Systematic Assessment of Hyperdimensional Computing for Epileptic Seizure Detection

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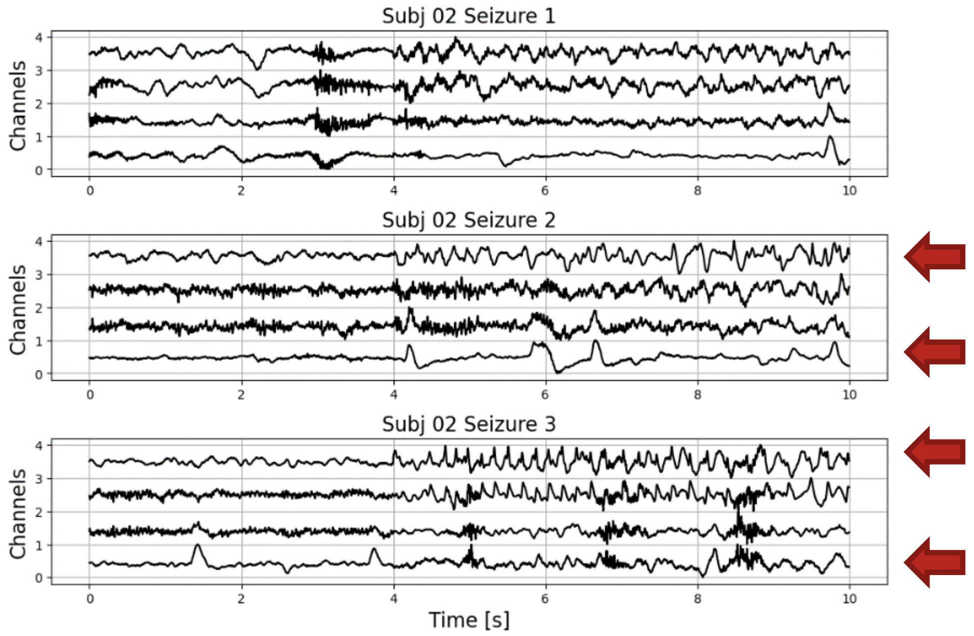
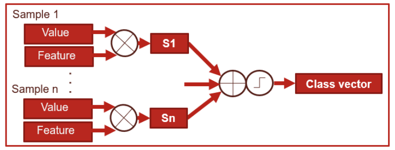
Epilepsy

- Chronic neurological disorder
  - Imposes serious health risks and restrictions on daily life
- EEG (electroencephalography) or IEEG (intracranial EEG) recordings
  - Complex and highly variable
- Challenges for continuous monitoring and detection
  - High sensitivity but with almost no false positives
  - Low complexity and memory requirements to be implementable on wearable devices
  - Low power requirements to allow extensive battery lifetime



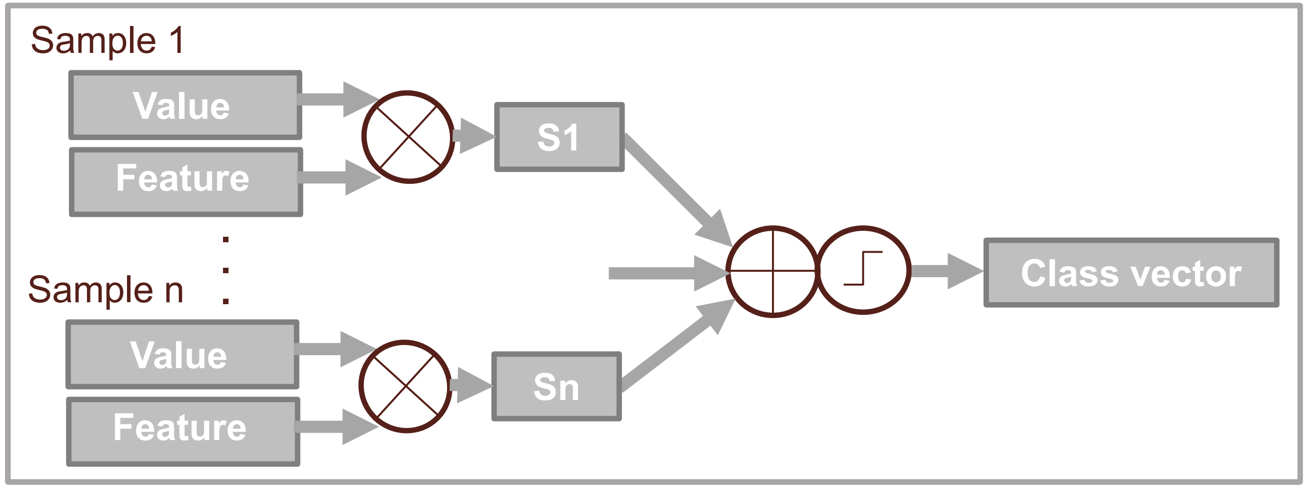
Hyperdimensional computing

- Promising new machine learning (ML) approach inspired by neuroscience
  - High-dimensional randomized representations of data rather than scalar numerical values
- Based on representing data as vectors with very high dimensionality
  - Usually > 10000 values, binary

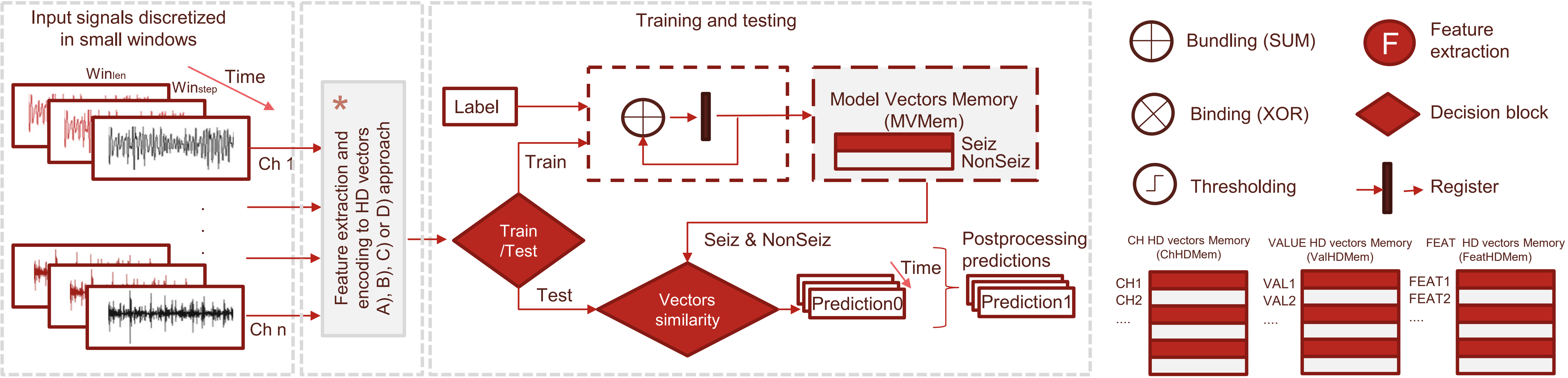


- Enables various properties and operations on such vectors
  - Any two random vector are orthogonal
  - Two summed vectors are more similar to their sum then any other random vector
  - Binding information (by summing)
  - Bundling information (by XOR)

Building vector representation of data class



Hyperdimensional computing workflow



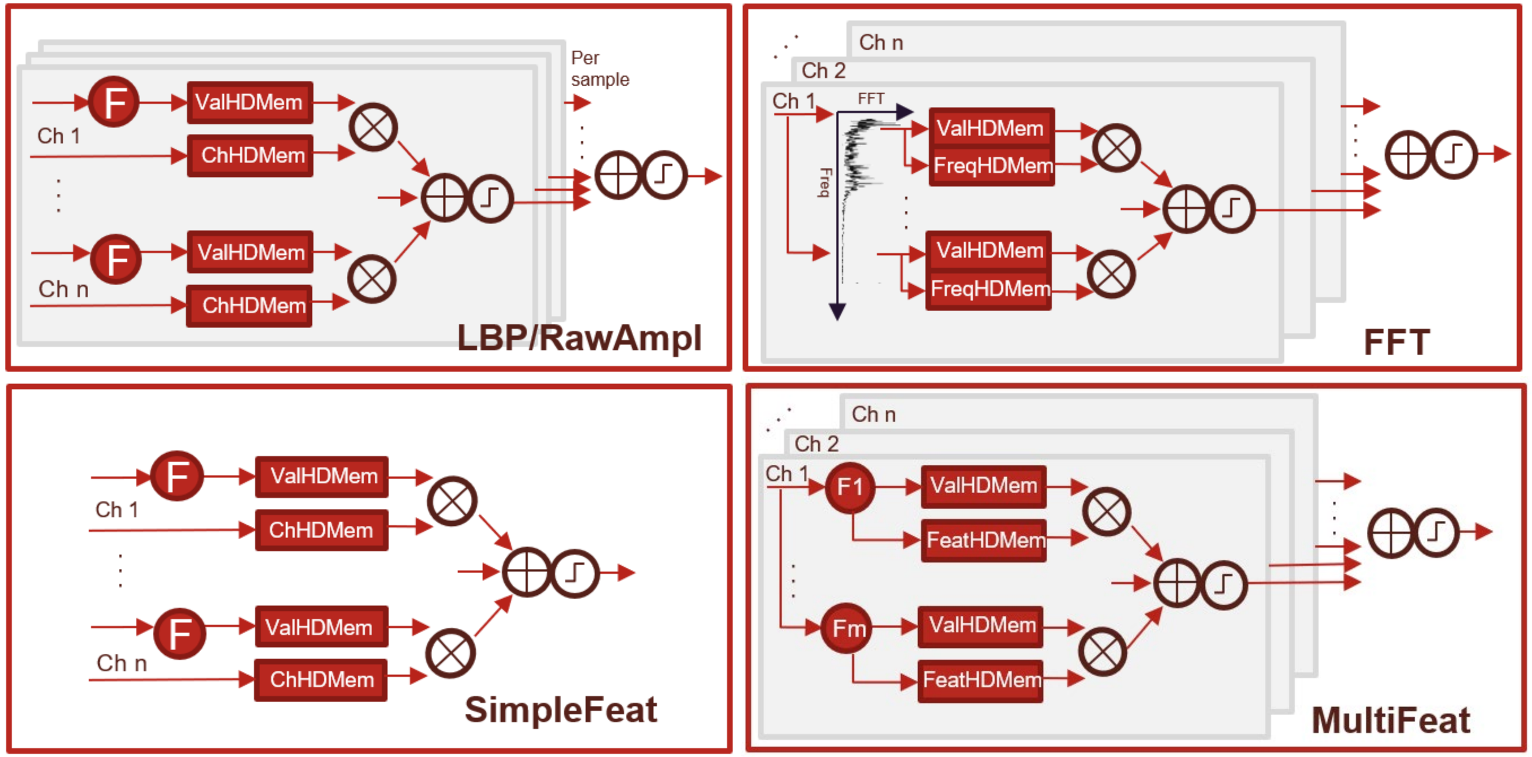
AIM OF THIS WORK

- Compare different approaches for feature encoding to HD on epilepsy detection task
- Evaluate performance, as well as computational and memory complexity

Data encoding approaches

- Two already applied on epilepsy
  - Local binary patterns (LBP)
  - Raw amplitude of each sample (RawAmpl)
- Several new ones
  - FFT of moving windows (FFT)
  - Individual feature value of each window (SimpleFeat)
    - Amplitude, Entropy, CWT
  - Combining multiple features
    - 3Feat: Ampl&Entropy&CWT
    - 45Feat

Data encoding from one discrete data window



Experimental setup

DATASETS

- The CHB-MIT database
  - Scalp EEG dataset, 24 subjects
  - 183 seizures, with an average of 7.6 ± 5.8 seizures per subject
- SWEC-ETHZ
  - IEEG, 16 patients
  - 100 seizures, with an average of 6.3 ± 3.8 seizures per subject
- Datasets preprocessing
  - Personalized approach, using leave one seizure out
  - Balanced subsets of original dataset

EVALUATION

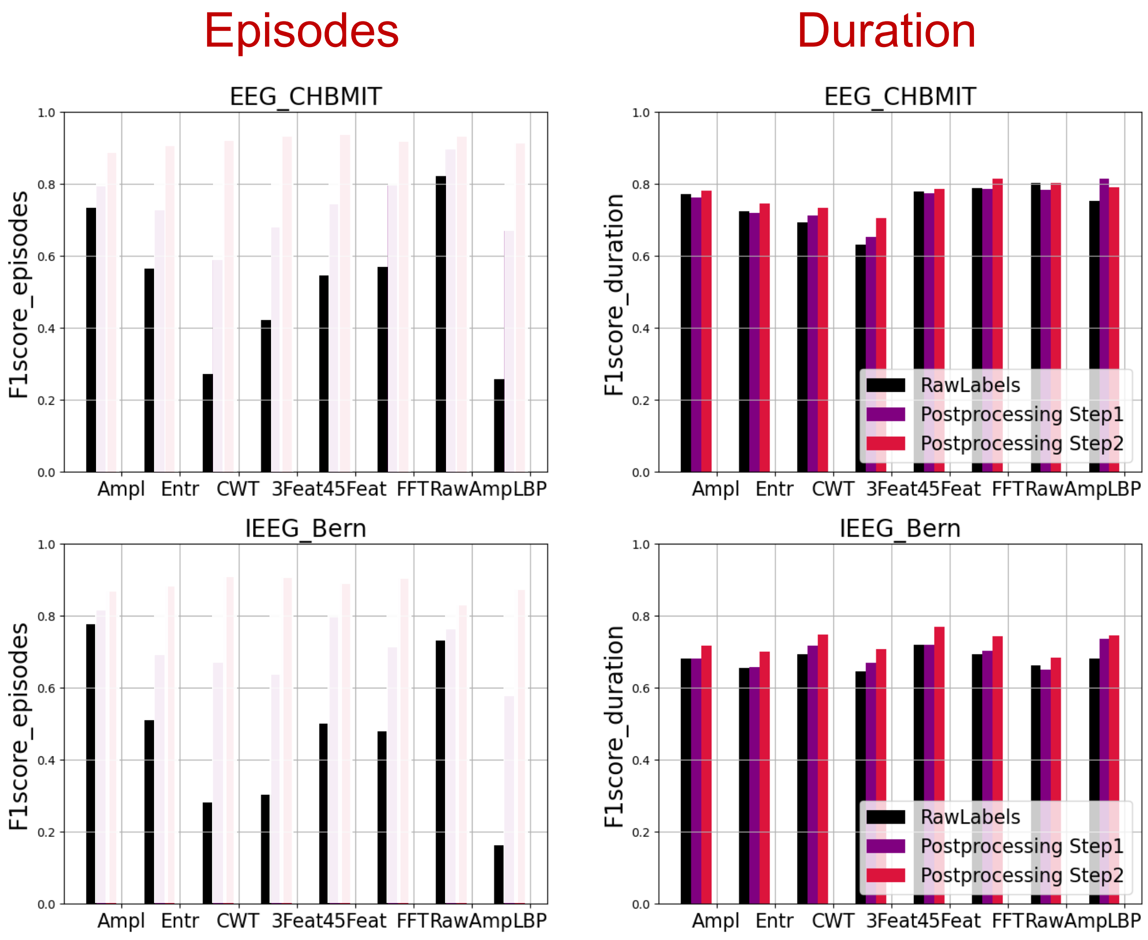
- Labels postprocessing
  - Step1: moving average
  - Step2: merging seizures
- Performance
  - Level of episodes and level of duration
  - Sensitivity, precision, F1 score
- Computational complexity
  - Number of SUM and XOR operations
  - Relative time for calculation
- Memory complexity
  - Memory needed to store all HD vectors

Episode level 0 1 0 1 0 0

Duration level 000000001010101111100000010100011111111111101011011000000000000011000000001000

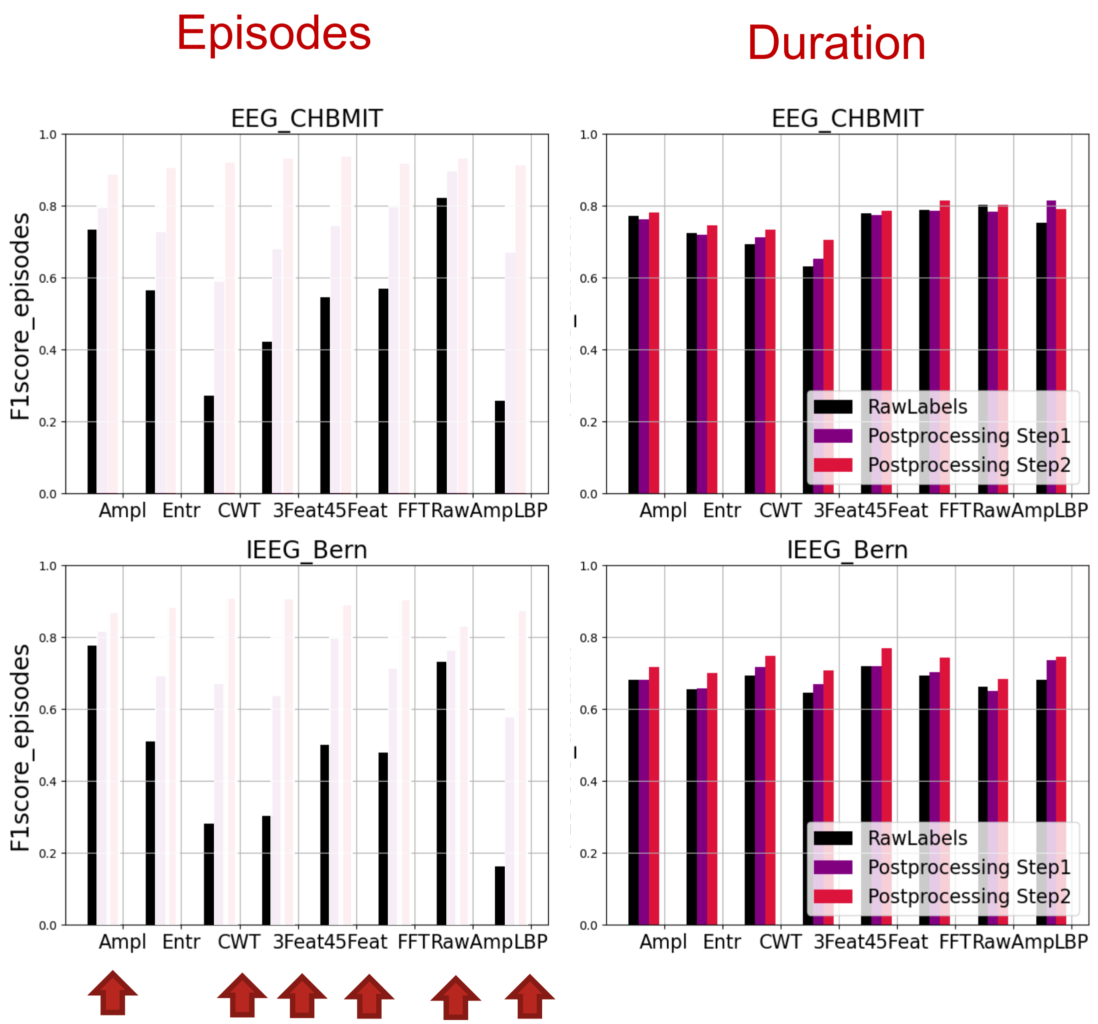
Results: Label postprocessing

- Improves performance at the episode level
  - First step: up to 41.2% for EEG and 41.5% for IEEG
  - Second step: up to 65.5% for EEG and 70.9% for IEEG
- Minor improvement on the seizure duration level
  - Up to 4.0% for EEG and 6.4% for IEEG after both steps



Results: Performance

- Differences between approaches much bigger before label postprocessing
- For episode level
  - The best performance by approaches including amplitude information
  - 45Feat better then 3Feat
  - LBP, CWT quite bad
- For duration level
  - Less variable between approaches

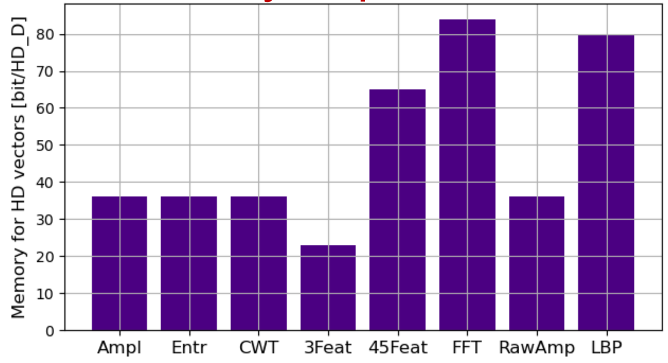


Results: Computational/memory complexity

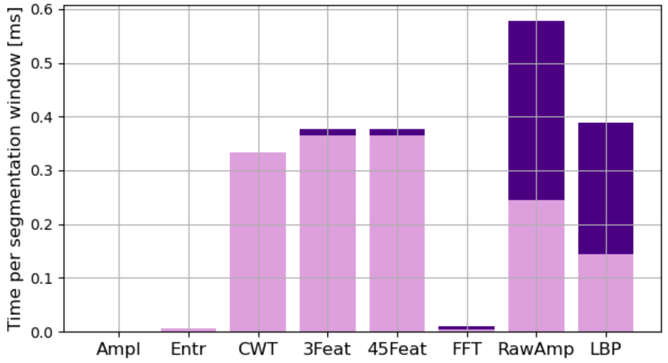
- LBP, FFT and 45Feat approaches have biggest memory requirements
- The ratio between the best and worst-case memory requirements is 3.8x

- Immense difference between approaches
  - Ampl, Entropy, and FFT are very computationally efficient
- Sources of complexity
  - HD vectors operations: RawAmpl and LBP
  - Feature calculation: CWT, 3Feat and 45Feat
- The ratio between the best and worst-case
  - In terms of number of operations is 1056x
  - In terms of computation time is 622X

Memory requirements



Computational complexity



Conclusions

- Different feature encoding strategies on HD vectors were compares
  - For detection of epileptic seizures
- Significant difference in performance especially on the episode level
  - Postprocessing reduces differences
- Computational complexity differences between approaches are much bigger than concerning memory than for computational complexity
  - Approaches with higher performance (such as RawAmpl or 45Feat) might not ideal for wearable applications due to high memory or computational requirements
- For a wearable implementation, feature selection and decisions based on several aspects are necessary
  - Results confirmed on two datasest: EEG and IEEG

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Questions?

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