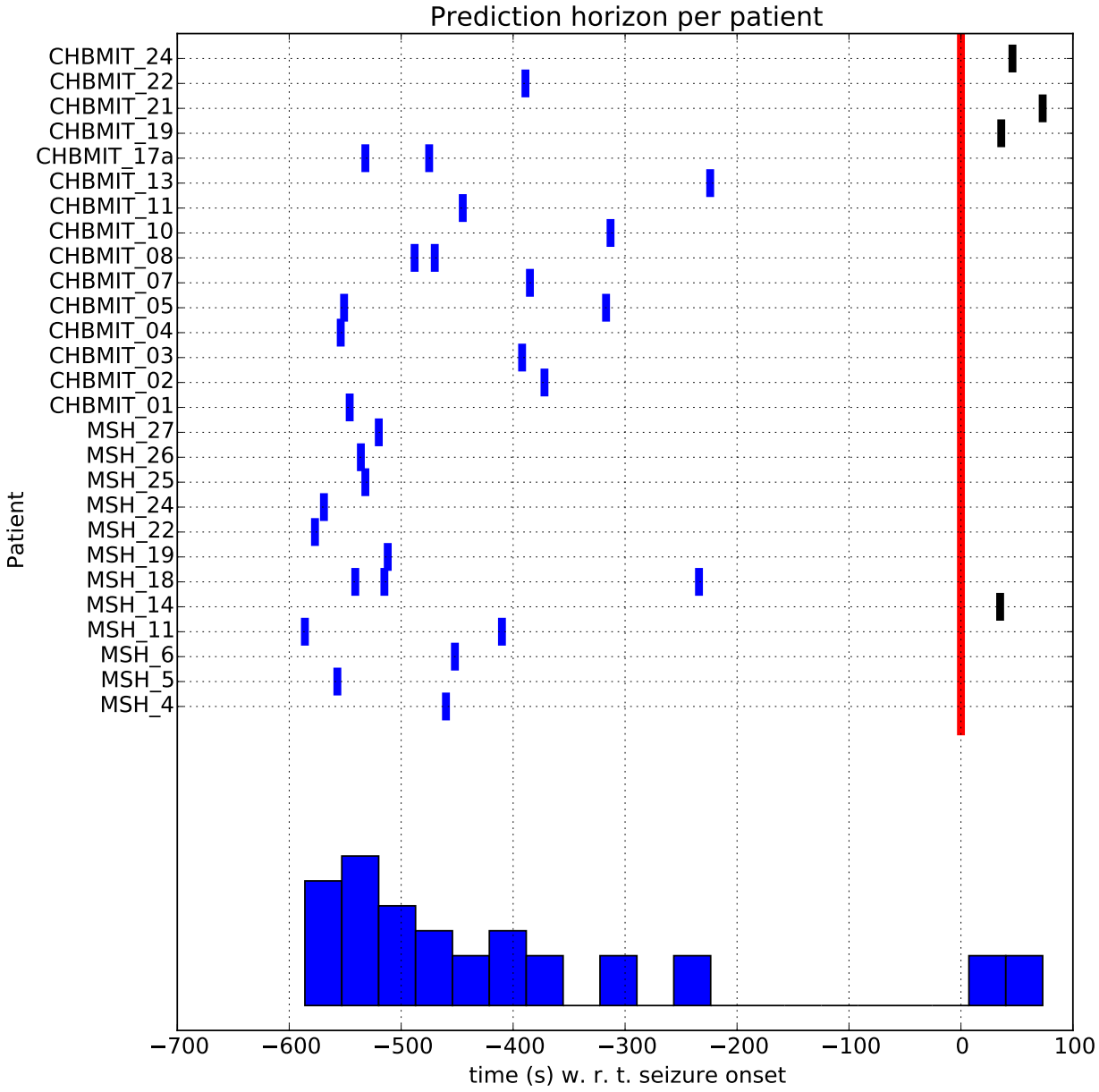
Prediction horizon per patient
Patient
CHBMIT_24
CHBMIT_22
CHBMIT_21
CHBMIT_19
CHBMIT_17a
CHBMIT_13
CHBMIT_11
CHBMIT_10
CHBMIT_08
CHBMIT_07
CHBMIT_05
CHBMIT_04
CHBMIT_03
CHBMIT_02
CHBMIT_01
MSH_27
MSH_26
MSH_25
MSH_24
MSH_22
MSH_19
MSH_18
MSH_14
MSH_11
MSH_6
MSH_5
MSH_4
−700
−600
−500
−400
−300
−200
−100
0
100
time (s) w. r. t. seizure onset

Conclusions

- A novel technique for seizure prediction based on the combination of deep representation learning and change point detection.
- Patient independent seizure prediction from scalp EEG
- How do factors such as vigilance, medication, etc. affect prediction?

Acknowledgements

DSRC DATA SCIENCE RESEARCH CENTER

Mount Sinai