Bidirectional Graph Reasoning Network for Panoptic Segmentation

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Abstract

Recent researches on panoptic segmentation resort to a single end-to-end network to combine the tasks of instance segmentation and semantic segmentation. However, prior models only unified the two related tasks at the architectural level via a multi-branch scheme or revealed the underlying correlation between them by unidirectional feature fusion, which disregards the explicit semantic and co-occurrence relations among objects and background. Inspired by the fact that context information is critical to recognize and localize the objects, and inclusive object details are significant to parse the background scene, we thus investigate on explicitly modeling the correlations between objects and background to achieve a holistic understanding of an image in the panoptic segmentation task. We introduce a Bidirectional Graph Reasoning Network (BGRNet), which incorporates graph structure into the conventional panoptic segmentation network to mine the intra-modular and inter-modular relations within and between foreground things and background stuff classes. In particular, BGRNet first constructs image-specific graphs in both instance and semantic segmentation branches that enable flexible reasoning at the proposal level and class level, respectively. To establish the correlations between separate branches and fully leverage the complementary relations between things and stuff, we propose a Bidirectional Graph Connection Module to diffuse information across branches in a learnable fashion. Experimental results demonstrate the superiority of our BGRNet that achieves the new state-of-the-art performance on challenging COCO and ADE20K panoptic segmentation benchmarks.

1. Introduction

Thanks to the visual reasoning based on human common sense, humans are capable of accomplishing recognition and segmentation of the objects and background of an image at a single glance. Recent researches have been devoted to developing numerous specific models for instance segmentation \cite{6, 23} and semantic segmentation \cite{27}. Generally, instance segmentation detects and segments each foreground object (named \textit{things}) while semantic segmentation parses amorphous regions and background (named \textit{stuff}). Tackling the two correlated tasks in separate models, these methods have sacrificed the holistic understanding of an image. Recently, a new proposed panoptic segmentation task has attracted researches \cite{19, 20, 22, 26} to develop end-to-end networks to segment all foreground objects and background contents at the same time. As shown in Figure 1(a, b), some of the previous works \cite{19, 20} unified instance segmentation and semantic segmentation at the architectural level via a multi-branch scheme. The others moved forward to reveal the underlying connection between the two related tasks by unidirectional feature fusion \cite{22}. Although successfully tackling two tasks in one network, these approaches overlooked the explicit semantic and co-occurrence relations between objects and background in a complicated environment, which leads to limited performance gain.

To address these realistic challenges, we reconsider the characteristics of object segmentation as well as scene parsing and investigate on robustly modeling the various relations between them to better tackle the panoptic segmentation task. Intuitively, visual context is essential for instance segmentation when predicting fine-grained objects categories and contours \cite{9}, while foreground object details can benefit the segmentation of global scene and stuff \cite{22}. It is obvious and remarkable that \textit{things} and \textit{stuff} can benefit each other by information propagation in one unified network to boost the overall performance of panoptic segmentation. Inspired by this, we introduce a new Bidirectional Graph Reasoning Network (named BGRNet) that incorporates graph structure into the conventional panoptic segment-
Semantic Segmentation. Semantic segmentation parses scene images into per-pixel semantic classes. Began with FCNs [27] and DeepLab family [2], methods like fully convolutional network and atrous convolution made semantic segmentation thriving by boosting the overall segmentation quality. Besides, the scene parsing method with global context information was also studied in [36, 37].

Panoptic Segmentation. Panoptic Segmentation, a novel task introduced by [20], has lately received extensive attention by researchers. The task, which unifies instance segmentation and semantic segmentation, requires an algorithm that can segment foreground instances and background semantic classes simultaneously. In [20], Kirillov et al. simply combined the results from PSPNet and Mask R-CNN heuristically to produce panoptic segmentation outputs. Not long after, [19] proposed an end-to-end network for the panoptic task with a shared backbone and two branches: thing branch for instance segmentation and stuff branch for semantic segmentation, respectively. Instead of learning two tasks separately, [22] tried to utilize the features of the instance segmentation branch to boost the performance of the semantic segmentation branch through an attention mechanism. [26] proposed a spatial ranking module, to address the occlusion problem which hinders the performance of panoptic segmentation. Moreover, UP-SNet [33] made use of deformable convolutions together with a parameter-free panoptic head in pursuit of more performance gain. A mini-deeplab module was also used to capture more contextual information in [29].

Graph Reasoning. There have been a surge of interest in graph-based methods [18, 30, 34, 35, 5] and graph reasoning has shown to have substantial practical merit for many tasks through modeling the domain knowledge in a single graph [4, 17, 32, 11] or directly fusing the graph reasoning results [10]. However, the mainstream approaches of panoptic segmentation are lack of the investigation on mining mutual relations from different domains (e.g. position and channel reasoning in network, things and stuff subsets) since different graph subsets need more explicit connections for mutual interaction and promotion. In this paper, we propose Bidirectional Graph Reasoning that propagates information from different graphs to support more flexible and
complex reasoning tasks in general cases. Moreover, different from [4, 17, 32] that use a single graph for reasoning, our method aims to build a Graph Connection Module, whose nodes have strong semantics (rather than ambiguous nodes in [4]) and are hence more explainable and capable of encoding various relations.

3. Bidirectional Graph Reasoning Network

3.1. Overview

The panoptic segmentation task is to assign each pixel in an image a semantic label and an instance id. Current methods typically address this issue with a unified model using two branches for foreground things and background stuff separately [8, 19, 21, 22]. In detail, for an input image, the final panoptic segmentation result was generated by combining results from two branches using fusion strategy following [20]. Extending the simple but effective baseline in [19], we aim at further mining the intra-branch and inter-branch relations within and between foreground things or background stuff. Firstly, as shown in Figure 3, we build image-specific graphs in two separate branches in the network to enable flexible reasoning at the proposal level and class level. In the instance segmentation branch, a region graph is established to capture the pairwise relationships among proposals. In the semantic segmentation branch, we build a graph based on the extracted class center that allows efficient global reasoning in a coarse-to-fine paradigm. Secondly, we propose a Bidirectional Graph Connection Module to deduce the implicit semantic relations between things and stuff in a learnable fashion. After diffusing information across various nodes, intra-modular reasoning is performed to refine the visual features of two branches. In this way, we explicitly model the correlations between things and stuff class and leverage their complementary relations in a global view, which facilitates panoptic segmentation and has substantial practical merit in our experiments. An overview of our Bidirectional Graph Reasoning Network is shown in Figure 2.

3.2. Graph Representation

Formally, we define a graph as \( G = (V, A, X) \) where \( V \) is the set of nodes, \( A \) denotes the adjacency matrix and \( X \) is the feature matrix where each row corresponds to a node in \( V \).

Building Thing-Graph. In the classic object detection paradigm, extracted regions are analyzed separately without considering the underlying dependencies between objects, which leads to inconsistent detection results and limited performance in more challenging tasks like panoptic segmentation. To remedy this issue, we introduce a Thing-Graph to reason directly beyond local regions, which can refine visual features of certain regions that suffer from occlusions, class ambiguities and tiny-size objects. Specifically, we build a Thing-Graph \( G_{th} = (V_{th}, A_{th}, X_{th}) \) on each input image, where \( |V_{th}| \) equals to the number of detected regions in the image. \( X_{th} \in \mathbb{R}^{|V_{th}| \times N} \) are extracted features from backbone of all regions and \( N \) is the dimension of the region feature. Considering the diverse relations among regions, we render the edges in \( G_{th} \) learnable to al-
Building Stuff-Graph. As for semantic segmentation, a naive idea of building a Stuff-Graph can be considering each pixel as a graph node similar to the non-local network [31]. However, this approach exhibits clear limitations in dense predictions of semantic segmentation since it requires a large amount of computation and vast GPU memory occupation. Thus, to reduce the computation overhead as well as capture the long-range dependencies, we project the entire feature map to the vertices of Stuff-Graph so that every vertex represents a specific stuff class. Regarding Stuff-Graph $G_{st} = (V_{st}, A_{st}, X_{st})$, given the coarse score map $S_{coarse} \in \mathbb{R}^{|V_{st}| \times HW}$ produced by the original segmentation head in the baseline network, and segmentation feature map $F \in \mathbb{R}^{N \times HW}$, where $N$ is the number of feature channels, we first reshape $S_{coarse}$ to $\mathbb{R}^{HW \times |V_{st}|}$ and $F$ to $\mathbb{R}^{N \times HW}$. After performing softmax along the $HW$ channel on score map, we can obtain class nodes feature $X_{st} \in \mathbb{R}^{V_{st} \times |N|}$ by matrix multiplication and transposition:

$$X_{st} = (F S_{coarse})^T,$$

where $F$ and $S_{coarse}$ represent $F$ and $S_{coarse}$ after reshaping. The intuition behind Equation 1 is that local features, i.e., the features of pixels, are gathered to obtain class nodes feature based on pixel affinity via soft-mapping. By assigning global class nodes features to $X_{st}$, we significantly reduce computation overhead in building a Stuff-Graph since $HW \gg |V_{st}|$. Besides, the extracted stuff nodes are more representative and can provide global clues to further benefit the final classification process after remapping them to local features. We further demonstrate the representative characteristics of the extracted class centers in Stuff-Graph in Section 4.3. The processes of building Thing-Graph and Stuff-Graph are visualized in Figure 3.

3.3. Bidirectional Graph Connection Module

Given the Thing-Graph and Stuff-Graph, we aim to model the mutual relations between things and stuff and propagate the features across all nodes in both $G_{th}$ and $G_{st}$. The rationale behind the design of graph nodes feature fusion module across branches is quite straightforward and comprehensible since there exists a consistent pattern of the co-occurrence of foreground things and background stuff in real-world scenarios. For example, when there exist objects like persons, sports balls, baseball bats and baseball gloves in an image, it is more reasonable to predict the stuff of sand and playing field, and vice versa. Therefore, we distill this insight into Graph Connection Module to bridge all semantic information across branches (between foreground things and background stuff). In this way, the information, relations or visual correlations of different categories from separate branches can be exploited.

The Graph Connection from Thing-Graph to Stuff-Graph can be formulated as:

$$X_{t \rightarrow s} = A_{t \rightarrow s} X_{th} W_{st},$$

where $A_{t \rightarrow s} \in \mathbb{R}^{|V_{st}| \times |V_{th}|}$ is a transfer matrix for propa-
gating the information from Thing-Graph to Stuff-Graph, \(W_{st} \in \mathbb{R}^{N \times D_0}\) is a trainable projection matrix. \(X_{t-s}\) is the mapped node features from Thing-Graph to Stuff-Graph. Similarly, the Graph Connection from Stuff-Graph to Thing-Graph can be obtained utilizing \(X_{st}\) and transfer matrix \(A_{s-t}\) with a trainable matrix \(W_{th}\). Therefore, we seek for appropriate transfer matrix \(A_{t-s} = \{a_{ij}^{t-s}\}\) and \(A_{s-t} = \{a_{ij}^{s-t}\} \in \mathbb{R}^{|V_t| \times |V_s|}\), where \(a_{ij}^{t-s}\) denotes the connection weight from the \(j^{th}\) node of Stuff-Graph to the \(i^{th}\) node of Thing-Graph.

Based on the graph representation and Graph Connection, our graph structure can be naturally decomposed into blocks, given by

\[
\hat{A} = \begin{bmatrix} A_{th} & A_{t-s} \\ A_{t-s}^T & A_{st} \end{bmatrix}, \quad \hat{X} = \begin{bmatrix} X_{th} \\ X_{st} \end{bmatrix},
\]

(3)

where \(A_{th}, A_{st}, A_{t-s}, A_{s-t}\) are normalized adjacency matrices for thing-to-thing pairs, stuff-to-stuff pairs, thing-to-stuff pairs, and stuff-to-thing pairs respectively. To model the distribution of different node features and adaptively handle their pairwise relations, we resort to attention mechanism \cite{vaswani2017attention} to obtain sufficient expressive power in our model. Formally, for any two nodes \(x_i, x_j\) in \(\hat{X}\), the edge weight \(\alpha_{ij}\) is computed by:

\[
\alpha_{ij} = \frac{\exp(\delta(W[x_i,x_j]))}{\sum_{k \in \mathcal{N}_i} \exp(\delta(W[x_i,x_k]))},
\]

(4)

where \(\otimes\) is the concatenation operation, \(\mathcal{N}_i\) is the neighborhood of node \(i\), \(\delta\) is LeakyReLU nonlinear activation function, and \(W\) is weight matrix. For simplicity, we build a fully connected graph for \(\hat{X}\), i.e., \(\mathcal{N}_i\) contains all nodes in \(\hat{X}\).

**Updating node features.** Formally, with normalized graph adjacency matrix \(\hat{A}\) and node features \(\hat{X}\), a single graph reasoning layer is given by

\[
\tilde{X} = \begin{bmatrix} \tilde{X}_{th} \\ \tilde{X}_{st} \end{bmatrix} = \hat{X} \oplus \sigma(\hat{A} \hat{X} \otimes \tilde{W}),
\]

(5)

where

\[
\tilde{W} = \begin{bmatrix} W_{th} \\ W_{st} \end{bmatrix}, \quad \hat{X} \otimes \tilde{W} = \begin{bmatrix} X_{th}W_{th} \\ X_{st}W_{st} \end{bmatrix},
\]

(6)

\(W_{th}, W_{st} \in \mathbb{R}^{D_0 \times D_0}\) are trainable weight matrices, \(\tilde{X}_{th}, \tilde{X}_{st}\) are node features of new Thing-Graph and Stuff-Graph respectively, \(\oplus\) denotes concatenation, and \(\sigma\) is ReLU nonlinear function. Using \(T\) Graph Reasoning layers, the model will propagate and update the information among classes to build more discriminating representations.

### 3.4. Project Nodes Features to Visual Features

To refine the results of instance and semantic segmentation, we project graph nodes features to visual features at the proposal and pixel level, respectively. We illustrate this process in Figure 3.

**Intra-modular reasoning for detection.** When enhancing the features of \(things\) branch, we only care about the features in proposals. Hence we concatenate the updated Thing-Graph features to each proposal after adjusting their dimension:

\[
f_{th} = A_{th}\tilde{X}_{th}W_{th}^{\text{intra}},
\]

(7)

where \(W_{th}^{\text{intra}} \in \mathbb{R}^{(N+D_0) \times D_1}\) is the weight matrix for intra-modular reasoning in \(things\) branch. Then we concatenate enhanced features \(f_{th}\) to the visual features of proposals and feed them into the final fully connected layer to obtain the detection results.

**Intra-modular reasoning for segmentation.** To facilitate the dense prediction in the \(stuff\) branch, we need to enhance the local feature of each pixel under the guidance of extracted class centers. This can be regarded as the inverse operation of Equation 1. We reshape \(S_{\text{coarse}}\) to \(\mathbb{R}^{HW \times |V_s|}\), the enhanced feature of \(stuff\) branch can be calculated as:

\[
f_{st} = S_{\text{coarse}}\tilde{X}_{st}W_{st}^{\text{intra}},
\]

(8)

where \(W_{st}^{\text{intra}} \in \mathbb{R}^{(N+D_0) \times D_2}\) is the weight matrix for intra-modular reasoning in \(stuff\) branch. Then \(f_{st}\) is concatenated with local feature \(F\), which is then fed into the final convolution layer to obtain semantic segmentation results.

### 4. Experiments

#### 4.1. Experimental Settings

**Implementation Details.** The architecture of BGRNet is built on Mask R-CNN \cite{he2017mask} with a simple semantic segmentation branch similar to \cite{yan2018view}. To be exact, the multi-level features from ResNet50-FPN \cite{he2016deep, lin2017feature} first undergo deformable subnets with 3 convolution layers per level and are then bilinearly upsampled to 1/4 of the original scale of the input image. Finally, features from different levels are added together and 1 \(\times\) 1 convolution with softmax is applied to predict all \(stuff\) classes. We follow all hyper-parameters settings and data augmentation strategies in Panoptic-FPN \cite{kirillov2019panoptic}. We implement our model using PyTorch \cite{paszke2017pytorch} and train all models with 8 GPUs with a batch size of 16. The initial learning rate is 0.02 and is divided by 10 two times during fine-tuning. For COCO, we train for 12 epochs, i.e., 1x schedule, following \cite{kirillov2019panoptic}. For ADE20K, we train for 24 epochs and keep the learning rate schedule in proportion to COCO. We adopt an SGD optimizer with a momentum of 0.9 and a weight decay of 5e-4. We find it beneficial to extend the attention mechanism to multi-head
Table 1. Performance comparisons with the state-of-the-art on the COCO val set. † indicates our implementation. Panoptic-FPN-D is the deformable counterpart of Panoptic-FPN [19]. All methods use ResNet50-FPN as the backbone network.

| Method       | DF Conv. | PQ  | PQ$^{Th}$ | PQ$^{St}$ |
|--------------|----------|-----|-----------|-----------|
| Panoptic-FPN[19] |         | 39.0 | 45.9 | 28.7 |
| Panoptic-FPN-D† | ✓       | 39.9 | 46.9 | 29.3 |
| AUNet[22]        |         | 39.6 | 49.1 | 25.2 |
| OANet[26]        |         | 39.0 | 48.3 | 26.6 |
| UPSNet-C[33]     | ✓       | 41.5 | 47.5 | 32.6 |
| UPSNet-CP[33]    | ✓       | 41.5 | 47.3 | 32.8 |
| UPSNet[33]       | ✓       | 42.5 | 48.5 | 33.4 |
| SpatialFlow[3]   |         | 40.9 | 46.8 | 31.9 |
| Our BGRNet      | ✓       | 43.2 | 49.8 | 33.4 |

Datasets and Evaluation Metrics. We evaluate our method on COCO [25] and ADE20K [38]. COCO is one of the most challenging datasets for panoptic segmentation consisting of 115k images for training, 5k images for validation, and 20k images for test-dev with 80 things and 53 stuff classes. ADE20K is a densely annotated dataset for panoptic segmentation containing 20k images for training, 2k images for validation, and 3k images for testing, with 100 things and 50 stuff classes. Following [20], we adopt panoptic quality (PQ), semantic quality (SQ), and recognition quality (RQ) for evaluation.

Table 2. Performance comparisons on ADE20K val set. Panoptic-FPN-D is the deformable counterpart of Panoptic-FPN [19]. † indicates our implementation.

| Methods       | PQ  | PQ$^{Th}$ | PQ$^{St}$ |
|---------------|-----|-----------|-----------|
| Panoptic-FPN† [19] | 29.3 | 32.5 | 22.9 |
| Panoptic-FPN-D† [19] | 30.1 | 33.1 | 24.0 |
| Our BGRNet    | 31.8 | 34.1 | 27.3 |

4.2. Comparisons with state-of-the-art

Comparisons with recent state-of-the-art methods on COCO and ADE20K dataset are listed in Table 1, 2. Some previous methods achieve high performance with over 42.5% PQ, thanks to the specially designed panoptic head [26], multi-scale information [19, 26], and two sources of attention [22]. Unlike previous methods [33, 26, 22], our BGRNet does not rely on complicated feature fusion process, i.e., RoI-Upsample [22], spatial ranking module [26], mask pruning process [33]. Instead, we utilize powerful graph models to capture intra-modular and inter-modular dependencies across separate branches. Thus, we achieve consistent accuracy gain over existed methods and set the new state-of-the-art results in terms of PQ, PQ$^{Th}$, PQ$^{St}$. The advanced results demonstrate the superiority of our BGRNet that incorporates the reciprocal information and deduces underlying relations between things and stuff appeared in the image.

The qualitative results on the ADE20K dataset are shown in Figure 5. As can be observed, our approach outputs more semantically meaningful and precise predictions than baseline methods despite the existence of complex object appearances and challenging background contents. For example, the baseline mistakes field for grass while our BGRNet predicts correctly thanks to the propagated information from the things in the image. More visual results on COCO and ADE20K can be found in Supplementary Materials.

Table 3. Ablation studies on ADE20K val set.

| Methods                   | PQ  | PQ$^{Th}$ | PQ$^{St}$ |
|---------------------------|-----|-----------|-----------|
| Baseline                  | 30.1 | 33.3 | 23.7 |
| w Thing-Graph             | 30.6 | 33.7 | 24.9 |
| w Stuff-Graph             | 30.7 | 33.0 | 26.2 |
| w Thing-Graph/Stuff-Graph | 31.1 | 33.5 | 26.5 |
| Our BGRNet                | 31.8 | 34.1 | 27.3 |

4.3. Ablation Study

Combinations of intra-modular and inter-modular graphs. Table 3 shows the performance of different components of our BGRNet on ADE20K val set. “w Thing(Stuff)-Graph” only has a single graph for foreground or background branch, while “w Thing-Graph/Stuff-Graph” contains graphs in both two branches with no inter-branch interaction, and the graph nodes are re-projected to visual features similar to Section 3.4.

We first analyze the effect of a single graph in either things branch or stuff branch. For single Thing-Graph, both PQ$^{Th}$ and PQ$^{St}$ get improved thanks to the region-wise reasoning that considers the correlations among proposals. For single Stuff-Graph, PQ$^{St}$ got a 2.5% relative improvement, which showcases the great effect of extracting class centers to refine local features in a coarse-to-fine paradigm. Incorporating these two graphs with no connection across branches, the overall PQ is already 1% higher than the baseline, which is a considerable improvement on challenging ADE20K dataset. Furthermore, we introduce graph connection module, which greatly improves the segmentation quality of things and stuff, due to the ability to mine the underlying relations between foreground and background. As can be seen from the last row in Table 3, our BGRNet improves PQ$^{Th}$ and PQ$^{St}$ by 0.8% and 3.6% respectively, resulting in 31.8% overall PQ, which outperforms Panoptic-FPN [19] by a large margin.

Thing/Stuff-Graph Construction. To validate the efficiency of the proposed Thing-Graph and Stuff-Graph, we...
consider different construction methods and compare their performance in Table 4(2,3). Regarding Thing-Graph, we consider establishing the region-wise relations via a fixed knowledge graph. As for the knowledge graph for foreground objects, we follow [17] to construct a fixed relation knowledge Thing-Graph and extract an adjacency matrix of regions according to their class predictions. This scheme achieves 30.4% PQ, which is inferior to the adopted multi-head attention mechanism in BGRNet. The weakness may lie in the wrong region graphs due to the misclassification of some proposals, which indicates that the edge weights between some proposals are not reasonable anymore. As for the non-local graph for background, though slightly higher PQ\textsuperscript{St} (26.3% vs 26.2%) is achieved, it incurs much larger computation since every pixel is regarded as a graph node. Furthermore, with a non-local graph, the subsequent graph connection will be prohibitively expensive when the region-based Thing-Graph is considered. As can be seen, constructions of attention-based Thing-Graph and class-center Stuff-Graph lead to higher performance and moderate computation.

**Different Graph Connection matrices.** We also investigate the performance of our model using a different graph connection method, i.e., semantic similarity. To be exact, the A in Equation 3 is built on the semantic similarity other than a multi-head mechanism under this setting. The word embeddings of predicted classes of regions and stuff names of class centers are used to calculate the cosine similarity.

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Table 4. Comparisons of different graphs and architectural designs on ADE20K val set.

| # | Basic network [14] | Thing-Graph Construction | Stuff-Graph Construction | Graph Connection | Reasoning direction | PQ | PQ\textsuperscript{Th} | PQ\textsuperscript{St} |
|---|---------------------|--------------------------|--------------------------|------------------|---------------------|----|----------------|----------------|
| 1 | ✓                   |                          |                          | Non-local [32]   | Class-center        | 30.1 | 33.3 | 23.7 |
| 2 | ✓                   |                          |                          |                  | Attention           | 30.4 | 33.5 | 24.2 |
| 3 | ✓                   |                          |                          |                  | Semantic similarity | 30.6 | 33.7 | 24.9 |
| 4 | ✓                   |                          |                          |                  | Attention           | 30.6 | 32.8 | 26.3 |
| 5 | ✓                   |                          |                          |                  | Thing-Stuff         | 30.7 | 33.0 | 26.2 |
| 6 | ✓                   |                          |                          |                  | Class-center Stuff  | 31.5 | 33.7 | 27.1 |
| 7 | ✓                   |                          |                          |                  | Class-center Stuff  | 31.4 | 33.6 | 27.9 |
| 8 | ✓                   |                          |                          |                  | Class-center Stuff  | 31.6 | 34.3 | 26.2 |
| 9 | ✓                   |                          |                          |                  | Class-center Stuff  | 31.8 | 34.1 | 27.3 |

Figure 4. Visualization of similarities between extracted class centers and pixels generated by our method. Class Centers are listed below the images. The deeper the color is, the stronger the similarity between the class center and pixels. Benefited from the Class-center Stuff-Graph Construction scheme, our BGRNet can refine the local features under the guidance of the class center from a global view. Best viewed in color.
to form an adjacency matrix. As can be seen in Table 4, the semantic similarity-based connection is also helpful in bridging the chasm between things and stuff and achieves 31.5% PQ, which is still lower than that of attention-based mechanism (31.8% PQ). This indicates that our Graph Connection Module is supposed to obtain more sufficient expressive power and discover the diverse relations between things nodes and stuff nodes in a complicated scene than merely depends on a fixed linguistic graph.

Unidirectional enhancement. We investigate the direction of Graph Connection by exploring unidirectional enhancement in Table 4. Previous method [22] uses two sources of attention to perform unidirectional enhancement from the foreground branch to background branch. To fully leverage the reciprocal relations between foreground and background, we thus investigate and compare the performance with different enhance directions. ‘Thing-Stuff’ stands for only enhancing the feature of semantic segmentation branch after Graph Connection. ‘Stuff-Thing’ represents only enhancing the feature of detection branch after Graph Connection. It can be found that although unidirectional enhancement can lead to considerable performance gain, merely performing Graph Connection in one direction is not able to fully enhance the feature, and a two-way graph connection further boosts the overall PQ to 31.8%.

Visualize the correlations. To demonstrate the representative characteristics of the extracted class centers described in Section 3.2, we visualize the similarity between particular stuff class centers and local features of pixels in Figure 4. As can be seen, the extracted stuff class center correlates well with corresponding area and the responses in other area are inhibited, despite the existence of multiple stuff classes, class ambiguity and fuzzy edges between different stuff classes. For example, in the third row, the extracted class centers correlate well with the confusing stuff class including plant, water and earth. Under the guidance of the class center features from a global view, local features can be refined. This greatly improves the performance of our model in terms of PQ$_{St}$.

5. Conclusion

This paper introduces a Bidirectional Graph Reasoning Network (BGRNet) for panoptic segmentation that simultaneously segments foreground objects at the instance level and parses background contents at the class level. We propose a Bidirectional Graph Connection Module to propagate the information encoded from the semantic and co-occurrence relations between things and stuff, guided by the appearances of the objects and the extracted class centers in an image. Extensive experiments demonstrate the superiority of our BGRNet, which achieves the new state-of-the-art performance on two large-scale benchmarks.

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