RESIDUAL GATED GRAPH CONVNETS

Anonymous authors
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ABSTRACT

Graph-structured data such as functional brain networks, social networks, gene regulatory networks, communications networks have brought the interest in generalizing neural networks to graph domains. In this paper, we are interested to design efficient neural network architectures for graphs with variable length. Several existing works such as Scarselli et al. (2009); Li et al. (2016) have focused on recurrent neural networks (RNNs) to solve this task. A recent different approach was proposed in Sukhbaatar et al. (2016), where a vanilla graph convolutional neural network (ConvNets) was introduced. We believe the latter approach to be a better paradigm to solve graph learning problems because ConvNets are more pruned to deep networks than RNNs. For this reason, we propose the most generic class of residual multi-layer graph ConvNets that make use of an edge gating mechanism, as proposed in Marcheggiani & Titov (2017). Gated edges appear to be a natural property in the context of graph learning tasks, as the system has the ability to learn which edges are important or not for the task to solve. We apply several graph neural models to two basic network science tasks; subgraph matching and semi-supervised clustering for graphs with variable length. Numerical results show the performances of the new model.

1 INTRODUCTION

Convolutional neural networks of LeCun et al. (1998) and recurrent neural networks of Hochreiter & Schmidhuber (1997) are deep learning architectures that have been applied with great success to computer vision (CV) and natural language processing (NLP) tasks. Such models require the data domain to be regular, such as 2D or 3D Euclidean grids for CV and 1D line for NLP. Beyond CV and NLP, data does not usually lie on regular domains but on heterogeneous graph domains. Users on social networks, functional time series on brain structures, gene DNA on regulatory networks, IP packets on telecommunication networks are a a few examples to motivate the development of new neural network techniques that can be applied to graphs. One possible classification of these techniques is to consider neural network architectures with fixed length graphs and variable length graphs.

In the case of graphs with fixed length, a family of convolutional neural networks has been developed on spectral graph theory, Chung (1997). The early work of Bruna et al. (2013) proposed to formulate graph convolutional operations in the spectral domain with the graph Laplacian, as an analogy of the Euclidean Fourier transform as proposed in Hammond et al. (2011). This work was extended in Henaff et al. (2015) to smooth spectral filters for spatial localization. Defferrard et al. (2016) used Chebyshev polynomials to achieve linear complexity for sparse graphs, Levie et al. (2017) applied Cayley polynomials to focus on narrow-band frequencies, and Monti et al. (2017b) dealt with multiple (fixed) graphs. Finally, Kipf & Welling (2017) simplified the spectral convnets architecture using 1-hop filters to solve the semi-supervised clustering task. For related works, see also Bronstein et al. (2017b), Bronstein et al. (2017a) and references therein.

For graphs with variable length, a generic formulation was proposed in Gori et al. (2005); Scarselli et al. (2009) based on recurrent neural networks. The authors defined a multilayer perceptron of a vanilla RNN. This work was extended in Li et al. (2016) using a GRU architecture and a hidden state that captures the average information in local neighborhoods of the graph. The work of Sukhbaatar et al. (2016) introduced a vanilla graph ConvNet and used this new architecture to solve learning communication tasks. Marcheggiani & Titov (2017) introduced an edge gating mechanism in graph ConvNets for semantic role labeling. Finally, Bruna & Li (2017) designed a network to learn non-

linear approximations of the power of graph Laplacian operators, and applied it to the unsupervised graph clustering problem. Other works for drug design, computer graphics and vision are presented in Duvenaud et al. (2015); Boscaini et al. (2016); Monti et al. (2017a).

In this work, we investigate new neural networks for graphs with arbitrary length. Section 2 introduces the related literature. Section 3 presents our new models. And Section 4 reports the numerical experiments.

2 NEURAL NETWORKS FOR GRAPHS WITH ARBITRARY LENGTH

2.1 RECURRENT NEURAL NETWORKS

Generic formulation. Consider a standard RNN for word prediction in natural language processing. Let h_i be the feature vector associated with word i in the sequence. In a regular vanilla RNN, h_i is computed with the feature vector h_j from the previous step and the current word x_i, so we have:

$$h_i = f_{\text{VRNN}}\left(x_i \ , \ \{h_j : j = i-1\} \right)$$

The notion of neighborhood for regular RNNs is the previous step in the sequence. For graphs, the notion of neighborhood is given by the graph structure. If h_i stands for the feature vector of vertex i, then the most generic version of a feature vector for a graph RNN is

$$h_i = f_{\text{G-RNN}}\left(x_i \ , \ \{h_j : j \to i\} \right) \tag{1}$$

where x_i refers to a data vector and $\{h_j : j \to i\}$ denotes the set of feature vectors of the neighboring vertices. Observe that the set $\{h_j\}$ is unordered, meaning that h_i is intrinsic, i.e. invariant by vertex re-indexing (no vertex matching between graphs is required). Other properties of $f_{\text{G-RNN}}$ are locality as only neighbors of vertex i are considered, weight sharing, and such vector is independent of the graph length. In summary, to define a feature vector in a graph RNN, one needs a mapping f that takes as input an unordered set of vectors $\{h_j\}$, i.e. the feature vectors of all neighboring vertices, and a data vector x_i, Figure 1(a).

We refer to the mapping $f_{\text{G-RNN}}$ as the neighborhood transfer function in graph RNNs. In a regular RNN, each neighbor as a distinct position relatively to the current word (1 position left from the center). In a graph, if the edges are not weighted or annotated, neighbors are not distinguishable. The only vertex which is special is the center vertex around which the neighborhood is built. This explains the generic formulation (1). This type of formalism for deep learning for graphs with variable length is described in Scarselli et al. (2009); Gilmer et al. (2017); Bronstein et al. (2017a) with slightly different terminology and notations.

Graph Neural Networks of Scarselli et al. (2009). The earliest work of graph RNNs for arbitrary graphs was introduced in Gori et al. (2005); Scarselli et al. (2009). The authors proposed to use a vanilla RNN with a multilayer perceptron to define the feature vector h_i:

$$h_i = f_{\text{G-VRNN}}\left(x_i, \{h_j : j \to i\}\right) = \sum_{j \to i} \mathcal{C}_{\text{G-VRNN}}(x_i, h_j) \tag{2}$$

with

$$\mathcal{C}_{\text{G-VRNN}}(x_i, h_j) = A\sigma(B\sigma(Ux_i + Vh_j)),$$

and σ is the sigmoid function, A, B, U, V are the weight parameters to learn.

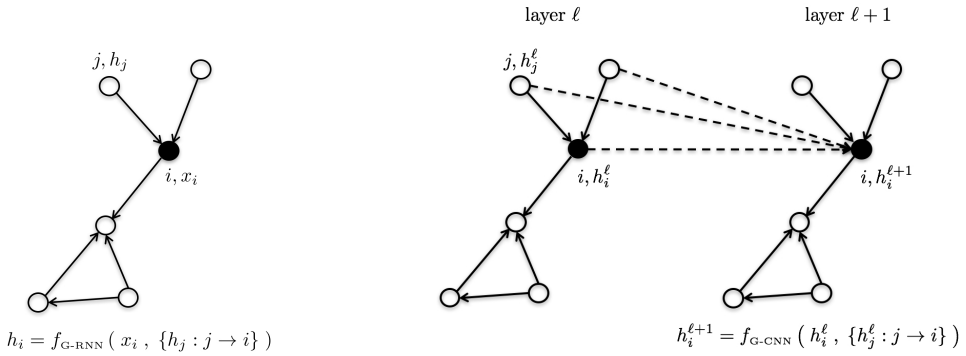
As Eq. (2) does not have a closed-form solution, Scarselli et al. (2009) used a fixed-point iterative scheme: for $t = 0, 1, 2, ...$

$$h_i^{t+1} = \sum_{j \to i} \mathcal{C}(x_i, h_j^t), \quad h_i^{t=0} = 0 \ \ \forall i. \tag{3}$$

The iterative scheme is guaranteed to converge as long as the mapping is contractive, which can be a strong assumption. Besides, a large number of iterations can be computational expensive.

Gated Graph Neural Networks of Li et al. (2016). In this work, the authors use gated recurrent units (GRU) of Chung et al. (2014):

$$h_i = f_{\text{G-GRU}}\left(x_i, \{h_j : j \to i\}\right) = \mathcal{C}_{\text{G-GRU}}(x_i, \sum_{j \to i} h_j) \tag{4}$$



(a) Graph RNN (b) Graph ConvNet

Figure 1: Generic feature representation h_i of vertex i on a graph RNN (a) and a graph convNet (b).

As previously, Eq. (4) does not have an analytical solution, and Li et al. (2016) designed the following iterative scheme:

$$\begin{aligned} h_i^{t+1} &= \mathcal{C}_{\text{G-GRU}}(h_i^t, \bar{h}_i^t), \quad h_i^{t=0} = x_i \;\; \forall i, \\ \text{where} \quad \bar{h}_i^t &= \sum_{j \to i} h_j^t, \end{aligned}$$

and $\mathcal{C}_{\text{G-GRU}}(h_i^t, \bar{h}_i^t)$ is equal to

$$\begin{aligned} z_i^{t+1} &= \sigma(U_z h_i^t + V_z \bar{h}_i^t) \\ r_i^{t+1} &= \sigma(U_r h_i^t + V_r \bar{h}_i^t) \\ \tilde{h}_i^{t+1} &= \tanh\big(U_h(h_i^t \odot r_i^{t+1}) + V_h \bar{h}_i^t\big) \\ h_i^{t+1} &= (1 - z_i^{t+1}) \odot h_i^t + z_i^{t+1} \odot \tilde{h}_i^{t+1}, \end{aligned}$$

where $\odot$ is the Hadamard point-wise multiplication operator. This model was used for NLP tasks in Li et al. (2016) and also in quantum chemistry by Gilmer et al. (2017) for fast organic molecule properties estimation, for which standard techniques (DFT) require expensive computational time.

Tree-Structured LSTM of Tai et al. (2015). The authors extended the original LSTM model of Hochreiter & Schmidhuber (1997) to a tree-graph structure:

$$h_i = f_{\text{T-LSTM}}\,(x_i, \{h_j : j \in C(i)\}) = \mathcal{C}_{\text{T-LSTM}}(x_i, h_i, \sum_{j \in C(i)} h_j), \tag{5}$$

where $C(i)$ refers the set of children of node i. $\mathcal{C}_{\text{T-LSTM}}(x_i, h_i, \sum_{j \in C(i)} h_j)$ is equal to

$$\begin{aligned} \bar{h}_i &= \sum_{j \in C(i)} h_j \\ i_i &= \sigma(U_i x_i + V_i \bar{h}_i) \\ o_i &= \sigma(U_o x_i + V_o \bar{h}_i) \\ \tilde{c}_i &= \tanh\big(U_c x_i + V_c \bar{h}_i\big) \\ f_{ij} &= \sigma(U_f x_i + V_f h_j) \\ c_i &= i_i \odot \tilde{c}_i + \sum_{i \in C(i)} f_{ij} \odot c_j \\ h_i &= o_i \odot \tanh(c_i) \end{aligned}$$

Unlike Scarselli et al. (2009); Li et al. (2016), Tree-LSTM does not require an iterative process to update its feature vector h_i as the tree structure is also a directed acyclic graph (DAG) as original

LSTM. Consequently, the feature representation (5) can be updated with a recurrent formula. Nevertheless, a tree is a special case of graphs, and such recurrence formula cannot be directly applied to arbitrary graph structure. A key property of this model is the function f_{ij} which acts as a gate on the edge from neighbor j to vertex i. Given the task, the gate will close to let the information flow from neighbor j to vertex i, or it will open to stop it. It seems to be an essential property for learning systems on graphs as some neighbors can be irrelevant. For example, for the community detection task, the graph neural network should learn which neighbors to communicate (same community) and which neighbors to ignore (different community). In different contexts, Dauphin et al. (2017) added a gated mechanism inside the regular ConvNets in order to improve language modeling for translation tasks. And van den Oord et al. (2016) considered a gated unit with the convolutional layers after activation, and used it for image generation.

2.2 CONVOLUTIONAL NEURAL NETWORKS

Generic formulation. Consider now a classical ConvNet for computer vision. Let h_{ij}^{ℓ} denote the feature vector at layer ℓ associated with pixel (i, j). In a regular ConvNet, $h_{ij}^{\ell+1}$ is obtained by applying a non linear transformation to the feature vectors $h_{i'j'}^{\ell}$ for all pixels (i', j') in a neighborhood of pixel (i, j). For example, with 3×3 filters, we would have:

$$h_{ij}^{\ell+1} = f_{\text{CNN}}^{\ell} \left(\{h_{i'j'}^{\ell} : |i - i'| \leq 1 \text{ and } |j - j'| \leq 1\} \right)$$

In the above, the notation $\{h_{i'j'}^{\ell} : |i - i'| \leq 1 \text{ and } |j - j'| \leq 1\}$ denote the concatenation of all feature vectors $h_{i'j'}^{\ell}$ belonging to the 3×3 neighborhood of vertex (i, j). In ConvNets, the notion of neighborhood is given by the euclidian distance. As previously noticed, for graphs, the notion of neighborhood is given by the graph structure. Thus, the most generic version of a feature vector h_i at vertex i for a graph ConvNet is

$$h_i^{\ell+1} = f_{\text{G-CNN}} \left(h_i^{\ell} \, , \, \{h_j^{\ell} : j \to i\} \right) \tag{6}$$

where $\{h_j^{\ell} : j \to i\}$ denotes the set of feature vectors of the neighboring vertices. In other words, to define a graph ConvNet, one needs a mapping $f_{\text{G-CNN}}$ taking as input a vector h_i^{ℓ} (the feature vector of the center vertex) as well as an unordered set of vectors $\{h_j^{\ell}\}$ (the feature vectors of all neighboring vertices), Figure 1(b). We also refer to the mapping $f_{\text{G-CNN}}$ as the neighborhood transfer function. In a regular ConvNet, each neighbor as a distinct position relatively to the center pixel (for example 1 pixel up and 1 pixel left from the center). As for graph RNNs, the only vertex which is special for graph ConvNets is the center vertex around which the neighborhood is built.

CommNets of Sukhbaatar et al. (2016). The authors introduced one of the simplest instantiations of a graph ConvNet with the following neighborhood transfer function:

$$h_i^{\ell+1} = f_{\text{G-VCNN}}^{\ell} \left(h_i^{\ell} \, , \, \{h_j^{\ell} : j \to i\} \right) = \text{ReLU} \left(U^{\ell} h_i^{\ell} + V^{\ell} \sum_{j \to i} h_j^{\ell} \right), \tag{7}$$

where ℓ denotes the layer level, and ReLU is the rectified linear unit. We will refer to this architecture as the vanilla graph ConvNet. Sukhbaatar et al. (2016) used this graph neural network to learn the communication between multiple agents to solve multiple tasks like traffic control.

Syntactic Graph Convolutional Networks of Marcheggiani & Titov (2017). The authors proposed the following transfer function:

$$h_i^{\ell+1} = f_{\text{S-GCN}}^{\ell} \left(\{h_j^{\ell} : j \to i\} \right) \quad = \quad \text{ReLU} \left(\sum_{j \to i} \eta_{ij} \odot V^{\ell} h_j^{\ell} \right) \tag{8}$$

where η_{ij} act as edge gates, and are computed by:

$$\eta_{ij} = \sigma \left(A^{\ell} h_i^{\ell} + B^{\ell} h_j^{\ell} \right). \tag{9}$$

These gated edges are very similar in spirit to the Tree-LSTM proposed in Tai et al. (2015). We believe this mechanism to be important for graphs, as they will be able to learn what edges are important for the graph learning task to be solved.

3 MODELS

Proposed Graph LSTM. First, we propose to extend the Tree-LSTM of Tai et al. (2015) to arbitrary graphs and multiple layers:

$$h_i^{\ell+1} = f^{\ell}_{\text{G-LSTM}}\left(x_i^\ell, \{h_j^\ell : j \to i\}\right) = \mathcal{C}_{\text{G-LSTM}}(x_i^\ell, h_i^\ell, \sum_{j\to i} h_j^\ell, c_i^\ell) \tag{10}$$

As there is no recurrent formula is the general case of graphs, we proceed as Scarselli et al. (2009) and use an iterative process to solve (10): At layer ℓ, for $t = 0, 1, ..., T$

$$\begin{aligned}
\bar{h}_i^{\ell,t} &= \sum_{j\to i} h_j^{\ell,t}, \\
i_i^{\ell,t+1} &= \sigma(U_i^\ell x_i^\ell + V_i^\ell \bar{h}_i^{\ell,t}) \\
o_i^{\ell,t+1} &= \sigma(U_o^\ell x_i^\ell + V_o^\ell \bar{h}_i^{\ell,t}) \\
\tilde{c}_i^{\ell,t+1} &= \tanh\big(U_c^\ell x_i^\ell + V_c^\ell \bar{h}_i^{\ell,t}\big) \\
f_{ij}^{\ell,t+1} &= \sigma(U_f^\ell x_i^\ell + V_f^\ell h_j^{\ell,t}) \\
c_i^{\ell,t+1} &= i_i^{\ell,t+1} \odot \tilde{c}_i^{\ell,t+1} + \sum_{j\to i} f_{ij}^{\ell,t+1} \odot c_j^{\ell,t+1} \\
h_i^{\ell,t+1} &= o_i^{\ell,t+1} \odot \tanh(c_i^{\ell,t+1})
\end{aligned}$$

$$\text{and initial conditions:} \quad \begin{aligned}
h_i^{\ell,t=0} &= c_i^{\ell,t=0} = 0, \ \ \forall i, \ell \\
x_i^\ell &= h_i^{\ell-1,T}, \ x_i^{\ell=0} = x_i, \ \ \forall i, \ell
\end{aligned}$$

In other words, the vector $h_i^{\ell+1}$ is computed by running the model from $t = 0, .., T$ at layer ℓ. It produces the vector $h_i^{\ell,t=T}$ which becomes $h_i^{\ell+1}$ and also the input $x_i^{\ell+1}$ for the next layer. The proposed Graph LSTM model differs from Liang et al. (2016); Peng et al. (2017) mostly because cell $\mathcal{C}_{\text{G-LSTM}}$ in these previous models is not iterated over multiple times T, which reduces the performance of Graph LSTM (see numerical experiments on Figure 4).

Proposed Gated Graph ConvNets. We leverage the vanilla graph ConvNet architecture of Sukhbaatar et al. (2016), Eq.(7), and the edge gating mechanism of Marcheggiani & Titov (2017), Eq.(8), by considering the following model:

$$h_i^{\ell+1} = f^{\ell}_{\text{G-GCNN}}\left(\ h_i^\ell\ ,\ \{h_j^\ell : j \to i\}\ \right) \quad = \quad \text{ReLU}\left(U^\ell h_i^\ell + \sum_{j\to i} \eta_{ij} \odot V^\ell h_j^\ell\right) \tag{11}$$

where $h_i^{\ell=0} = x_i, \forall i$, and the edge gates η_{ij} are defined in (9). This model is the most generic formulation of a graph ConvNet (because it uses both the feature vector h_i^ℓ of the center vertex and the feature vectors h_j^ℓ of neighboring vertices) with the edge gating property.

Residual Gated Graph ConvNets. In addition, we formulate a multi-layer gated graph ConvNet using residual networks (ResNets) introduced in He et al. (2016). This boils down to add the identity operator between successive convolutional layers:

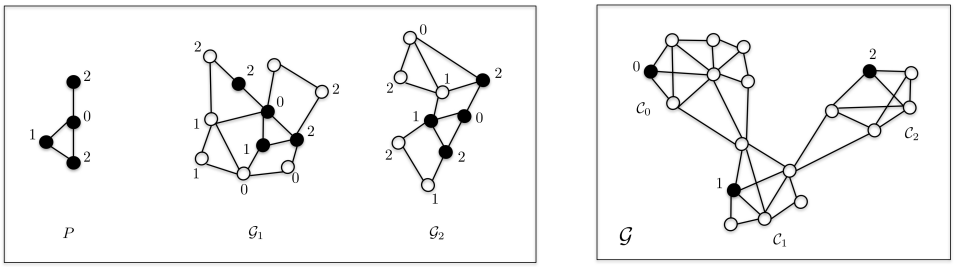
$$h_i^{\ell+1} \quad = \quad f^\ell\left(\ h_i^\ell\ ,\ \{h_j^\ell : j \to i\}\ \right) + h_i^\ell. \tag{12}$$

As we will see, such multi-layer strategy work very well for graph neural networks.

4 EXPERIMENTS

4.1 SUBGRAPH MATCHING

We consider the subgraph matching problem presented in Scarselli et al. (2009), Figure 2(a). The goal is to find the vertices of a given subgraph P in larger graphs G_k with variable sizes. Identifying



(a) Subgraph matching (b) Semi-supervised clustering

Figure 2: Graph learning tasks.

similar localized patterns in different graphs is one of the most basic tasks for graph neural networks. The subgraph P and larger graph G_k are generated with the stochastic block model (SBM), see e.g. Abbe (2017). A SBM is a random graph which assigns communities to each node as follows: any two vertices are connected with the probability p if they belong to the same community, or they are connected with the probability q if they belong to different communities. For all experiments, we generate a subgraph P of 20 nodes with a SBM $q = 0.5$, and the signal on P is generated with a uniform random distribution with a vocabulary of size 3, i.e. $\{0, 1, 2\}$. Larger graphs G_k are composed of 10 communities with sizes randomly generated between 15 and 25. The SBM of each community is $p = 0.5$. The value of q, which acts as the noise level, is 0.1, unless otherwise specified. Finally, the signal on G_k is also randomly generated between $\{0, 1, 2\}$.

All reported results are averaged over 5 trails. We run 5 algorithms; Gated Graph Neural Networks of Li et al. (2016), CommNets of Sukhbaatar et al. (2016), SyntacticNets of Marcheggiani & Titov (2017), and the proposed Graph LSTM and Gated ConvNets from Section 3. We upgrade the existing models of Li et al. (2016); Sukhbaatar et al. (2016); Marcheggiani & Titov (2017) with a multilayer version for Li et al. (2016) and using ResNets for all three architectures. We also use the batch normalization technique of Ioffe & Szegedy (2015) to speed up learning convergence for our algorithms, and also for Li et al. (2016); Sukhbaatar et al. (2016); Marcheggiani & Titov (2017). The learning schedule is as follows: the maximum number of iterations, or equivalently the number of randomly generated graphs with the attached subgraph is 5,000 and the learning rate is decreased by a factor 1.25 if the loss averaged over 100 iterations does not decrease. The loss is the cross-entropy with 2 classes (the subgraph P class and the class of the larger graph G_k) respectively weighted by their sizes. The accuracy is the average of the diagonal of the normalized confusion matrix w.r.t. the cluster sizes (the confusion matrix measures the number of nodes correctly and badly classified for each class). We also report the time for a batch of 100 generated graphs. The choice of the architectures will be given for each experiment. All algorithms are optimized as follow. We fix a budget of parameters of $B = 100K$ and a number of layers $L = 6$. The number of hidden neurons H for each layer is automatically computed. Then we manually select the optimizer and learning rate for each architecture that best minimize the loss. For this task, Li et al. (2016); Sukhbaatar et al. (2016); Marcheggiani & Titov (2017) and our gated ConvNets work well with Adam and learning rate 0.00075. Graph LSTM uses SGD with learning rate 0.075. Besides, the value of inner iterative steps T for graph LSTM and Li et al. (2016) is 3.

The first experiment focuses on shallow graph neural networks, i.e. with a single layer $L = 1$. We also vary the level of noise, that is the probability q in the SBM that connects two vertices in two different communities (the higher q the more mixed are the communities). The hyper-parameters are selected as follows. Besides $L = 1$, the budget is $B = 100K$ and the number of hidden neurons H is automatically computed for each architecture to satisfy the budget. First row of Figure 3 reports the accuracy and time for the five algorithms and for different levels of noise $q = \{0.1, 0.2, 0.35, 0.5\}$. RNN architectures are plotted in dashed lines and ConvNet architectures in solid lines. For shallow networks, all RNN architectures (graph LSTM and Li et al. (2016)) performs much better, but they also take more time than the graph ConvNets architectures we propose, as well as Sukhbaatar et al. (2016); Marcheggiani & Titov (2017). As expected, all algorithms performances decrease when the noise increases.

The second experiment demonstrates the importance of having multiple layers compared to shallow networks. We vary the number of layers $L = \{1, 2, 4, 6, 10\}$ and we fix the number of hidden neurons to $H = 50$. Notice that the budget is not the same for all architectures. Second row of Figure 3 reports the accuracy and time w.r.t. L (middle figure is a zoom in the left figure). All models clearly benefit with more layers, but RNN-based architectures see their performances decrease for a large number of layers. The ConvNet architectures benefit from large L values, with the proposed graph ConvNet performing slightly better than Sukhbaatar et al. (2016); Marcheggiani & Titov (2017). Besides, all ConvNet models are faster than RNN models.

In the third experiment, we evaluate the algorithms for different budgets of parameters $B = \{25K, 50K, 75K, 100K, 150K\}$. For this experiment, we fix the number of layers $L = 6$ and the number of neurons H is automatically computed given the budget B. The results are reported in the third row of Figure 3. For this task, the proposed graph ConvNet best performs for a large budget, while being faster than RNNs.

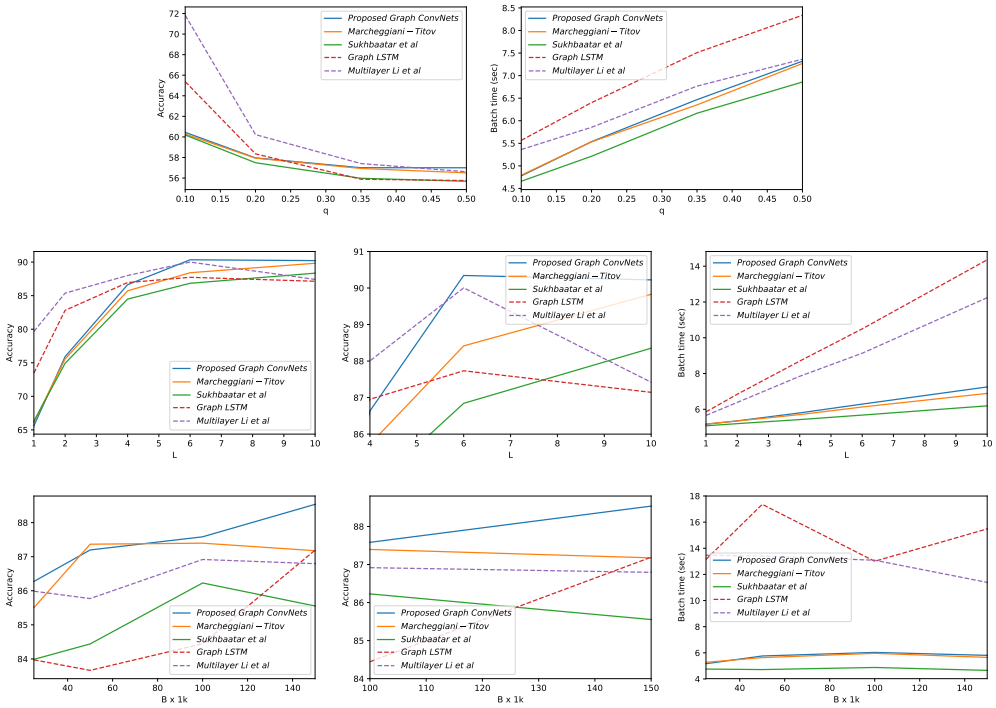


Figure 3: Subgraph matching: First row studies shallow networks w.r.t. noise. Second row investigates multilayer graph networks. Third row reports graph architectures w.r.t. budget.

We also show the influence of hyper-parameter T for Li et al. (2016) and the proposed graph LSTM. We fix $H = 50$, $L = 3$ and $B = 100K$. Figure 4 reports the results for $T = \{1, 2, 3, 4, 6\}$. The T value has an undesirable impact on the performance of graph LSTM. Multi-layer Li et al. (2016) is not really influenced by T. The computational time naturally increases with larger T values.

4.2 Semi-supervised clustering

Next, we consider the semi-supervised clustering problem, Figure 2(b). This is also a standard task in network science. For this work, it consists in finding 10 communities on a graph given 1 single label for each community. This problem is more discriminative w.r.t. to the architectures than the previous single pattern matching problem where there were only 2 clusters to find (i.e. 50% random chance). For clustering, we have 10 clusters (around 10% random chance). As in the previous section, we use SBM to generate graphs of communities with variable length. The size for each community is randomly generated between 5 and 25, and the label is randomly selected in each community. Probability p is 0.5, and q depends on the experiment. For this task, Li et al. (2016);

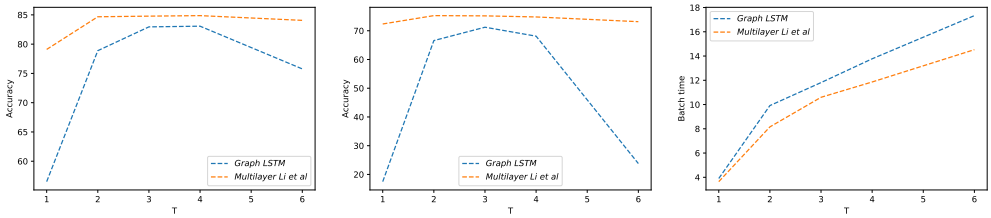


Figure 4: Influence of hyper-parameter T on RNN architectures. Left figure is for graph matching, middle figure for semi-supervised clustering, and right figure are the batch time for the clustering task (same trend for matching).

Sukhbaatar et al. (2016); Marcheggiani & Titov (2017) and the proposed gated ConvNets work well with Adam and learning rate 0.00075. Graph LSTM uses SGD with learning rate 0.0075. The value of T for graph LSTM and Li et al. (2016) is 3.

The same set of experiments as in the previous task are reported in Figure 5. ConvNet architectures get clearly better than RNNs when the number of layers increase (middle row), with the proposed Gated ConvNet outperforming the other architectures. For a fixed number of layers $L = 6$, our graph ConvNets and Marcheggiani & Titov (2017) best perform for all budgets, while paying a reasonable computational cost.

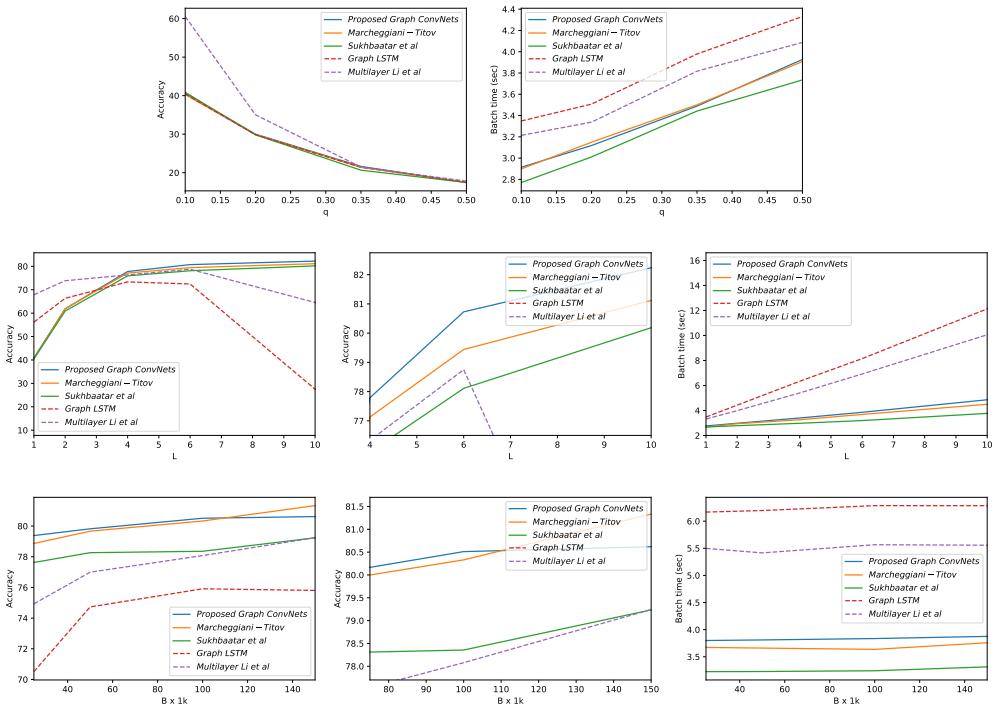


Figure 5: Semi-supervised clustering: First row reports shallow networks w.r.t. noise q. Second row shows multilayer graph networks w.r.t. L. Third row is about graph architectures w.r.t. budget B.

For the last experiment, we report the learning speed of the models. We fix $L = 6$, $B = 100K$ with H being automatically computed to satisfy the budget. Figure 6 reports the accuracy w.r.t. time. The ConvNet architectures converge faster than RNNs, in particular for the semi-supervised task.

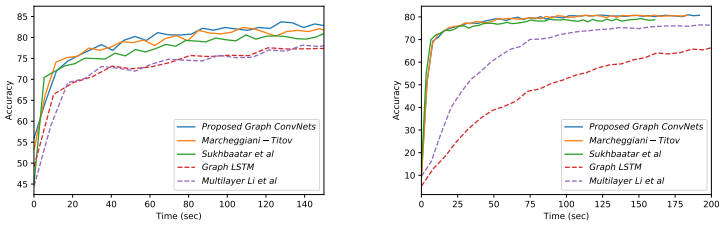


Figure 6: Learning speed of RNN and ConvNet architectures. Left figure is for graph matching and right figure semi-supervised clustering.

5 Conclusion

First graph neural networks with arbitrary length have focused on RNN-based architectures. But RNNs are less favorable to fully exploit multi-layer architectures. In the other hand, simpler ConvNet-like architectures appear to be more suitable to build deep graph neural networks. This led us to develop the most generic residual formulation of gated graph ConvNets that has the potential to work with a large number of layers. Numerical experiments demonstrated different properties of these networks for two basic graph learning tasks. Future work will focus on solving more specific problems.

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