# Learning Self-Supervised Dynamic Networks for Seizure Analysis

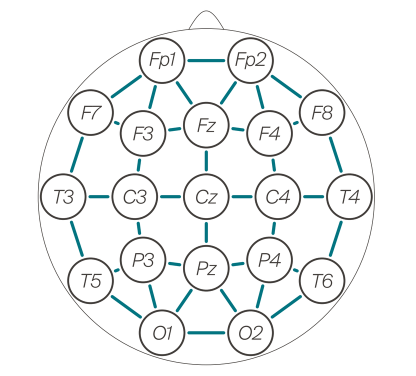
William Cappelletti, Yuhan Xie, Pascal Frossard
LTS4, EPFL, Switzerland

## Seizure Analysis

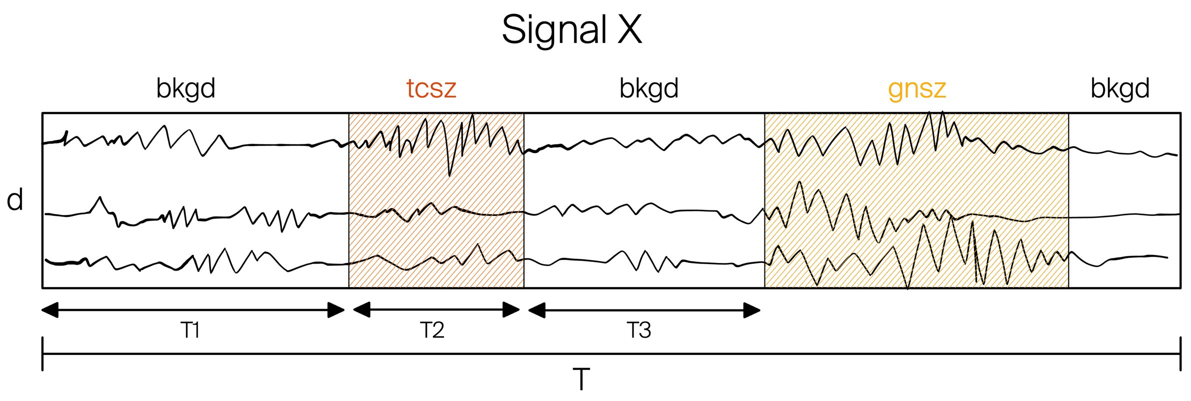
**Epilepsy** is a **cerebral disease** consisting of recurrent **seizures**, i.e. transient occurrence of signs and/or symptoms due to **abnormal excessive or synchronous neuronal activity in the brain** [2]. Epilepsy affects nearly 50 million people worldwide, 30% of which has no relief from treatment. Being able to reliably detect, and if possible predict, their attacks could improve the life standard of these untreatable subjects.

**Electroencephalography** (EEG) captures **neuronal activity** with electrodes placed over the scalp in a standard system, and is the main non-intrusive tool for seizure diagnosis and analysis. EEG measures voltage fluctuations resulting from ionic current within neurons, which provide us multiple time series in which **neurologists search epileptic patterns** and **manually annotate** seizure occurrences.

Reliable and explainable machine learning methods would be greatly beneficial for both doctors and patients.




Electrode placement for the 10-20 EEG system, with the induced distance-based graph.




Representation of annotated EEG session, with two seizures of different type and duration.

**Automated seizure analysis** consists of detection and classification tasks:

- **Seizure detection** is the binary separation of seizures from regular brain activity;
- **Seizure classification** aims at identifying the type of seizure among multiple classes.

Seizure events are very sparse over EEG sessions, and highly imbalanced. It is critical to leverage the large amount of background signals, and the functional relations in the data.

We propose a novel architecture to **learn task-specific networks** for GNNs, jointly with a **self-supervised pretraining strategy**.

## Modelling

**Deep-learning-based approaches** are increasingly used in EEG analysis, with the most successful architectures being convolutional (CNN) and recurrent neural networks (RNNs), which are designed to work with sequential data.

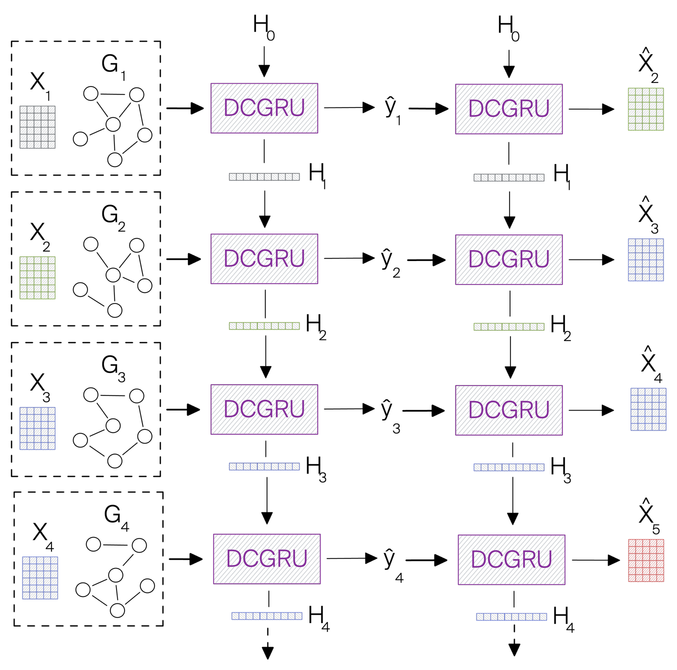
**Graphs** provide a natural representation to leverage the **spatial information** inherent to EEGs, and the **functional connectivity** of the brain, and **Graph Neural Networks** (GNNs) have shown impressive performances on seizure analysis.

### Recurrent Graph Neural Networks

Li et al. [4] proposed the **Diffusion Convolutional RNN** (DCRNN) model for forecasting on directed graphs. Its building block is **DCGRU**, which models

- **spatial dependencies** with bidirectional random walks, using **diffusion convolutions** instead of matrix multiplications;
- **temporal dependencies** with hidden states updated by **Gated Recurrent Units**.

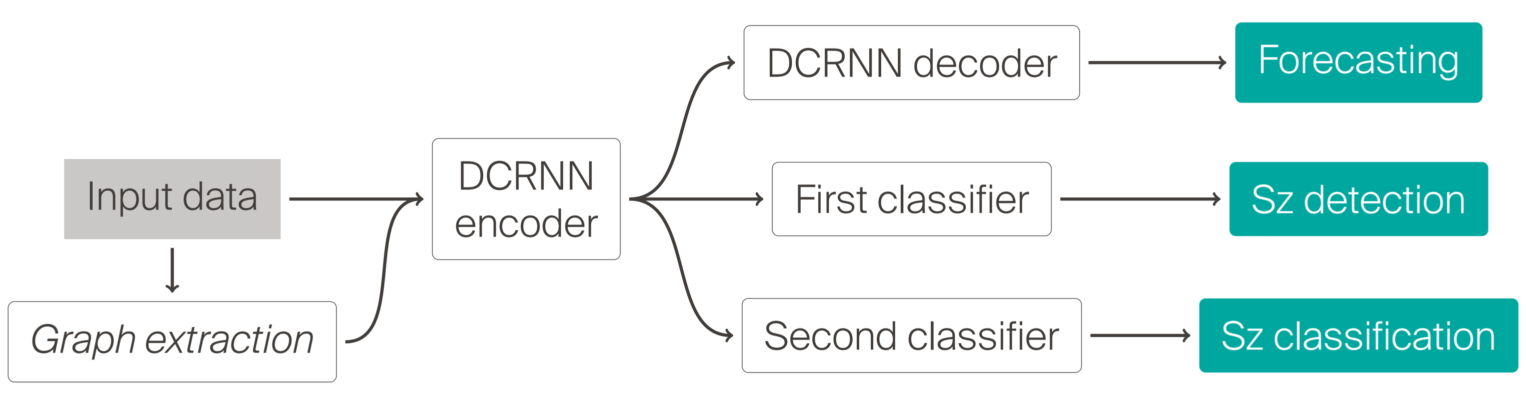
DCRNN can predict the following snapshots from graph signals as a **sequence-to-sequence** model.




## Self-Supervised Learning

**Self-supervised learning** defines tasks intrinsic to the structure of the data, so that model embeddings can capture those properties. A natural SSL task for time series data is **forecasting**.

We design models to have an **encoding block** shared by **multiple heads**, for instance a decoder block for and a classifier.



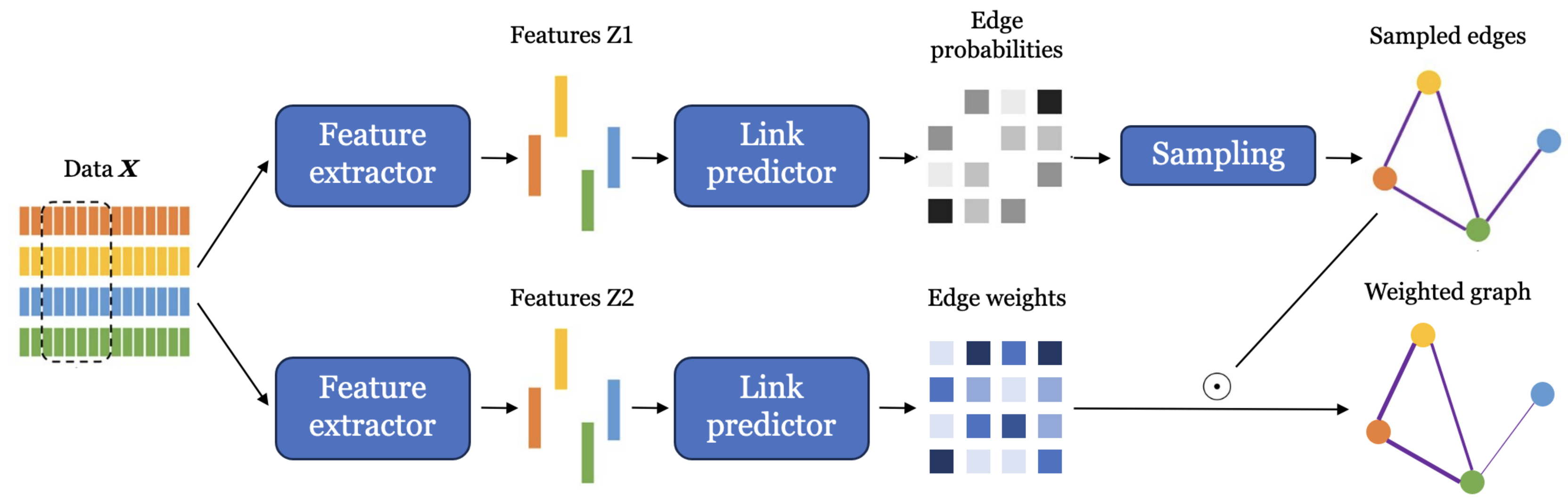

Tang et al. [7], for instance, propose a three-headed model from which perform either of three downstream tasks, namely **graph-signals forecasting** (self-supervised pretraining), **seizure detection**, or **seizure classification**.

## Learning Graphs from Data

Learning **task-specific networks** could improve seizure-analysis models by capturing:

- Hidden **functional dependencies** within multivariate time series;
- Evolving patterns and **dynamic relations**.

We learn data-driven **weighted graphs** building on top of the **Graph Time Series** (GTS) parameterized sampling scheme from Shang et al. [6], and extended by Xu et al. [8] for dynamic graphs.




We design **WGTS**, a weighted version of GTS blocks, with two **parallel structure learning blocks**, for edge probabilities and weights respectively.

## Experimental Results

### Dataset

We focus on the public **Temple University Hospital EEG Seizure Corpus** (TUSZ) v1.5.2 [5]:

- EEG signals from **637 patients** split in predefined training and test sets, with 591 and 46 subjects respectively;
- **3050 annotated seizures** which span 6.3% of the training and 9.8% of the test data;
- **Four seizure categories**, namely combined focal (CF), generalized nonspecific (GN), absence (AB), and combined tonic (CT), which amount respectively to 2165, 523, 99, and 109 events of various durations.

### Baselines

We compare our WGTS architecture to the following baselines:

- **LSTM** [3], a Long-Short-term memory RNN, with linear layers in its update blocks;
- **CNN-LSTM** [1], which shares the LSTM recurrent mechanism, but uses convolutional layers in its update blocks;
- **Dist-DCRNN** [7], a recurrent GNN based on the 10-20 EEG distance graph.

We study the influence of multiple factors in our architecture by ablation. In particular, we focus on the following properties:

- **SSL**, self-supervised pretraining on one-step ahead forecasting;
- **dist**, we always include the edges of the 10-20 EEG graph on top of the learned one.

### Results

Average and STD test values obtained across multiple random initializations of our models (*) and benchmarks. **Best scores** are bold and <u>second best</u> are underlined.

| Model and properties | Classification F1 | Detection AUROC |
|---|---|---|
| *CNN-LSTM* | 0.617 ±0.023 | 0.755 ±0.010 |
| *LSTM* | 0.650 ±0.080 | 0.767 ±0.026 |
| *Dist-DCRNN* | 0.717 ±0.074 | 0.856 ±0.008 |
| *Dist-DCRNN + SSL* | 0.729 ±0.023 | 0.860 ±0.015 |
| *GTS* | 0.710 ±0.050 | 0.856 ±0.020 |
| **WGTS* | 0.716 ±0.036 | 0.822 ±0.031 |
| **WGTS + dist* | 0.710 ±0.036 | 0.845 ±0.016 |
| **WGTS + SSL* | <u>0.762</u> ±<u>0.013</u> | 0.847 ±0.003 |
| **WGTS + SSL + dist* | 0.753 ±0.035 | <u>0.861</u> ±<u>0.013</u> |
| **WGTS Dynamic* | 0.737 ±0.062 | 0.843 ±0.008 |
| **WGTS Dynamic + dist* | 0.735 ±0.025 | **0.867** ±**0.007** |
| **WGTS Dynamic + SSL* | 0.708 ±0.055 | 0.828 ±0.032 |
| **WGTS Dynamic + SSL + dist* | **0.769** ±**0.036** | 0.851 ±0.023 |

### Comments

Learning a task-specific graph improves the results when paired with self-supervised pretraining, or with a meaningful prior, such as the 10-20 distance graph. WGTS paired with SSL leverages its overparameterization by boosting test scores by 0.05 for seizure classification, and 0.02 for detection.

## Read me!

## References

[1] D. Ahmedt-Aristizabal, T. Fernando, S. Denman, L. Petersson, M. J. Aburn, and C. Fookes. Neural Memory Networks for Seizure Type Classification. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pages 569–575, 2020.

[2] R. S. Fisher, W. v. E. Boas, W. Blume, C. Elger, P. Genton, P. Lee, and J. Engel Jr. Epileptic Seizures and Epilepsy: Definitions Proposed by the International League Against Epilepsy (ILAE) and the International Bureau for Epilepsy (IBE). *Epilepsia*, 46(4):470–472, 2005.

[3] S. Hochreiter and J. Schmidhuber. Long Short-Term Memory. *Neural Computation*, 9(8): 1735–1780, 1997.

[4] Y. Li, R. Yu, C. Shahabi, and Y. Liu. Diffusion Convolutional Recurrent Neural Network: Data-Driven Traffic Forecasting. In *International Conference on Learning Representations*, 2018.

[5] I. Obeid and J. Picone. The Temple University Hospital EEG Data Corpus. *Frontiers in Neuroscience*, 10:196, 2016.

[6] C. Shang, J. Chen, and J. Bi. Discrete Graph Structure Learning for Forecasting Multiple Time Series. In *International Conference on Learning Representations*, 2022.

[7] S. Tang, J. Dunnmon, K. K. Saab, X. Zhang, Q. Huang, F. Dubost, D. Rubin, and C. Lee-Messer. Self-Supervised Graph Neural Networks for Improved Electroencephalographic Seizure Analysis. In *International Conference on Learning Representations*, 2021.

[8] N. Xu, C. Kosma, and M. Vazirgiannis. TimeGNN: Temporal Dynamic Graph Learning for Time Series Forecasting, 2023.