LEARNING TO GENERATE SCENE GRAPH FROM HEAD TO TAIL

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ABSTRACT

Scene Graph Generation (SGG) represents objects and their interactions with a graph structure. Recently, many works are devoted to solving the imbalanced problem in SGG. However, underestimating the head predicates in the whole training process, they wreck the features of head predicates that provide general features for tail ones. Besides, assigning excessive attention to the tail predicates leads to semantic deviation. Based on this, we propose a novel SGG framework, learning to generate scene graphs from Head to Tail (SGG-HT), containing Curriculum Re-weight Mechanism (CRM) and Semantic Context Module (SCM). CRM learns head/easy samples firstly for robust features of head predicates and then gradually focuses on tail/hard ones. SCM is proposed to relieve semantic deviation by ensuring the semantic consistency between the generated scene graph and the ground truth in global and local representations. Experiments show that SGG-HT significantly alleviates the biased problem and achieves state-of-the-art performances on Visual Genome.

Index Terms— Scene Graph Generation, Vision and Language, Curriculum Learning

1. INTRODUCTION

Scene Graph Generation is a fundamental task of computer vision that involves detecting the objects and their relationships in an image to generate a graph structure. Such a structured representation is helpful for downstream tasks such as Visual Question Answering \cite{1} and Image Captioning \cite{2}.

Although previous works \cite{3, 4, 5} make great efforts to improve the context aggregation capacity of the model, their performances are disappointed due to the long-tailed data distribution. Especially, the predictions of previous models are dominated by the head predicates, \textit{e.g.}, falsely predicting “on” instead of “riding” and coarsely predicting “on” instead of “sitting on”. To solve this problem, \cite{6} proposes a novel re-weighting method that utilizes the correlation among predicate classes to seek out appropriate loss weights adaptively. \cite{7} builds a hierarchical cognitive structure from the cognition perspective to make the tail relationships receive more attention in a coarse-to-fine mode.

However, underestimating the head predicates during training, these debiasing methods wreck the features of head predicates. Moreover, since the features of tail predicates may depend on those of head ones, \textit{e.g.}, the feature of “sitting on” depends on that of “on”, these wrecked features of head predicates also harm the learning of tail ones. Therefore, handling the biased problem in SGG requires the robustness of head predicates firstly. As shown in Fig. 1, the head predicate “on”...
may benefit the learning of its correlated tail predicates, e.g., “lying on”, “sitting on” and “riding”, sharing general features that one object is on top of the other. Besides, they ignore the semantic deviation problem caused by assigning excessive weights to tail predicates that may incorrectly predict a head predicate as an unrelated tail predicate, e.g., wrongly predicting the “on” to “using”. Thus, their performances are sub-optimal.

In this paper, we propose an SGG framework, learning to generate scene graphs from Head to Tail (SGG-HT), consisting of Curriculum Re-weight Mechanism and Semantic Context Module. The Curriculum Re-weight Mechanism adjusts relative weights between head and tail predicates through a curriculum decay factor. It regulates the model to learn the robust features of the head predicates at first and then gradually focus on the tail ones to better use the general features provided by the head predicates. Semantic Context Module takes the local semantic representations of relation triplets and the global semantic representation of the whole graph as inputs and generates the contextual semantic representations. The global contextual representation is used to measure the overall semantic gap between the generated scene graph and the ground truth. The local contextual representations can correct mispredictions in each triplet individually. With the Semantic Context Module, the model can alleviate the problem of semantic deviation and generate a scene graph consistent with the actual semantics, i.e., the semantics of the ground truth scene graph.

Our proposed method is model-agnostic so that it can be integrated with most existing models. We extensively validate our method with different models. The experiments results show that our approach significantly improves the performance and consistently achieves state-of-the-art performance. The main contributions of our works are three-folds:

• We propose a Curriculum Re-weight Mechanism, which benefits the learning of tail predicates by taking advantage of the general features from the head predicates.

• We propose a Semantic Context Module to alleviate the semantic deviation problem, which can make the semantics of the generated scene graph closer to the actual semantics.

• Our method achieves state-of-the-art performances with different models on Visual Genome. For instance, our method improves Motif [3] from 16.08 to 39.60, VCTree [4] from 18.16 to 40.61 and Transformer [8, 9] from 17.63 to 42.60 on Predcls mR@100.

2. RELATED WORK

2.1. Scene Graph Generation
Scene Graph Generation (SGG) is a task that takes an image as input and generates a structured graph. Early work [10] detects objects and relationships via independent networks. Subsequently, [11] proposed a message passing model to aggregate context information for reasoning. Afterward, other architectures [5, 3, 4, 12] were designed to improve the context aggregation capacity for better performance. Recently, [12] and [4] both notice the imbalanced problem in SGG and propose balanced metric Mean Recall@k. [13] solves this problem by employing causal inference in the inference stage to remove the bad bias. [14] designs a framework to adjust the learning of the model from semantics and sample spaces to generate scene graphs with rich information. Our method generates an unbiased scene graph by providing the robust features of head predicates for tail ones and ensuring semantic consistency between the generated scene graph and the ground truth.

2.2. Long-Tailed Classification
The data in the real world has a natural long-tailed distribution: a few categories (head class) have abundant samples while the majority categories (tail class) only have a few samples. A classic method to deal with long-tailed distribution is re-sampling. It makes the data distribution balanced, including oversampling for the tail classes [15, 16] and undersampling for the head classes [17]. Another effective method is to re-weight the loss function [18, 19], which assigns different weights for different classes to balance the loss. However, ignoring the correlation between predicates that head predicates can provide general features for tail ones, these methods are not entirely appropriate for the scene graph generation.

3. METHOD
We first give the problem definition of SGG in Sec. 3.1. Then, a method is proposed to generate an unbiased scene graph, as illustrated in Fig. 2. In particular, our method consists of two components: a Curriculum Re-weight Mechanism in Sec. 3.2 and a Semantic Context Module in Sec. 3.3.

3.1. Problem definition
Scene graph generation is a two-stage classification task. In the first stage, the Faster RCNN [20] framework is used to obtain object features for each image, including:

• A set of spatial features \( B = \{b_1, b_2, ..., b_n\} \), where \( b_i \in \mathbb{R}^d \) denotes the the spatial locations of detected regions.

• A set of region proposals’ visual features \( V = \{v_1, v_2, ..., v_n\} \), where \( v_i \in \mathbb{R}^{4096} \).

• A set of object labels \( L = \{l_1, l_2, ..., l_n\} \), where \( l_i \in \mathbb{R}^{O+1} \), \( O \) is the number of object classes. Then we obtain the semantic features \( S^O = \{s^O_1, s^O_2, ..., s^O_n\} \) by mapping the object label \( l_i \) to a 200 dimensional vector with a word embedding model.
In the second stage, the object features are refined by a context encoding module, such as BiLSTM [3], GCN [5], or TreeLSTM [4]. Finally, possible object pairs’ contextual features are fed into a classifier to predict the predicate probability $p_i \in \mathbb{R}^{R+1}$.

Generally, the standard cross-entropy loss is used for predicate classification in the optimization process of the above methods. Given the predicate predicted logits $z = [z_1, z_2, ..., z_{R+1}]$ ($R$ predicate classes and a background class) and ground truth label $y = [y_1, y_2, ..., y_{R+1}]$, in which $y_i$ equals 1 or 0, the cross-entropy loss is formed as:

$$\mathcal{L}_{CE}(z, y) = -\sum_{i=1}^{R+1} y_i \log \frac{e^{z_i}}{\sum_{j=1}^{R+1} e^{z_j}}.$$  

Due to the long-tailed data distribution, the predicates of tail classes have less frequency of occurrence. With the optimization of this loss function, the model’s predictions will be dominated by head predicates. Thus, the classifier tends to predict biased classification scores resulting in low accuracy of tail predicates. In this work, we propose a novel SGG-HT framework to generate an unbiased scene graph, as described below.

### 3.2. Curriculum Re-weight Mechanism

Many methods [19, 18, 17] are proposed to solve the imbalanced data distribution problem, but they can’t achieve satisfying performance in SGG. As mentioned in Sec. 1, handling the imbalanced issue requires the robust features of head predicates at first. To this end, we introduce the Curriculum Re-weight Mechanism, which adjusts the relative weights between head and tail predicates with the progress of training through a Curriculum Decay Factor $\lambda$, rather than assigning large weights to the tail and minor weights to the head directly. The refined loss function is as follows:

$$\mathcal{L}_{CRW}(z, y) = -\sum_{i=1}^{R+1} \lambda_i w_i y_i \log \frac{e^{z_i}}{\sum_{j=1}^{R+1} e^{z_j}},$$  

where $w_i$ is the weight of class $i$ computed with a state-of-the-art re-weighting method [18]. The Curriculum Decay Factor $\lambda_i$ is defined as:

$$\lambda_i = \begin{cases} 
\max(\varphi(l), \alpha) & \text{if } i \in H \\
1 & \text{otherwise}
\end{cases},$$  

where $H$ is the set of head predicate indexes selected by the number of predicate samples. $\varphi(l)$ is a decreasing function from 1 to 0 that represents the weights allocated to the head predicates. In order to prevent the forgetting of head predicates, a threshold hyperparameter $\alpha$ is used to avoid zero weights for them. The $\varphi(l)$ is defined as:

$$\varphi(l) = 1 - \frac{l}{L},$$  

where $l$ is the current training iteration, and $L$ refers to the total training iterations. It is a linear function.

### 3.3. Semantic Context Module

After the prediction of predicates, we get a set of predicate probabilities $\{p_1, p_2, ..., p_N\}$, where $N$ is the total number of relations in an image and $p_i \in \mathbb{R}^{R+1}$. Next, we obtain the predicate semantic representations $\{s_1, s_2, ..., s_N\}$ by mapping each predicate probability to a 200 dimensional vector with a pre-trained word embedding model (GloVe). Then, the semantic representations of the subject and object are concatenated with the corresponding predicate semantic representation to get the relation triplet semantic representation, as follows:

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**Fig. 2.** Overview of the SGG-HT framework. The basic SGG framework adopts Faster RCNN to obtain spatial, visual, and semantic features. Next, a context encoding module is used to generate the contextual features for predicate classification. Our proposed SGG-HT framework includes two new components: (1) a Curriculum Re-weight Mechanism that gradually transfers the learning focus from head predicates to tail ones with Curriculum Re-Weight Loss; (2) a Semantic Context Module that relieves the semantic deviation between the generated scene graph and the ground truth.
\[ s_i^r = \text{Concat}(s_i^1; s_i^2; s_i^3)W, \quad W \in \mathbb{R}^{600 \times D}. \]  
\tag{5}

where \( W \) is a trainable linear projection that maps the concatenated semantic representation to \( D \) dimensions. In addition, we add a global node \( s_{\text{global}} \) as the global semantic representation of the whole graph, defined as follows:

\[ s_{\text{global}} = \frac{1}{N} \sum_{i=1}^{N} s_i^r. \]  
\tag{6}

The same processing is performed on the ground truth relation triplets to get \( t_i' \) and \( t_{\text{global}} \). Then, the conventional Transformer [9] encoder is used to construct contextual semantic representations for relation triplets. For simplicity, we denote the conventional Transformer as \( \text{Trans}(\cdot) \), where the queries \( Q \), keys \( K \) and values \( V \) share the same input. The input of \( \text{Trans}(\cdot) \) is \( S' = \{ s_1^r, s_2^r, \ldots, s_N^r, s_{\text{global}} \} \) and then the contextual semantic representation, \( \tilde{S}' \), is computed as follows:

\[ \tilde{S}' = \text{Trans}(S'), \]  
\tag{7}

where \( \tilde{S}' = \{ \tilde{s}_1^r, \tilde{s}_2^r, \ldots, \tilde{s}_N^r, \tilde{s}_{\text{global}} \} \). The ground truth contextual semantic representation \( T' \) is also obtained with \( \text{Trans}(\cdot) \). Then, the \( \tilde{s}_{\text{global}} \) and \( t_{\text{global}} \) are used to compute the semantic gap, and a mean-squared loss is used to minimize it:

\[ \mathcal{L}_{SC} = \frac{1}{D} \| \tilde{s}_{\text{global}} - t_{\text{global}} \|^2, \]  
\tag{8}

where \( D \) is the same as in Eq. (5). Besides, \( \{ \tilde{s}_1^r, \tilde{s}_2^r, \ldots, \tilde{s}_N^r \} \) are used for predicate classification to obtain refined predicate logits \( \tilde{z} \). Afterward, the refined predicate logits combine the original predicate logits \( z' \) to get the final predicate logits, as follows:

\[ z = z' + \tilde{z}. \]  
\tag{9}

It can correct the prediction errors from the semantic perspective. Finally, the total loss for training the scene graph generator is computed by:

\[ \mathcal{L}_{\text{total}} = \mathcal{L}_{\text{CRW}} + \mathcal{L}_{\text{SC}}. \]  
\tag{10}

### 4. EXPERIMENT

#### 4.1. Experimental Settings

**Datasets.** Our models is evaluated on the widely used benchmark, Visual Genome (VG), which is composed of 108K images with 75K object categories and 37K predicate categories. Since the majority of the annotations are noisy, we follow previous works [13, 14, 7] and adopt the most popular split from [11], which contains the most frequent 150 object categories and 50 predicate categories. Moreover, the VG dataset is divided into a training set with 70% of the images and a testing set with the remaining 30% and 5 images from the training set for validation.

**Evaluation.** We follow previous works [14, 7, 5, 13] to evaluate our method on three subtasks: (1) Predicate Classification (PredCls): given the ground-truth bounding boxes and object labels in an image, predict the relationship labels; (2) Scene Graph Classification (SGCls): given the ground-truth bounding boxes in an image, predict the object labels and the relationship labels; (3) Scene Graph Detection (SGDet): given an image, predict the scene graph from scratch. Due to the extremely long-tailed data distribution in VG dataset, we use the **Mean Recall**@K (mR@K) as our main evaluation metric, and the **Recall@K** is also reported briefly.

#### 4.2. Implementation Details

We adopt a pre-trained Faster RCNN [20] with ResNeXt-101-FPN [21, 22] as the backbone object detector, and freeze the model parameters during the training. The \( \alpha \) in Curriculum Re-weight Mechanism is set to 0.25 and the \( D \) in Semantic Context Module is set to 512. Models are trained by SGD optimizer with 30K iterations. The batch size and learning rate are set to 12 and \( 12 \times 10^{-3} \). Besides, we incorporate frequency bias [3] into the training and inference stages. Experiments are implemented with PyTorch and trained with

| Models | PredCls | SGCls | SGDet |
|--------|---------|-------|-------|
|        | mR@20  | mR@50 | mR@100 | mR@20 | mR@50 | mR@100 | mR@20 | mR@50 | mR@100 |
| Motifs' [3, 8] | 11.67 | 14.79 | 16.08 | 6.68 | 8.28 | 8.81 | 4.98 | 6.75 | 7.90 |
| VCTree' [4, 8] | 13.12 | 16.74 | 18.16 | 9.59 | 11.81 | 12.52 | 5.38 | 7.44 | 8.66 |
| Transformer' [8] | 12.77 | 16.30 | 17.63 | 8.14 | 10.09 | 10.73 | 6.01 | 8.13 | 9.56 |
| PCPL [6] | - | 35.2 | 37.8 | - | 18.6 | 19.6 | - | 9.5 | 11.7 |
| Motifs (TDE) [13] | 18.5 | 24.9 | 28.3 | 11.1 | 13.9 | 15.2 | 6.6 | 8.5 | 9.9 |
| VCTree (TDE) [13] | 18.4 | 25.4 | 28.7 | 8.9 | 12.2 | 14.0 | 6.9 | 9.3 | 11.1 |
| Motifs (CogTree) [7] | 20.9 | 26.4 | 29.0 | 12.1 | 14.9 | 16.1 | 7.9 | 10.4 | 11.8 |
| SG-Transformer (CogTree) [7] | 22.9 | 28.4 | 31.0 | 13.0 | 15.7 | 16.7 | 7.9 | 11.1 | 12.7 |
| Transformer (BA-SGG) [14] | 26.7 | 31.9 | 34.2 | 15.5 | 17.8 | 19.7 | 7.5 | 10.2 | 11.2 |
| Motifs (BA-SGG) [14] | 24.8 | 29.7 | 31.7 | 14.0 | 16.5 | 17.5 | 10.7 | 13.5 | 15.6 |
| VCTree (BA-SGG) [14] | 26.2 | 30.6 | 32.6 | 17.2 | 20.1 | 21.2 | 10.6 | 13.5 | 15.7 |

| Transformer (SGG-HT) | 34.52 | 40.28 | 42.60 | 18.86 | 22.36 | 24.71 | 13.73 | 17.68 | 20.64 |
| Motifs (SGG-HT) | 32.09 | 38.01 | 39.43 | 19.35 | 22.43 | 23.42 | 13.10 | 17.21 | 20.19 |
| VCTree (SGG-HT) | 32.28 | 38.32 | 40.21 | 22.36 | 25.23 | 27.11 | 12.37 | 16.05 | 18.36 |
Table 2. State-of-the-art comparison on R@K.

| Method                  | PredCls     |
|-------------------------|-------------|
|                         | R@20 | R@50 | R@100|
| Motifs (CogTree) [7]    | 31.1  | 35.6 | 36.8 |
| VCTree (CogTree) [7]    | 39.0  | 44.0 | 45.4 |
| Motifs (TDE) [13]       | 33.6  | 46.2 | 51.4 |
| VCTree (TDE) [13]       | 36.2  | 47.2 | 51.6 |
| PCPL [6]                | -     | 50.8 | 52.6 |
| Motifs (SGG-HT)         | 42.41 | 49.75| 51.88|
| VCTree (SGG-HT)         | 43.51 | 50.85| 52.94|

Table 3. Ablation study for the proposed components.

| Exp | CRM | SCM | PredCls     |
|-----|-----|-----|-------------|
|     |     |     | mR@20 | mR@50 | mR@100 |
| 1   | -   | -   | 30.07 | 35.52 | 37.88  |
| 2   | √   | -   | 33.21 | 34.14 | 34.81  |
| 3   | -   | √   | 32.04 | 31.97 | 32.53  |
| 4   | √   | √   | 34.52 | 44.45 | 40.28  |

NVIDIA TITAN XP GPUs.

4.3. Comparison with State-of-the-art Methods

We compare our method with state-of-the-art methods. The comparison results are summarized in Tab. 1. The results show that our method achieves the best performance in all evaluation metrics among all the comparison methods, reaching 40.28 mR@50 for PredCls, 23.62 mR@50 for SGCls and 17.68 mR@50 for SGDet with Transformer. As for the Recall@K metric, we compare our method with debiasing methods CogTree, TDE and PCPL on the task of PredCls, and the results are shown in Tab. 2. Our method also outperforms them with this metric because they pay too much attention to the tail predicates. Overall, these results demonstrate that our method can maintain the performance of the head predicates while significantly improving the performance of the tail predicates.

4.4. Ablation Study

Extensive experiments are conducted to investigate each component's contribution and possible variants in our proposed SGG-HT framework. Moreover, we use Transformer with re-weighting [18] as the baseline and only perform the task of PredCls for fast validation.

Effectiveness of CRM and SCM. An ablation study is performed to validate the effectiveness of Curriculum Re-weight Mechanism (CRM) and Semantic Context Module (SCM). Results are shown in Tab. 3. There are the results of four experiments in the table. Exp (1): Baseline, Transformer trained with re-weighting [18]. Exp (2): CRM is added to the baseline to learn from head to tail. Exp (3): SCM is used to relieve semantic deviation. Exp (4): CRM and SCM are combined as mentioned in Sec. 3. Compared with baseline, CRM and SCM increase the mR@50 metric by 3.45 and 2.53, respectively. Moreover, combining CRM and SCM, our method further improves the performance, demonstrating the effectiveness of our SGG-HT framework.

Variants to Curriculum Re-weight Mechanism. For Curriculum Re-weight Mechanism, we investigate the variants of $\varphi(l)$ mentioned in Eq. (4) and compare the linear function with the other two decreasing functions as follows:

1. Exponential function, indicates the speed of transfer from fast to slow, defined as:
   $$
   \varphi(l) = \nu^l, (0 < \nu < 1).
   $$

2. Cosine function, indicates the speed of transfer from slow to fast, defined as:
   $$
   \varphi(l) = \cos(\frac{\pi \times l}{L}).
   $$

The experimental results are shown in Tab. 4. These results show that the linear function outperforms the cosine function in mR@50 and mR@100 and achieves better performance than the exponential function in all metrics. Therefore, in the SGG-HT framework, the Linear function is utilized to decay the weights on the head predicates.

Variants to Semantic Context Module. In this module, a global node is utilized as $s_{global}$ (Global) mentioned in Sec. 3.3 for the semantic representation of the whole graph. In order to demonstrate the effectiveness of $s_{global}$, we first remove $s_{global}$ in $S'$, and then take the average of
\{ \tilde{s}_1, \tilde{s}_2, ..., \tilde{s}_N \} (\text{Mean}) as \tilde{s}_{\text{global}} \text{ in Eq. (8). Shown in Tab. 5, Global exceeds Mean in all metrics, which shows the superiority of the global node \( s_{\text{global}} \). It indicates that the Global fully considers the semantic context correlations among all relation triplets, which better represents the semantics of the whole scene graph, compared with the Mean.

4.5. Qualitative Results

Some scene graph generation visualization results of VC-Tree and VCTree (SGG-HT) are in Fig. 3. It is obvious that VCTree (SGG-HT) generates more fine-grained relationships than plain VCTree, such as “man wearing shirt”, “man playing skateboard”, “car parked on street” and “street in front of building1”. These results demonstrate the effectiveness of our method for the balanced scene graph generation.

5. CONCLUSION

In this work, for learning robustness scene graphs, we propose a novel framework SGG-HT, which contains a Curriculum Re-weight Mechanism that regulates the model to learn to generate scene graphs from head to tail, and a Semantic Context Module that alleviates the semantic deviation by ensuring the semantic consistency between the generated scene graph and the ground truth. Extensive experiments show that our SGG-HT framework significantly improves the performance of scene graph generation and achieves the new state-of-the-art performance.

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