Graph Neural Network for Seizure Detection in EEG Signals

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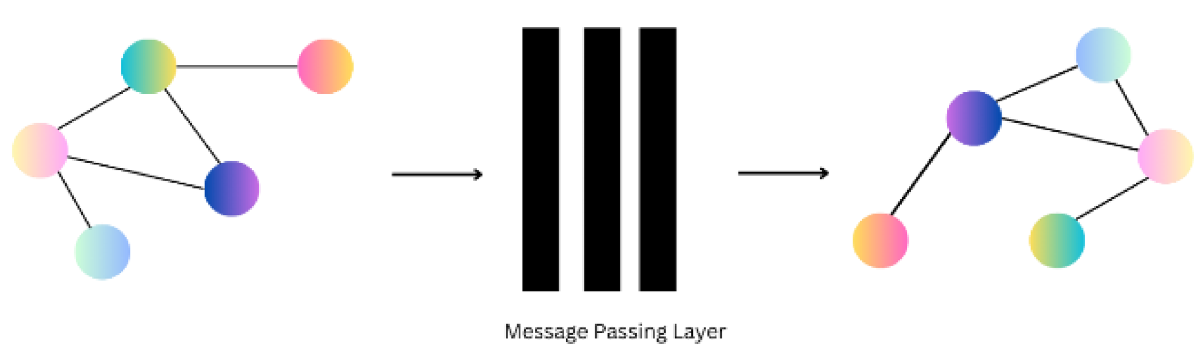
NEURAL INFORMATION PROCESSING SYSTEMS

Introduction

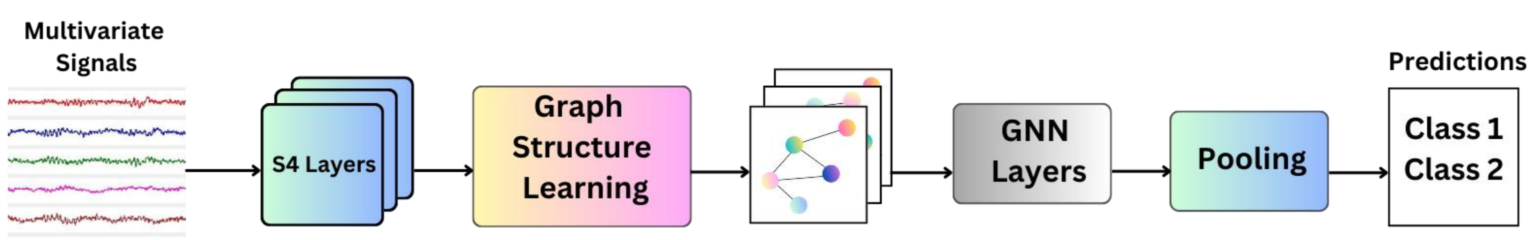
- Traditional deep learning methods like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) excel at processing Euclidean data, such as images or time-series data. However, they struggle with non-Euclidean data that represent complex relationships, such as brain signals (EEG data).
- Brain signals exhibit intricate spatial and temporal dependencies that are difficult for CNNs and RNNs to model effectively.
- Graph Neural Networks (GNNs) address this limitation by representing brain regions as nodes and their interconnections as edges.



- This graph-based approach captures the nuanced structure of brain activity and can detect subtle anomalies, such as seizures, which traditional methods might overlook.

Proposed Solution (S4GNN)

- Introduction of the S4GNN framework, which integrates Structured State Space models (S4) and Graph Signal Learning (GSL) for advanced bio signal analysis.

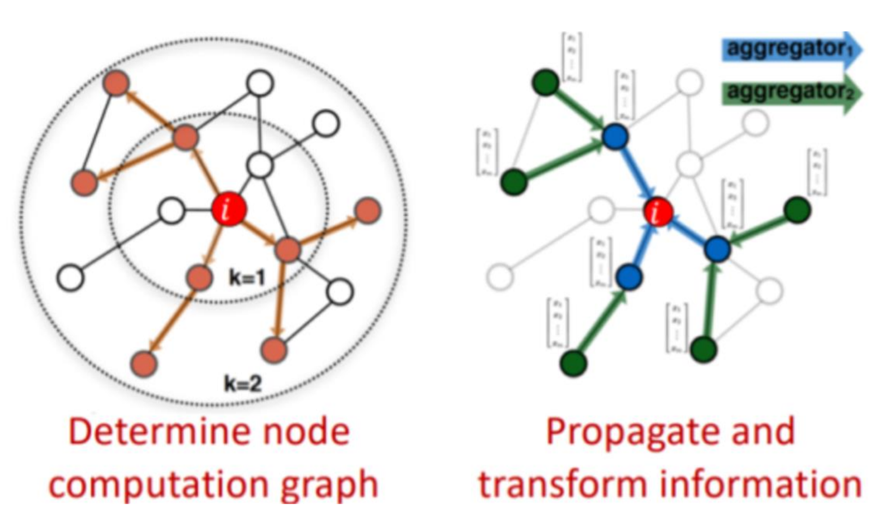


- The methodology involves:
- S4 efficiently processes lengthy EEG sequences by capturing long-range correlations with lower complexity compared to attention mechanisms.
- The GSL layer learns the dynamic relationships between different parts of the signal by constructing a graph. The GSL layer operates on the S4 embeddings and adapts to the evolving relationships over time.
- The iterative message-passing mechanism of GNNs allows nodes to aggregate information from further connected regions, capturing complex cascading effects within the brain network.

This enables GraphS4mer to effectively detect subtle anomalies like seizures in EEG signals.

Graph Neural Networks

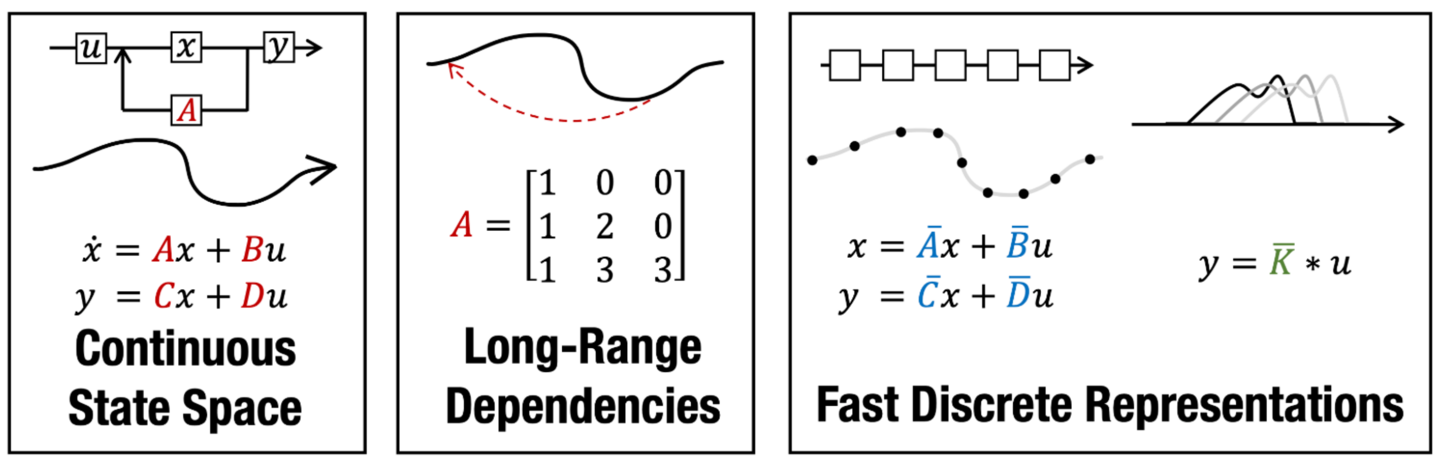
- GNN process nodes (brain regions) and edges (connections between brain regions) to capture both local and global relationships.
- GNNs use message-passing mechanisms where nodes iteratively exchange information with their neighbors.



- Enables robust and scalable bio signal analysis by addressing the limitations of traditional models like CNNs and RNNs.

Structured State Spaces Sequence Model

- S4 is a sequence modeling framework designed for efficient processing of long-range temporal dependencies in sequential data.
- It utilizes state-space models (SSMs), which represent a sequence as a combination of states and their transitions, enabling efficient computation of sequential patterns.



Experimental Setup

- The model was evaluated using the publicly available Temple University Hospital Seizure Detection Corpus (TUSZ) v1.5.2 dataset.
- The experimental setup followed the seizure detection protocol of Tang et al. (2022b) using 60-second EEG clips.
- Each EEG sample contains signals from 19 sensors, sampled at 200 Hz, resulting in a sequence length of 12,000 time steps.
- The task involves binary classification to determine whether a 60-second EEG clip contains a seizure.
- The resolution r in the Graph Signal Learning (GSL) layer was set to 10 seconds (2,000 time steps), inspired by the analysis approach used by trained EEG readers.

Results

- Table compares our model performance on EEG-based seizure detection to existing models. $S4GNN^{dfc}$ outperforms the previous state-of-the-art, Dist-DCRNN, with pre-training by 3.1 points in AUROC.

Model	AUROC	F1-Score
LSTM	0.715	0.365
Dense-CNN	0.769	0.404
CNN-LSTM	0.682	0.330
Dist-DCRNN	0.793	0.341
$S4GNN^{dfc}$(ours)	0.930	0.668

Conclusion

- This study introduces **S4GNN**, a novel framework that combines Graph Neural Networks (GNNs), Structured State Space models (S4), and Graph Signal Learning (GSL) for robust analysis of EEG signals.
- Future work will explore adapting the model to varying signal lengths, enhancing its scalability, and extending its applications to other bio signal analysis tasks.