



EMRICK SINITAMBIRIVOUTIN

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# EPILEPTIC SEIZURE DETECTION USING MACHINE LEARNING

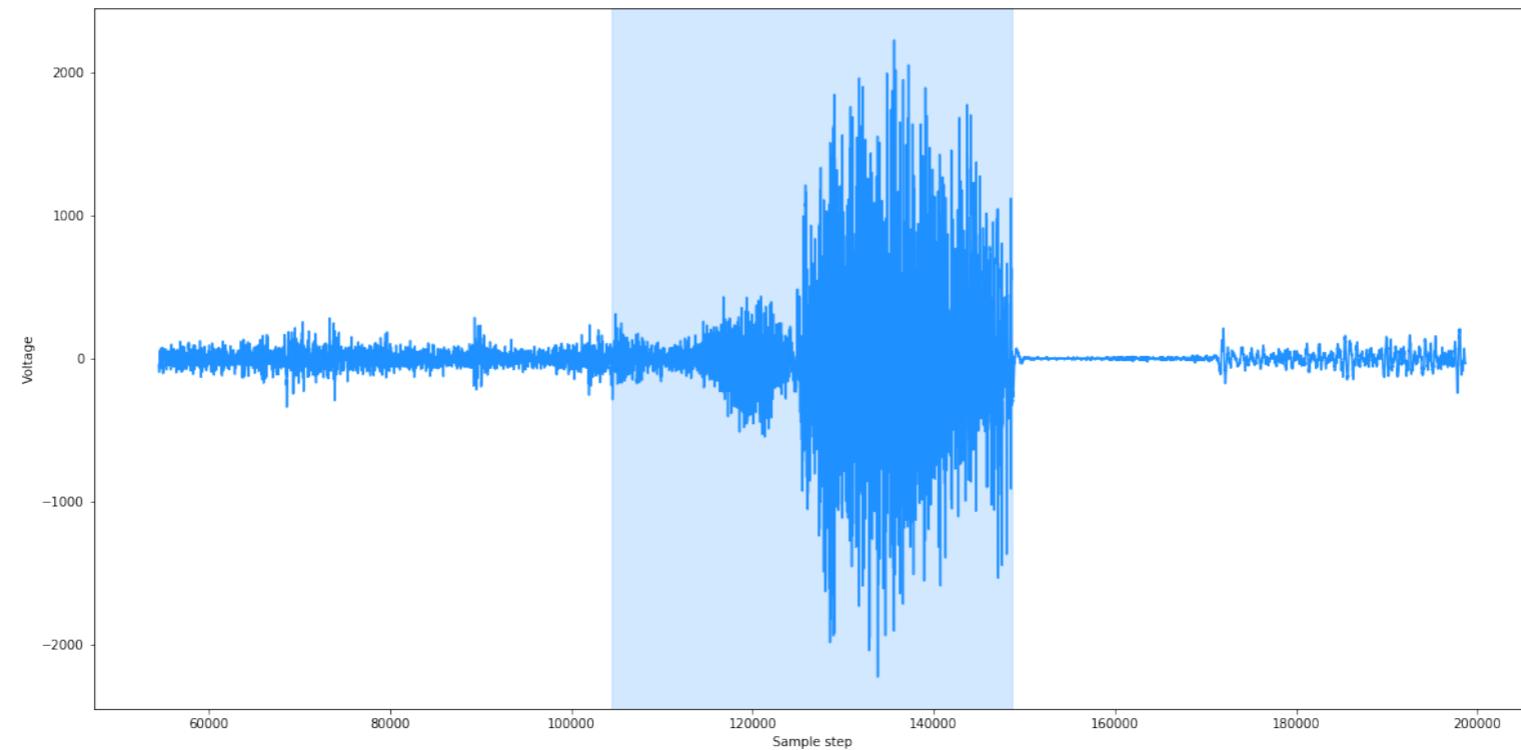
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## INTRODUCTION

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# EPILEPSY

- ▶ The disease is characterized by a recurrence of a brief abnormal and uncontrollable electrical discharge of the brain (**Seizure**)



- ▶ **50 million** people world- wide have epilepsy
- ▶ **30%** are untreated or poorly treated

## INTRODUCTION

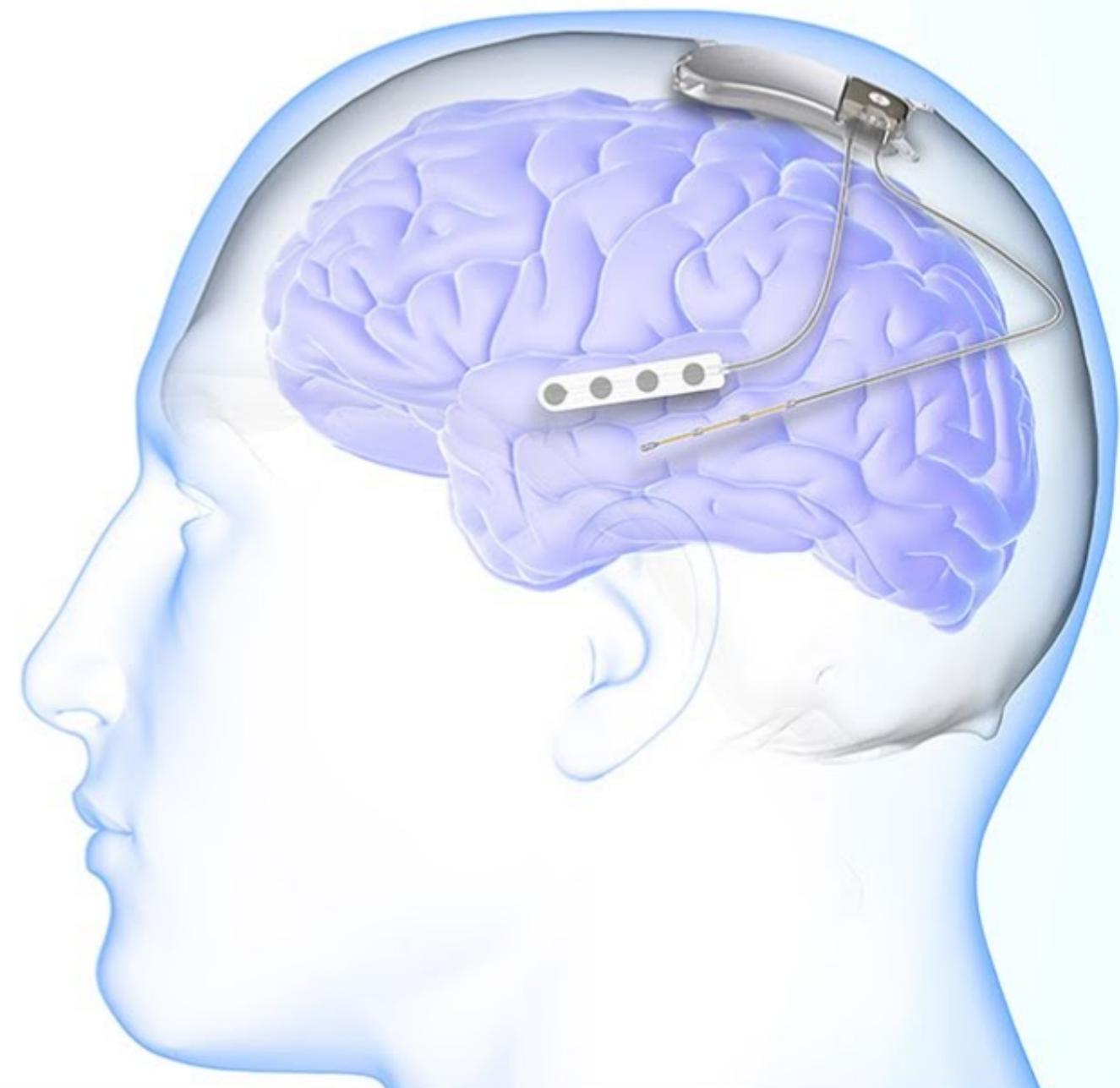
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# IMPLANTABLE DEVICES

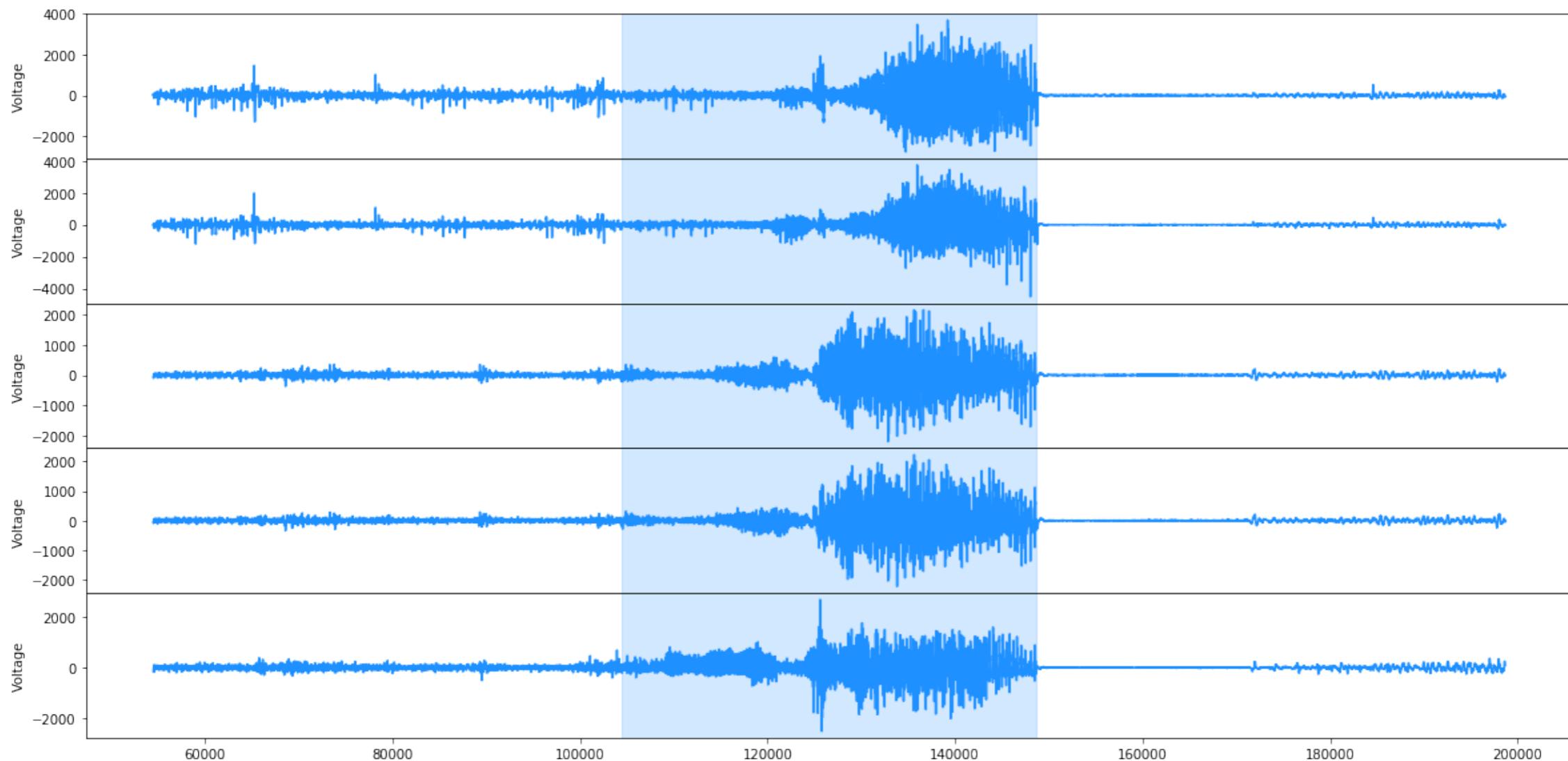
- ▶ Device that can monitor their brain activity and generate an electrical stimulation to stop their seizure when it is detected by the device.

## CHALLENGES

- ▶ Low power consumption
- ▶ Real time decision
- ▶ High accuracy

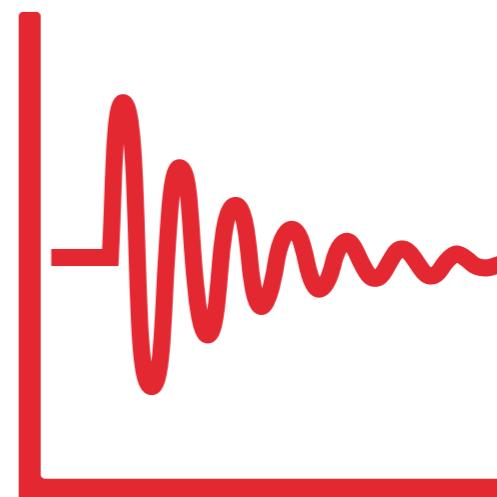
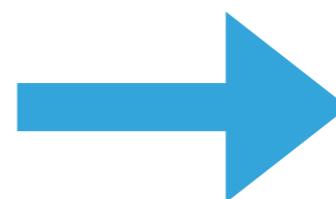
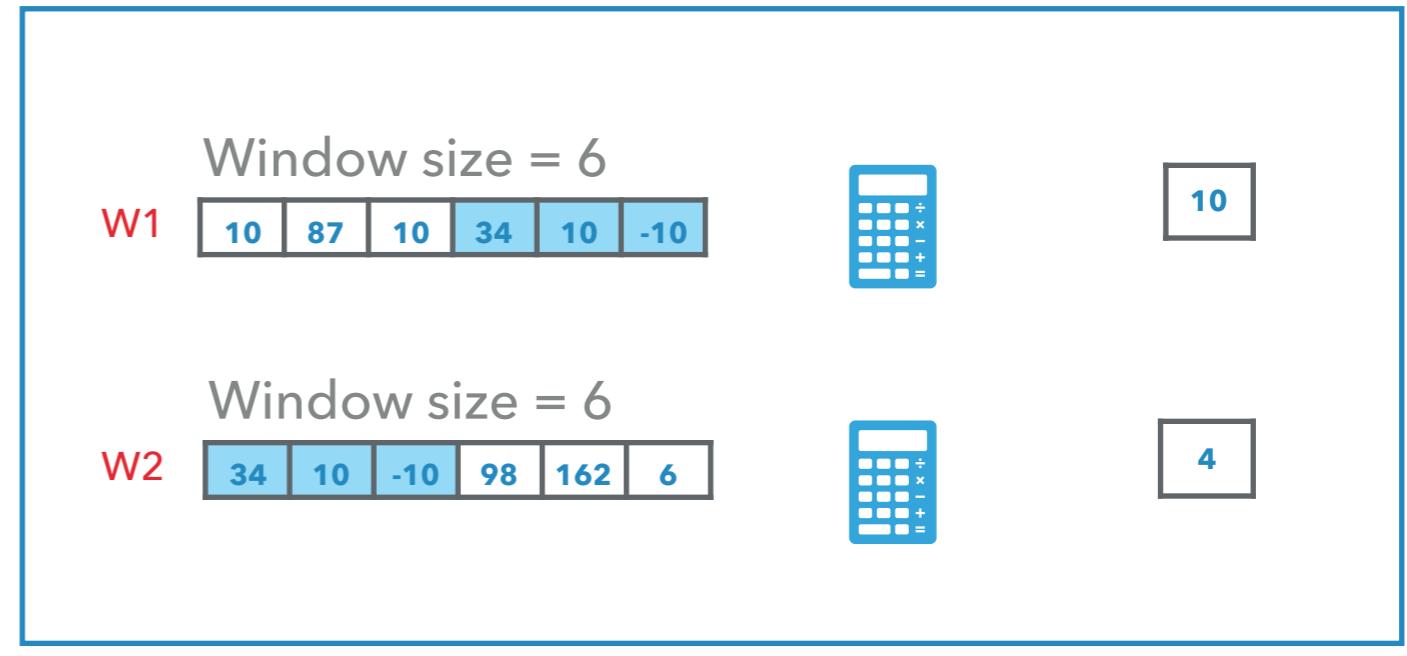
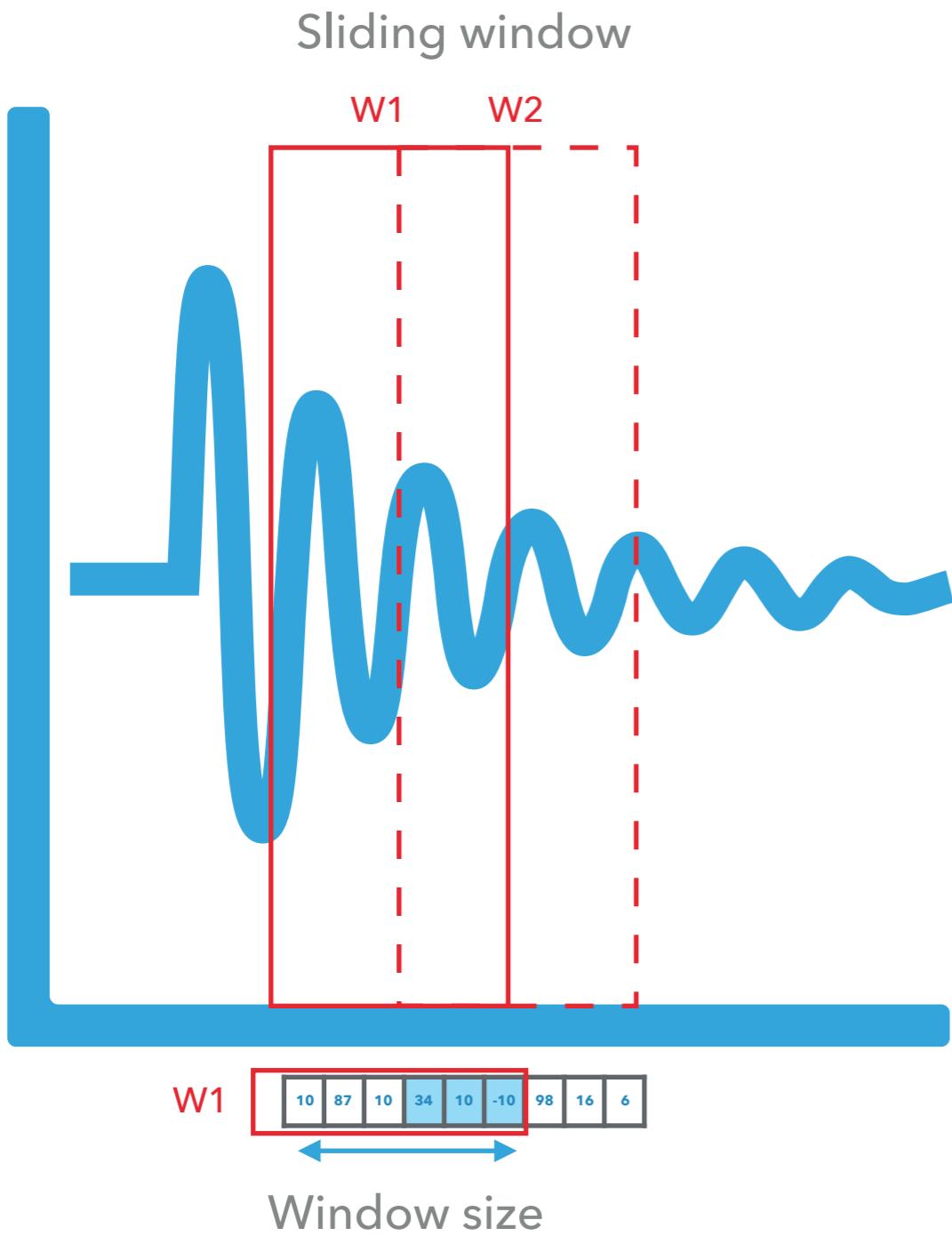


# EXAMPLE OF IEEG RECORDING



## INTRODUCTION

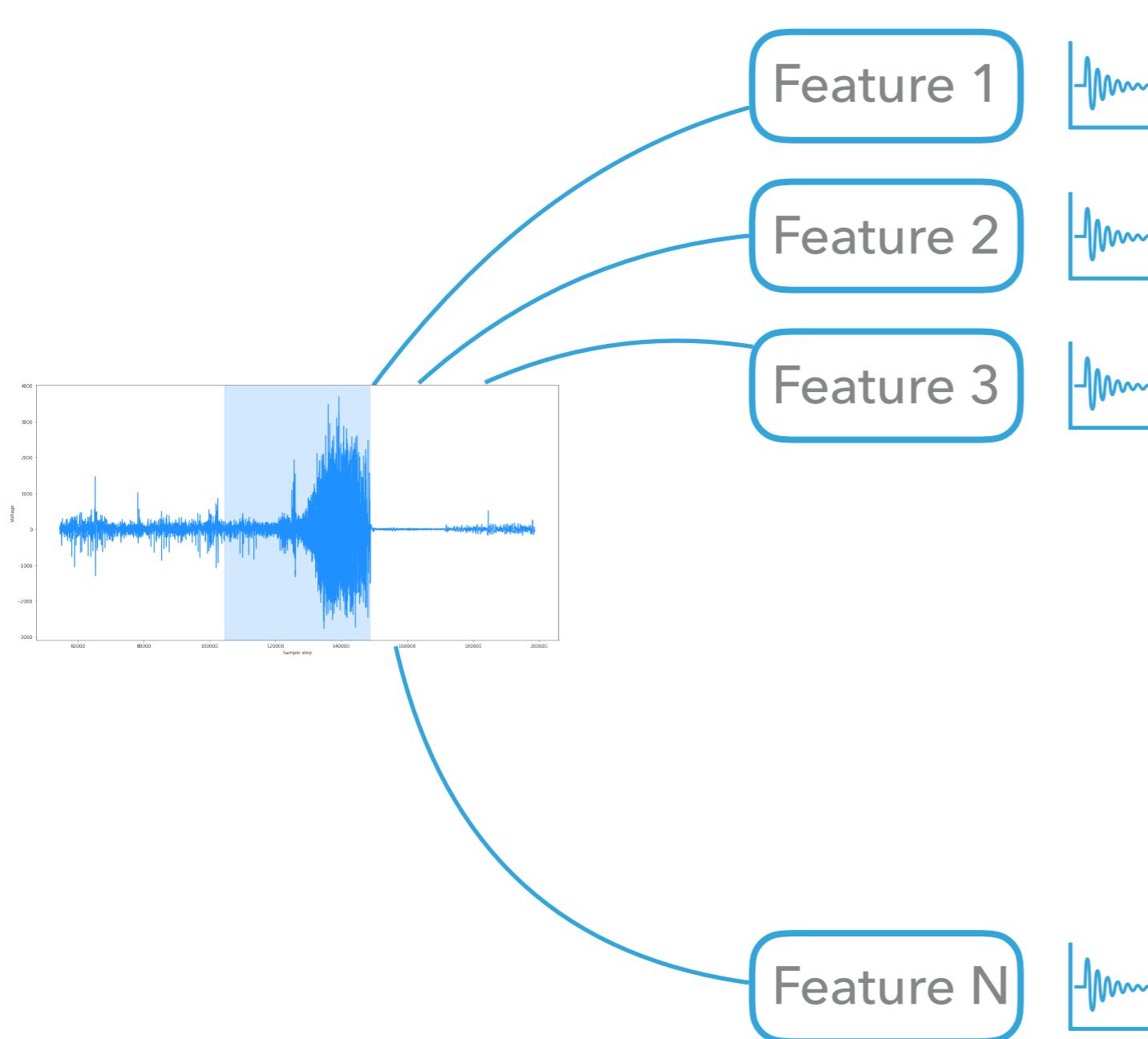
# SIGNAL FEATURE



Feature

## INTRODUCTION

# MACHINE LEARNING



Model input

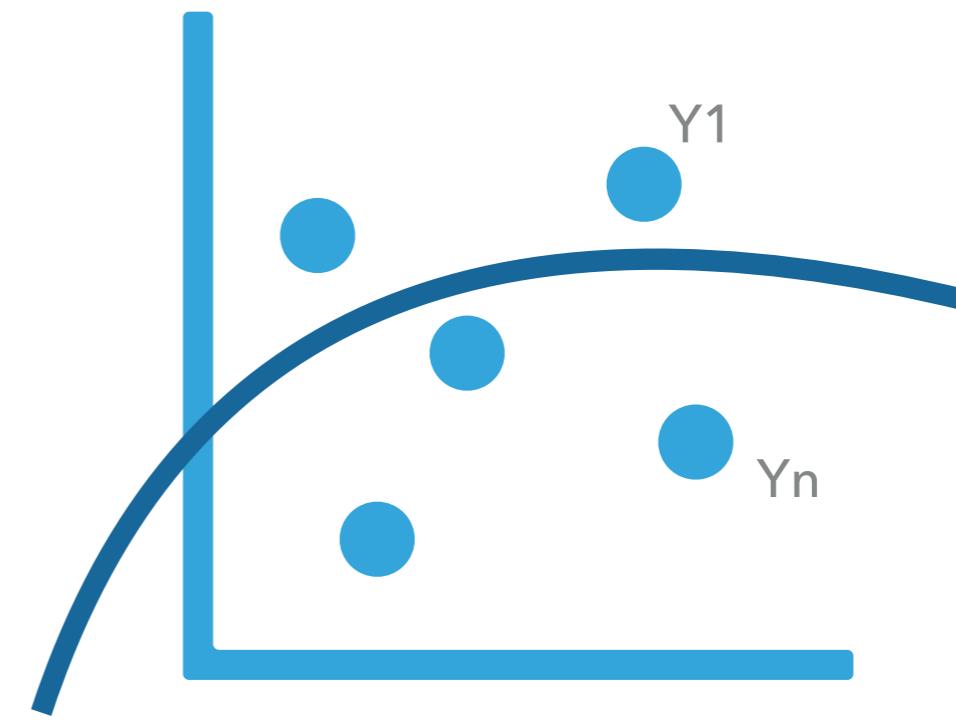
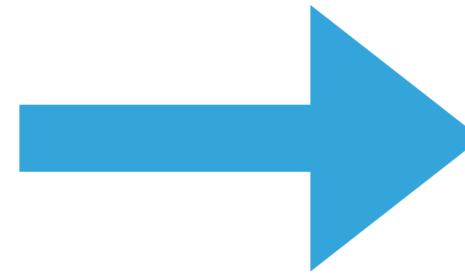
10	87	10	34	10	-10
12	34	49	23	10	-34
12	56	10	45	03	-10
10	87	-3	-87	10	-10

## INTRODUCTION

# MACHINE LEARNING

Y1						Yn
10	87	10	34	10	-10	
12	34	49	23	10	-34	
12	56	10	45	03	-10	
10	87	-3	-87	10	-10	

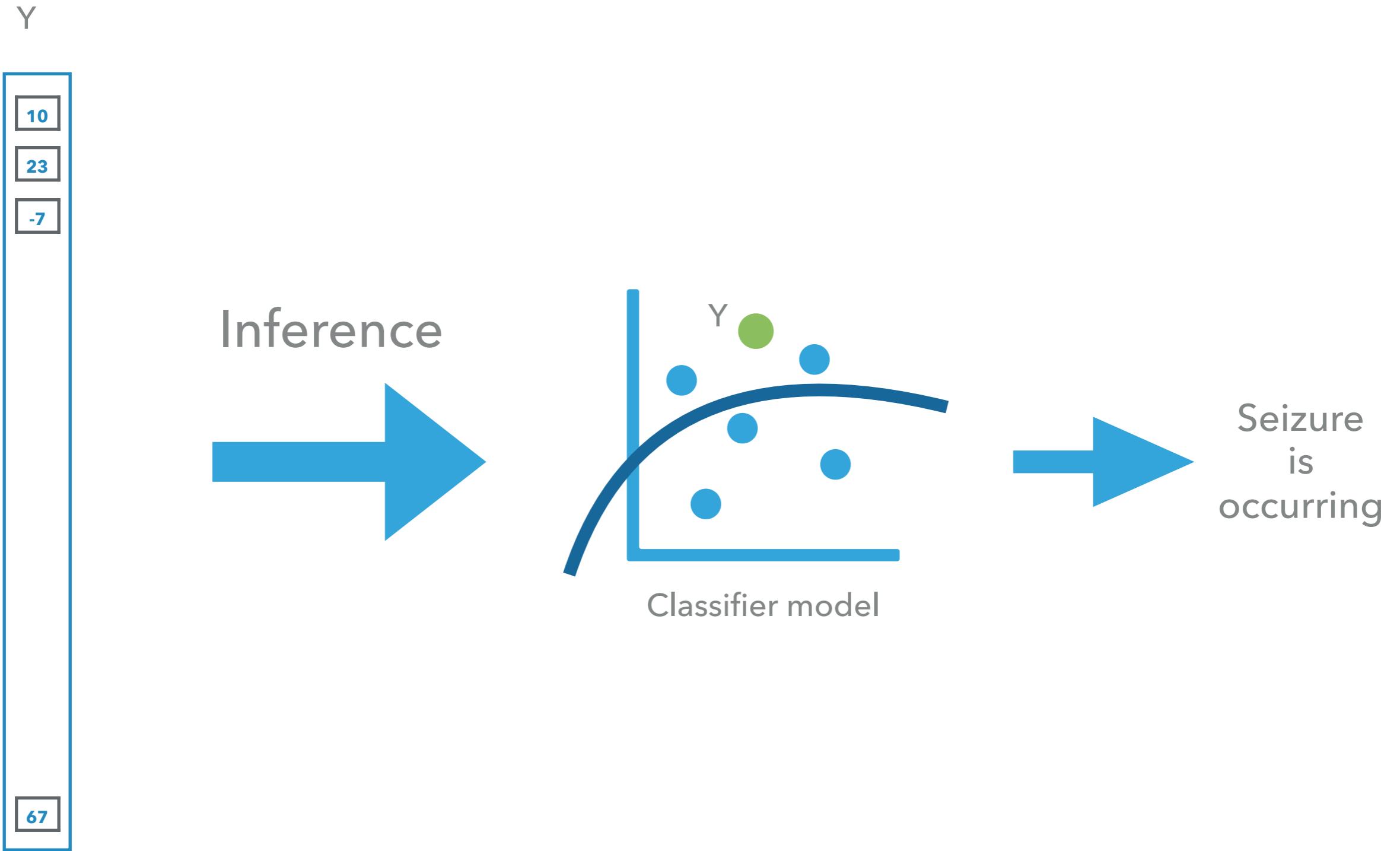
Training



Classifier model

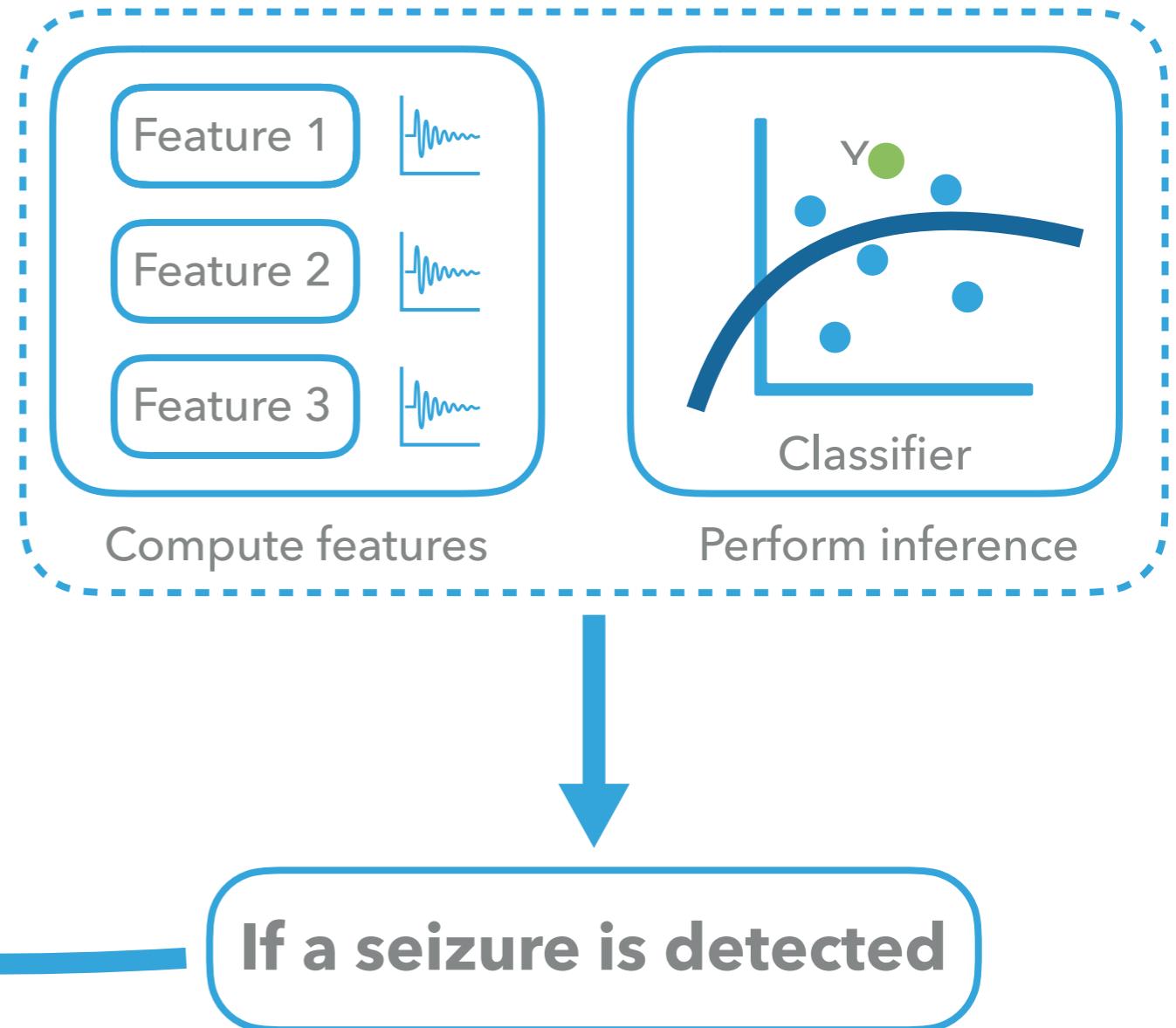
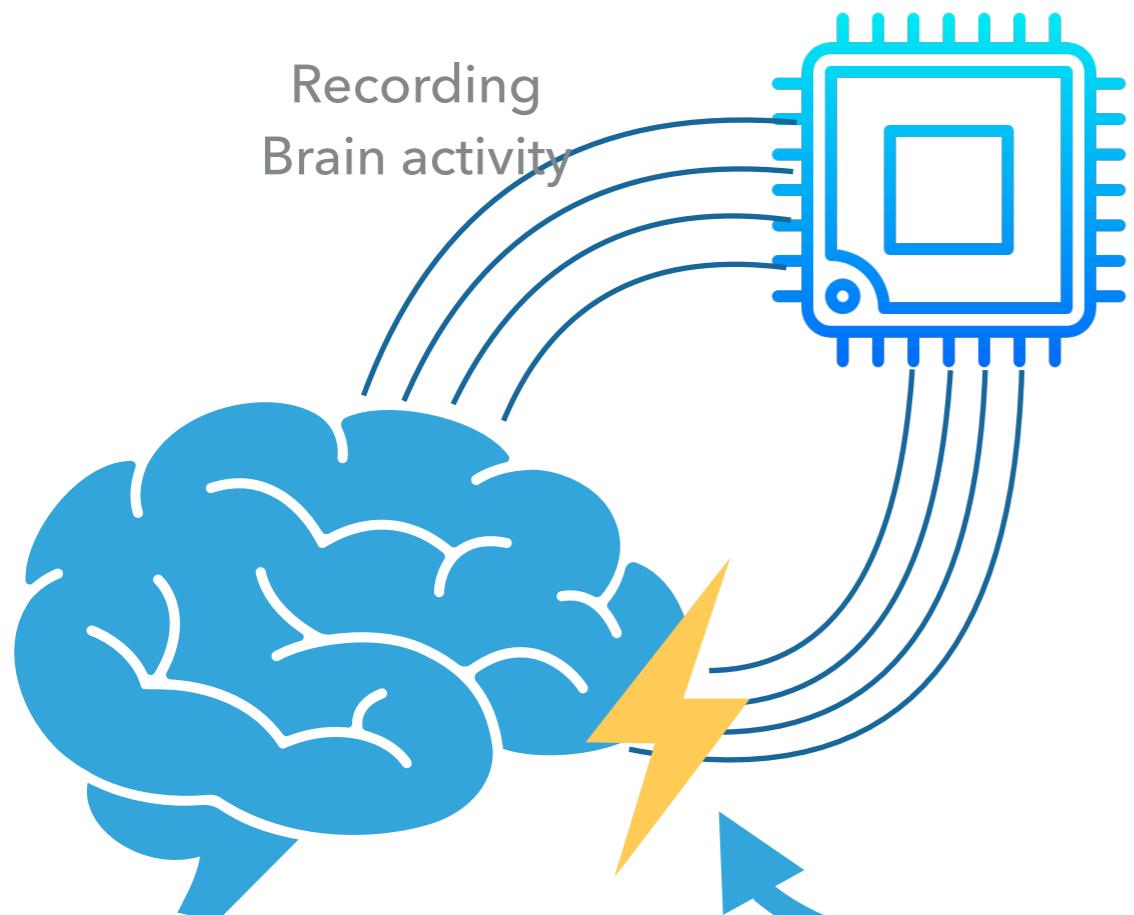
## INTRODUCTION

# MACHINE LEARNING



## INTRODUCTION

# THE FINAL GOAL



# TIME LINE

### ► Why do we need specific features for a patient

- ▶ Heterogeneity between patient data
- ▶ Seizures between patient can differ a lot
- ▶ Why do we need features to train a classifier

### ► How do we choose the right feature

- ▶ The metrics that we want to use (Precision, specificity, FA)
- ▶ The scoring method that I propose (why this method, how it meets our objectives)
- ▶ The features that I've tried and how do we calculate them

### ► Results

- ▶ Score results obtained with the method
- ▶ Comparison between different patients



WHY DO WE NEED  
SPECIFIC FEATURES FOR A PATIENT ?

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# 1. PATIENTS HETEROGENEITY

## SWEC-ETHZ IEEG DATABASE

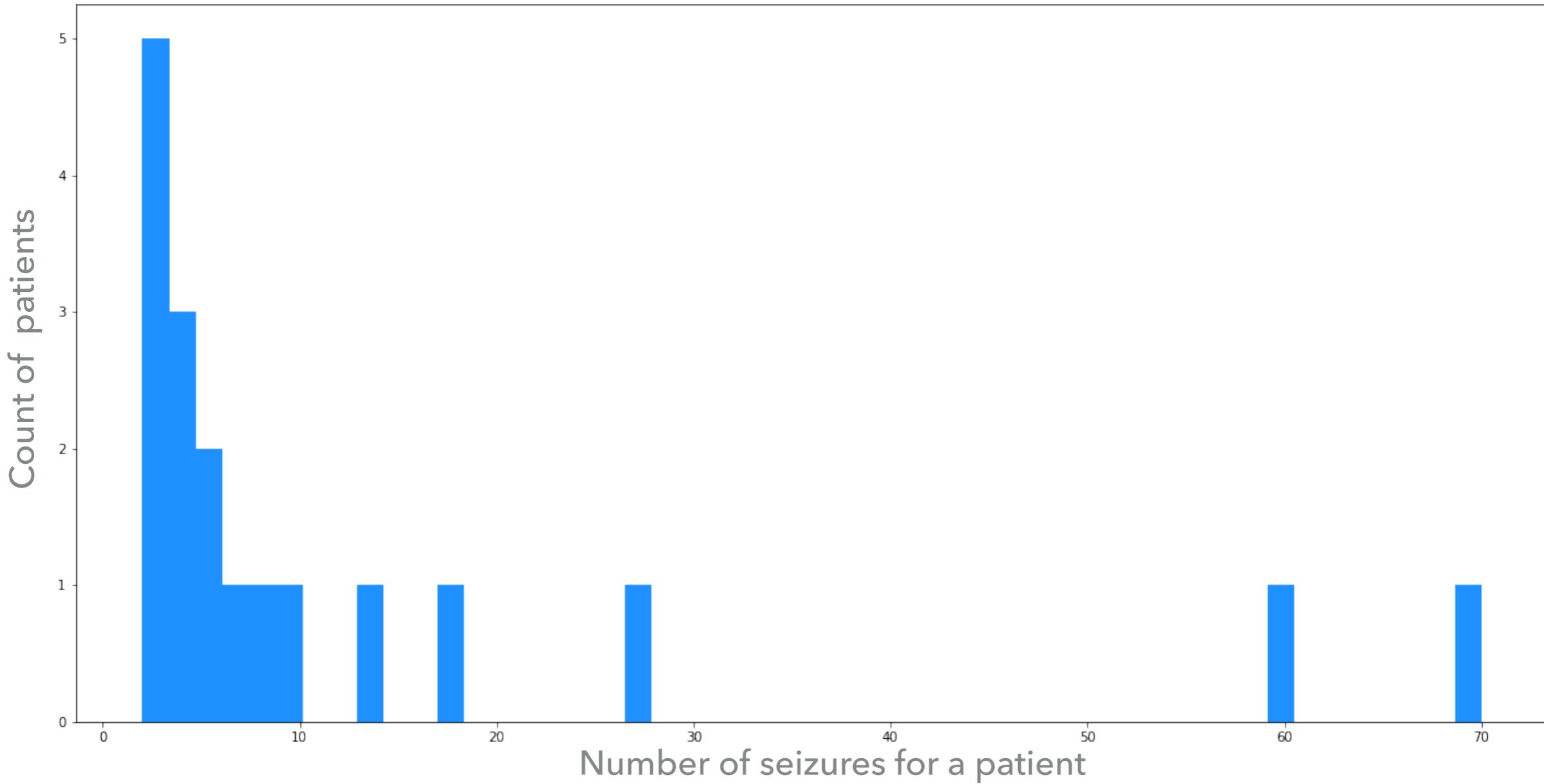
- ▶ **Long-term Dataset:** 2656 hours of anonymized and continuous intracranial electroencephalography (iEEG) of 18 patients with pharmaco-resistant epilepsies.
- ▶ **Short-term Dataset:** 100 anonymized intracranially recorded electroencephalographic (iEEG) datasets of 16 patients with pharmaco-resistant epilepsy.
- ▶ All the iEEG recordings were visually inspected by an EEG board-certified and experienced epileptologist (K.S.) for identification of seizures.

## PATIENT HETEROGENEITY

### SEIZURE FREQUENCY

- Some patients have much more seizure during a period of time than other patient.

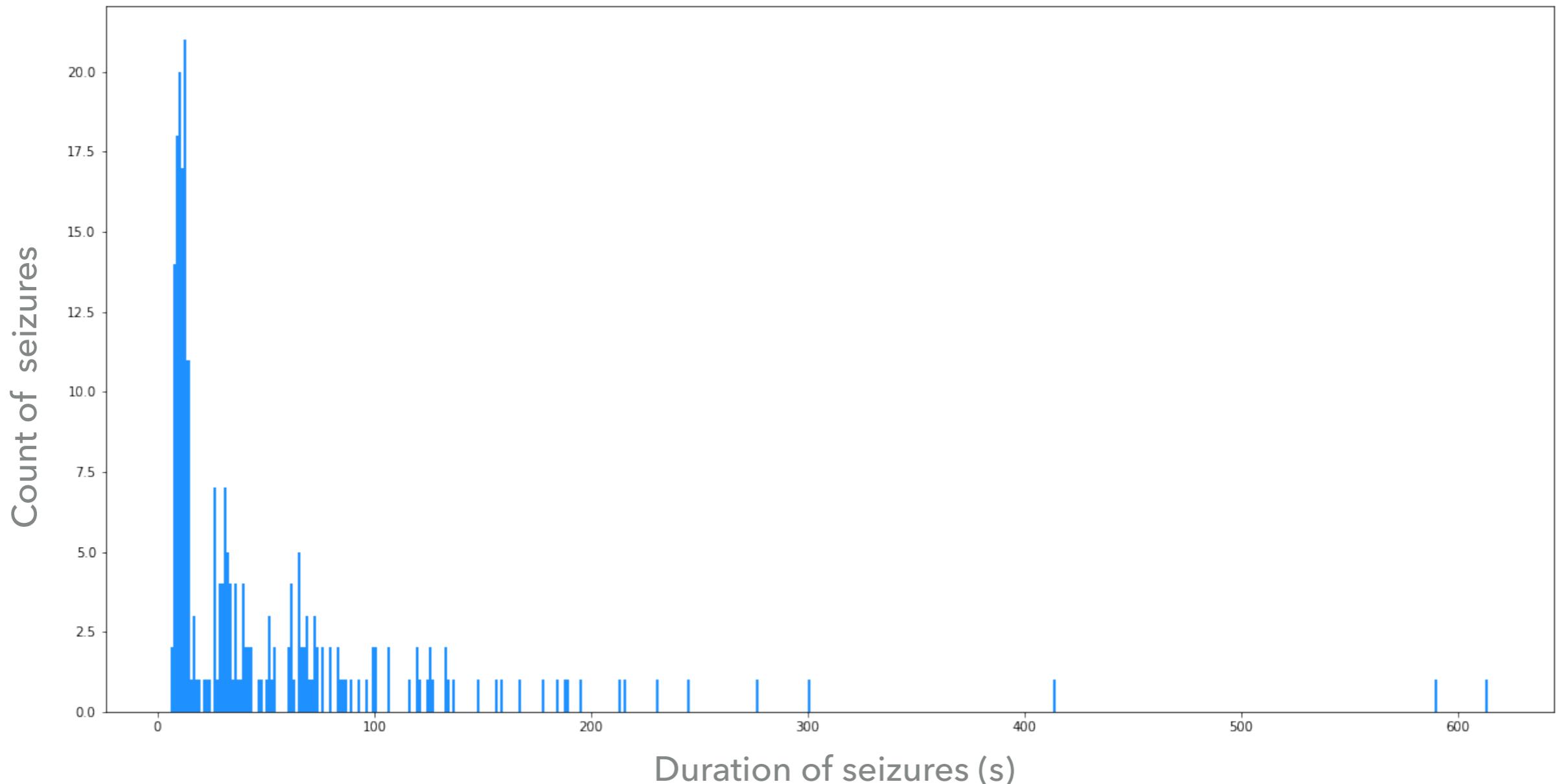
Histogram of patients according to their number of seizures



# SEIZURE DURATION

- ▶ Seizure duration can vary a lot.

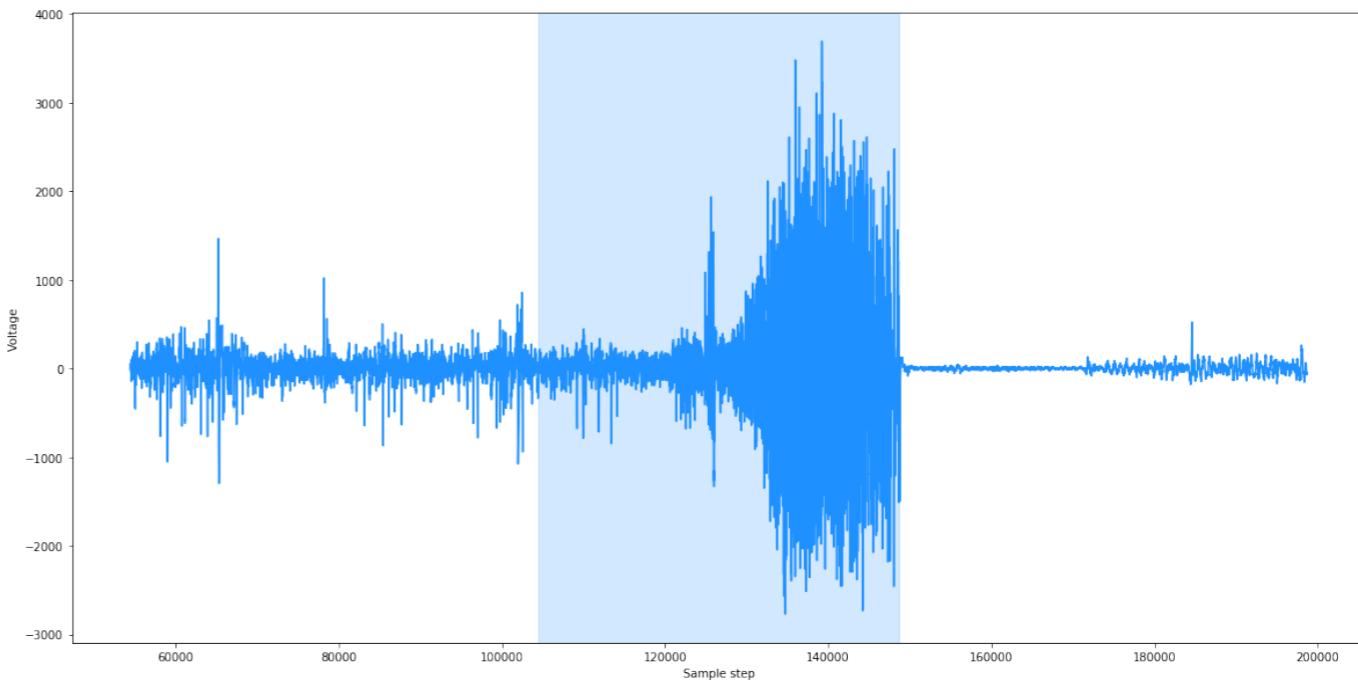
Histogram of seizures according to their duration



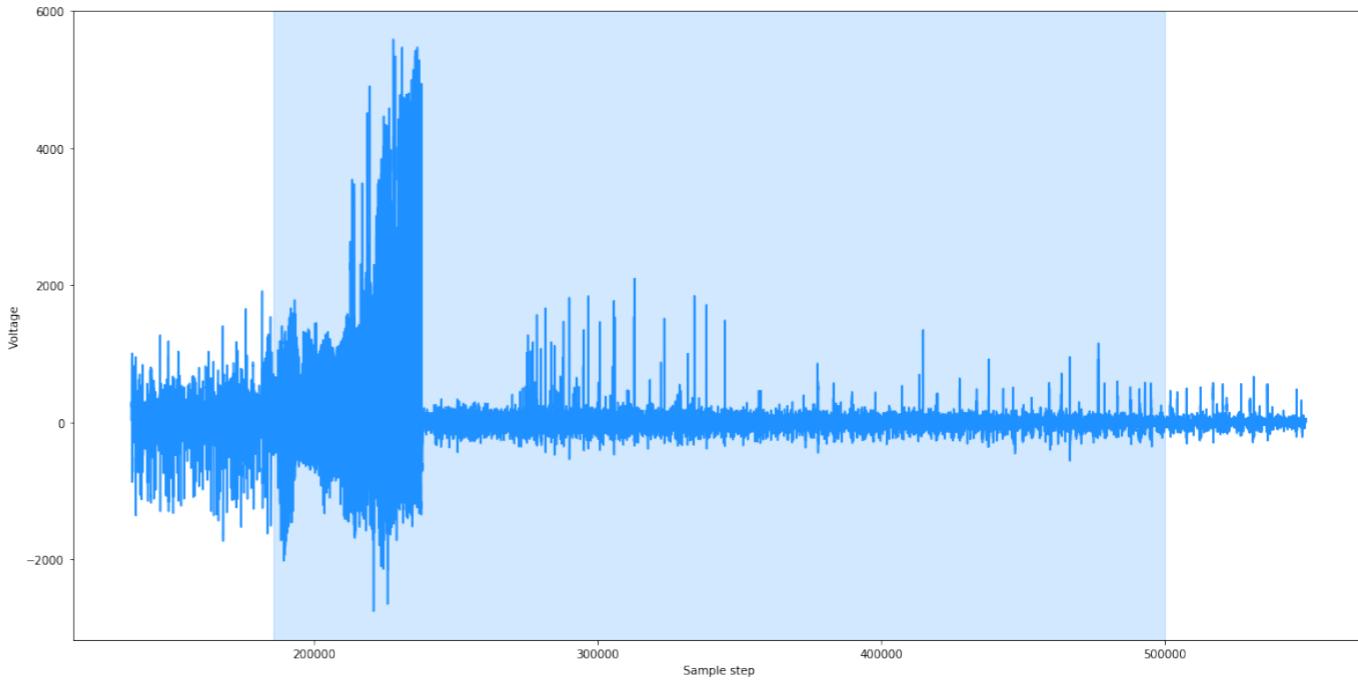
## PATIENT HETEROGENEITY

# SEIZURE SIGNALS

**Patient 1 (First seizure)**



**Patient 2 (First seizure)**



## PATIENT HETEROGENEITY

# SEIZURE DURATIONS STATISTICS

- ▶ Statistics show that some patients have a high variability in term of seizure duration.
- ▶ Some patients have much more seizures than others

Low variance in term  
of duration

Patient	number of seizures	mean duration	std duration	min duration	max duration
1	2	601.787	16.9381	589.81	613.764
2	2	88.0625	2.55547	86.2555	89.8695
3	4	64.6619	4.14865	60.5449	68.234
4	14	41.9404	13.779	7.77257	68.6968
5	4	16.6878	0.512328	15.9232	17.013
6	8	45.8905	32.8707	29.3444	126.882
7	4	69.5688	38.6222	14.1287	98.8148
8	70	21.9668	53.88	6.22336	413.385
9	27	42.377	35.5274	18.7427	148.283
10	17	70.8471	10.7102	61.2513	106.262
11	2	91.5471	11.9259	83.1142	99.98
12	9	146.461	33.0413	106.836	194.754
13	7	103.004	60.9422	40.1964	188.44
14	60	25.8067	24.3826	6.37323	100.775
15	2	94.5809	35.5882	69.4163	119.746
16	5	190.445	50.6856	120.293	245.196
17	2	97.9362	1.28925	97.0246	98.8479
18	5	199.132	100.565	71.4387	300.651

High variance in term  
of duration



HOW DO WE CHOOSE THE RIGHT  
FEATURE ?

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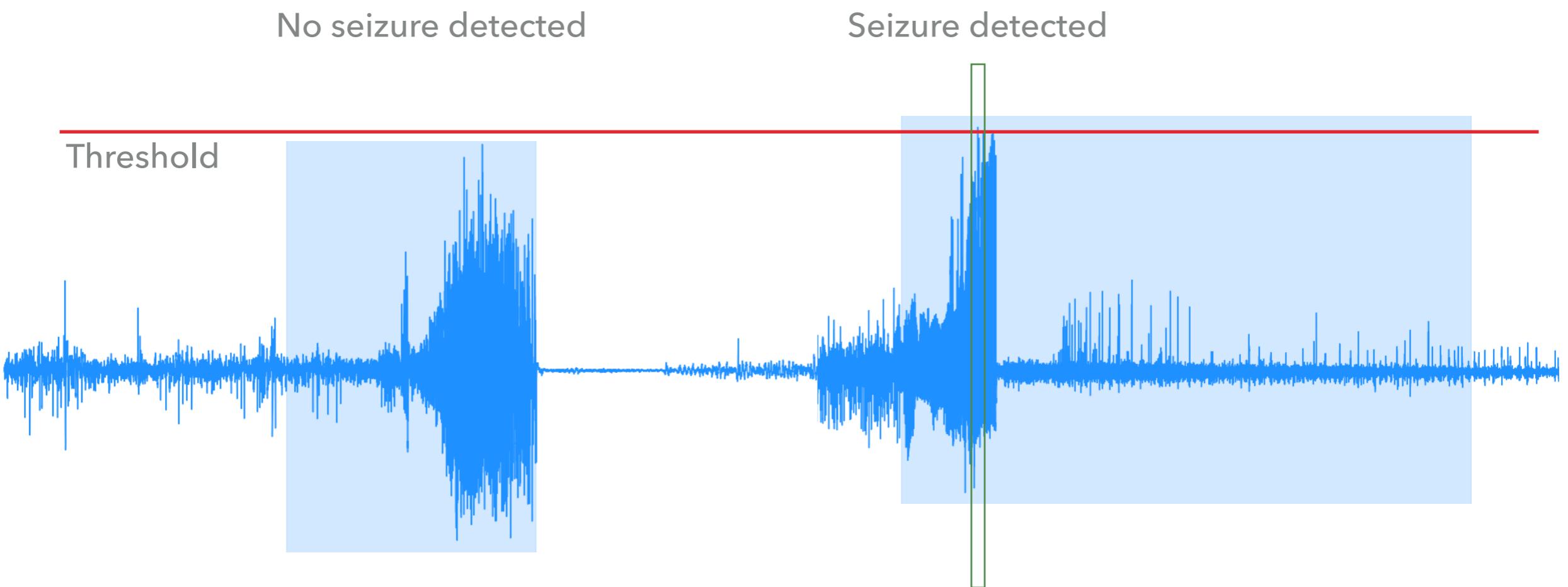
## 2.FEATURE SELECTION AND SCORING

# METRICS

- ▶ **Accuracy** : The number of detected seizure other all seizures
- ▶ **False alarms** : The number of seizure detection that didn't occurred during a true seizure
- ▶ **Delay** : The time between the real start of a seizure and the moment of the first valid detection

## FEATURE SELECTION AND SCORING

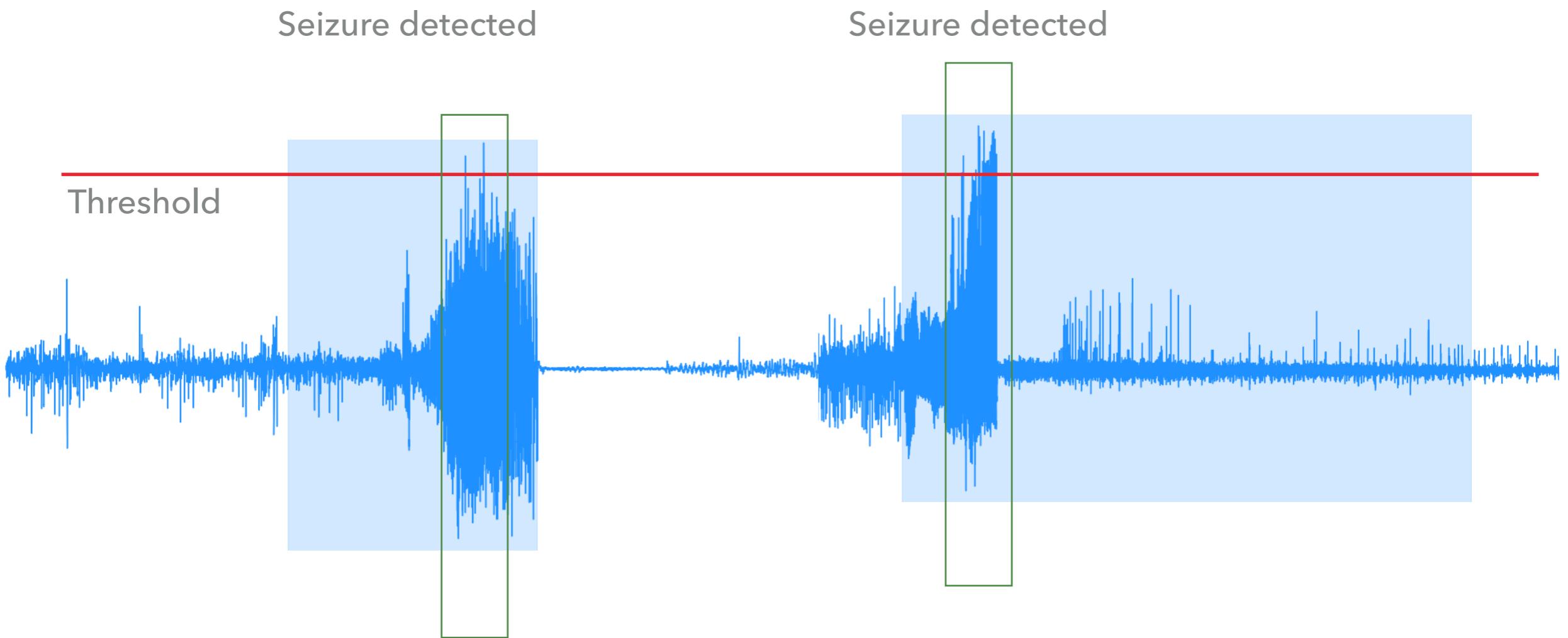
### METRICS: ACCURACY



**ACCURACY: 50%**

## FEATURE SELECTION AND SCORING

# METRICS: ACCURACY

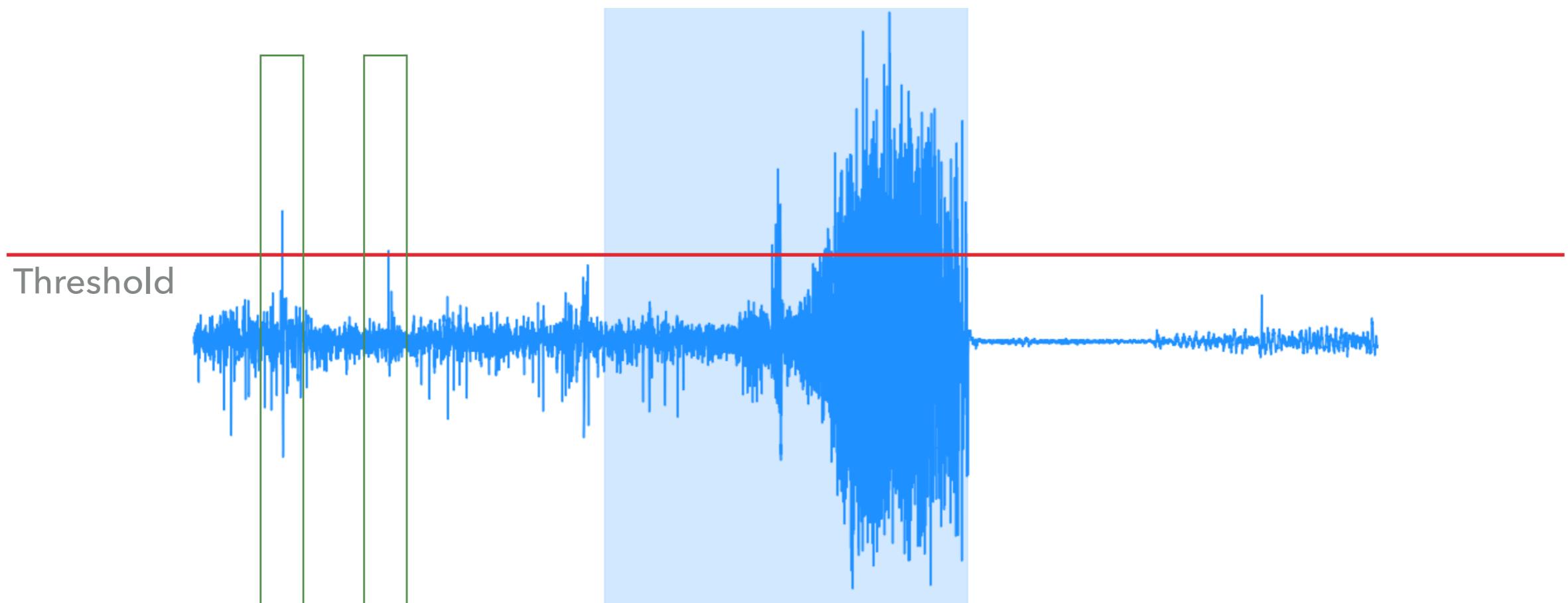


ACCURACY: 100%

## FEATURE SELECTION AND SCORING

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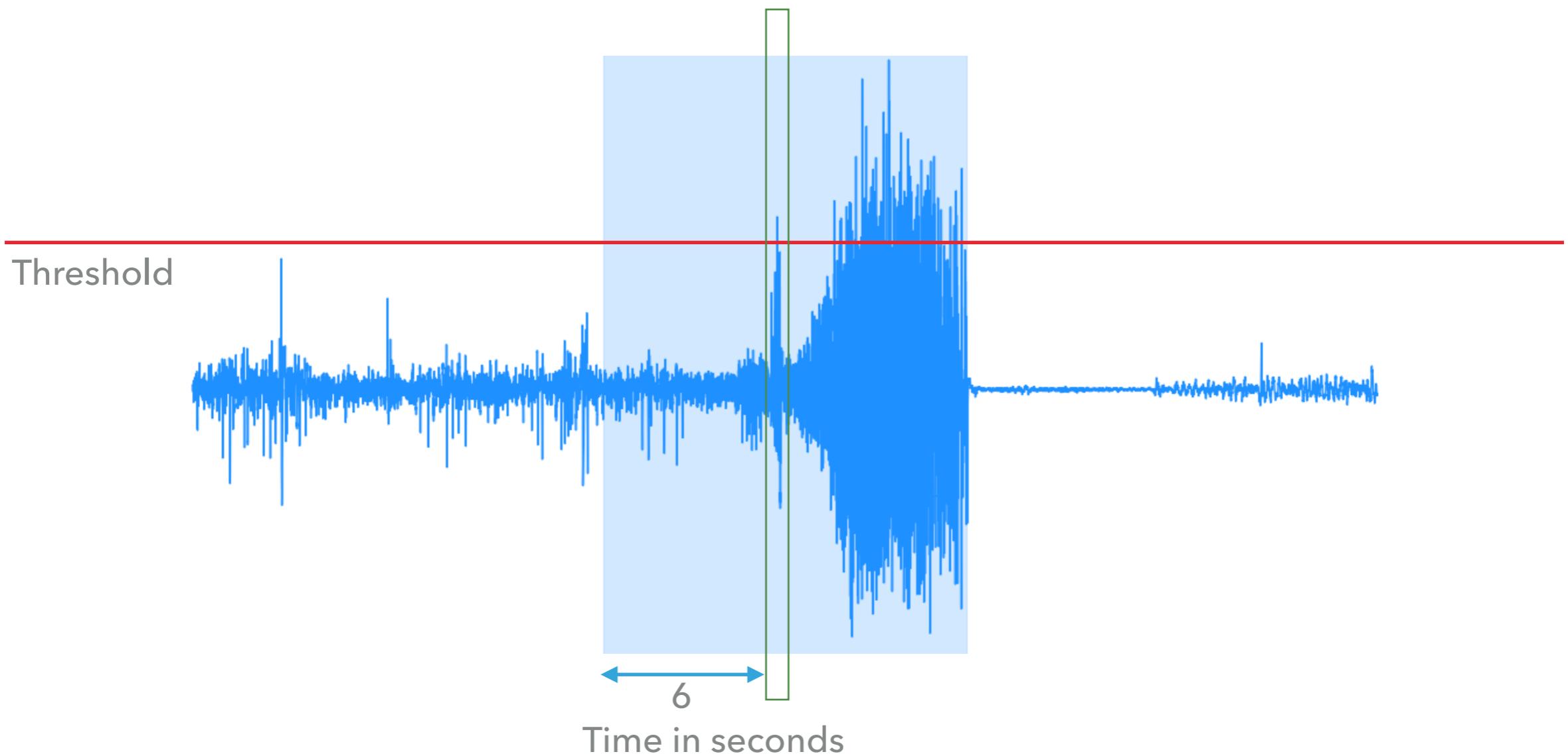
### METRICS: FALSE ALARM



**FALSE ALARM: 2**

## FEATURE SELECTION AND SCORING

### METRICS: DELAY

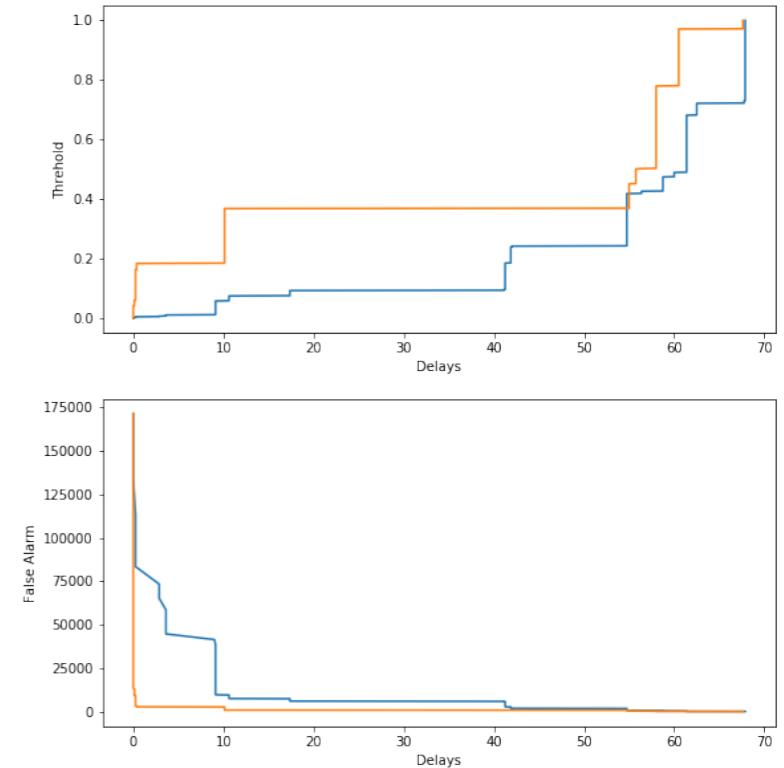
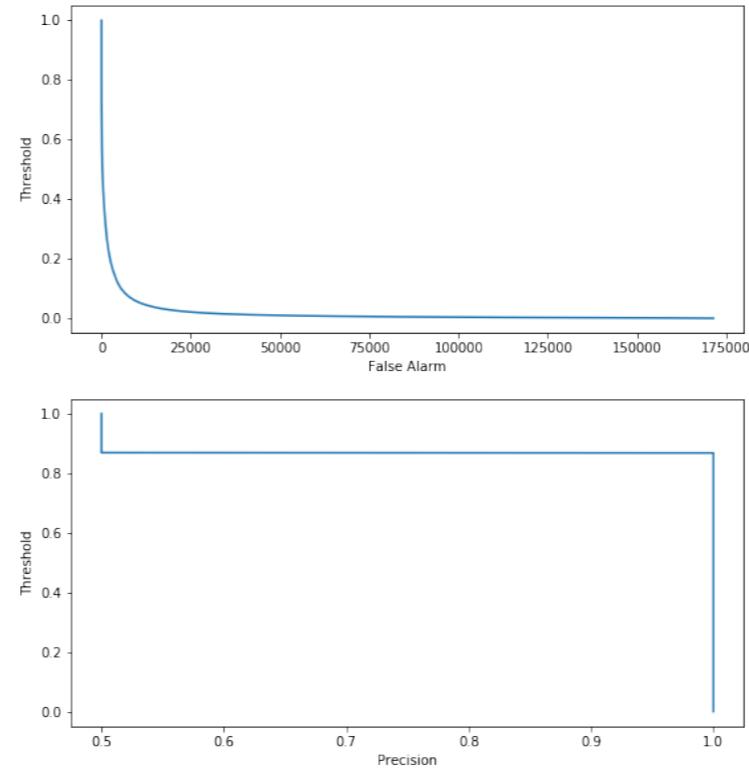


**DELAY: 6S**

# GOALS OF THE SCORING

## Goal 1 (for each seizure)

- ▶ Minimize False Alarms
- ▶ Minimize delays (lower than 10 seconds)
- ▶ Accuracy of 1



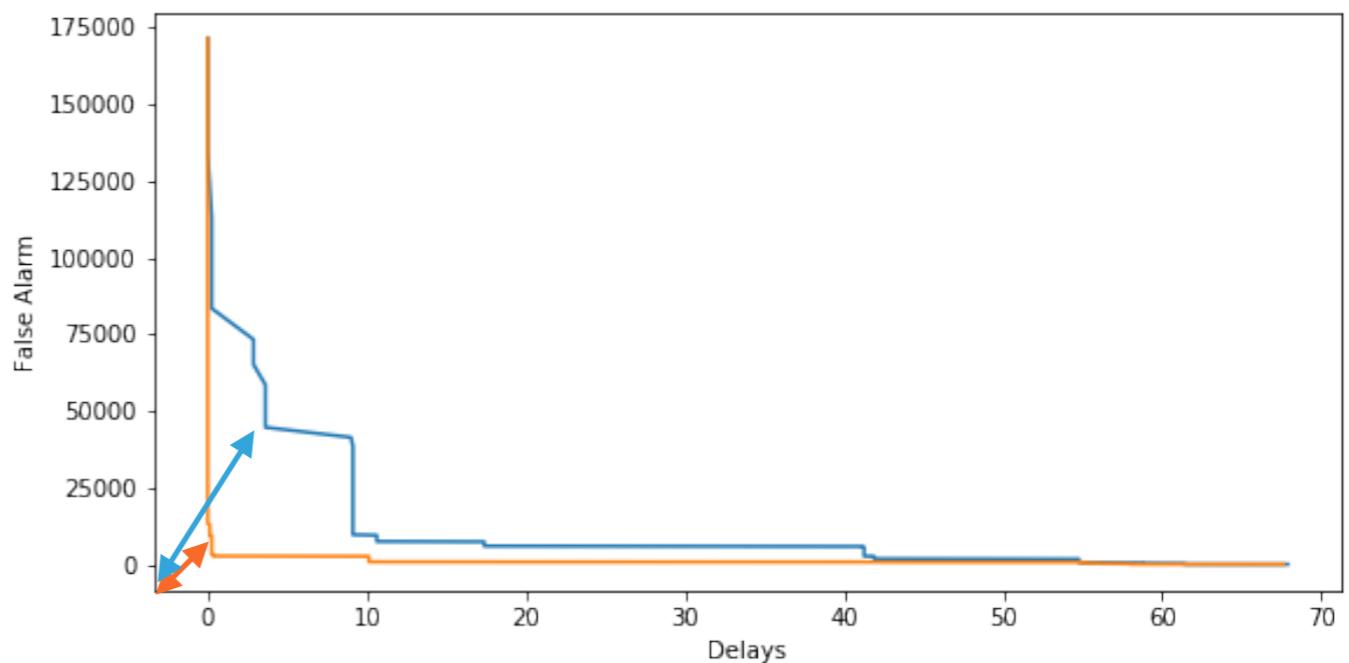
## Goal 2 (for all patient seizure)

- ▶ Have a high average score
- ▶ Have low variation of the threshold value

## FEATURE SELECTION AND SCORING

# SOLUTION FOR GOAL 1 (SCORE 1)

The higher the score S1 is, the best FA and Delay combination that we found for the seizure



We compute the inverse of the norm 2 :  $\|(x, y, z)\|^2 = \sqrt{x^2 + y^2 + z^2}$ .

With  $x = w_1 * FA$ ,  $y = w_2 * D$ ,  $z = w_3 * 1/P$

$$\frac{1}{\sqrt{(w_1 * FA)^2 + (w_2 * D)^2 + \frac{1}{(w_3 * P)^2} + \lambda}}$$

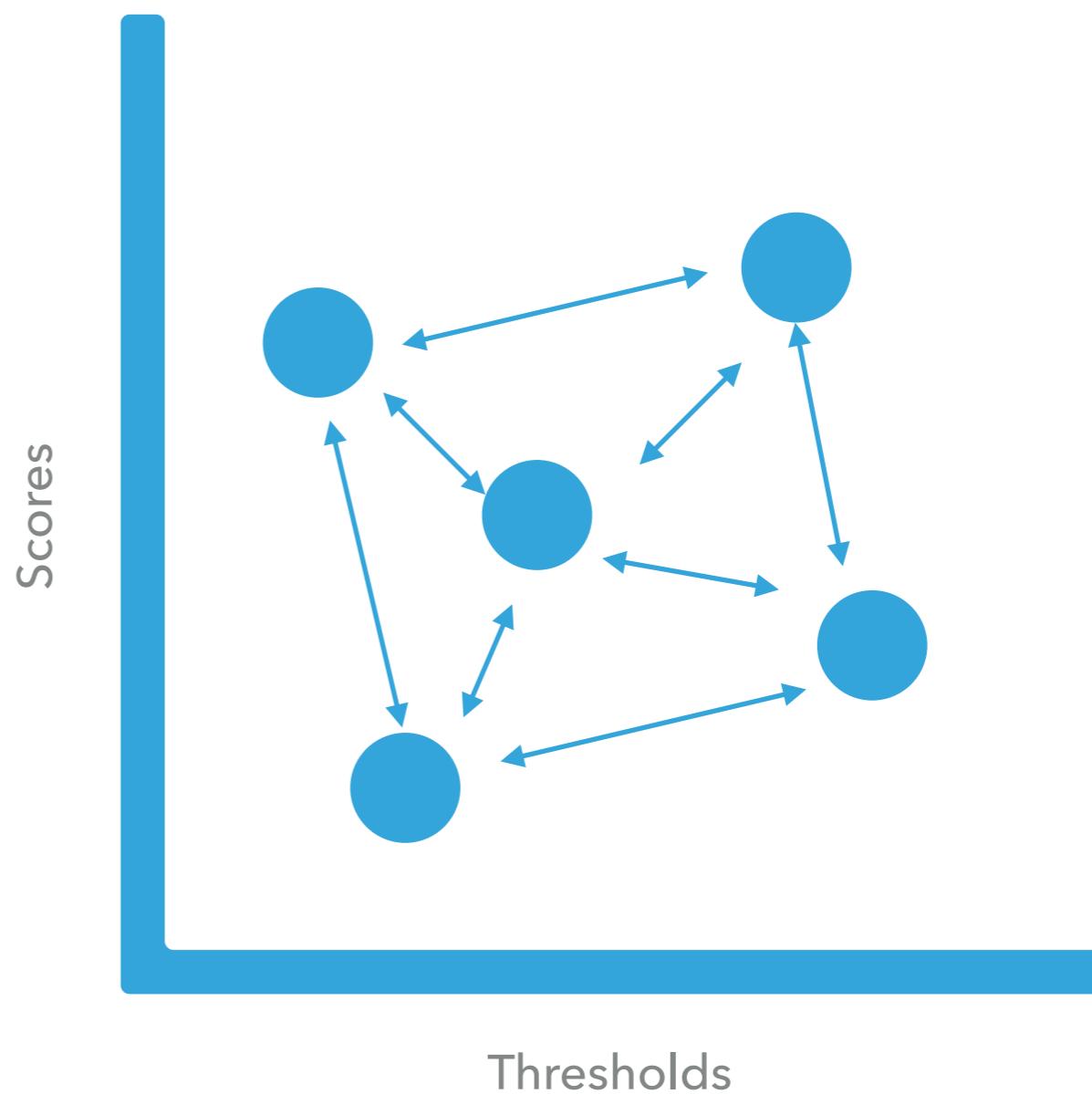
Remarks:

- $\lambda$  is a small number avoiding division by zero
- We consider that each point in a 3-D coordinates point in the space of False Alarm, Delay and Precision for a given threshold value
- FA and D are normalised before the computation of the score
- We enforce the Delay to be inferior to  $D_{max}$
- $w_1, w_2, w_3$  are weights that can be defined to give more importance of some metrics upon others

# SOLUTION TO GOAL 2 (SCORE S2)

We want to minimize the distance between all the points.

Closer points means better generalization



### FINAL SCORE

$$S = \frac{\sum_{k=0}^n S1_k}{n} \frac{1}{S2}$$



WHAT DO WE LEARN FROM THIS  
NEW SCORING METHOD ?

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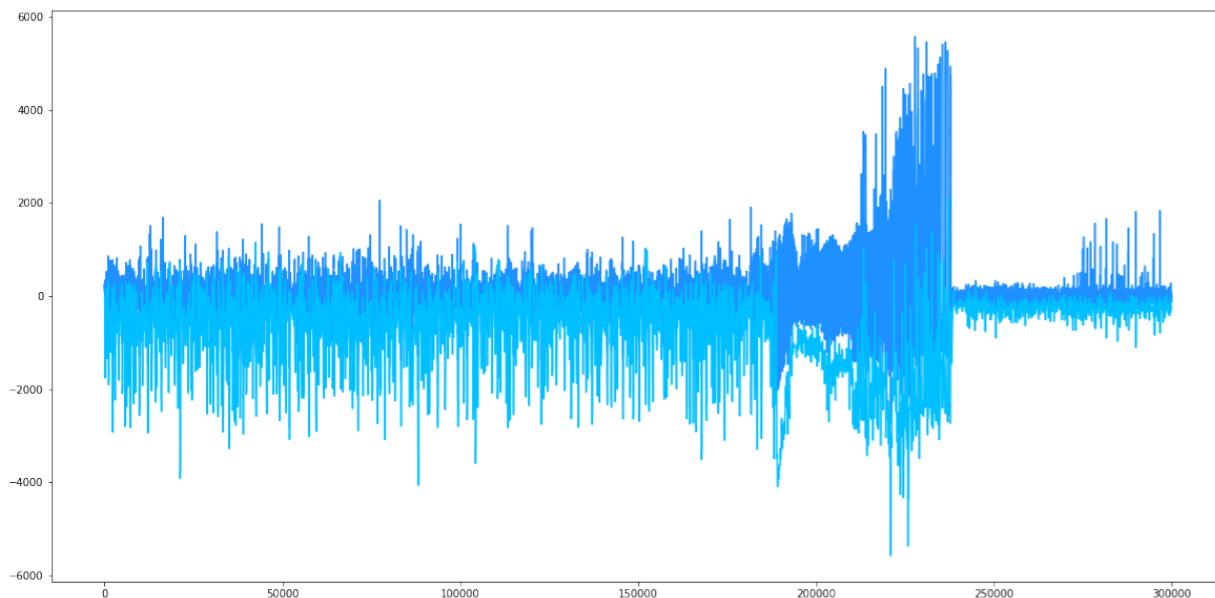
# RESULTS

## RESULTS

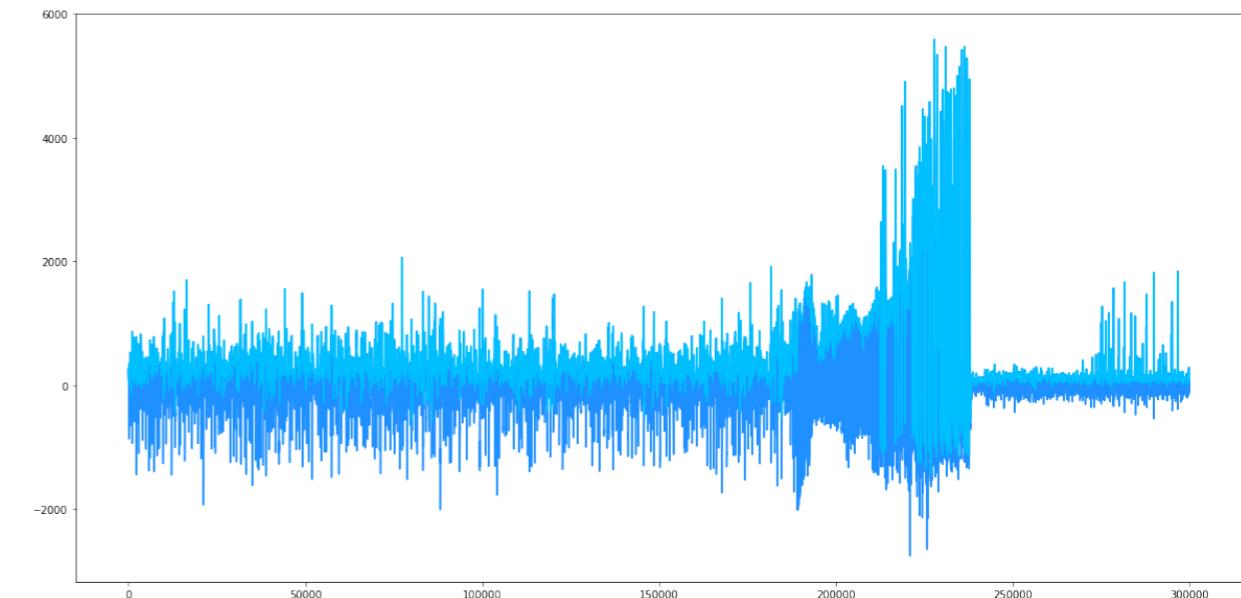
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# SIMPLE FEATURES

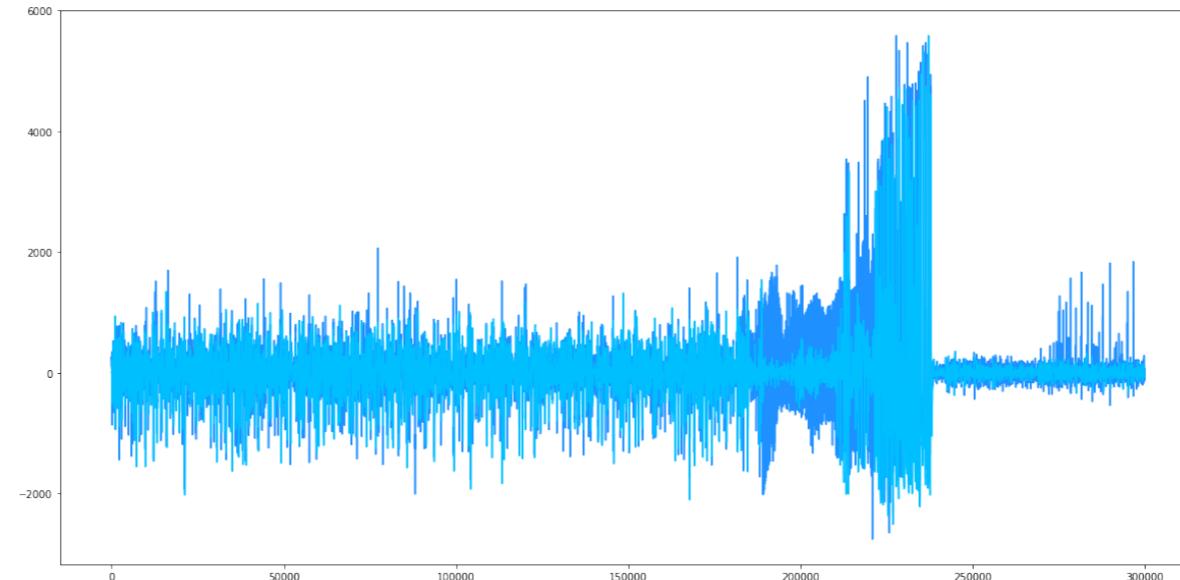
Minimum



Maximum



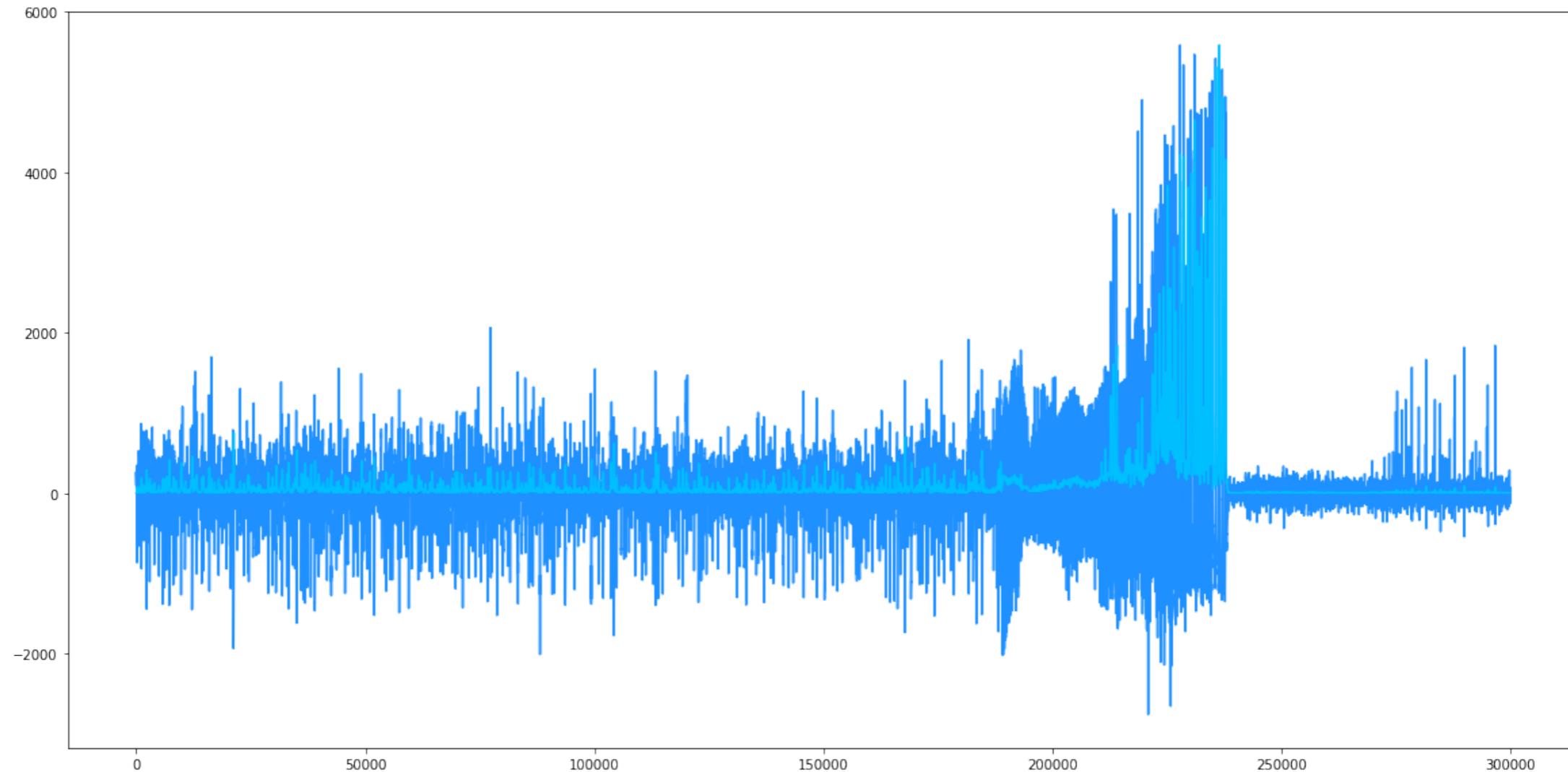
Moving AVG



## RESULTS

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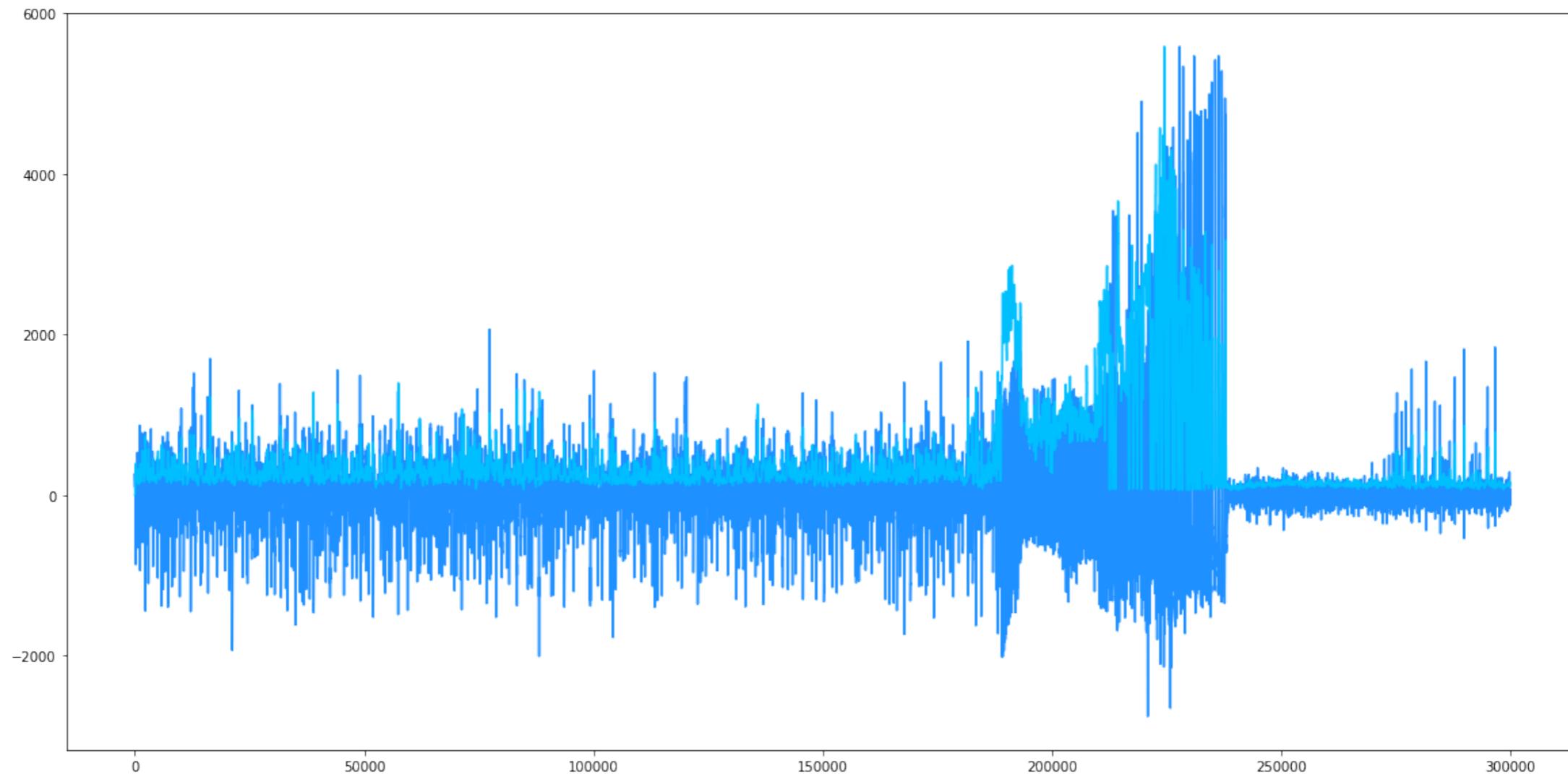
# ENERGY



## RESULTS

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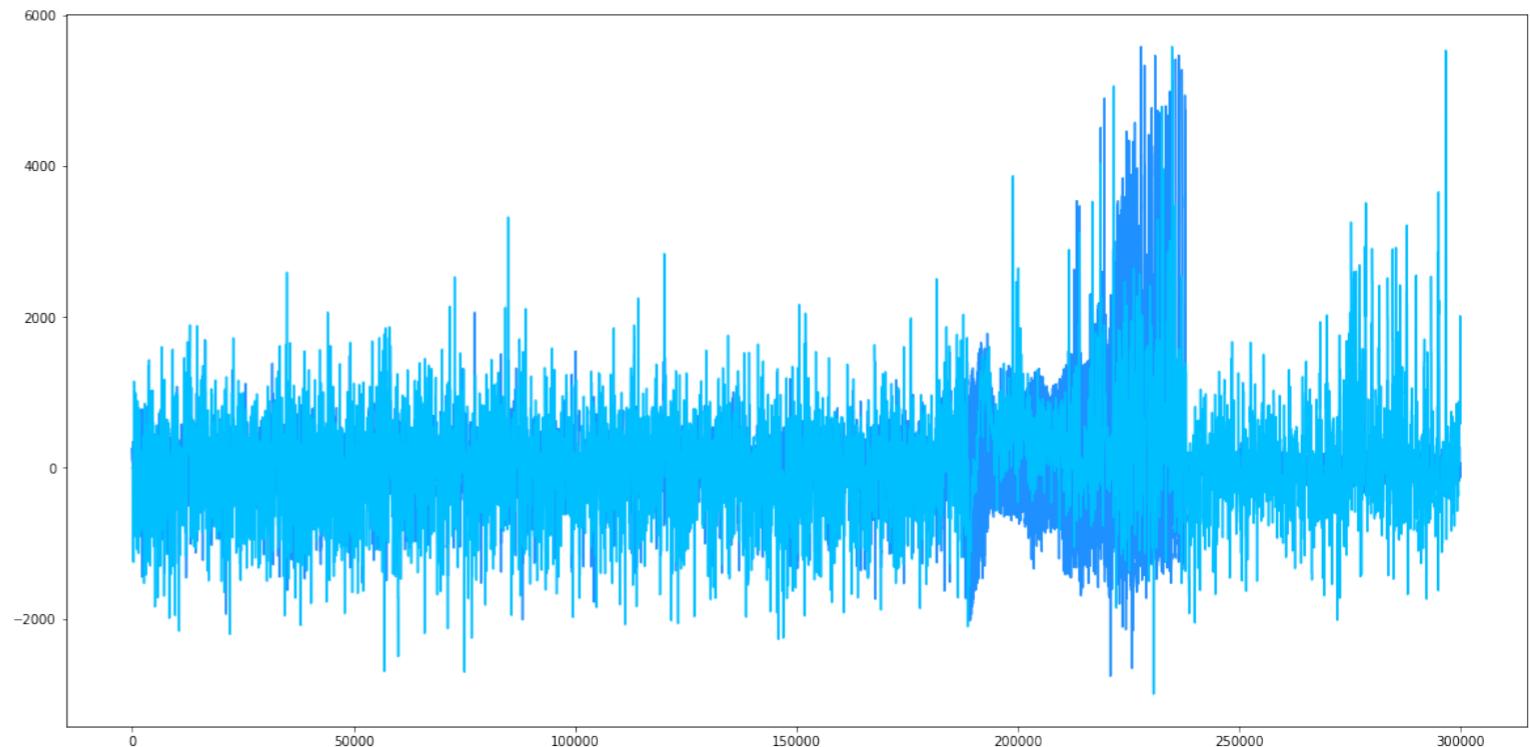
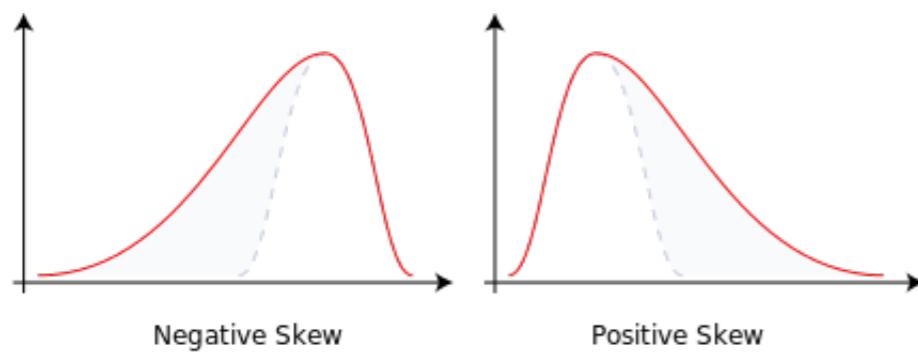
### LINE LENGTH



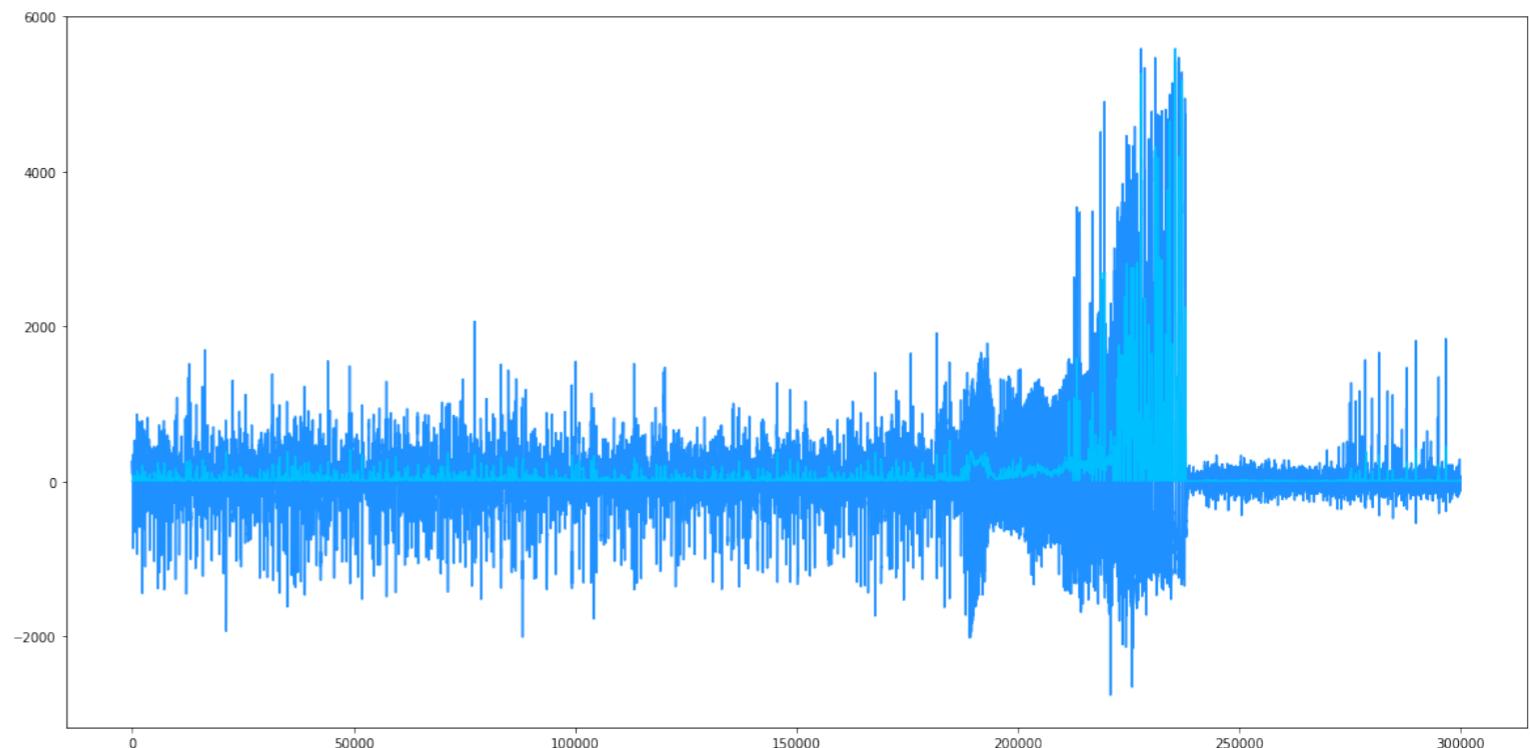
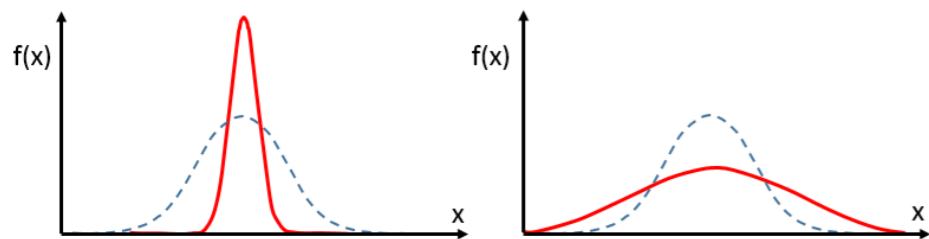
## RESULTS

# SKEWNESS AND KURTOSIS

### Skewness



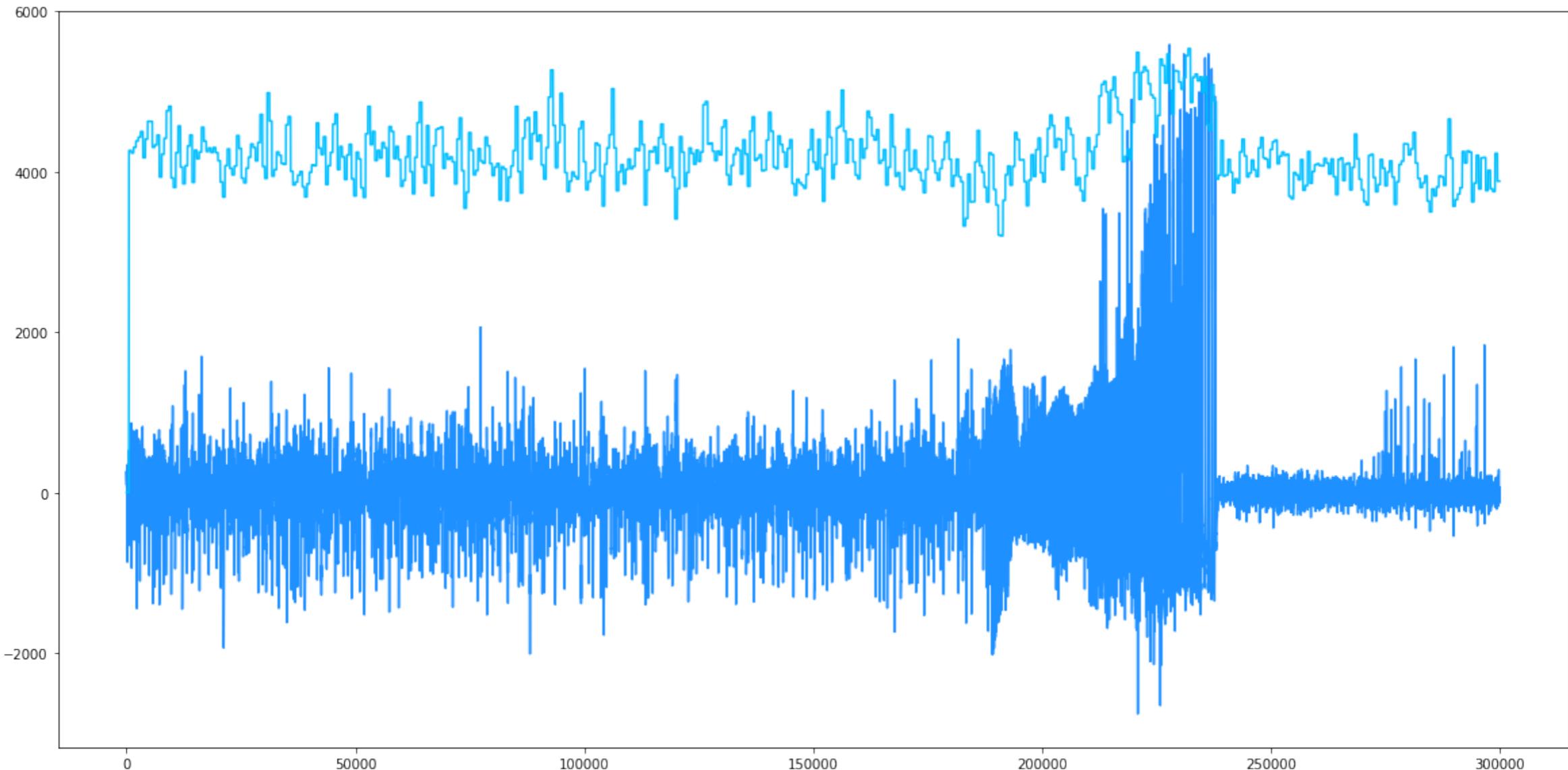
### Kurtosis



## RESULTS

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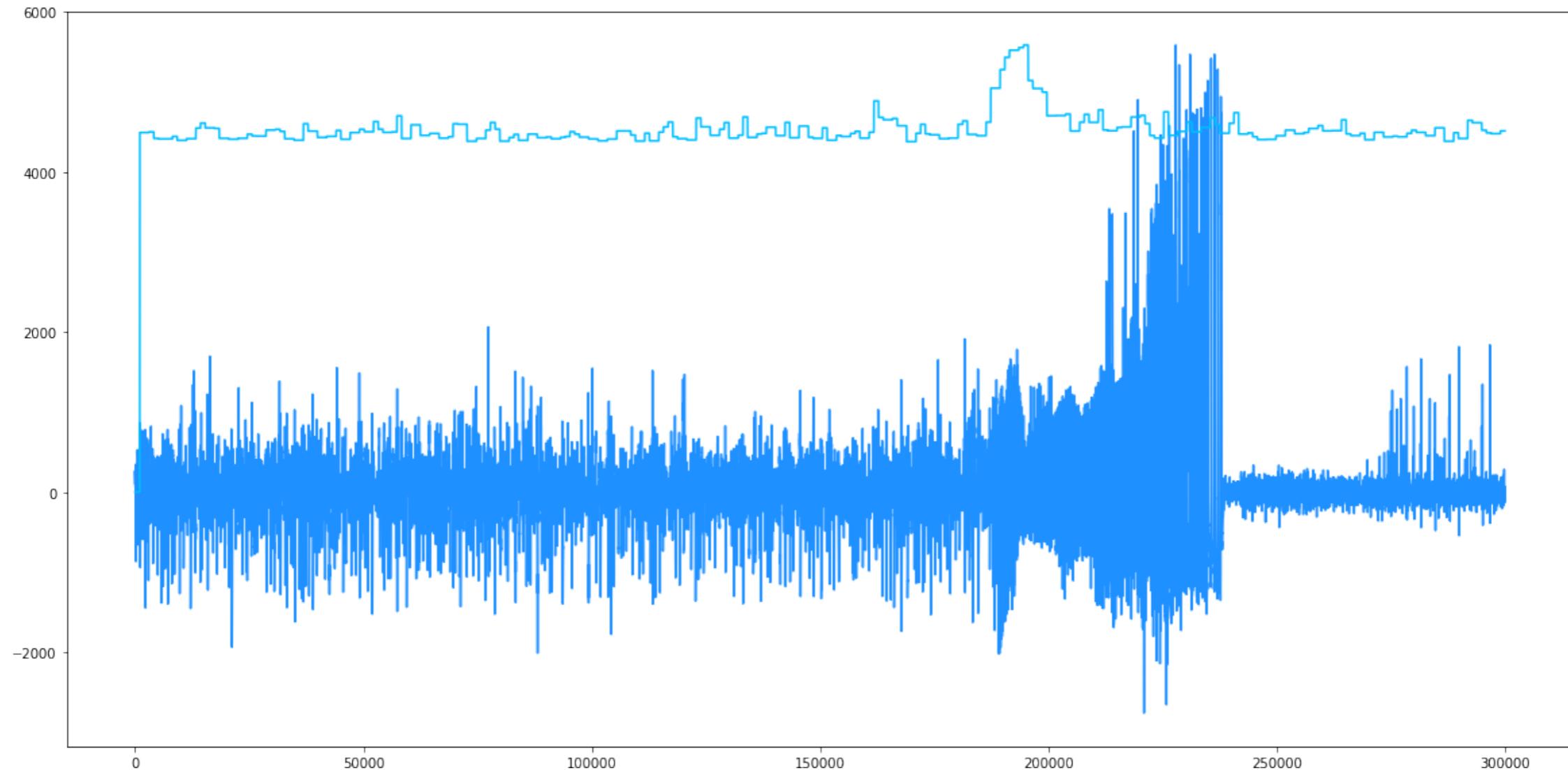
# LOCAL BINARY PATTERNS



## RESULTS

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# PHASE SYNCHRONY



## RESULTS

# RESULTS FOR PATIENTS 1 AND 2

	Patient 1	Patient 2
Min	<b>6875.6</b>	<b>85.7</b>
Max	10.9	15.8
Moving AVG	31.8	10.4
Energy	23.4	15.7
Line length	48.6	27.9
Kurtosis	28.1	55.8
Skewness	8.4	10.1
Local Binary Pattern	<b>201.5</b>	<b>166.3</b>
Phase synchrony	140.4	32.6

## RESULTS

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### PATIENT 1

	Seizure 1			Seizure 2		
	False Alarms	Delays	Threshold	False Alarms	Delays	Threshold
Min	<b>76</b>	6.1	<b>0.151</b>	<b>76</b>	6.9	<b>0.151</b>
Local binary pattern	<b>2658</b>	<b>0.0</b>	<b>0.81</b>	<b>3216</b>	6.0	<b>0.80</b>
Skewness	2469	1.2	<b>0.32</b>	92	0.1	<b>0.55</b>

## RESULTS

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# PATIENT 2

	Seizure 1			Seizure 2		
	False Alarms	Delays	Threshold	False Alarms	Delays	Threshold
Local binary pattern	157	0	0.75	108	3	0.77
Min	2024	8.7	0.19	2024	0.87	0.19
Skewness	3965	2	0.30	378	0	0.50



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# CONCLUSION

## SUMMARY

- ▶ We have seen how machine learning can help seizure detection
- ▶ Why feature selection is a key issue for doing seizure classification
- ▶ How the proposed method can help measuring how good is a feature for a given patient regarding our key metrics