An Attention-based Architecture for EEG Classification

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Abstract: Emerging studies in the deep learning community focus on techniques aimed to identify which part of a graph can be suitable for making better decisions and best contributes to an accurate inference. These researches (i.e., “attentional mechanisms” for graphs) can be applied effectively in all those situations in which it is not trivial to capture dependency between the involved entities while discharging useless information. This is the case, e.g., of functional connectivity in human brain, where rapid physiological changes, artifacts and high inter-subject variability usually require highly trained clinical expertise. In order to evaluate the effectiveness of the attentional mechanism in such critical situation, we consider the task of normal vs abnormal EEG classification using brain network representation of the corresponding EEG recorded signals.

1 INTRODUCTION

Current networks not only involve social and technological aspects of our life but are considered as fundamental tools for studying many natural phenomena and conceptual problems. In particular, we have recently witnessed a significant growth of neuroscience studies that use networks as a new paradigm to better understand cognition (Varela et al., 2001), brain cell organization (Rubinov and Sporns, 2010), and functional connectivity (Towlson et al., 2013; Shih et al., 2015; van den Heuvel et al., 2012). Moreover, recent advances in deep learning approaches have provided the opportunity to dig into the understanding of brain diseases and to develop effective neuro-markers for diagnosis and prognosis (Durstewitz et al., 2019; Corchs et al., 2019). Similarly, there have been several attempts in literature to extend deep learning techniques to deal with network data. Some initial work in this context used recursive networks to process structured data such as direct acyclic graphs (Frasconi et al., 1998; Sperduti and Starita, 1997). More recently, Graph Neural Networks (GNNs) have been introduced (Gori et al., 2005; Scarselli et al., 2008) as a generalization of recursive networks capable of handling more general classes of graphs.

Despite the excellent performances and robustness of deep learning for network data, current induction has to deal with large multivariate and noisy data sets, thus posing critical issues for an effective mining and inference. This is the case of EEG signals, in which rapid physiological changes, artifacts and high inter-subject variability require a highly trained (human) clinical expertise. In this regard, emerging researches on deep architectures focus on how to bring out relevant parts of a network to provide better decisions (Veličković et al., 2017), and knowledge representation. Technically, this approach is known as “attentional mechanism”. Introduced for the first time in the deep learning community in order to access important parts of the data (Bahdanau et al., 2014), the attention mechanism has recently been successful for the resolution of a series of tasks (Lee et al., 2018).

The key ideas of our study are that: 1) interactions between brain regions can be used to extract useful features in order to classify anomalies and 2) features of pairs of brain region are related with each others. Using a correlation matrix, we are able to express the strength of the interaction between pairs of electrodes, which can be directly mapped to a graph representation: each node is an electrode and each edge

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is added if the correlation is strong enough. This is motivated by the spatial positioning of the electrodes and the biological mechanisms, that actually include more than one brain region together during everyday tasks. Furthermore, by construction, an edge is added to the graph if and only if it is a valid representation of the interaction between a pair of nodes (alias a pair of brain regions), so for each node the attention is performed on a well-structured and physiological-motivated neighborhood.

In this paper, by focusing on these researches, we investigate the performance of the graph attentional mechanism for providing case/control, i.e., abnormal/normal EEG, classification of functional brain networks obtained from EEG recorded signals.

In Sec. 2, we highlight some critical issues that could affect the inference when blindly applying brain networks as a tool for the analysis of functional connectivity. In Sec. 3, we give the main definitions and concepts. In Sec. 4, we describe the Graph Attention Network (GAT) mechanism on which we apply our inference problem. In Sec. 4.1, we conveniently adapt and extend such mechanism for EEG signal classification. In Sec. 5, we describe the experimental setting. We conclude the paper reporting and discussing the results in Sec. 6 and Sec. 7.

2 EEG SIGNALS: CRITICAL ASPECTS FOR NETWORK BASED INFERENCE

Although the network representation of brain signals has had an evident impact on the scientific community, it cannot be uncritically applied to inference and data mining. In fact, to perform a pertinent analysis and properly extract brain functional network properties it is important to know the neural phenomenon under study.

Different pathologies, such as stroke, are usually associated to lesions in different brain regions. This can cause problems in obtaining accurate inference, as the location and the shapes of these lesions can largely differ from individual to individual. Clearly, this has an impact on the definition of the network, on its nodes and even on the correspondences that these elements find in different subjects.

Moreover, because of rapid physiological changes, artifacts, and high inter-subject variability, EEG data are non-stationary multivariate time series that are difficult to summarize with broadly network statistics, and the corresponding inductive tasks could generalize poorly, or even be unable to capture specific extreme situations. This is the case, for example, of epileptic seizures where abnormal neuronal activities lead to convulsions and / or mild loss of awareness. In such case, most seizures (e.g., temporal lobe epilepsy) begin as focal and rapidly generalize for several seconds. If we were interested in identifying epileptic foci during a generalized attack, the use of "graph-based" inference should be carefully applied, in order to provide a proper identification.

In order to fill, at least in part, some of the issues described for brain network based inference in the following paragraphs we evaluate an attentional (graph-based) architecture for selecting relevant network topology, discharging useless information, and at the same time acquiring the temporal functional dependence of EEG recorded traces.

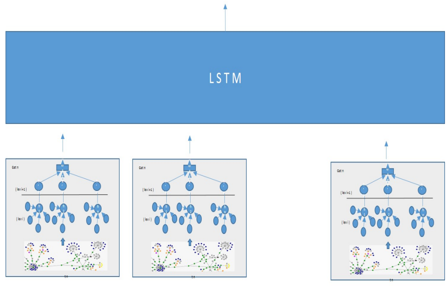
3 MAIN CONCEPTS AND DEFINITIONS

From a theoretical perspective, networks can be modeled through graphs, i.e., abstract objects representing collection of "entities", V (vertices or nodes), and relationships between them, i.e., edges, E. In this paper, we use attributed graphs, $G = (V,E)$, where each vertex $v \in V$ is labeled with a vector of attribute values. Moreover, given a vertex $v \in V$, we indicate with $\mathcal{N}(v) = \{u : \{v,u\} \in E\}$ the neighborhood of the vertex v.

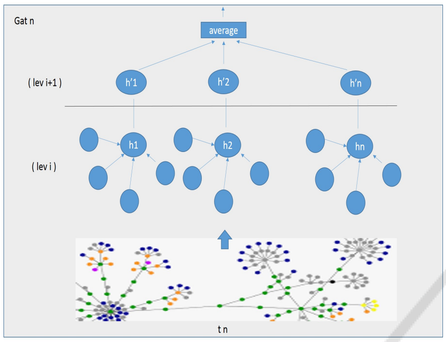
In order to summarize relationships between vertices and capture relevant information in a graph, embedding (i.e., objects transformation to lower dimensional spaces) is typically applied (Goyal and Ferrara, 2018). This approach allows to use a rich set of analytical methods, offering to deep models the capability of providing different levels of representation. Embedding can be performed at the node level, at the graph level, or through different mathematical strategies, and it is typically realized by fitting (deep) network's parameters using standard gradient-based optimization. In particular, the following definitions can be useful (Lee et al., 2018).

Definition 3.1. Given a graph $G = (V,E)$ with V as the set of vertices and E the set of edges, the objective of node embedding is to learn a function $f : V \rightarrow \mathcal{R}^k$ such that each vertex $i \in V$ is mapped to a k-dimensional vector, $\vec{h}$.

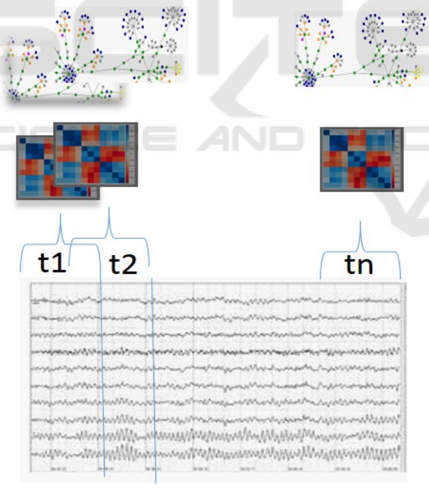
Definition 3.2. Given a set of graphs, $\mathcal{G}$, the objective of graph embedding is to learn a function $f : \mathcal{G} \rightarrow \mathcal{R}^k$ that maps an input graph $G \in \mathcal{G}$ to a low dimensional embedding vector, $\vec{h}$.



(a)



(b)



(c)

Figure 1: System Architecture. (c) The adjacency matrix is computed for each window; (b) From adjacency to GAT (for each window); (a) LSTM processes the sequence of GAT embedded vectors.

4 GAT MODELS

In this paper, we apply the attentional-based node embedding as recently proposed in (Veličković et al., 2017) by introducing a stacked architecture for case/control classification of recorded EEG traces. For a general, yet formal, definition of the notion of "attention" here we conveniently adapt the one reported in (Lee et al., 2018).

Definition 4.1. An attentional mechanism is a function $a : \mathcal{R}^n \times \mathcal{R}^n \rightarrow \mathcal{R}$ which computes coefficients $e_{i,j} = a(\vec{h}_i^{(l)}, \vec{h}_j^{(l)})$ across pairs of vertices, i, j, based on their feature representation $\vec{h}_i^{(l)}, \vec{h}_j^{(l)}$ at level l.

The coefficients $e_{i,j}$ can be interpreted as the relevance of vertex j's features to i. Accordingly to (Veličković et al., 2017), let a be a single-layer feed-forward neural network parametrized by a weight vector $\vec{a}$ with nonlinear *LeakyReLU* activation. In this case we have,

$$e_{i,j}^{(l)} = \text{LeakyReLU}\left(\vec{a}^{(l)T}\left[\mathbf{W}^{(l)}\vec{h}_i^{(l)} || \mathbf{W}^{(l)}\vec{h}_j^{(l)}\right]\right).$$

where $\mathbf{W}$ is a learnable parameter matrix and $\mathbf{W}^{(l)}\vec{h}_i^{(l)} || \mathbf{W}^{(l)}\vec{h}_j^{(l)}$ is the concatenation of the embedded representation for the vertices i, j. The coefficients $e_{i,j}$ are generally normalized using, e.g., a *softmax* function,

$$\alpha_{i,j}^{(l)} = \frac{\exp(e_{i,j}^{(l)})}{\sum_{k \in \mathcal{N}(i)} \exp(e_{i,k}^{(l)})}.$$

Notice that the mechanism's parameters, $\vec{a}$, are trained jointly with the others network's parameters with standard optimization. Finally, the normalized (attention) coefficients $\alpha_{i,j}$ are then applied to compute a linear combination of the features "around" i (i.e., features of the vertices in $\mathcal{N}(i)$). In this way, the next level feature vector for i is obtained, i.e.,

$$\vec{h}_i^{(l+1)} = \sigma\Big(\sum_{j \in \mathcal{N}(i)} \alpha_{i,j}^{(l)} \mathbf{W}^{(l)} \vec{h}_j^{(l)}\Big)$$

where σ is non linear vector-valued function (in our case, sigmoid). In this way, embedding from neighbors is aggregated together and scaled by the attention scores.

4.1 A Stacked GAT-LSTM for EEG Traces

Long-Short Term Memory networks have successfully contributed to model temporal sequences with long lag time dependency. Furthermore because of their *forget gates*, LSTM are able to filter out irrelevant data from "memory" (Gers et al., 1999). On the basis of these arguments, here we apply a stacked LSTM layer built on top of the level reported above. In this way, we try to capture both the relevant topology of the corresponding network and the temporal dependency responses, while discharging ineffective data from LSTM's "memory". The LSTM layer is composed by 32 units. The resulting architecture is reported in Fig. 1a.

5 EXPERIMENTAL SETTING

In order to capture temporal information from the recorded EEG traces, we apply a sliding window approach. Specifically:

- The whole multivariate data are framed into different overlapping windows on the temporal domain, and each corresponding sub-sampled cross-section series is used to obtain a cross-correlation matrix built with Spearman correlation values between every pairs of recorded channels (Fig. 1c). In this way each window is associated with a graph adjacency matrix using a threshold-based approach.
- For each graph, a GAT network is obtained as reported in Sec. 1b (Fig. 1b).
- The GAT embedding from the j-th GAT network (which characterizes the j-th graph embedded representation) is aligned with the other (GATs) output to obtain a sequence of GAT embedded vectors. This sequence is processed as input by the stacked LSTM layer (Fig. 1a).
- The input set of node features $\vec{h} = \{\vec{h}_1, \vec{h}_2, \ldots, \vec{h}_N\}$ is composed by features vectors $\vec{h}_i \in \mathbb{R}^F$, with F the number of features for each node. In this paper, a single feature vector is made by five features and is calculated by extracting the average power for five well-established frequency bands, such as delta (0.5-4Hz), theta (4-8Hz), alpha (8-12Hz), beta (12-30Hz) and gamma (30-100Hz), in the corresponding window.

5.1 Dataset

The dataset used in this paper is the "TUH Abnormal EEG Corpus", a large corpus of data derived from the EEG Data Corpus of Temple University Hospital of Philadelphia, Pennsylvania (Obeid and Picone, 2016). This dataset was previously used in other publications (Lopez et al., 2015; Schirrmeister et al., 2017; Özal Yıldırım et al., 2017). It contains up to 2993 EDF files, divided in 1472 abnormal EEGs and 1521 normal EEGs, a total of approximately 1142 hours of recording. For each record there is a plain text report of the session describing the patient: clinical history, medications, first impression of the EEG record and clinical correlations. Each EEG record contains 22 channels with a 10/20 configuration.

6 RESULTS

The objective of our experiments were to evaluate the accuracy of the attentional-based architecture to classify normal and abnormal signals of the data reported in Sec.5.1.
As a reference for our comparisons, we used Convolutional Neural Networks (CNNs). In order to design homogeneous comparisons, CNNs are equipped with dense (feed-forward) layers, that (similarly to the architecture based on "attention") allows to obtain, for each window, an embedded vector, which in turn represents the corresponding graph. The embedding sequence can then be processed as input from the stacked LSTM.
It is worth to note that in our experiments we have also evaluated a "CCN + Dense" architecture. In this case, a CNN supplies the graph embedding for every window. The sequence of all embedding is then passed as input to the dense layer.

For each neural architecture, the number of epochs is fixed to 100 and the loss function is a cross entropy function. The selected optimizer is an *Adam Optimizer* with a learning rate of 10^{-5}. To obtain more robust error estimation, we applied for each classifier, a standard 10-fold cross-validation. The resulting performances are averaged on the number of folds.

The results are reported in Tab. 1 and Tab. 2. Results reported in Tab. 2 shares the same experimental settings as those in Tab. 1, with the only difference that, here, we previously band-pass filtered signals (from 0.1 to 47 Hz). In both cases, GAT-based architectures outperform CNN-based architectures.

The architecture described in this paper was implemented in Python using Keras library (Chollet et al., 2015) and Spektral library (Grattarola, 2019). The dataset preprocessing library is PyEEGLab (Zanga, 2019). Numerical evaluations were executed on Ubuntu 18.04.2 LTS; Processor: AMD®, Threadripper™ 1900X CPU @ 3.89GHz, 4.20 Ghz, 8 Core(s), 16 Logical Processors; GPU: NVIDIA®, GeForce RTX™ 2070 8GB GDDR6; Installed Physical Memory (RAM) 32.00 GB ECC.

7 CONCLUSIONS

EEG-based brain networks are rather complex, yet promising, tools, which typically need for a highly-trained knowledge of the underlying neurophysiolog-

Table 1: Classification Performances [%].

Architecture	Accuracy	Sensitivity	Specificity	Precision	F1 Score
CNNs + Dense	67.89%	68.67%	67.11%	67.76%	68.21%
CNNs + LSTM	68.56%	67.26%	70.23%	74.34%	70.63%
GATs + LSTM	**81.27%**	**77.27%**	**86.99%**	**89.47%**	**82.93%**

Table 2: Classification Performances [%] with band-pass filtered signals.

Architecture	Accuracy	Sensitivity	Specificity	Precision	F1 Score
CNNs + Dense	69.90%	71.23%	68.63%	68.42%	69.80%
CNNs + LSTM	69.97%	72.59%	67.86%	64.47%	68.29%
GATs + LSTM	**76.92%**	**77.85%**	**76.00%**	**76.32%**	**77.08%**

ical processes, to provide accurate inference and modeling. It turns out that the development of methods to properly measure the brain functional connectivity at different time steps is fundamental for classification and, more generally, for induction.

The work presented here has focused on the formulation of the recent "attentional mechanism" for graphs (Veličković et al., 2017). In particular, we introduced a stacked GAT-LSTM architecture aimed to classify abnormal vs normal EEG signals. The proposed architecture intends to benefit on the one side, from the potential LSTM capability to model long lag time dependency while discharging information, and one the other, from being able to exploit the "attentional mechanism" for capturing most task-relevant information from brain network's complex dynamic.

Although the reported results are encouraging for this purpose – outperforming a typical CNN application, a larger dataset has to be investigated to further support the impact of the newly proposed GAT-based approach for physiological signals. This in turn reflects the needs to focus on specific pathologies, as highlighted in this paper. Our research will follow this target by specializing the analysis to clinical oriented studies for a more complete modeling and interpretation. Others experiments will be performed to describe more extensively the effects of the application of a band-pass filtering.

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