

# Epileptic Seizure Detection in EEG via Fusion of Multi-View Attention-Gated U-net Deep Neural Networks

**NEUREKA™ 2020  
EPILEPSY CHALLENGE**



+



**Novela Neurotech and NeuroTechX**

join forces to accelerate epilepsy  
research and EEG data mining.

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M. De Vos, A. Bertrand, S. Van Huffel

# Outline

- Neureka Challenge: An international seizure detection challenge organized by Novella Neurotech and NeuroTechX
- Build a seizure detection model based on the *TUH EEG Seizure* database
- Approximately 1.5 months to train, validate and submit results
- The model that *performs the best in terms of the challenge's scoring system* wins

**Points = %SENS – alpha \* FAs/24hr – beta \* (avg # chans)/19**

*where alpha = 2.5 and beta = 7.5*

# Dataset

- Archive hospital data (previous 14 years):
  - > 3000 seizures
  - > 600 patients
  - > 6000 recordings
  - ~700 hours of data
- Long term monitoring split in several files
- Documentation is excellent
- More than 1 year of continuous data not (yet) annotated
- Reviewers are trained undergraduate students

## Dream Team: Biomed Irregulars



Christos Chatzichristos  
*Wearable seizure detection*  
Postdoc



Nick Seeuws  
*Deep learning networks*  
2nd year PhD student  
Supervisors: Maarten de Vos and  
Alexander Bertrand



Jonathan Dan  
*Low complexity seizure  
detection algorithms*  
3rd year PhD student  
Supervisor: Alexander Bertrand



Abhijith Mundanad Narayanan  
*EEG sensor devices for auditory  
attention detection*  
4th year PhD student  
Supervisor: Alexander Bertrand

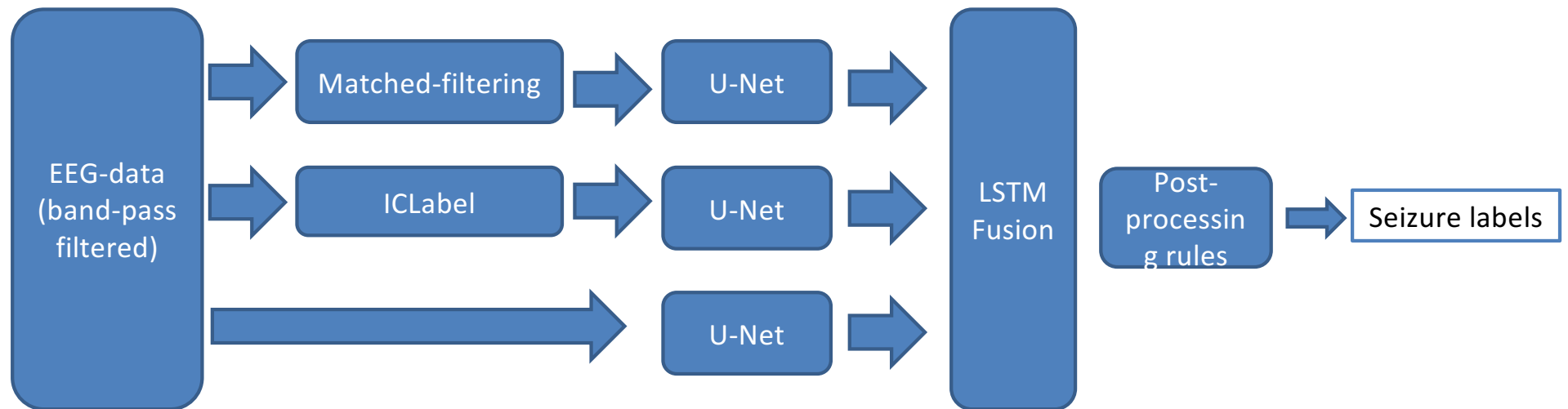


Kaat Vandecasteele  
*Wearable seizure detection*  
4th year PhD student  
Supervisor: Sabine Van Huffel

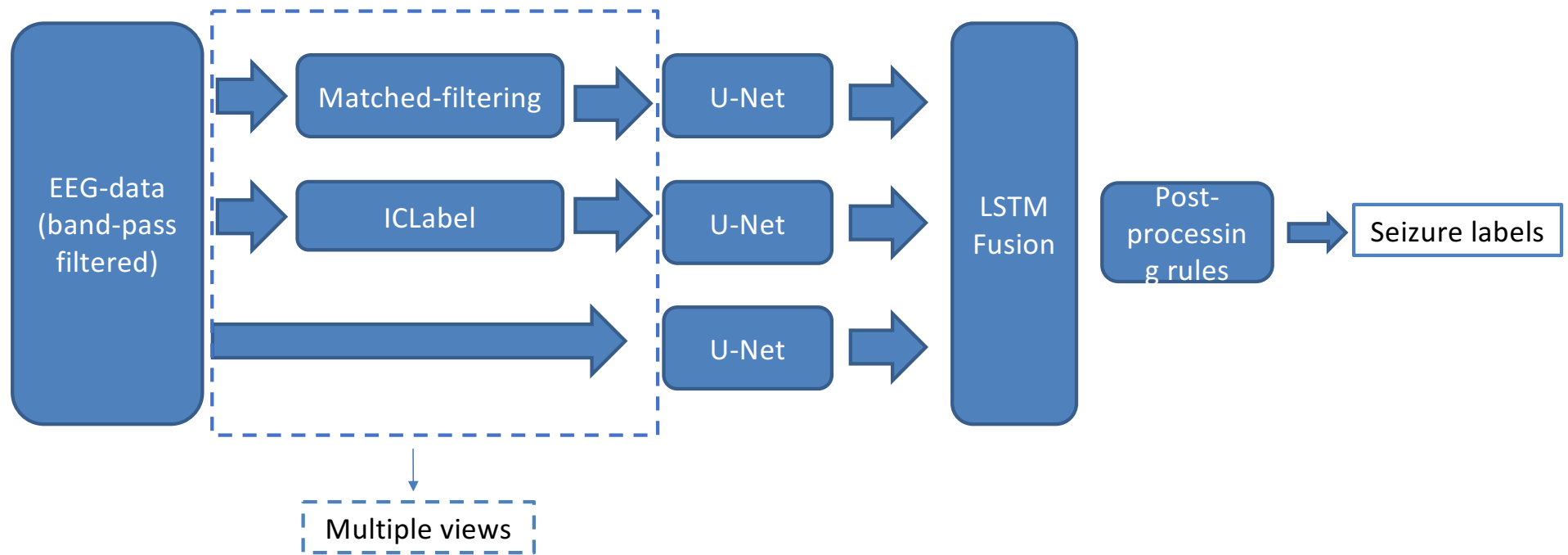
# Novelties of our approach

- Multi-view approach: Plug-and-play seizure detection framework
  - Allows addition of new pre-processing framework
  - Expandable and easily modifiable
- Intuitive fusion of multiple Deep Neural Network outputs: Using an LSTM
  - LSTMs' inherent feature of time series prediction

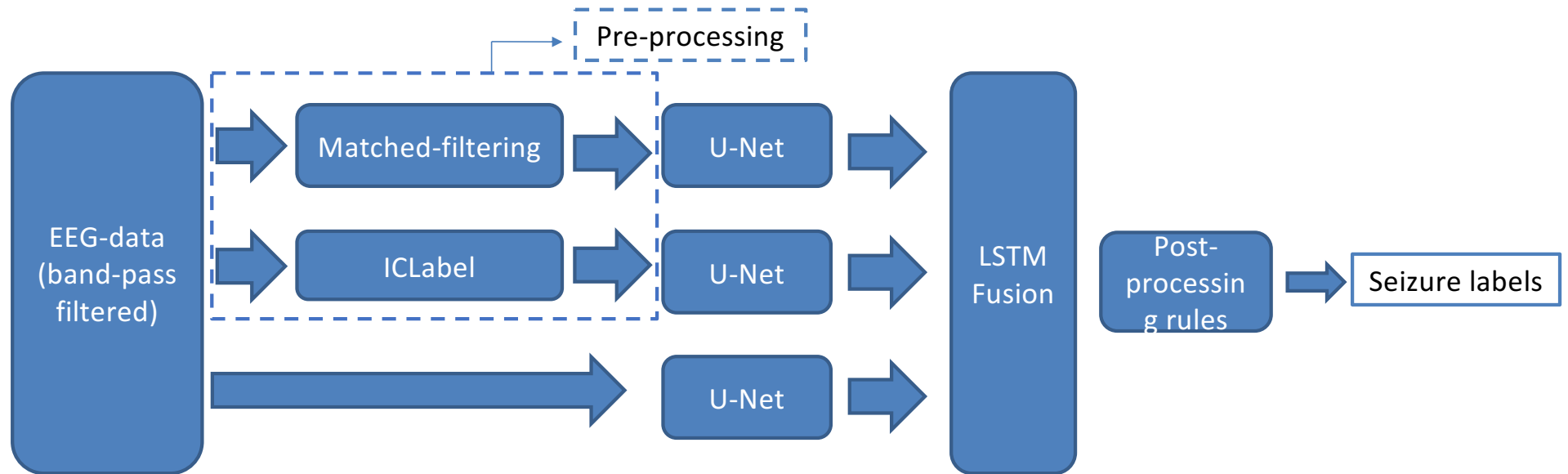
## Seizure detection pipeline: Multi-view fusion of attention-gated U-nets



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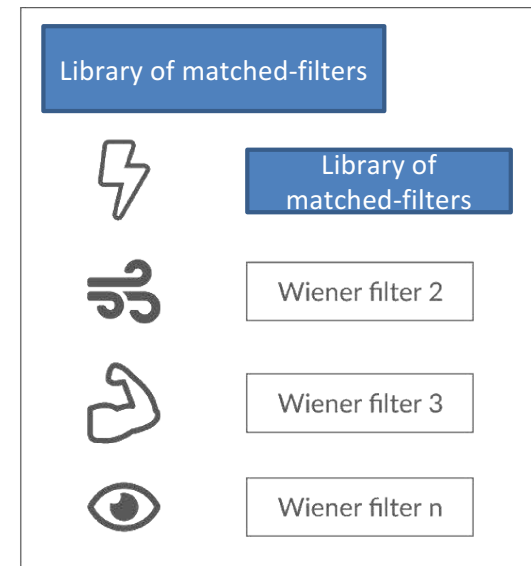
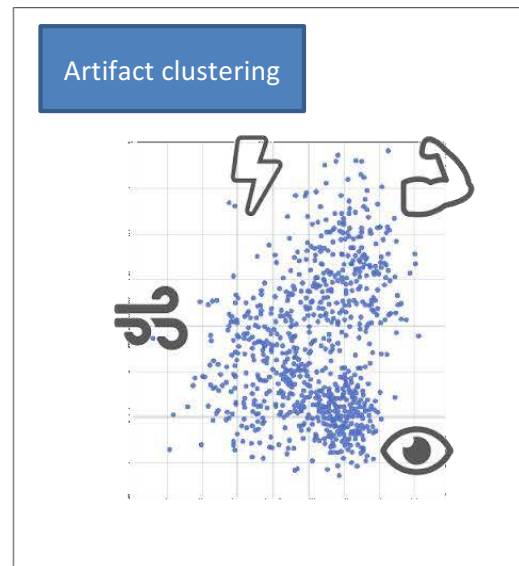
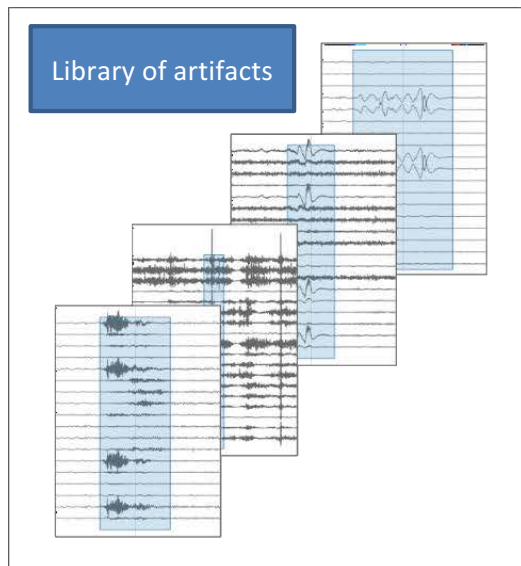
## Seizure detection pipeline: Pre-processing





# Pre-processing: Multi-channel Wiener filtering

## Matched-filter based artifact removal

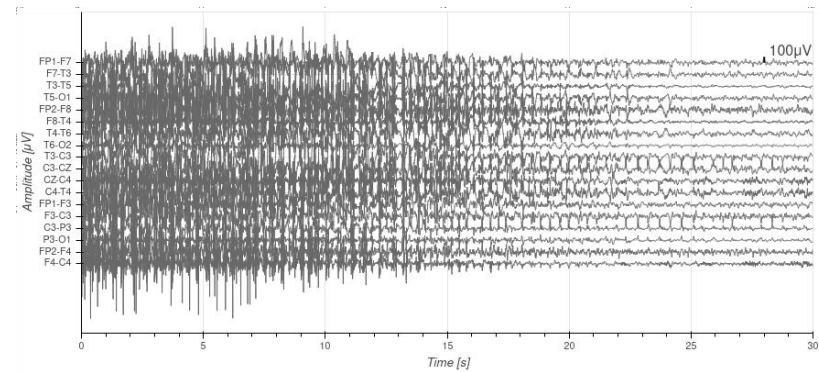
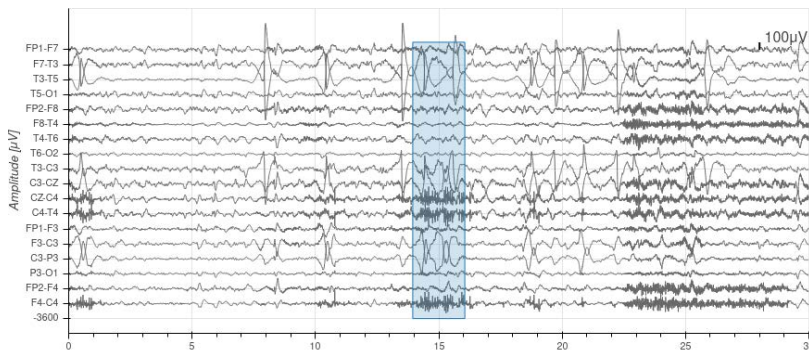


# Pre-processing: Multi-channel Wiener filtering

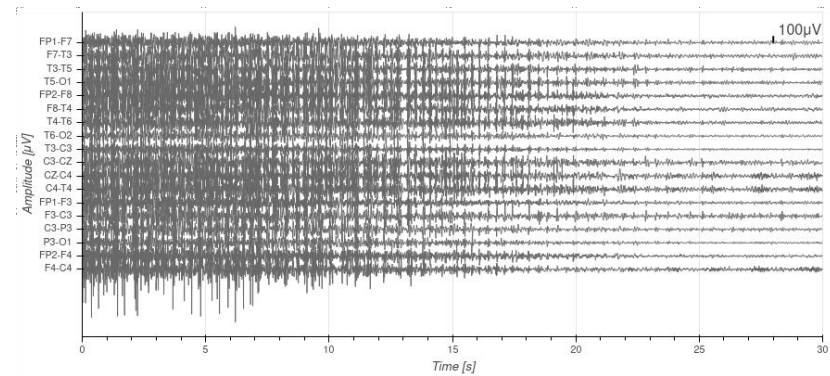
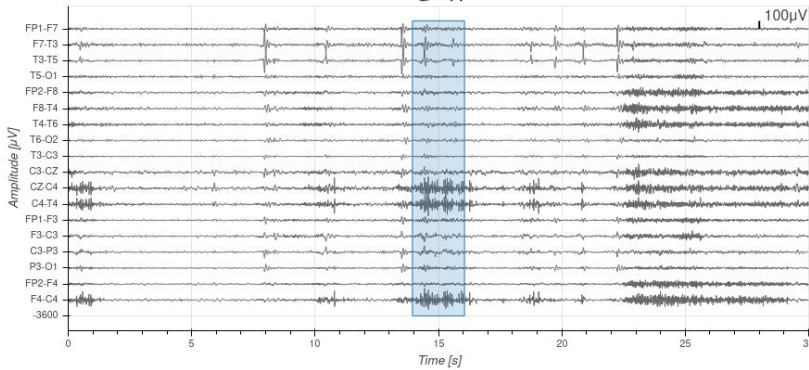
Artifact

Seizure

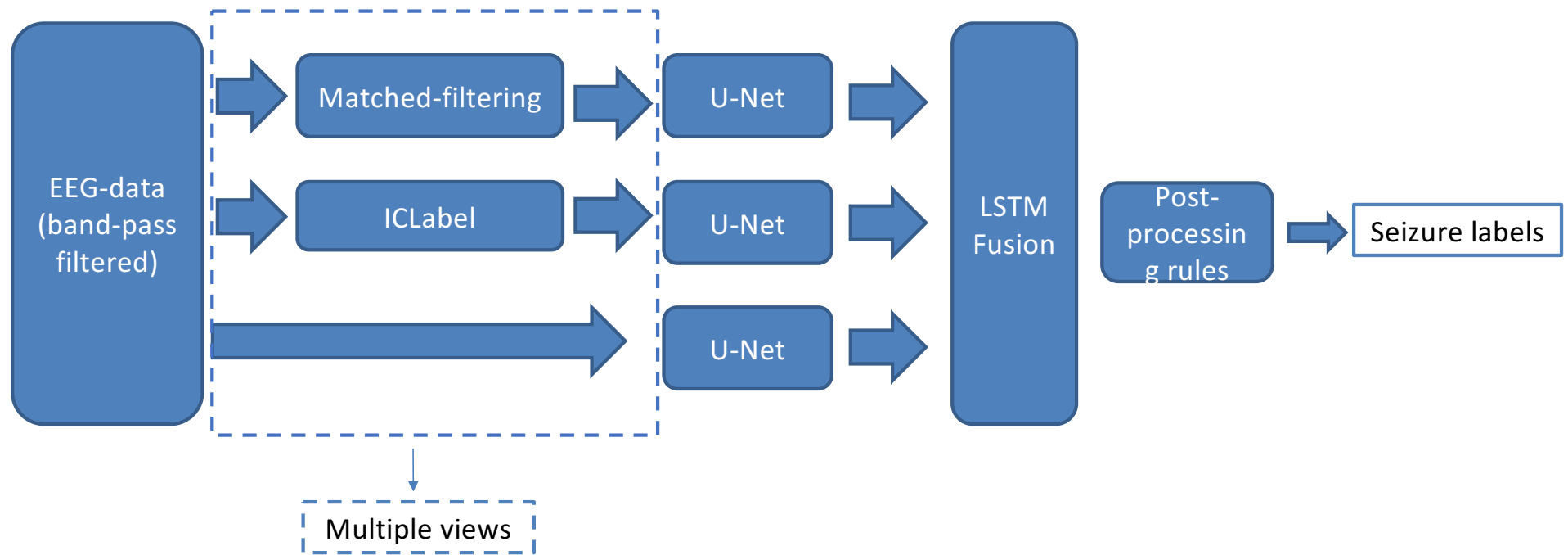
Raw



Filtered

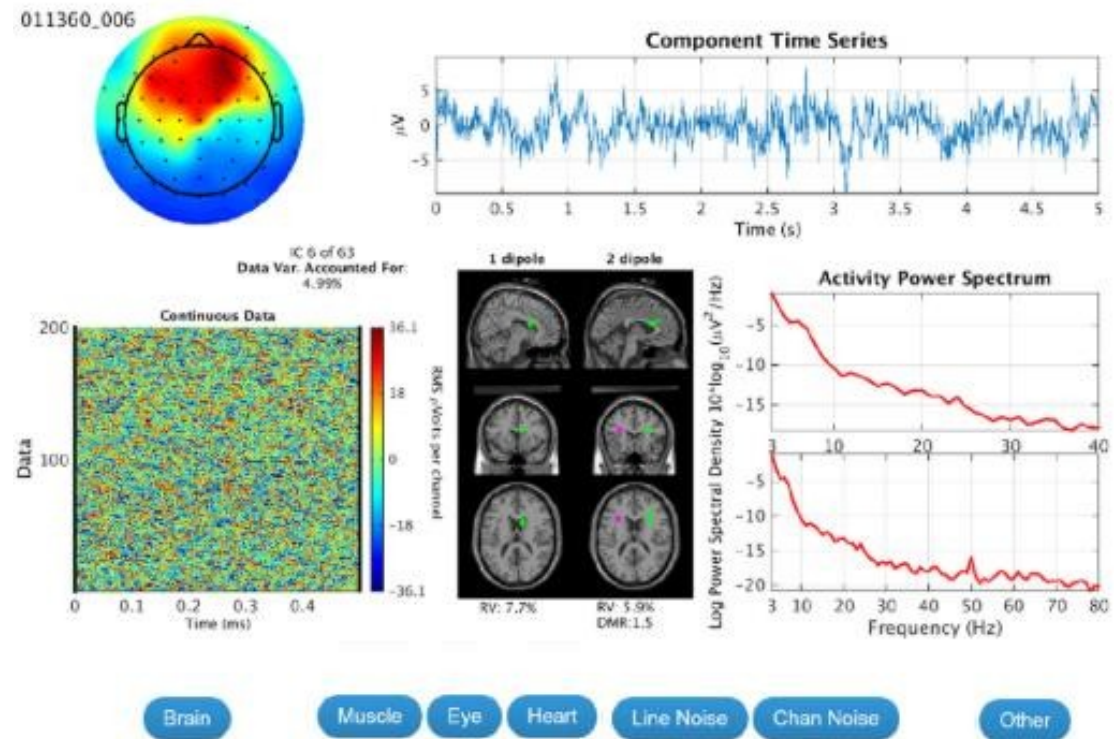


# Seizure detection pipeline: Multi-view fusion of attention-gated U-nets

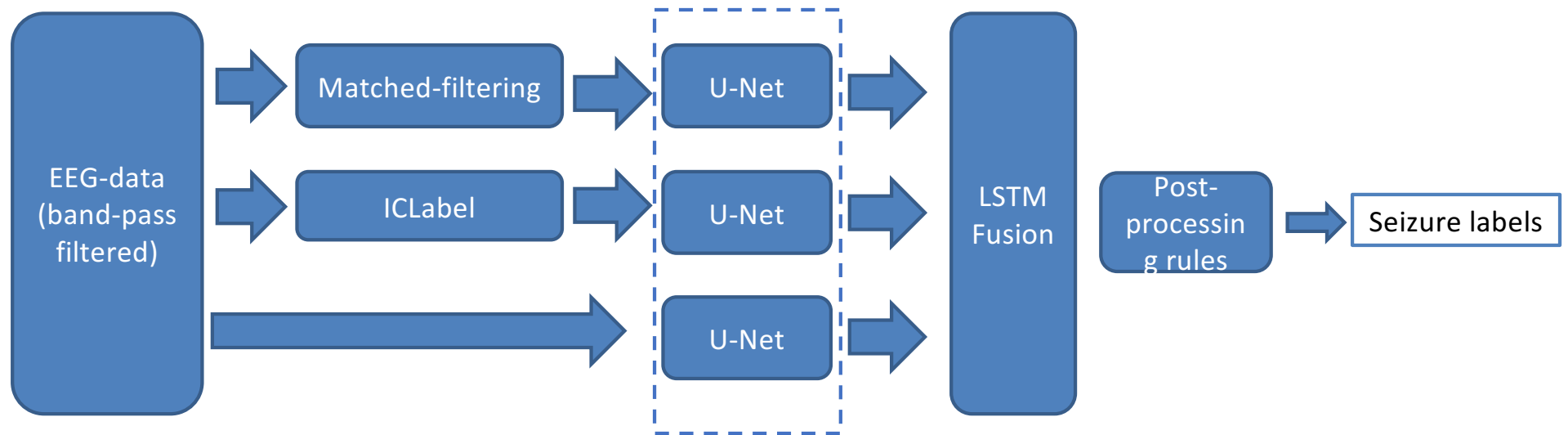


# Pre-processing: IClabel

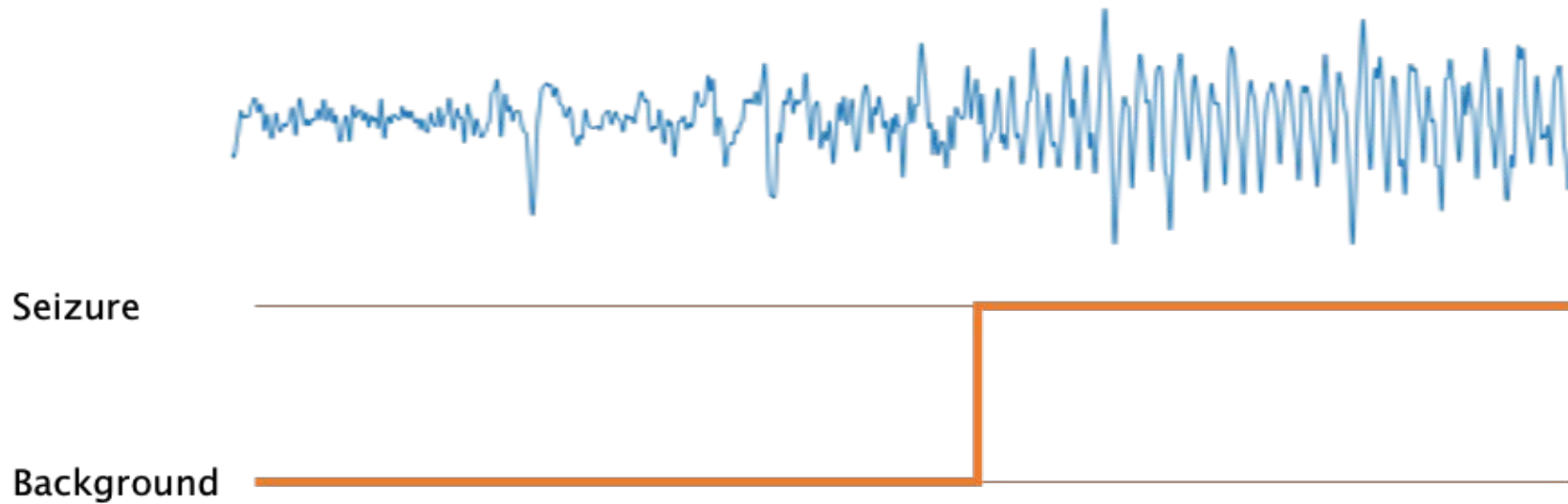
- 1.Reject bad channels
- 2.Run SOBI ICA
- 3.Classify components
- 4.Remove artifacts



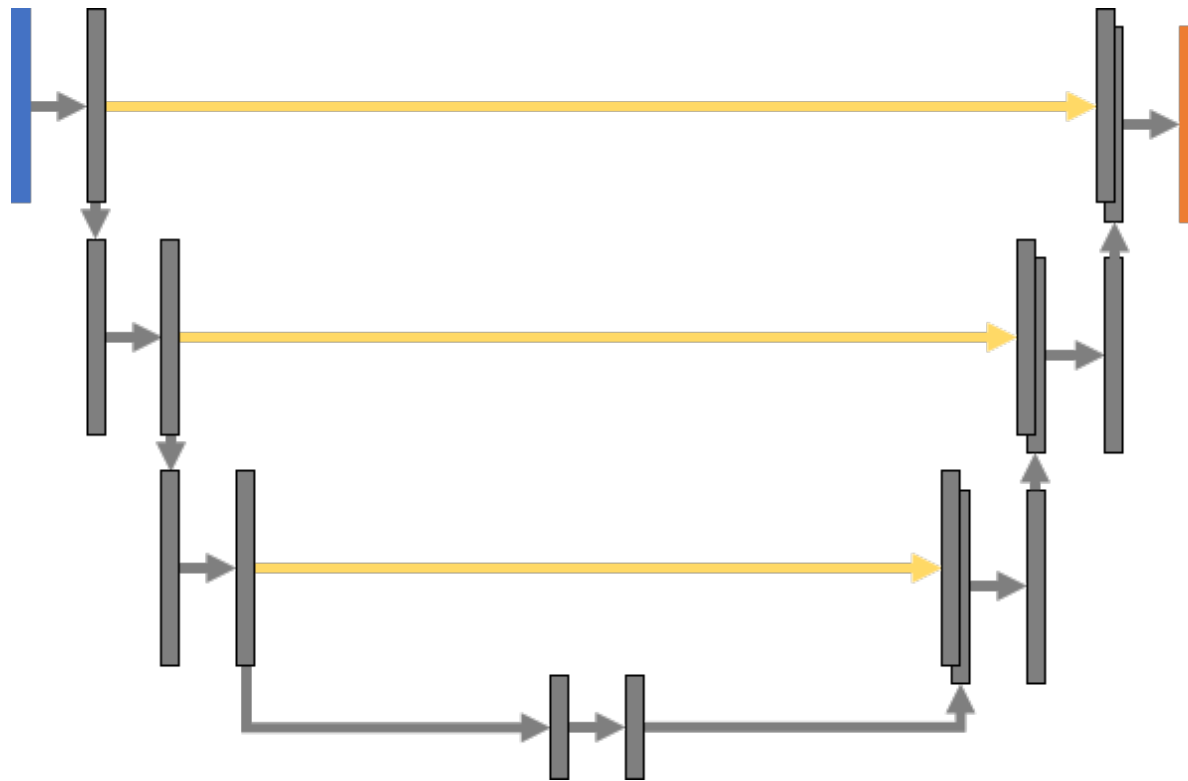
## Seizure detection pipeline: Deep neural networks



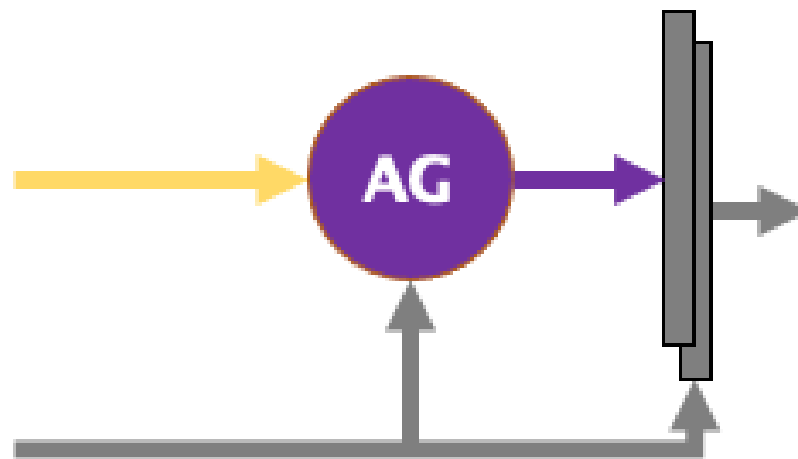
We predict a seizure *signal* from EEG signals



The U-Net allows us to merge local and global information



Attention attenuates the network  
to meaningful local information





## Use Attention-gating to determine importance of specific time-channel feature-vector

Working with (*time x channel x feature*) tensors

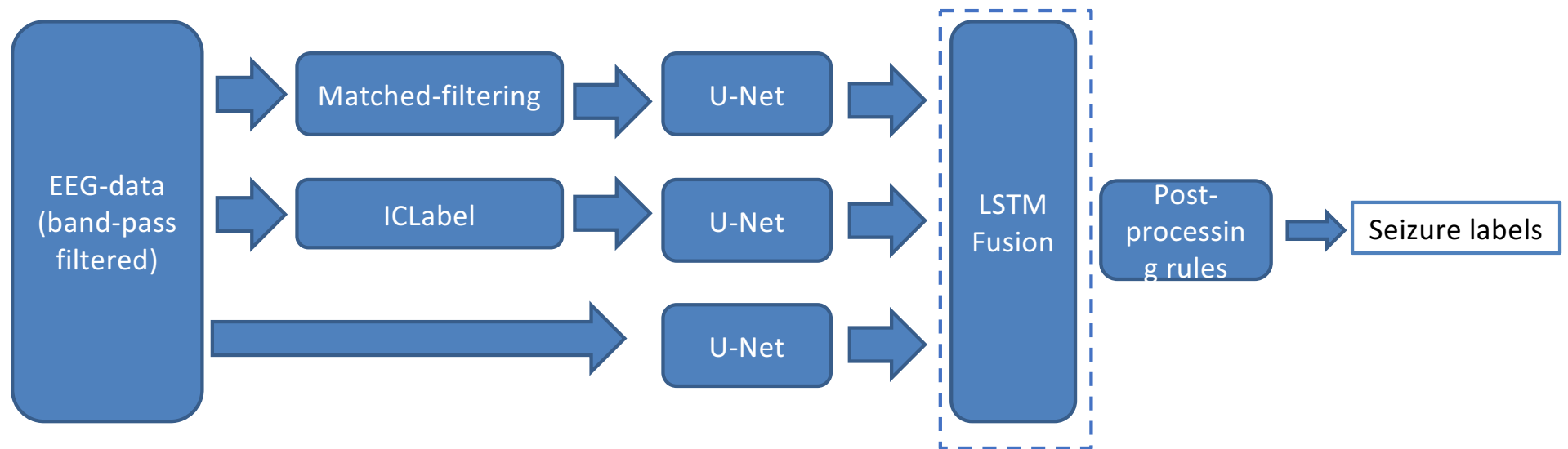
Gating implemented as a convolution with kernel size 1

$$\alpha = \sigma(\mathbf{w}^T \sigma(W_x \mathbf{x} + W_g \mathbf{g} + \mathbf{b})) + b$$

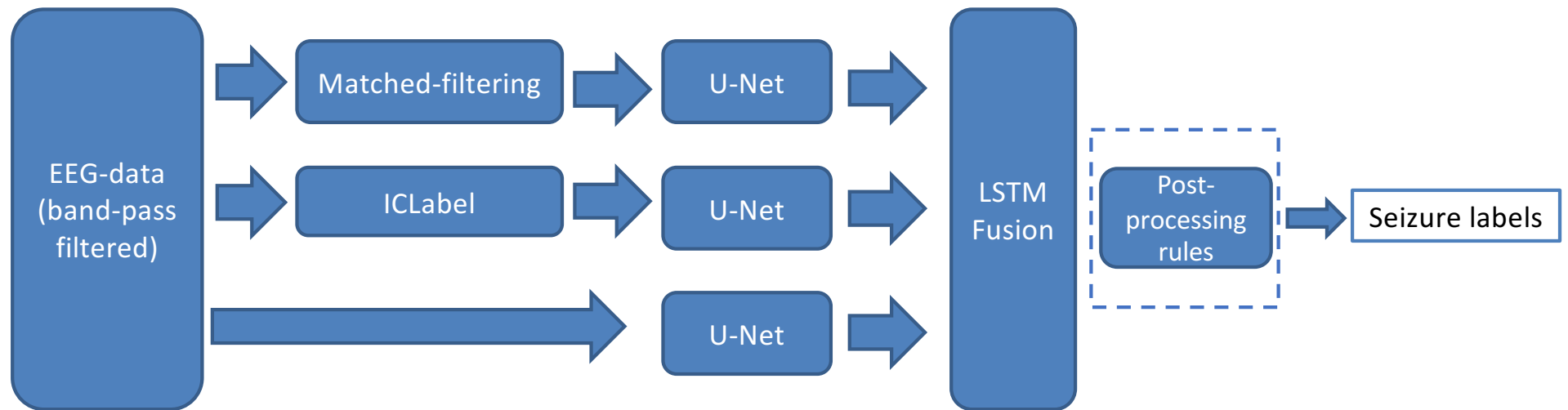
$\mathbf{x}$  = data(i, j, :)

$\mathbf{g}$  = gating\_signal(i, j, :)

## Seizure detection pipeline: Fusion of DNN outputs



## Seizure detection pipeline: Rules on seizure labels



## TAES score: Counting true positives, false positives



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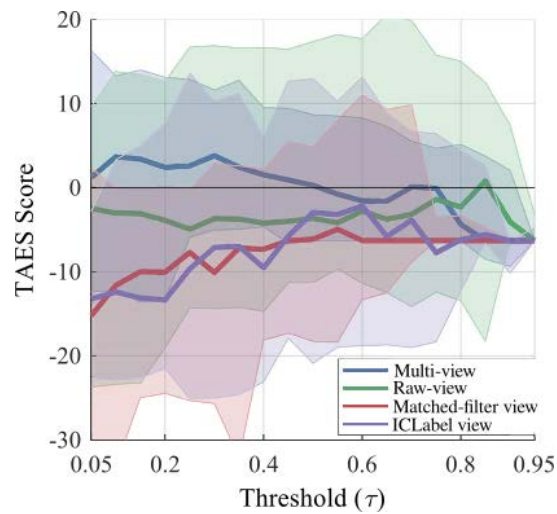
Time-Aligned Event Scoring (TAES)

- TP: 0.5
- FN: 2.5
- sensitivity  $0.5 / 3 = 16.66\%$
- FA: 1

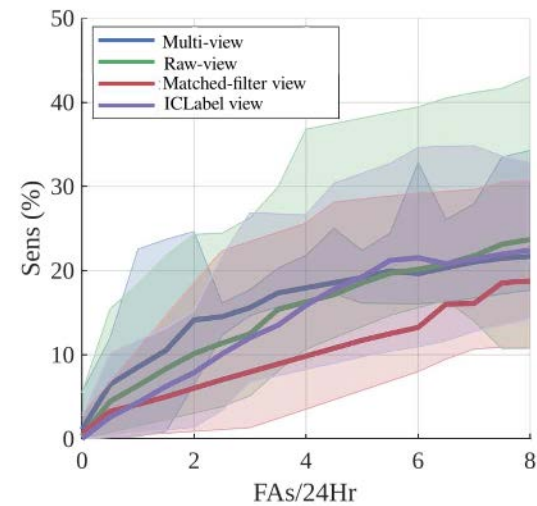
## Post-processing rules

1. If  $S_{i+1} - S_i < 30s$  : Merge  $S_i$  and  $S_{i+1}$  ;  $S_{i+1}, S_i$  are two successive seizure events
2.  $\text{Prob}(S_i)$  is a Seizure = mean (probabilities of all time points in  $S_i$ )
3.  $\text{Prob}(S_i < 0.82)$  is rejected as a seizure
4. If duration of  $S_i < 15$ , seizure event rejected

## Results on validation set



Cross-validation results:  
TAES performance using  
multi-view and other views



Cross-validation results:  
ROC curves using multi-  
view and other views

## Results – Neureka Challenge leaderboard

Position	Team or Individual	Sensitivity	FAs/24hr	Avg. No. Channels	Score
1	<b>Biomed Irregulars</b>	<b>12.37</b>	<b>1.44</b>	<b>16</b>	<b>2.46</b>
2	<b>NeuroSyd</b>	<b>2.04</b>	<b>0.17</b>	<b>2</b>	<b>0.82</b>
3	USTC-EEG	8.93	0.71	17	0.45
4	RocketShoes	5.98	3.36	3	-3.60
5	Lan Wei (Ind.)	20.00	15.59	4	-20.56
6	EEG Miners	16.00	16.54	9	-28.89
7	Anonymous (Ind.)	21.65	28.05	4	-50.05
8	James Msonda (Ind.)	11.33	29.27	10	-65.79
9	TABS	9.03	31.21	19	-76.50
10	cpl team	5.66	94.34	1	-230.59
11	DeepAlert	9.86	172.92	10	-426.40
12	Interfaces	26.53	186.63	1	-440.44
13	Neurocomputación	0.22	758.48	11	-1,900.32
14	TeamPT2	34.75	927.12	19	-2,290.53
15	Last Dance	10.13	1,385.03	1	-3,452.83



## Conclusions

- Deep convolutional neural networks seem like a good solution to seizure detection problem
- TUH EEG dataset is a great resource (with challenges)
- A *one-size-fits-all* algorithm remains too hard (today)

**QUESTIONS??**