Graph Reasoning Transformer for Image Parsing

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ABSTRACT

Capturing the long-range dependencies has empirically proven to be effective on a wide range of computer vision tasks. The progressive advances on this topic have been made through the employment of the transformer framework with the help of the multi-head attention mechanism. However, the attention-based image patch interaction potentially suffers from problems of redundant interactions of intra-class patches and unoriented interactions of inter-class patches. In this paper, we propose a novel Graph Reasoning Transformer (GReaT) for image parsing to enable image patches to interact following a relation reasoning pattern. Specifically, the linearly embedded image patches are first projected into the graph space, where each node represents the implicit visual center for a cluster of image patches and each edge reflects the relation weight between two adjacent nodes. After that, global relation reasoning is performed on this graph accordingly. Finally, all nodes including the relation information are mapped back into the original space for subsequent processes. Compared to the conventional transformer, GReaT has higher interaction efficiency and a more purposeful interaction pattern. Experiments are carried out on the challenging Cityscapes and ADE20K datasets. Results show that GReaT achieves consistent performance gains with slight computational overheads on the state-of-the-art transformer baselines.

CCS CONCEPTS

• Computing methodologies → Artificial intelligence; Computer vision; Computer vision tasks;

KEYWORDS

Graph Reasoning, Transformer, Image Parsing, Patch Interaction

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1 INTRODUCTION

Image Parsing (IP) is a fundamental yet challenging research task in the community of multimedia and computer vision, which aims to assign each pixel of the input image a unique category label. In the past years, this task has been intensively studied and applied to various applications, e.g., autonomous driving [48], computer-aided diagnosis [34], and makeup transfer [15].

Thanks to the tremendous advances of Convolutional Neural Network (CNN) in image processing [25, 32, 56, 74], successful IP models [1, 52, 59] are mainly built on Fully Convolutional Network (FCN) [41] with a CNN as the backbone. However, due to the limited local receptive fields of the standard convolution operations, FCN can only capture short-range dependencies (also known as the local contexts) of the given image, which are insufficient for some complex and diverse scenes. To alleviate this problem, a number of reformative methods [7, 20, 26, 28, 46, 79, 83, 85, 86, 89] have been proposed. These methods stand on the shoulders of FCN with the objective of capturing the global long-range dependencies by either actively expanding the effective receptive fields [46, 79, 83, 84] of the backbone or using some specific global context modeling schemes [7, 20, 26, 28, 85, 86, 89], or both.

Despite the limited success of FCN and its extensions specifically targeting IP, the inherent locality problem in convolutions still exists. Recently, inspired by the mature applications of the transformer framework [18, 62, 87] on natural language processing, vision transformer has been studied extensively in the computer vision domain and has achieved a number of dazzling results on both images and videos [5, 19, 40, 61, 73, 90]. For a vision transformer model, it mainly consists of a patch partition operation, patch/position embedding layers, layer norms, multi-head attention layers, multi-layer perception layers, and some task-specific operations (e.g., vectorization of feature maps [19], multi-scale operation [68] and patch merging operation [90]). As one of the core
components, the multi-head attention is implemented in an unbiased, fully connected pattern for image patch interactions, which can capture the long-range dependencies (i.e., the global contexts) of the input. Therefore, the inherent locality problem in convolution operations can be completely solved in a vision transformer.

However, the existing patch interaction in the multi-head attention potentially suffers from the following two problems: 1) redundant interactions of intra-class patches and 2) unoriented interactions of inter-class patches. They are the key motivations of this paper. For problem 1, as illustrated in Figure 1 (a), some image patches (marked with X) belonging to the same category (the “sky”) do not contain any object boundary information, and thus the interaction among them would not be informative and necessary. This is also why spatial dropout/dropblock [12, 21] and token reorganization [37] are effective in vision recognition. For problem 2, the existing patch interactions under the help of the multi-head attention mechanism do not distinguish among different object categories and are performed in a roughly unbiased manner. For example, as illustrated in Figure 1 (b), image patches B, C, and D (which contain the “horse”, the “person”, and the “sky” categories respectively) are equal important to patch A (which contains the “horse” category) in the current interaction, i.e., $a_1 = a_2 = a_3$ (where $a_i$ denotes the interaction weight between two patches). However, this does not match the common sense [67, 82]. The interactions between one part of the “horse” with another part, and between the “horse” and the “person” should be much more important than the interaction between the “horse” and the “sky”.

To address the above two problems, we propose a novel Graph Reasoning Transformer (GReaT) model. Compared with the conventional transformer, GReaT has higher interaction efficiency and a more purposeful interaction pattern. Different from the existing patch interaction in the multi-head attention (as illustrated in Figure 2 (a)) module, we propose a Graph Reasoning Block (GReaB) for the vision transformer, which enables image patches to interact following a global relation reasoning pattern. Specifically, as illustrated in Figure 2 (b), the linearly embedded image patches are first projected into a graph representation via a patch projection operation, where each node represents the implicit visual center for a cluster of image patches and each edge reflects the relation weight between two adjacent nodes. It is then followed by the global relation reasoning on this graph by an information diffusion procedure. Finally, all nodes including the relation weight information are mapped back into the original space via the node mapping operation for subsequent processes. GReaT can be obtained by replacing the attention module in a vision transformer baseline model with the proposed GReaB. To demonstrate the superiority of our GReaT, experiments are carried out on the challenging Cityscapes [14] and ADE20K [91] datasets. Results show that GReaT can bring consistent performance gains with slight computational overheads on the state-of-the-art baseline models.

The main contributions of this paper are: 1) a novel interaction module for vision transformer to enable image patches to interact in the graph space, and 2) deploying a Graph Reasoning Block on a vision transformer baseline and achieving the competitive performance on two public IP datasets.

## 2 RELATED WORK

### Image Parsing (IP)
As one of the fundamental computer vision tasks (e.g., image classification [25], object detection [50], object localization [60], and instance segmentation [72] and IP [41]), IP has been intensively studied and made great advances in the past few years. Based on the idea of FCN [41], the existing IP methods can be mainly divided into the following three camps: 1) CNN-based methods, 2) transformer-based methods and the hybrid (i.e., mixed CNN and transformer) methods. In the first camp, these methods mainly use a CNN as the backbone, and add some specific operations for upsampling [1, 19, 38, 52, 59, 65, 79, 83] or context aggregation [7, 20, 26, 28, 46, 85, 86, 89]. In the second camp, the input image is first divided into image patches, and then converted into sequences. On this basis, the transformer encoding is then completed via a series of repeated operations (e.g., layer norm, patch interaction and residual connection). Finally, upsampling and patch merging operations are deployed on the encoded image sequences before the model output. Methods [5, 19, 40, 61, 68, 73, 90] in this camp have the advantage of being inherently able to obtain long-range dependencies. In the third camp, methods are mainly based on utilizing advantages of both CNN and transformer at the same time as their starting point, e.g., TransUnet [6], ConFormer [22] and nnFormer [92]. In this work, we follow the transformer-based framework for IP.

### Vision Transformer
Since ViT [19] was successfully used in image classification, the transformer-based vision recognition models have been extended to a large number of computer vision tasks, e.g., object detection [5], instance segmentation [72], and object tracking [43]. For a computer vision transformer model, improving the computational efficiency of the multi-head attention module is one of the most key research topics. To this end, an intuitive approach is to shorten the image sequence length as in [68, 69]. However, this shoddy approach may lead to the problem that some critical feature cues are lost, which is particularly critical for the current IP models. To retain as much features as possible while reducing the computational costs, some efficient attention methods are also proposed for vision transformer, e.g., dynamic token [71], shifted windows [40] and focal attention [78]. Although the above methods can alleviate the low efficiency problem, the problem of the unoriented interactions of inter-class patches in the vision transformer still exists (cf. Figure 1 (b)). In this paper, we propose to use the global relation reasoning for patch interaction.

### Long-Range Dependency
In the era of deep learning, the previous methods mainly obtain long-range dependencies by increasing the effective receptive fields (e.g., dilated/atrous convolution [79], self-regulation [57, 83] and large kernel operation [46]), or use the multi-scale features (FPN [89], ASPP [7] and MPM [26]). In recent years, inspired by the non-local mean operation [4], the progressive studies [19, 20, 26, 28, 40, 58, 61, 63, 68, 73, 75, 76, 86, 90] mainly use a multi-head attention operation [62, 69] as the way to obtain the long-range dependencies. One of the core operations of the multi-head attention is to calculate similarities among image pixels, and redistribute similarities (i.e., weights) to each pixel to achieve the purpose of a global interaction. Although this mechanism can solve the inherent locality problem in CNN, it is virtually unreasonable to use it in a vision transformer for image patch interactions.
We revisit the vision transformer for image parsing. For a given task, which are usually regarded as the post-processing steps in a fully-supervised model. Recently, the graph convolution operation (e.g., conditional random field [47] and random walk operation [3]) have been used in IP and prediction masks with a satisfactory recognition performance, which are usually regarded as the post-processing steps in a fully-supervised model. The graph convolution operation (e.g., non-local [69], GloRe unit [10], and SGR [36]) using a structured densely connected graph (is also named as the affinity matrix) is proposed and swimmingly used in a number of computer vision tasks, e.g., classification [10, 30], instance segmentation [35, 36], and object detection [70, 77]. A common characteristic of these methods is that they are trained in an end-to-end manner and have the advantage of being plug-and-play. In this paper, our method is implicitly inspired by [10, 29, 35, 36], and our contribution lies in using GR to solve two potential problems in image patch interaction of the vision transformer.

3 METHODOLOGY

In this section, we first make a general preliminary on the vision transformer framework for image parsing in Section 3.1. We then introduce motivations and the overall architecture of our proposed Graph Reasoning Transformer (GReaT) in Section 3.2. Finally, we show implementation details of the proposed Graph Reasoning Block (GReaB) in Section 3.3.

3.1 Preliminaries

Vision transformer is proposed to mainly make up shortcomings of the traditional CNN model in capturing long-range dependencies. We revisit the vision transformer for image parsing. For a given image $\mathbf{I} \in \mathbb{R}^{H \times W \times C}$, we first use a patch partition operation to divide it into $N$ image patches, and of which is expressed as $\mathbf{P}_n \in \mathbb{R}^{L \times L \times C}$, where $H$ and $W$ denotes the image height and width, respectively. $C$ denotes the channel size, and $L$ denotes the image patch resolution in both height and width. $n$ denotes the $n$-th image patch and $n = 1, 2, ..., N$. Therefore, there are $N = H \times W / L^2$ patches, which are used as the input of the transformer model. After the patch is flattened into a 2D sequence and linearly embedded into the feature space (i.e., $\mathbf{P}_n \rightarrow \mathbf{X}_n^{\text{patch}} \in \mathbb{R}^{L \times C}$), we then add a learnable relative position encoding to each sequence to ensure the spatial information of each patch can be preserved. This process can be formulated as:

$$\mathbf{X}_n = \text{pos}(\mathbf{X}_n^{\text{patch}}) + \mathbf{X}_n^{\text{patch}},$$  \hspace{1cm} (1)

where $\text{pos}()$ denotes the learnable relative position encoding layer. $\mathbf{X}_n$ denotes an image patch including the relative position encoding information. For convenience, we omit patch flatten and linear embedding in Eq. (1). After that, the layer norm and the multi-head attention operations are performed on $\mathbf{X}_n$ for normalization and interaction, respectively. With the help of a residual connection, we can obtain the interacted image patch:

$$\mathbf{Y}_n = \text{MHA}(\text{Norm}(\mathbf{X}_n)) + \mathbf{X}_n,$$  \hspace{1cm} (2)

where $\text{Norm}()$ denotes the layer norm operation, $\text{MHA}()$ denotes the multi-head attention operation across all the image patches. $\mathbf{Y}_n$ denotes the patch after interacting with other image patches. Then, a layer norm operation and a feed-forward network are implemented on $\mathbf{Y}_n$. After a residual connection from $\mathbf{Y}_n$, the current output can be obtained by:

$$\mathbf{Z}_n = \text{FFN}(\text{Norm}(\mathbf{Y}_n)) + \mathbf{Y}_n,$$  \hspace{1cm} (3)

where $\text{FFN}()$ denotes the feed-forward network, and $\mathbf{Z}_n$ denotes the current output. In a vision transformer model, the above steps (i.e., from Eq. (1) to Eq. (3)) are cascaded to form a holistic layer, termed as the transformer encoding. When we implement this transformer encoding layer multiple times (the residual connection and the downsampling operation are also contained if needed), a transformer encoder is formed, which can be used to extract the semantic patch features of the input image. Compared to a CNN backbone, patch features have more and abundant long-range dependency information. Finally, these features are reshaped and upsampled to the same spatial resolution as the input patch and used for predictions after a patch merging operation.
3.2 Graph Reasoning Transformer (GReaT)

Although a vision transformer can eliminate the inherent locality problem in a CNN model, it potentially suffers from problems of redundant interactions of intra-class patches and unoriented interactions of inter-class patches. In particular, these two problems are more serious in dense prediction tasks, such as IP, because methods \([68, 73, 90]\) in this task usually adopt a relatively small patch size (e.g., \(L = 4\)), resulting in a large number of trivial image patches. In this work, our purpose is to alleviate these two problems and enable image patches to interact in graph space.

The model input is an RGB image \(I\) and the output is the predicted mask \(V \in \mathbb{R}^{H \times W \times C_{\text{cls}}}\), where each mask grid has been assigned a category label. \(C_{\text{cls}}\) denotes the class size of the used dataset. Following the previous vision transformer \([68, 73, 90]\) for IP, GReaT mainly consists of a transformer encoder and a transformer decoder. For the transformer encoder, there are four ordinal Stages\(^1\), and features from Stage-1 to Stage-4 have the spatial resolution of \(1/4, 1/8, 1/16\) and \(1/32\) of the input, respectively. Within each Stage, as in \([19, 40, 61, 68]\), there are several repeated transformer encoding layers. In this work, the transformer encoding layer refers to the proposed GReaT layer. As shown in Figure 3 (a), GReaT consists of layer norm operations, the proposed GReaB, residual connections, and an MLP. Compared to a conventional transformer encoding layer, our contribution lies in proposing a GReaB for patch interactions, i.e., replacing each attention head of the MHA operation with a GReaB. For the transformer decoder, we follow the same settings as in the previous vision transformer methods \([40, 73, 90]\) by using a progressive upsampling strategy or a multi-level feature aggregation strategy in our model. Implementation details of the baseline decoder are given in Section 4.2.

\(^1\)In this work, we follow the common definition on “Stage” that features with the same spatial resolution are in the same “Stage” \([24, 61, 90]\).

3.3 Graph Reasoning Block (GReaB)

As the core element in a GReaT layer, GReaB takes the linearly embedded image patches including the relative position encoding information as the input, and outputs a set of patches with the same scale as the input but including sufficient long-range dependencies. As illustrated in Figure 3 (b), GReaB contains three steps: 1) patch projection; 2) information diffusion; 3) node mapping.

**Step 1. Patch Projection.** Patch projection aims to project image patches from the geometric space into the graph space, where each node represents an implicit visual center for a cluster of image patches. It is worth noting that each node here does not represent any specific “instance” or a “category” (i.e., the continuous visual features), but a discrete region representation. Following \([10, 36]\), we first use the learnable patch projection weights to achieve this purpose, which can be formulated as:

\[
G_m = \sum_{n} W_{mn} X_n, \tag{4}
\]

where \(W_{mn} \in \mathbb{R}^{1 \times L^2}\) denotes the \(m\)-th projection weight for the \(n\)-th image patch. \(m\) is an index, and \(m = 1, 2, ..., M\). \(M\) is the total number of nodes. \(G_m \in \mathbb{R}^{1 \times C}\) denotes a projected node in the graph.

**Step 2. Information Diffusion.** After obtaining \(M\) nodes via patch projection, we then can establish a graph representation, where each edge reflects the relation weight between two nodes. Based on this graph, the information diffusion procedure is implemented across all nodes via a single-layer graph convolution network, which can be expressed as:

\[
F = ((R - A)G)W_u, \tag{5}
\]

where \(R \in \mathbb{R}^{M \times M}\) is an identity matrix, which is used to reduce the resistance during the model optimization stage. \(A \in \mathbb{R}^{M \times M}\) denotes an adjacency matrix for diffusing information, which contains the relation weight between any two nodes. In our work, \(A\)
is randomly initialized and trained in an end-to-end manner along with the whole model. Following [10, 30, 33, 36], the item \((R - A)\) in information diffusion step plays a role in Laplacian smoothing. \(W_n \in \mathbb{R}^{C \times C}\) denotes a trainable state update weight. Through Step 2, the global relation information between different nodes can fully interact via this single-layer graph convolution network. Praiseworthy, since the number of graph nodes is plenarily smaller than the number of image patches, the information diffusion step has lower complexity (cf. Section 4.4). In reality, we can also design the current network as a multi-layer structure (i.e., multi-layer graph convolution network). However, it will unquestionably bring significant parameter growth. Detailed trade-off analysis between the computational overheads and efficiency is given in Section 4.3.

**Step 3, Node Mapping.** After information diffusion, we map the feature representation from the graph space back into the geometry space. Considering a fact that the node mapping procedure is the reverse operation of patch projection and to reduce model parameters as much as possible, following [10, 33], we use the transpose of \(W_{nn}\) for the node mapping. After a residual connection with the input, the output \(O\) can be formulated as:

\[
O = \sum_{v_n} W_{nn}F_n + X_n.
\]

where \(F_n \in \mathbb{R}^{1 \times C}\) denotes the \(n\)-th item in \(F\).

Compared to the multi-head attention-based patch interaction, since each node of GReaB is an intensive semantic representation for a cluster of image patches, GReaB can alleviate the problem of redundant interactions of intra-class patches. Besides, due to the relation information among nodes in the graph-based interaction is learned, GReaB can also alleviate the problem of unoriented interactions of inter-class patches.

**4 EXPERIMENTS**

**4.1 Datasets and Evaluation Metrics**

**Datasets.** In this paper, experiments are carried out on two challenging image parsing datasets, i.e., Cityscapes [44] and ADE20K [91].

- Cityscapes [14] is a high-resolution \((1024 \times 2048)\) pixel-level annotated street scene dataset by 19 classes, which has images of 2,975 for the training set, 500 for the val set, and 1,525 for the test set, respectively. To make a fair comparison with other methods, we only use the finely annotated training images in our work as in [26, 28].
- ADE20K [91] is one of the most challenging image parsing datasets, which contains up to 150 classes of common scene. This dataset contains about 20k, 2k, and 3k images for the training set, val set, and test set, respectively. For data augmentation on the training set, following [40, 73, 84, 90], we first use the randomly scaling in the range of 0.5 to 2.0. Then, images are randomly cropped into a fixed size by \(1024 \times 1024\) for Cityscapes, and by \(512 \times 512\) for ADE20K. Besides, random horizontal flip and random brightness jittering are also used.

**Evaluation Metrics.** Following the existing methods [7, 80, 84, 86], we use the standard mean Intersection over Union (mIoU) as the primary evaluation metric. Besides, to verify the model efficiency, the model Parameters (Params), FLOPs, and model Complexity analysis are also taken into consideration.

**4.2 Implementation Details**

**Baselines.** Three representative vision transformer IP models are chosen as baselines, i.e., Segmentation TRansformer (SETR) [90], SegFormer [73] and Swin Transformer [40]. To assess the value of our method, we chose the stronger version of each baseline. A brief experimental setting to these three baselines is given below.

- SETR [90]. A powerful encoder with 24 layers (is named as T-Large) is set as the backbone, where the pre-trained weight is provided by [61]. As for the transformer decoder, we choose the multi-level feature aggregation (i.e., SETR-MLA) version. Following [89, 90], the auxiliary classification loss, the synchronized batch norm in the decoder, and the multi-scale text strategy are also used.
- SegFormer [73]. The largest SegFormer-B5, where the hierarchical encoder is pre-trained on ImageNet-1K [17], is chosen as the baseline. The lightweight all MLP decoder is set as the transformer decoder and randomly initialized. Besides, the overlapped patch merging, the efficient self-attention, and the mix-FFN are used in the whole model.
- Swin Transformer [40]. The powerful swin-B variant (i.e., the channel number of the hidden layer is set to 128, and the layer number is set to \(\{2, 2, 18, 2\}\) is set as the baseline, which is pre-trained on ImageNet-22K [17]. The window size is set to 7, and the expansion layer of each MLP is set to 4. Following its default setting, the transformer decoder is based on the hierarchical feature pyramid.

**Training Details.** All models in this work including baselines are implemented on the MMSegmentation⁴ by using the PyTorch [45] deep learning framework on 8 NVIDIA Tesla V100 GPUs. The batch size is set to 16 for ADE20K and 8 for Cityscapes.

**Hyper-parameter Settings.** Following [85, 89, 90], the weight for auxiliary classification loss and segmentation loss is set to 0.2 and 0.8, respectively. In inference, the multi-scale scaling with the scaling factor of \((0.5, 0.75, 1.0, 1.25, 1.5, 1.75)\) and random horizontal flip are deployed. It’s worth noting that OHEM [54] and the class balance loss are not used in our model for a fair comparison.

**4.3 Ablation Study**

The ablation study is implemented on the val set of Cityscapes [14]. Unless otherwise stated, the number of graph nodes \(M\) is set to 16 and the single-layer graph convolution network is adopted.

**Effectiveness on different baselines.** We first analyze the effectiveness by implementing GReaB on different baseline models. Table 1 shows the performance on mIoU and Params. We can observe that GReaB can boost all the baseline performance with a slight of computational overheads. There is an average increase of 0.9% mIoU on these three baselines. Specifically, with the help of GReaB, GReaT can respectively bring 1.1%, 0.7%, and 0.9% mIoU improvements on SETR-MLA, SegFormer-B5, and Swin Transformer. Accordingly, the model parameters are increased by 15.8M (↑ 5.1%), 9.4M (↑ 11.1%) and 8.6M (↑ 6.0%), respectively. These results validate the effectiveness of GReaB on different baseline models and settings, and also reflect the superiority of the graph-based patch interaction in the vision transformer.

⁴https://github.com/open-mmlab/mmsegmentation
GR
Transformer
Swin
SETR
“sidewalk”, the “road”, and the nearby “meadow”). These visualiza-
tions results validate that GReaB has a more productive interaction.

We then analyze the influence of the number of graph nodes.

Besides, we also give a qualitative visualization analysis in Fig-
ure 4. Compared to these three baselines, we can see that GReaT
has more accurate prediction masks. Its superiority is embodied in
the unique baseline, which is the most difficult one to optimize
among these baselines because of the large number of parameters.
Experimental results are given in the upper part of Table 2. Under
the increase of M, we can observe that the performance shows a
trend of first increasing and then decreasing on a single-layer graph
convolution network. Meanwhile, the model parameters show a
progressively increasing trend. Particularly, GReaT achieves the
best performance by 80.1% mIoU (with 326.4 M Params) when
M = 16. When M = 64, the performance is surprisingly lower
(1 8% with 383.0 M Params) than the baseline. The reason may
be that it is difficult for a graph transformer model to learn useful
correlations under excessive graph nodes. Under this observation,
therefore, we set M = 16 in the following experiments.

Single-layer or multi-layer GReaB? In the lower part of Table 2,
we show experimental results on the different number of graph
layers (i.e., Graph No.). We can observe that as the increase of
Graph No., so does the performance. The more Graph No., the greater
the amount of matrix calculation overhead. Nonetheless, we summarily
found that when Graph No. is greater than 1, the performance gain vs the parameter increase is not cost-effective. Therefore, to
balance the model performance and the computational overheads,
we set Graph No. = 1 (i.e., the single-layer GReaB) in the following experiments.

Influence of L. In Step 1 of subsection 3.3, N image patches are
projected into M graph nodes. In this ablation study, we analyze
the influence of image patch size L × L. The baseline model is
SETR-MLA [90]. Experimental results are shown in Table 3. We
can see that when L is small (i.e., L = 4, 8 and 16), GReaT can

Table 1: Quantitative result comparisons with the baseline
model on the val set of Cityscapes [14]. + denotes that the
results are derived based on re-implementation.

| Method               | Backbone | mIoU   | #Params |
|----------------------|----------|--------|---------|
| SETR-MLA             | T-Large  | 79.0%  | 310.6 M |
| GReaT(SETR-MLA)      | T-Large  | 80.1%  | 326.4 M |
| SegFormer-B5         | MiT-B5   | 83.5%  | 84.7 M  |
| GReaT(SegFormer-B5)  | MiT-B5   | 84.2%  | 94.1 M  |
| Swin Transformer*    | Swin-B   | 80.2%  | 142.2 M |
| GReaT(Swin Transformer) | Swin-B | 81.1%  | 150.8 M |

Table 2: The effect of the number of graph nodes and the
number of graph convolutions on model performance. We
show results on the val set of Cityscapes [14]. “Graph No.”
denotes the number of graph layers in GReaT.

| Method               | M    | Graph No. | mIoU   | #Params |
|----------------------|------|-----------|--------|---------|
| SETR-MLA             | -    | -         | 79.0%  | 310.6 M |
| GReaT(SETR-MLA)      | 8    | 1         | 79.3%  | 318.5 M |
| GReaT(SETR-MLA)      | 16   | 1         | 80.1%  | 326.4 M |
| GReaT(SETR-MLA)      | 64   | 1         | 77.2%  | 383.0 M |
| GReaT(SETR-MLA)      | 16   | 2         | 80.4%  | 375.2 M |
| GReaT(SETR-MLA)      | 16   | 3         | 80.5%  | 512.6 M |

Table 3: The effect of the image patch size L × L on model
performance. We show results on the val set of Cityscapes [14].

| Method               | Patch Size (L × L) | mIoU   | FLOPs |
|----------------------|-------------------|--------|-------|
| SETR-MLA             | 8 × 8             | 79.9%  | 2263.7 G |
| GReaT(SETR-MLA)      | 4 × 4             | 79.2%  | 2270.5 G |
| GReaT(SETR-MLA)      | 8 × 8             | 80.1%  | 2261.8 G |
| GReaT(SETR-MLA)      | 16 × 16           | 80.0%  | 2257.2 G |
| GReaT(SETR-MLA)      | 32 × 32           | 75.2%  | 2226.3 G |

Figure 4: Qualitative result comparisons with baselines. The white dotted frames highlight the improved regions.
achieve a better performance than the baseline. When \( L = 32 \), the performance of GReaT is even worse than the baseline. The reason for this phenomenon may be that when the patch size is large, the model cannot completely capture the detailed information, resulting in some critical clues being lost, which is important for the dense prediction tasks. In terms of FLOPs, it can be observed that when we set \( L \geq 8 \), GReaT consumes lower FLOPs than the baseline model. When we set \( L = 8 \), GReaT has 2261.8 G FLOPs, which is 1.9 G less than the baseline model. Based on these observations, we set \( L = 8 \) in the following experiments.

### 4.4 Efficiency Analysis

To demonstrate the efficiency of our GReaT, we analyze the space complexity for various model architectures in Table 4. For a global input token with the sequence length of \( HW \), compared to the existing transformer architectures \([2, 11, 13, 27, 31, 42, 62, 66, 68, 81]\), we can observe that GReaT has a less space complexity by only \( O(M^2) \). For example, the classical transformer model \([62]\) has the space complexity of \( O(H^2W^2) \), since each item of the input token participates in. Although some approaches are to shorten the length of the token via learnable sampling strategies, some potentially critical cues may be dropped in training, such as Spatial Reduction Transformer \([68]\), Reformer \([31]\) and Sparse Transformer \([11]\). Even compared to the progressive linear transformer architectures \([2, 11, 13, 27, 31, 66, 81]\), our GReaT still has an obvious advantage in efficiency (\( M^2 \ll HW \)). More importantly, this advantage is more pronounced when the input token has a large length.

### 4.5 Comparisons with State-of-the-art Methods

In Table 5, we make comparisons with the state-of-the-art methods on the \( val \) set of Cityscapes \([14]\). Our proposed GReaT achieves the competitive mIoU of 83.02% with MiT-B4 as the backbone, which surpasses the baseline SegFormer \([73]\) with MiT-B4 by 0.93% mIoU. When we adopted MiT-B5 as the backbone, GReaT can achieve the mIoU of 84.21%, which demonstrates that our model brings consistent improvements on a stronger backbone. Result comparisons with state-of-the-art methods on the \( val \) set of ADE20K are shown in Table 6. We can see that under the help of GReaT, the model performance consistently improves as well. We finally achieve 51.77% and 52.58% mIoU, and 83.91% and 84.10% PixAcc on ADE20K. Besides, we also show some qualitative visualization comparisons with the state-of-the-art methods on \( val \) sets of Cityscapes \([14]\) and ADE20K \([91]\) in Figure 5. The progressive Seg-L-Mask \([55]\),
Figure 5: Qualitative result comparisons with the state-of-the-art methods on val sets of Cityscapes [14] and ADE20K [91]. The white dotted frames highlight the improved regions predicted by our proposed GReaT.

SegFormer [73] and SETR [90] are used for the result comparison. We observe that our proposed GReaT achieves better segmentation mask predictions on some small objects (e.g., the "person", the "lamp" and the "flower basket"), large objects (e.g., the "pillow", the "footstool" and the "TV bench") and object boundaries (e.g., the "sidewalk" and the "carpet") at the same time.

5 CONCLUSION
In this work, we address the problems of redundant interactions of intra-class patches and unoriented interactions of inter-class patches in the existing vision transformer. We propose a GReaT which enables image patches to interact in the graph space following a relation reasoning pattern. GReaT has higher interaction efficiency and a more purposeful interaction pattern than the conventional transformer. Experimental results on two challenging IP datasets validate that GReaT can bring consistent performance gains with a slight computational overhead. GReaT being a general model for vision transformer, we plan to apply it to some other computer vision tasks, e.g., object detection, object localization, person re-identification, and image generation in the future.

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