Superpixel Image Classification with Graph Attention Networks

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Abstract

This document reports the use of Graph Attention Networks for classifying oversegmented images, as well as a general procedure for generating oversegmented versions of image-based datasets. The code and learnt models for/from the experiments are available on github1. The experiments were ran from June 2019 until December 2019. We obtained better results than the baseline models that uses geometric distance-based attention by using instead self attention, in a more sparsely connected graph network.

1 Introduction

In this technical report, we present the results obtained by applying Graph Attention Networks (GATs) [15] to classify images based on their superpixel representation. This preliminary work may serve as a stepping stone for more evolved research on this topic.

This document is organised as follows: In Section 2 we provide a non exhaustive exposition of related works that motivated this research, as well as peering approaches. Section 3 explains how the superpixel segmentation techniques are used to represent graphs, exposing the differences with the competing approach. We show how we built our model in Section 4. In Section 5 we explicit the experimental settings, and the results obtained. Finally, we conclude this report in Section 6.

2 Related Work

Monti et al. [8] provided, to the best of our knowledge, the first application of Graph Neural Networks (GNNs) to image classification, as well as proposing the MoNET framework for dealing with geometric data in general. Their framework worked by weighting the neighbourhood aggregation through a learnt scaling factor based on geometric distances.

Velickovic et al. [15] proposed a model using self-attention for weighting the neighbourhood aggregation in GNNs, recognising that this model could be seen as a sub-model of the MoNET framework, nonetheless providing extraordinary results on other datasets, namely Cora and Citeseer, two famous citation networks [11], and on the FAUST humans dataset [3].

Superpixels group pixels similar in colour and other low-level properties, like location, into perceptually meaningful representation units (regions or segments) [14]. These oversegmented, simplified, images can be applied in a number of common tasks in computer vision, including depth estimation, segmentation, and object localization [1]. A comprehensive survey on superpixels is found in [14].

The abovementioned work on using GNNs on images, alongside the work on adapting self-attention for GNNs and the works for generating superpixels of images form the pillars on which we based our experiments.

Two other models later came to our knowledge, which extended or could be seen as sub-models of the MoNET framework, using geometric information to weight neighbourhood aggregation, and provided results for the MNIST dataset. One of those is the SplineCNN model [5], which leverages properties of B-spline bases in their neighbourhood aggregation procedure. The other is the Geo-GCN model [13],...
which is a MoNEXT sub-model with a differently engineered learned distance function performing data augmentation using rotations and conformations.

3 Superpixel Graphs

A number of techniques exist to generate superpixels from images, such as SLIC [1], SNC [2], SEEDS [4], ETPS [18], and the hierarchical approach from [10]. For our experiments, we chose to use SLIC [1] since it was readily available and had a spatial component in its superpixel segmentation. SLIC is stable and it is still recommended among other state-of-the-art oversegmentation algorithms [14]. Nonetheless, we believe that other segmentation techniques with similar characteristics could be used.

After using a superpixel segmentation technique, we generate a Region Adjacency Graph (RAG) by treating each superpixel as a node and adding edges between all directly adjacent superpixels. Note that this differs from [8], since their superpixel graphs have connections that span more than one neighbour level, with edges formed with the K nearest neighbours. Each graph node can have associated features, providing an aggregate information based on characteristics of superpixel itself. One can see the adopted procedure in Algorithm 1. Figure 1 depicts the generation of a RAG from an image.

There are many possible ways to build the features for each node. Example information that can be readily available are the statistics about the colour and position of a superpixel, such as the mean, standard deviation, and correlation matrices of its pixels. Note that when we say position, this could be extended for the position in spaces other than the Cartesian plane, such as for use in omnidirectional images. We do not build features for the edges, since we use an attention-based technique, and believe that the edge feature will be learned accordingly from the attention mechanism using both nodes’ features.

In this work in particular, we apply this procedure to the MNIST [6] and FashionMNIST [17] datasets. Both datasets contain grayscale images of 28 by 28 pixels and 10 classes. [8] used the MNIST dataset and converted it into a graph-based format by using a superpixel-based representation. But whereas they connected nodes through a K-nearest neighbour procedure, we do so using RAGs, and thus our dataset has a lower-connectivity graph, which could impair information flow and make the classification problem harder. We also provide results for the RAG representation of the FashionMNIST dataset, since it is a harder dataset, where the information loss from the superpixel representation could impact more significantly the model.

Since both datasets contain only grayscale images, we build each superpixel’s feature vector as the concatenation of the average luminosity of the pixels in a superpixel and the average of each cartesian coordinate.

4 Our Model

We transform the Undirected Graph produced from the oversegmented image’s RAG into a Directed Graph \( \mathcal{G} = (\mathcal{N}, \mathcal{E}) \), and feed it to a Neural Network model that operates on Graphs, mode specifically, we use GAT layers, stacked on top of each other using the same adjacency graph on each layer.

Our model is a version of the GAT model by Velickovic et al. [15], roughly based on the implementation by Nathani et al. [9]. Attention is implemented by scattering the source and target nodes’ input features into their respective edges, making the transition and activation function on both these inputs and then summing them up over each target node through the edges.

Therefore, for each layer with input dimension \( d_i \) and output dimension \( d_o \) we learn two functions. The
Algorithm 2: Implemented GAT Layer

1: procedure GAT-FORWARD((Directed graph $G = (\mathcal{N}, \mathcal{E})$, Node Features $x(n)\forall n \in \mathcal{N}$, learnable transition function $f$ and learnable attention function $\alpha$)
2: $M_{tgt}(t_e, e) \leftarrow 1 \{e = (s_e, t_e)\}\forall e \in \mathcal{E}$
3: $h_{src}(s_e) \leftarrow x(s_e)\forall e \in \mathcal{E}$
4: $h_{tgt}(t_e) \leftarrow x(t_e)\forall e \in \mathcal{E}$
5: $h(e) \leftarrow h_{src}(s_e)[|h_{tgt}(t_e)|\forall e = (s_e, t_e) \in \mathcal{E}$
6: $y(e) \leftarrow f(h(e))\forall e \in \mathcal{E}$
7: $\alpha(e) \leftarrow \alpha(h(e))\forall e \in \mathcal{E}$
8: $\alpha_{base}(e) \leftarrow \max_{e \in \mathcal{E}} \alpha(e)$
9: $\alpha_{norm}(e) \leftarrow \frac{\alpha(e) - \alpha_{base}(e)}{\forall e \in \mathcal{E}}$
10: $\alpha_{exp}(e) \leftarrow e^{\alpha_{norm}(e)}\forall e \in \mathcal{E}$
11: $\alpha_{sum} \leftarrow (M_{tgt} \times \alpha_{exp}(e)) + \epsilon$
12: $y_{\alpha}(e) \leftarrow y(e)\alpha_{exp}(e)\forall e \in \mathcal{E}$
13: return $\alpha = (M_{tgt}, y_{\alpha})/\alpha_{sum}$
14: end procedure

The detailed algorithm showing the optimisation can also be seen in Algorithm 2. Each of these layers can be arranged in a multi-head model by concatenating their outputs after the forward pass of each layer. That is, given $k$ heads, the joint output of the $k$-headed layer, where each head has its own transition and attention functions $f_i$ and $\alpha_i$ (as well as the intermediary $\alpha_i$), would be as in Equation 3, where $\sum_{i=1}^{k} a_k$ is the concatenation of all vectors/tensors $a_k$:

$$o(t) = \sum_{s \in \mathcal{T}(t)} \alpha(s, t)f(x(s)||x(t))$$ (2)

$$o(t) = \sum_{s \in \mathcal{T}(t)} \sum_{i=1}^{k} \alpha_i(s, t)f_i(x(s)||x(t))$$ (3)

The output of the final GAT layer can then be sumpooled, having all the values added, and then passed through a MultiLayer Perceptron (MLP) for the final prediction. The Python/Pytorch implementation in its fullest can be seen in the provided Github repositories as well. Most operations have been parallelised as much as the authors could fathom, with some operations done in a preprocessing phase to avoid overload.

5 Experiments

In this section we show our experiments with the MNIST and FashionMNIST datasets supersegmented to have approximately 75 nodes on each image, and present the results within.

All experiments were ran either in a computer with a NVIDIA Quadro P6000 or one with a NVIDIA GTX 1070 Mobile. Both computers have 32GB of RAM. For development, we adopted the Pytorch library, version 1.8, using CUDA.
For both experiments we set a budget of 100 epochs for optimisation, with a batch size of 32 images, using a 90/10 split for training and validation in the dataset’s original training data. We use Adam as the optimiser, with a learning rate of 0.001, $\beta_1 = 0.9$, and $\beta_2 = 0.999$, using the model with the best validation accuracy on the test dataset.

5.1 MNIST

We trained two versions of the GAT model: A single-headed GAT with 3 layers, with 32, 64 and 64 neurons, and a two-headed GAT, where each head has the same amount of neurons as the single-headed model. Both models used sum-pooling and a MLP with two layers of 32 and $d_o$ neurons for the final classification, where $d_o = 10$ is the number of classes in MNIST. All neurons use ReLU activations, except for those at the last layer of the classification MLP, which use softmax activations. We did not use any regularisation technique.

All dataset images are converted to a corresponding RAG, using SLICO[12], a zero-parameter variant the SLIC algorithm. We set the target number of nodes as 75, but the generated RAGs are not guaranteed to have exactly 75 nodes due to how the SLIC algorithm works.

Table 1 shows that both GAT models performed better than the MoNET model [8], showing that a learned representation of the geometric distance can lead to better performance than the fixed one of [8]. Note that our model has also to deal with graphs that are sparser than the ones used in the baselines [8] [5] [13], since in their graph edges are formed through K-nearest neighbours and ours use only directly adjacent nodes. Although one could expect worse accuracy, the results suggest that our approach is able to learn relevant geometric information relating the features from all neighbour superpixels. We also report the performance of SplineCNN [5] and Geo-GCN [13].

Table 1: Test accuracy for the tested models on MNIST and FashionMNIST, processed as RAGs with approximately 75 nodes (called MNIST-75 and FashionMNIST-75), compared to the baseline models. Bold values show the best of the Graph-based models. We also present the mean accuracies of the two best classifiers for the non-oversegmented MNIST and FashionMNIST datasets, available in the FashionMNIST benchmark.

5.2 FashionMNIST

We trained the single-headed and multi-headed GAT models with the same configuration of Section 5.1. Since the FashionMNIST dataset also has 10 classes, the number of output neurons is $d_o = 10$ as well. The RAGs were also generated as in Section 5.1.

Since none of the papers we found with results for MNIST also provided results for FashionMNIST, we provide here a comparison of the performance between our models and the two best classifiers from the FashionMNIST benchmark [17] in Table 1. The gap on the performance between the traditional ML models, using the full features of the dataset, and our models, which use a reduced representation based on the oversegmented image, is higher on FashionMNIST. This shows how much harder the FashionMNIST dataset is for oversegmented images, where the information loss is greater with the aggregation of the features of the pixels in the superpixel.

Another interesting fact to note is that the multi-headed model had a worse performance than the single-headed one. This was further confirmed when we tried learning with a 4-headed model, which performed slightly worse than the 2-headed one.

6 Conclusion

In this report we have shown the results of applying Graph Attention Networks (GATs) [15] to image classification problems, using Region Adjacency Graphs (RAGs) computed from an image segmented using a technique such as SLIC [1]. We show that using attention-based graph neural networks on a feature space that contains the geometric information can be better performing for weighting the edges of a superpixel graph than using a learned function which operates solely on the geometric information.
However, this approach to image classification has its shortcomings. The information loss in the pixels aggregation for more complex images can result in significant performance degradation when compared to using the full image. Also, graph-based approaches come with the same limitations intrinsic to the models they use, and in our case the GNN-based architecture imposes some limitations in terms of memory usage for larger graphs (and thus finer segmentations). Training in small batches lead to an unreliable training pattern, further aggravating such issues.

Some of these limitations can, however, be seen as venues for future work. It has been shown that architectures based on graph convolutional networks, such as the GAT, suffer from an oversmoothing of node-level information, thus acting like low-pass filters \[10\]. While GATs might not be subject to the same limitation, this could be investigated to allow deeper GATs with potentially better performance in this domain. Another venue is helping scaling Graph Neural Networks, of which GAT is a representative, to larger graphs (and thus larger images) or to make them work in an online manner, or with smaller batches.

These graph-based approaches to image classification are also a prime example of application to non-euclidean images, such as omnidirectional images \[7\]. The flexibility of a graph-based approach could be more invariant to the domain of the image, possibly allowing pre-training on planar images and transfer to spheric images.

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