An untrained neural model for fast and accurate graph classification

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Abstract. Recent works have proven the feasibility of fast and accurate time series classification methods based on randomized convolutional kernels [5, 32]. Concerning graph-structured data, the majority of randomized graph neural networks are based on the Echo State Network paradigm in which single layers or the whole network present some form of recurrence [8, 7].
This paper aims to explore a simple form of a randomized graph neural network inspired by the success of randomized convolutions in the 1-dimensional domain. Our idea is pretty simple: implement a no-frills convolutional graph neural network and leave its weights untrained. Then, we aggregate the node representations with global pooling operators, obtaining an untrained graph-level representation. Since there is no training involved, computing such representation is extremely fast. We then apply a fast linear classifier to the obtained representations. We opted for LS-SVM since it is among the fastest classifiers available. We show that such a simple approach can obtain competitive predictive performance while being extremely efficient both at training and inference time.

Keywords: Graph Neural Network · Graph Convolution · Reservoir Computing · Structured Data · Machine Learning on Graphs · Deep Randomized Neural Networks.

1 Introduction

In this paper, we develop efficient graph neural networks for graph classification. When dealing with machine learning for structured data, there are typically two distinct families of tasks that can be tackled that have to be addressed with different neural architectures. The first task is node property prediction (e.g., *node* classification) which is defined as predicting one or more values associated with each node in a graph. Graph Neural Networks (GNNs) have shown promising performance on such tasks [26]. The second task is graph property prediction (e.g., *graph* classification), in which the property that has to be predicted is a global property of a graph. In this case, the training set is composed of a set

of graphs, each with the corresponding associated label. Such tasks require the inclusion of additional components in the GNN architecture, allowing the transformation of a set of node-wise representations to a single graph-level one before performing the prediction.

While many different architectures for node and graph classification have been proposed in the literature, most of the proposals have in common the end-to-end nature of their training, which results in fairly high computational complexity. Recently, in order to circumvent the need for expensive end-to-end training, a family of neural network models that are highly efficient to train have been receiving increasing attention. Most proposals along these lines so far have focused on the study of dynamic systems on discrete graphs in the area of Reservoir Computing (RC) [20, 22]. In this case, a reservoir layer randomly initialized under asymptotic stability constraints, and left untrained, is responsible for computing the encoding of each node, while training is restricted only to the output *readout* layer [8, 7]. However, although this approach enables learning tasks on graphs in an extremely efficient way, it involves a fixed-point convergence process of the dynamic reservoir layer on the graph. This process, in turn, requires a number of iterations that can undermine the overall efficiency of the approach. More recently, it has been shown [27, 15] that the randomized approach on graphs can also be exploited without resorting to an iterative process. In particular, it is possible to perform node classification using randomized graph convolutions, i.e., without the necessity of training the convolution parameters, and still obtain competitive predictive performance when training is restricted to the readout part, as in RC-based approaches. While recently the approach has been proven feasible for tasks defined on graph nodes, it is still unclear if it also applies to graph classification tasks. This research question is not straightforward since the aggregation layer tends to lose a significant amount of information. A similar problem was already tackled in the case of randomized convolutions for time series analysis in a recent work [5].

In this paper, we show that by paying attention to some core aspects of the network architecture, it is possible to define a very efficient, randomized GNN model for graph classification tasks. Such critical components are: 1. the presence of non-linearity between graph convolution layers; 2. the adoption of a *good* aggregation scheme; 3. a wise initialization of the network weights. We analyze each one of these critical aspects in our ablation studies and show how each component influences the resulting predictive performance of the model. We refer to our proposed model as Untrained-GCN or U-GCN, acknowledging the intuitions behind it to come from the worlds of randomized neural networks and graph convolutional networks.

The rest of this paper is organized as follows. In Section 2 we introduce some background concepts that are necessary to present our contribution in Section 3. In Section 4 we present and discuss our experimental comparisons and ablation studies. Section 5 concludes the paper.

2 Background

In the following, we use italic letters to refer to variables, bold lowercase letters to refer to vectors, and bold uppercase letters to refer to matrices. The elements

of a matrix $\mathbf{A}$ are referred to as a_{ij} (and similarly for vectors). We use uppercase letters to refer to sets or tuples.

Let $G = (V, E, \mathbf{X})$ be a graph, where $V = \{v_0, \ldots, v_{n-1}\}$ denotes the set of vertices (or nodes) of the graph, $E \subseteq V \times V$ is the set of edges and $\mathbf{X} \in \mathbb{R}^{n \times s}$ is a multivariate signal on the graph nodes with the i-th row representing the attributes of v_i. We define $\mathbf{A} \in \mathbb{R}^{n \times n}$ as the adjacency matrix of the graph, with elements $a_{ij} = 1 \iff (v_i, v_j) \in E$. With $\mathcal{N}(v)$ we denote the set of nodes adjacent to node v.

2.1 Graph neural networks

As a machine learning model for graph problems, graph neural networks [34, 12, 33] have emerged in recent years. A Graph Neural Network (GNN) is a model that exploits the structure of the graph and the information embedded in feature vectors of each node to learn a representation $\mathbf{h}_v \in \mathbb{R}^m$ for each vertex $v \in V$. In many GNN models, the computation of $\mathbf{h}_v$ can be divided into two main steps: *aggregate* and *combine*. We can define aggregation and combination by using two functions, $\mathcal{A}$ and $\mathcal{C}$, respectively: $\mathbf{h}_v = \mathcal{C}(\mathcal{L}(v), \mathcal{A}(\{\mathcal{X}(u) : u \in \mathcal{N}(v)\}))$.
The kind of aggregation function $\mathcal{A}$ and combination function $\mathcal{C}$ determinate the type of *Graph Convolution (GC)* adopted by the GNN. The first model that relies on graph convolutions was proposed by Micheli *et. al* in 2019 [21]. Recently, many novel GCs base models have been proposed [18, 4, 37, 13, 19, 39].

The model proposed in this paper is built on top of one of the most common and widely adopted GC operators: the GCN [18]

$$\mathbf{H}^{(i)} = \mathcal{F}\left(\mathbf{S}\,\mathbf{H}^{(i-1)}\mathbf{W}^{(i)}\right), i > 1 \tag{1}$$

where $\mathbf{S} = \tilde{\mathbf{D}}^{-\frac{1}{2}}(\mathbf{I} + \mathbf{A})\tilde{\mathbf{D}}^{-\frac{1}{2}}$, $\mathbf{A}$ denotes the standard adjacency matrix of the graph G and $\tilde{\mathbf{D}}$ the diagonal degree matrix with the diagonal elements defined as $\tilde{d}_{ii} = 1 + \sum_j a_{ij}$. Further, $\mathbf{H}^{(i)} \in \mathbb{R}^{n \times m_i}$ is the matrix containing the representation $\mathbf{h}_v^{(i)}$ of all nodes in the graph (one per row) at layer i, $\mathbf{W}^{(i)} \in \mathbb{R}^{m_{i-1} \times m_i}$ denotes the matrix of the layer's parameters, and $\mathcal{F}$ is the element-wise (usually, nonlinear) activation function.

2.2 Graph neural networks with random weights

In structured data domains, the models proposed in the last few years show increasing complexity, leading to novel architectures with a considerably high number of parameters. Unfortunately, this implies a high computational cost, especially in training the models.

For sequential data, many efficient architectures rely on the Reservoir Computing (RC) paradigm [20], which is based on exploiting fixed (randomized) values of the recurrent weights. The random weights are defined following the Echo State Property (ESP) [17] that ensures stability conditions of the dynamical system. In particular, the Echo State Networks (ESN) [17] are widely used when an efficient recursive model is required.

Gallicchio *et al.* in [7] proposed in 2010 the first model for graph domain that exploits RC framework. The proposed model, dubbed GraphESN is composed of

a non-linear reservoir and a feed-forward linear readout. The reservoir computes a fixed recurrent encoding function over the whole nodes of the graph as follows:

$$\mathbf{h}_v[t+1] = f(\mathbf{W}_{in}\mathbf{x}_v + \sum_{u \in \mathcal{N}(v)} \hat{\mathbf{W}}_h \mathbf{h}_u[t]), \tag{2}$$

where $\mathbf{W}_{in} \in \mathbb{R}^{m \times s}$, and $\hat{\mathbf{W}}_h \in \mathbb{R}^{m \times m}$. For each vertex $v \in V$, $\mathbf{h}_v[0]$ is initialized to $\mathbf{0} \in \mathbb{R}^m$. The computation of the global state $\mathbf{h}_v[t^*]$ involves the iteration of eq. (2) till $|\mathbf{h}_v[t^*+1] - \mathbf{h}_v[t^*]| \leq \epsilon$. Then, the global state is used by the readout of the model to compute the output using a linear projection:

$$\mathbf{o} = \mathbf{W}_{out} \sum_{v \in V} \mathbf{h}_v[t^*]. \tag{3}$$

in 2020 an evolution of the GraphESN was introduced in [8]. The FDGNN (Fast and Deep GNN) model constructs a progressively more abstract neural representation of the input graph by stacking successive layers of GNN. The formulation of this model is reminiscent of the original formulation of GNN [33], but the parameters of each layer are initialized by taking into account some stability constraints and then left untrained. The GC-layer i computes, $\forall v \in V$, the following equations:

$$\begin{aligned} \mathbf{h}_v^{(i)}[0] &= \mathbf{h}_v^{(i-1)}[t_v^{(i-1)*}], \\ \mathbf{h}_v^{(i+1)}[t] &= tanh(\mathbf{W}_{in}^{(i)}\mathbf{x}_v + \sum_{u \in \mathcal{N}(v)} \mathbf{W}_h^{(i)} \mathbf{h}_u^{(i)}[t-1]) \end{aligned}$$

where $\mathbf{h}_v^{(i-1)}[t_v^{(i-1)*}]$ is the state computed by the previous layer. This equation is iterated for each node till convergence or till a maximum predetermined maximum number of iterations T is reached. Regarding the readout, the FDGNN computes a graph-level representation based only on the node representations computed on the last convolutional layer of the architecture. For k GC-layers, the output is defined as $\mathbf{o} = \mathbf{W}_{out} tanh(\mathbf{W}_n \sum_{v \in V} \mathbf{h}_v^{(k)}[t_v^{(k)*}])$. Further evolution of this kind of model is proposed in [7] where the Graph Ring-reservoir Network (GRN) is introduced. The GRN simplifies the FDGNN, based on a particular organization of the hidden neurons. In particular, it exploits a particular reservoir with a ring topology so that each neuron propagates its activation to the successive one (and is fed by the previous one) in a single cycle (ring). This is implemented by multiplying the reservoir weight matrix by a permutation matrix $\mathbf{P}$, obtaining $\mathbf{h}_v[t+1] = tanh(\mathbf{W}\mathbf{x}_v + \lambda \mathbf{P} \sum_{u \in \mathcal{N}(v)} \mathbf{h}_u[t])$, where λ is a scalar hyper-parameter and all non-zero weights are set to the same value. thank this λ can be used to control the spectral radius of the reservoir weights matrix $\mathbf{W}_r = \lambda \cdot \mathbf{P}$. Regarding the readout, the model uses the same linear feedforward layer defined in eq. (3).

In [7] an even more simplified model is introduced: the Minimal Graph Network (MGN). Also, in this case, the reservoir weights are arranged in a ring shape. The main difference with the GRN lies in a further architectural simplification applied to the matrix $\mathbf{W}$ where all the entries are set to the value ω, while their signs are chosen following the idea of "minimal complexity" [31].

In [27], the authors propose a model, dubbed Multi-resolution Reservoir Graph Neural Network (MRGNN) model, that exploits a Reservoir Convolutional layer for graphs able to simultaneously and directly consider all topological receptive fields up to $k - hops$. The convolutional layer relies on a multi-resolution[3, 28] structure that exploits nonlinear neurons followed by a standard feed-forward readout. The multi-resolution reservoir is defined as follows: $\mathbf{H}^r = \mathbf{H}^{k,\mathcal{T}}\mathbf{W}^r$, where $\mathbf{H}^{k,\mathcal{T}} = [\underbrace{\mathbf{XW}}_{\mathbf{H}^{k,\mathcal{T}}_{(0)}}, \underbrace{\sigma(\tilde{\mathbf{A}}\mathbf{XW})}_{\mathbf{H}^{k,\mathcal{T}}_{(1)}}, \underbrace{\sigma(\tilde{\mathbf{A}}\sigma(\tilde{\mathbf{A}}\mathbf{XW})\mathbf{W}))}_{\mathbf{H}^{k,\mathcal{T}}_{(2)}}, \dots]$, σ is the *tanh* activation function, $\tilde{\mathbf{A}}$ is is a generic transformation of the adjacency matrix that preserves its shape, $\mathbf{W}^r$ is a randomly projection matrix and $\mathbf{H}^{k,\mathcal{T}}_{(i)}$ represents the i-th column block of $\mathbf{H}^{k,\mathcal{T}}$. Note that each $\mathbf{H}^{k,\mathcal{T}}_{(i)}$ contains information only about random walks of length exactly equal to i.

Recently, Huang et al. [15] explored randomized graph convolutions for the task of node classification (differently from this paper in which we consider the more challenging setting of graph classification). The authors propose a single-layer architecture defined as $Z = \sigma(A^2XW)\beta$, where σ is the sigmoid function, $W \in \mathbb{R}^{d\times m}$ is the (random) wight matrix for m hidden neurons (that is left untrained), and β are the trained output weights. Notice that, contrarily to many graph neural networks, authors propose to adopt a single hidden layer with an increased receptive field instead of non-linearly stacking multiple layers with a smaller receptive field.

2.3 Untrained convolutions for time series

The design of deep randomized neural networks represents one of the emerging topics in Deep Learning (see, e.g., [10]). The fundamental idea behind these approaches is to replace as much as possible the optimization of the parameters of a deep learning model with their randomization [30]. This usually results in a neural architecture in which hidden layers are initialized randomly and left untrained, while training algorithms operate only on the output *readout* layer. It is interesting to note how this paradigm, on the one hand, allows for the design of extremely efficient baselines while, on the other hand, allows for highlighting and exploiting the architectural biases of neural information processing models. Another advantage of this approach is its marked suitability for implementations in neuromorphic hardware [36] and, in general, in hardware with low computational resources, e.g., for AI applications of a pervasive nature [1].

When dealing with temporal information, i.e., for sequence processing, the paradigm of choice in this context is represented by Reservoir Computing (RC) [20], and in particular Echo State Networks [17, 16]. Here, the crucial idea is to build an RNN whose internal connections are randomly initialized under asymptotic stability constraints. As an alternative to the RC recurrent approach, the idea of exploiting randomized convolutions has recently been explored for time series analysis in the ROCKET model [5]. ROCKET is a method based on randomized one-dimensional convolutions for efficient feature extraction on time series, performing consistently well on a diverse range of datasets. The core contributions of the ROCKET model were: 1. showing that the approach of exploiting

randomized convolutional kernels (instead of learning them with backpropagation) is feasible; 2. the adoption of a new non-differentiable readout function that being associated with the more commonly adopted global max pooling showed an improvement in the overall predictive performance. The paper also empirically identified a core set of hyper-parameters that were shown to obtain good predictive performance on heterogeneous tasks. However, the hyper-parameters of the features extraction procedure remain of utmost importance, especially considering that there is no learning involved.

3 Untrained GCN for graph classification

In this section, we present our model for efficient graph classification. We start in Section 3.1 detailing our graph convolution layers and how they are combined. Then, in Section 3.2 we describe the pooling operators we adopt, and finally in Section 3.3 we describe the readout and the possible alternatives.

3.1 Untrained GCN feature extraction

As previously discussed in Section 2.2, recent results in literature have shown that for the task of semi-supervised node classification, graph neural networks with random weights are a feasible option. However, it is known in the literature that for the problem of node classification, even simple models perform well [25, 29, 24]. In this paper, we propose a randomized architecture that is inspired by fully trained graph neural networks, including the non-linearity scheme. In particular, we instantiate multiple graph convolution layers (see section 2.1), each one followed by an element-wise non-linear activation function.

Following the literature on untrained neural networks we decided to exploit the hyperbolic tangent activation function. We considered the simple and widespread GCN definition (see Section 2.1). The hidden node representation computed by the l-th layer is defined as:

$$\mathbf{H}^{(l)} = tanh(\mathbf{S}\mathbf{H}^{(l-1)}\mathbf{W}^{(l)}), \tag{4}$$

where $\mathbf{S}$ is the normalized Laplacian adopted by the GCN, $\mathbf{W}^{(l)}$ are the layer parameters and $\mathbf{H}^0 = \mathbf{X}$. Note that we omit the bias terms for the sake of simplicity. The final node representations are obtained concatenating the representation computed by each graph convolution layer, i.e. $H = [H^{(1)}, \ldots, H^{(L)}]$, where L is the number of layers of the network.

While we leave as a future work the exploration of other activation functions, in our ablation studies we consider the network without activation functions between layers and show that the non-linearity has a significant effect on the overall performance of our method. Our approach is in contraposition to Huang et al. [15] that instead apply the non-linearity only after the message passing phase. Crucially, the weight values in $\mathbf{W}^{(l)}$ in eq. 4 are initialized randomly and left untrained. For the random initialization, we resort to the widely adopted Glorot uniform approach [11]. In particular, to control the stability of the expansion of the input information through the successive layers in the architecture, we introduce a *gain* hyperparameter θ to control the effective scaling of $\mathbf{W}^{(l)}$. In the

resulting process, a weight matrix of shape $n \times m$ will have entries sampled from a uniform distribution $\mathcal{U}(-a, a)$ where $a = \theta\sqrt{\frac{6}{n+m}}$. In our ablation study, we show that considering this hyperparameter significantly improves the predictive performance of the overall network.

3.2 The global pooling layer

The untrained graph convolution layer presented in eq. 4 produces node representations that include information about each node's local connectivity. To perform graph-level tasks we shall obtain a single representation for the whole graph. Usually, neural architectures for graph classification achieve this using global pooling operators, e.g. global *maximum, minimum* or *average* pooling. Notice that in the standard end-to-end training fashion, the pooling operators have to be differentiable. Instead, if no gradient has to pass through the pooling operator, we can choose also non-differentiable options. This is the case for the ROCKET model, presented in Section 2.3. The authors proposed a non-differentiable pooling mechanism that, in the context of randomized 1-D convolutions, was shown to consistently improve the predictive performance compared to other widespread pooling operators. This operator is referred to as *Percentage of Positive Values* (PPV) and is defined as: $PPV(\mathbf{z}) = \frac{1}{n}\sum_{i=0}^{n-1} I[z_i > 0]$, where $I[z_i > 0]$ is the indicator function which value is 1 if $z_i > 0$, 0 otherwise.

As suggested in the original paper, we used as global pooling both the *global max pooling* and *PPV*, concatenating the resulting representations. Note that this choice doubles the size of the global graph representation compared to the representations of the single nodes provided in output by the untrained graph convolution. We conducted ablation studies to show the impact of different aggregation functions on the overall performance of our proposed method.

3.3 Efficient readout

As mentioned before, our focus in this paper is the development of efficient and effective neural network models for graph classification. As discussed in Sections 3.1 and 3.2, the network that computes the graph-level representation does not need to be trained. This leaves the only trained parameters of the model to be those in the readout, i.e., the function mapping from the graph-level representation to the appropriate output for the task. In the case of classification tasks, one of the fastest linear classifiers in the literature is the Least Squares SVM (LS-SVM) [35] with a linear kernel (also known as Ridge Classifier). In the binary case, this classifier follows the simple idea of mapping the two possible classes in $\{-1, 1\}$, and then treats the problem as a regression task, solved with ridge regression. While other classifier choices may lead to improved results, in this paper we test only this very efficient classifier, and leave the exploration of other more complex readouts as future work.

4 Results and discussion

In this section, we present our experimental setting. A critical point when comparing different models is the possible dataset augmentation that is applied, and

the considered validation strategy. We decided to use a common setting for the chemical domain, where the nodes are labelled with a one-hot encoding of their atom type. The only exception is ENZYMES, where it is common to use 18 additional available features, and we followed this convention. Moreover, in the literature, different validation strategies have been applied, making it difficult to perform a fair comparison between the various methods. For the reported results we follow the validation strategy discussed in [6]. We estimate the performance of the U-GCN model by performing 10-fold cross-validation and repeating the whole procedure 5 times to account for the random initialization. To select the best model, we used the average accuracy of 10-fold cross-validation on the validation sets, and we used the same set of selected hyper-parameters for each fold. We did not perform an extensive hyperparameter search on the network architecture since our goal is to design an untrained GCN model whose performance is relatively stable on hyperparameter choice. For this reason, for U-GCN, we fixed the number of layers to four. As for the number of neurons, from preliminary experiments, it was clear that the more hidden neurons, the higher the predictive performance. We set the number of hidden neurons to $5,000$ per layer. Since we use four layers, and concatenate two different readouts, the resulting graph representation is of size $40,000$. Notice however that since the weights are not trained, we just have to perform the forward phase which is extremely fast. We then train an LS-SVM classifier that depends on a regularization hyperparameter α that we choose in the set $\{10^{-4}, 10^{5}\}$. We also select the θ parameter for weight initialization in the set $\{0.01, 0.1, 1, 3, 5, 10, 30, 50\}$.

4.1 Datasets

We empirically evaluated U-GCN on commonly adopted graph classification benchmarks. We considered four datasets modeling bioinformatic problems: PTC [14], NCI1 [38], PROTEINS, [2], and ENZYMES [2]. Moreover, we used two large social network datasets: IMDB-B and IMDB-M [40]. PTC, and NCI1 involve chemical compounds represented by their molecular graphs, where node labels encode the atom type, and bonds correspond to edges. PROTEINS and ENZYMES involve graphs that represent proteins. Amino acids are represented by nodes and the edges connect amino acids that in the protein are less than 6Å apart. IMDB-B and IMDB-M are composed of graphs derived from actor/actress and genre information of different movies on IMDB. The target value for each movie represents its genre. IMDB-B models a binary classification task, while IMDB-M considers three different classes.

4.2 Experimental results

In Table 1 we report the results of our experimental comparison. We considered seven datasets to allow for a comparison with many existing methods in the literature. We performed a pairwise Wilcoxon signed-rank test between our proposed *U-GCN* method and the others. We chose this test because our focus is to propose an efficient and effective alternative and we want to show that our method performs comparably to the state of the art. Thus, the absence of a statistically significant performance difference between our method and the alternatives is

already a good result in our point of view. From the test, it emerges that our method performs even significantly better than some state-of-the-art end-to-end trained architectures, showing that the approach we propose is indeed promising.

In Table 2 we perform an ablation study to show the contribution of each core component of our architecture. First, we consider a version of U-GCN that only uses the global max pooling as an aggregator, thus discarding the *PPV* presented in Section 3.3. For this ablation, we doubled the number of neurons in the network to consider graph representations of the same size. While there is no clear winner in the comparison, notice that the feature extraction of U-GCN is faster since it requires extracting half the number of features. The second ablation we consider is the same U-GCN where the *tanh* activation function between graph convolutional layers is removed, obtaining a linear model. In this case, U-GCN performs significantly better than linear ablation. Finally, we consider the impact of the θ parameter comparing U-GCN with a version where we fix $\theta = 1$ (its default value). In this case, U-GCN performs again significantly better than the ablation. Moreover, we explored different hidden layer sizes (number of neurons) and confirmed that a higher number of neurons always corresponds to higher predictive performance (plots not reported for lack of space).

Concerning the computational times, running on CPU on a server equipped with an Intel(R) Xeon(R) CPU E5-2630L v3 @ 1.80GHz, for instance for the ENZYMES dataset with $5,000$ neurons per layer the feature extraction on the whole dataset takes 33 seconds, while a single LS-SVM training takes on average 5 seconds. For NCI1, the times are 42 and 6 seconds, respectively. These times are orders of magnitude faster when compared to GNN models trained end-to-end with stochastic gradient descent. Concerning the test times, they correspond to the forward pass and the evaluation of the (linear) LS-SVM model, thus they are roughly equivalent to the ones of common GNN models. Notice that the forward pass could also be implemented on GPU for even faster feature extraction.

5 Conclusions

In this paper, we proposed a novel extremely efficient GNN model to perform graph classification. The proposed architecture, dubbed Untrained-GNN (U-GNN), is reminiscent of the models that rely on Reservoir Computing (RC). Indeed, as the name suggests, the U-GNN exploits simple stacked graph convolutional layers where the weights are randomly initialized and then left untrained. The random convolutional projections of the graph's nodes computed by the GC layers are aggregated using a global pooling operator to obtain a graph-level representation that is composed of two functions: the global max pooling and the percentage of positive values (PPV). Finally, the classification task is performed using one of the fastest linear classifiers in the literature: LS-SVM. We assessed the performance of the U-GNN on 7 datasets from different application areas, comparing our proposal both with models that exploit standard end-to-end training and with GNN based on the RC framework. The empirical results show that our approach achieved results comparable to the state-of-the-art methods.

Model \ Dataset	PTC	NCI1	PROTEINS	D&D	ENZYMES	IMDB-B	IMDB-M
FGCNN[23]	58.8±1.8	81.5±0.4	74.6±0.8	77.5±0.9	-	-	-
DGCNN[23]	57.1±2.2	73.0±0.9	74.0±0.4	78.1±0.7	-	-	-
DGCNN[6] *	-	76.4±1.7	72.9±3.5	76.6±4.3	38.9±5.7	53.3±5.0	38.6±2.2
SGC[28] *	55.6±7.6	76.3±2.5	75.4±3.4	77.1±4.4	31.3±5.6	66.4±5.5	43.3±3.4
Cheb-Net[28]	55.2±6.5	80.9±1.9	75.8±5.1	77.9±3.7	38.1±6.2	70.6±3.8	43.9±3.4
GIN[6] *	-	80.0±1.4	73.3±4.0	75.3±2.9	59.6±4.5	66.8±3.9	42.2±4.6
DIFFPOOL[6] *	-	76.9±1.9	73.7±3.5	75.0±3.5	59.5±5.6	68.3±6.1	45.1±3.2
GraphSAGE[6]	-	76.0±1.8	73.0±4.5	72.9±2.0	58.2±6.0	69.9±4.6	47.2±3.6
Baseline[6]	-	69.8±2.2	75.8±3.7	**78.4±4.5**	65.2±6.4	50.7±2.4	36.1±3.0
FDGNN[8]	**63.4±5.4**	77.8±1.5	**76.8±2.9**	-	-	**72.4±3.6**	50.0±1.3
MGN[9]	-	78.8±2.3	-	-	-	72.7±3.2	49.5±2.2
GRN [9]	-	78.2±2.2	-	-	-	71.7±2.8	**50.5±1.4**
GESN[9]	-	77.8±2.0	-	-	-	71.7±3.6	48.7±2.1
MRGNN[27]	57.6±10.0	80.6±1.9	75.8±3.5	-	68.2±6.9	72.1±3.6	46.9±3.7
U-GCN	61.2±2.2 ($\theta = 0.1$)	**82.2±0.4** ($\theta = 30$)	74.2±1.4 ($\theta = 10$)	78.0±1.0 ($\theta = 5$)	**68.8±0.6** ($\theta = 3$)	68.7±1.2 ($\theta = 1$)	45.8±0.6 ($\theta = 1$)

Table 1. Experimental comparison between the proposed U-GCN and many state-of-the-art methods.

Model \ Dataset	PTC	NCI1	PROTEINS	D&D	ENZYMES	IMDB-B	IMDB-M
U-GCN	61.2±2.2 ($\theta = 0.1$)	82.2±0.4 ($\theta = 30$)	74.2±1.4 ($\theta = 10$)	78.0±1.0 ($\theta = 5$)	68.8±0.6 ($\theta = 3$)	68.7±1.2 ($\theta = 1$)	45.8±0.6 ($\theta = 1$)
U-GCN ablation (max aggr.)	64.1 ± 1.5 ($\theta = 50$)	80.6 ± 0.5 ($\theta = 30$)	74.7 ± 0.9 ($\theta = 3$)	74.7 ± 0.8 ($\theta = 30$)	70.1 ± 0.8 ($\theta = 5$)	69.8 ± 1.1 ($\theta = 1$)	45.8 ± 0.7 ($\theta = 0.01$)
U-GCN ablation (linear) *	60.6 ± 1.0 ($\theta = 1$)	80.5 ± 0.3 ($\theta = 30$)	73.3 ± 0.7 ($\theta = 50$)	76.8 ± 0.5 ($\theta = 30$)	65.7 ± 1.9 ($\theta = 10$)	65.5 ± 1.9 ($\theta = 30$)	45.5 ± 1.38 ($\theta = 1$)
U-GCN ablation ($\theta = 1$) *	60.8 ± 1.3	80.2 ± 0.5	73.9 ± 0.5	77.2 ± 0.6	67.6 ± 1.3	68.7 ± 1.2	45.8 ± 0.62

Table 2. Ablation study: comparison of the proposed U-GCN with different variations.

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