SGTR: End-to-end Scene Graph Generation with Transformer

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Abstract

Scene Graph Generation (SGG) remains a challenging visual understanding task due to its complex compositional property. Most previous works adopt a bottom-up two-stage or a point-based one-stage approach, which often suffers from overhead time complexity or sub-optimal design assumption. In this work, we propose a novel SGG method to address the aforementioned issues, which formulates the task as a bipartite graph construction problem. To solve the problem, we develop a transformer-based end-to-end framework that first generates the entity and predicate proposal set, followed by inferring directed edges to form the relation triplets. In particular, we develop a new entity-aware predicate representation based on a structural predicate generator to leverage the compositional property of relationships. Moreover, we design a graph assembling module to infer the connectivity of the bipartite scene graph based on our entity-aware structure, enabling us to generate the scene graph in an end-to-end manner. Extensive experimental results show that our design is able to achieve the state-of-the-art or comparable performance on two challenging benchmarks, surpassing most of the existing approaches and enjoying higher efficiency in inference. We hope our model can serve as a strong baseline for the Transformer-based scene graph generation.

1. Introduction

Inferring structural properties of a scene, such as the relationship between entities, is a fundamental visual understanding task. The visual relationship between two entities can be formally represented by a triple \textlt{subject entity, predicate, object entity}\textgt. Based on these visual relationships, a scene can be modeled in a form of graph structure, with entities as nodes and predicates as edges, termed scene graph. Such a graph provides a compact structural representation for a visual scene, which has potential applications in many vision tasks such as visual question answering [8, 28, 34], image captioning [46, 47] and image retrieval [9].

Different from the traditional vision tasks (e.g., object detection), which focus on detecting individual instances, the main challenge of scene graph generation (SGG) lies in building an effective and efficient model for the pair-wise relations between the entities. The compositional property of visual relationships induces cubic complexity in terms of their constituents, which makes it difficult to learn a compact representation of the relationship concept for localization and/or classification.

Most previous works attempt to tackle this problem using two distinct design patterns: bottom-up two-stage \{1, 4, 5, 7, 15, 19, 44, 48\} and point-based one-stage design \{6, 24\}. The former design typically first detects \textit{N} entity proposals, followed by predicting the predicate categories of those entity combinations. While this strategy achieves high recalls in discovering relationship instances, its \textit{O}(\textit{N}^2) predicate proposals not only incur considerable computation cost but also produce substantial noise in context modeling. In the one-
stage methods, entities and predicates are often extracted separately from the image in order to reduce the size of relationship proposal set. Nonetheless, they rely on a strong assumption of the non-overlapping property of interaction regions, which severely restricts their application in modeling complex scenes.

In this work, we aim to tackle the aforementioned limitation by leveraging the compositional property of scene graphs. To this end, as illustrated in Fig. 1, we first formulate the SGG task as a bipartite graph construction problem, in which each relationship triplet is represented as two types of nodes (entity and predicate) linked by directed edges. Such a bipartite graph allows us to jointly generate entity/predicate proposals and their potential associations, yielding a rich hypothesis space for inferring visual relations. More importantly, we propose a novel entity-aware predicate representation that incorporates relating entity proposal information into each predicate node. This enriches the expressive power of predicates and therefore enables us to produce a relatively small number of high-quality predicate proposals. Moreover, such a representation encodes potential associations between each predicate and its subject/object entities, which can facilitate predicting the graph edges and lead to efficient generation of the visual relation triplets.

Specifically, we develop a new transformer-based end-to-end SGG model, dubbed Scene graph Generation Transformer (SGTR), for constructing the bipartite graph. Our model consists of three main modules, including an entity node generator, a predicate node generator and a graph assembling module. Given an image, we first introduce two CNN+Transformer sub-networks as the entity and predicate generator to produce a set of entity and predicate nodes, respectively. In order to compute the entity-aware predicate representations, we design a structural predicate generator consisting of two parallel transformer decoders, which integrate each predicate feature with an entity indicator representation. After generating entity and predicate node representations, we then devise a differentiable graph assembling module to infer the directed edges of the bipartite graph, which exploits the entity indicator to predict the best grouping of the entity and predicate triplets.

We validate our method by extensive experiments on two SGG benchmarks: Visual Genome and OpenImages-V6 datasets. We report both prediction accuracy and efficiency with comparisons to the previous state-of-the-art methods. The results show that our method outperforms or achieves comparable performance on both benchmarks with high efficiency during inference. We hope this work can serve as a strong baseline for the transformer-based scene graph generation.

The main contribution of our work has three-folds:

1. We propose a novel transformer-based end-to-end scene graph generation method with a bipartite graph construction process that inherits the advantages of both two-stage and one-stage methods.
2. We develop an entity-aware structure for incorporating the compositional properties of visual relationships.
3. Our method achieves state-of-the-art or comparable performance on all metrics w.r.t. the prior SGG methods but with fast inference.

2. Related Works

We categorize the related work of SGG/HOI into three directions: Two-stage Scene Graph Generation, One-stage Scene Graph Generation, and One-stage Human-Object Interaction.

Two-stage Scene Graph Generation Two-stage SGG methods predict the relationships between densely connected entity pairs. On dense relationship proposals, some works propose a contextual modeling structure [11, 19–21, 23, 27, 33, 38, 39, 41, 42, 45, 50–55]. Recent studies have focused on developing logit adjustment and training strategies to address the SGG task’s long-tail recognition [1, 4, 5, 7, 14, 15, 19, 29, 32, 38, 43, 44, 48]. The two-stage design is capable of dealing with the complicated scenarios encountered in SGG. However, as mentioned earlier in Sec. 1, the overhead relation proposal leads to large time complexity and unavoidable noise in context modeling. Many two-stage works propose heuristic designs to address these issues (e.g., proposal generation [45], efficient context modeling [19, 20, 27, 33, 39, 47]). However, these sophisticated two-stage designs often rely on their specific designs being based on the downstream tasks, which limits end-to-end optimization and the flexibility of their representation learning.

One-stage Scene Graph Generation Inspired by the fully convolutional one-stage object detection methods [2, 30, 36], the SGG community starts to explore the one-stage design. The fully convolutional network [24, 35] or CNN-Transformer [6] architecture is used in these one-stage methods to detect the relationship from image features directly. These one-stage frameworks perform efficiently due to their sparse proposal set. Nonetheless, with a less instance-aware structure, those designs may struggle to model the more complicated compositing situations associated with visual relationships. Additionally, the majority of one-stage methods ignore node-edge consistency because each relationship is predicted independently rather than a valid graph structure with consistent node consistency.

One-stage Human-Object Interaction Our work is also related to the Human-Object Interaction (HOI) task. There has been a recent trend toward studying the one-stage framework for Human-Object Interaction [3, 12, 13, 22, 31, 37, 56, 62].
We formulate the relationship triplet generation process as a dual decoder structure that simultaneously extracts the human, object, and interaction and then groups the components into final triplets. This decoding-grouping approach provides a divide-and-conquer perspective for detecting the human and interacted object. Inspired by this design, we propose the bipartite graph construction diagram in our SGTR for the more general SGG task. To further improve the association modeling between entity and predicate, we propose a predicate node generator with an entity-aware structure and a graph assembling mechanism. With such a design, the SGTR is able to handle the complex composition of relationships and achieve optimal performance on SGG benchmarks.

3. Preliminary

In the following of this section, we first introduce the problem setting of scene graph generation in Sec. 3.1. Then an overview of our approach is presented in Sec. 3.2.

3.1. Problem Setting

The task of scene graph generation aims to parse an input into a scene graph $G_{\text{scene}} = \{V_e, E_r\}$, where $V_e$ is the node set denoting noun entities, and $E_r$ is the edge set that represents predicates between pairs of subject and object entities. Specifically, each entity $v_i \in V_e$ has a category label from a set of entity classes $C_e$ and a bounding box depicting its location in the image, while each edge $e_{i\rightarrow j} \in E_r$ between a pair of nodes $v_i$ and $v_j$ is associated with a predicate label from a set of predicate classes $C_p$ in this task.

One feasible way to generate the scene graph $G_{\text{scene}}$ is by extracting the relationship triplet set of the given image. We formulate the relationship triplet generation process as a bipartite graph construction task [19]. Specifically, the graph consists of two groups of nodes $V_e, V_p$, which correspond to entity representation and predicate representation, respectively. These two groups of nodes are connected by two sets of directed edges $E_{e\rightarrow p}, E_{p\rightarrow e}$ representing the direction from the entities to predicates and vice versa. Hence the bipartite graph has a form as $G_b = \{V_e, V_p, E_{e\rightarrow p}, E_{p\rightarrow e}\}$.

3.2. Model Overview

Our model defines a differentiable function $F_{\text{sgg}}$ that takes an image $I$ as the input and outputs the bipartite graph $G_b$, denoted as $G_b = F_{\text{sgg}}(I)$, which allows end-to-end training. We propose to explicitly model the bipartite graph construction process by leveraging the compositional property of relationships. The bipartite graph construction is composed of two steps: (a) node (entity and predicate) generation, and (b) directed edge connection.

In node generation step, we extract the entity nodes and predicate nodes from the image with the entity node generator and the predicate node generator, respectively. Specifically, the predicate node generator utilizes three parallel sub-decoders to update the predicate proposals. In directed edge connection step, we design the graph assembling module to assemble the bipartite scene graph from the entity and predicate proposals. An overview of our method is illustrated in Fig. 2 and we will start with a detailed description of our model architecture below.

4. Model Architecture

Our model has a modular architecture consisting of four main submodules: (1) a backbone network to generate feature representation of the scene (Sec. 4.1); (2) a transformer-based entity node generator to predict entity proposals (Sec. 4.1); (3) a structural predicate node generator to decode predicate nodes (Sec. 4.2); (4) a differentiable bipartite graph assembling module to construct the final bipartite graph by connecting the entity node and entity-aware predicate node (Sec. 4.3). The learning and inference are detailed in Sec. 4.4.

4.1. Backbone and Entity Node Generator

We adopt a CNN backbone that consists of a ResNet network, which produces a convolutional feature representation for the subsequent modules. Motivated by the Transformer-based detector, DETR [2], we introduce a multi-layer Transformer encoder for entity node generator and predicate node generator. The output feature of the Transformer encoder is denoted as $Z \in \mathbb{R}^{w \times h \times d}$, where $w, h, d$ are the width, height, and channel of the feature map, respectively.

We adopt the decoder of DETR as the entity generator to decode the entity nodes from the learnable entity queries. Formally, we define the entity detector as a mapping function $F_e$ from initial entity query $Q_e \in \mathbb{R}^{N_e \times d}$ and the feature map $Z$ to entity predicted localization $B_e \in \mathbb{R}^{N_e \times 4}$ and class scores $P_e \in \mathbb{R}^{N_e \times (c+1)}$, along with its associated feature representation $H_e \in \mathbb{R}^{N_e \times d}$ as follows,

$$B_e, P_e, H_e = F_{dec}(Z, Q_e)$$

where $B_e = \{b_1, \cdots, b_{N_e}\}, b = (x_c, y_c, w_b, h_b), x_c, y_c$ are the normalized center coordinates of the instance, $w_b, h_b$ are the normalized width and height of each entity box.

4.2. Predicate Node Generator

Our predicate node generator aims to decode the entity-aware predicate representation by incorporating relevant entity proposal information into each predicate node. This design enables us to encode potential associations between each predicate and its subject/object entities, which can facilitate predicting the graph edges and lead to efficient generation of the visual relation triplets.

As shown in Fig. 3, the predicate node generator is composed of three components: (1) a predicate query initialization module for initializing the entity-aware predicate query
A simple strategy for initializing the predicate proposal is to which has a similar structure to the shared encoder, employs (in Sec. 4.2.3).

A graph assembling mechanism is developed to construct the final bipartite scene graph. The resulting representations are less expressive in capturing visual relationships but also

R

decoder for decoding a set of entity-aware predicate nodes.

Z

specific feature is denoted as CNN connected feed-forward network. The resulting predicate-specific image features. The predicate encoder, introduce a lightweight extra predicate encoder to extract a form of multi-layer multi-head self-attention via the skip-

Positional Encoding

Figure 2. An illustration of overall pipeline of our SGTR model. Left) We use CNN backbone together with transformer encoder for image feature extraction. The entity and predicate node generators are introduced to produce the entity node and entity-aware predicate node. Right) The predicate node generator consists of three parts: a) predicate query initialization, b) a predicate encoder, and c) a structural predicate decoder, which is designed to generate entity-aware predicate nodes.

( in Sec. 4.2.2), (2) a predicate encoder for image feature extraction (in Sec. 4.2.1), and (3) a structural predicate decoder for decoding a set of entity-aware predicate nodes. ( in Sec. 4.2.3).

4.2.1 Predicate Node Encoder

Based on the features provided by the shared encoder, we introduce a lightweight extra predicate encoder to extract predicate-specific image features. The predicate encoder, which has a similar structure to the shared encoder, employs a form of multi-layer multi-head self-attention via the skip-connected feed-forward network. The resulting predicate-specific feature is denoted as Zp ∈ Rn×h×d.

4.2.2 Predicate Query Initialization

A simple strategy for initializing the predicate proposal is to adopt a fixed set of holistic learnable queries as the same in the entity detector. However, such a holistic predicate query design ignores not only the compositional property of the visual relationships but also entity candidate information. The resulting representations are less expressive in capturing the structured and diverse visual relationships.

To cope with this challenge, we develop a compositional representation for learning the entity-aware predicate nodes by decoupling the predicate query Qp = {Qs, Qo, Qp} ∈ Rn×3d. It has three parts: subject/object entity indicator 2 Qs, Qo ∈ Rn×d and predicate representation Qp ∈ Rn×d. We use the decoupled queries Qs, Qo as entity indicator to explicitly modeling the predicate-entity association.

2The subscripts 's', 'o' stand for the subject and object entity, respectively.

We dynamically generate this query with the entity-aware and scene-adaptive predicate representation Qs, from the initial query initial predicate queries Qinit ∈ Rn×d and entities representation B, H. Inspired by the previous work [49], we build the geometric-aware entity representation as to the key and value as follows: Kinit = Vinit = (H + Ge) ∈ Rn×d, Ge = ReLU(B, Wg) ∈ Rn×d, where Ge is the learnable geometric embedding of each entity query, Wg ∈ R4×d is the transformation parameters from bounding box location to embedding space. To generate the entity-aware predicate queries, a multi-head cross-attention is conducted between the initial predicate queries Qinit ∈ Rn×d and Kinit. We use A(q, k, v) = FFN(MHA(q, k, v)) to denote the multi-head attention operation in the following sections for clarity. Thus we have Qp = A(Qinit, Kinit, Vinit)W ∈ Rn×3d and We ∈ Rdx3d. Finally, we split the Qp into three decoupled queries Qs, Qo, Qp. To this end, we obtain the structural query which incorporates the entity information into the predicate query explicitly.

4.2.3 Structural Predicate Node Decoder

To leverage the compositional property, we develop a structural predicate node decoder to decode each component of the entity-aware predicate query Qp in parallel. Our structural decoder consists of three modules: a) predicate sub-decoder; b) entity indicator sub-decoders; c) predicate indicator fusion. These two types of decoders take the encoder feature map Zp and the entity instance feature from entity generator H, respectively. Based on the updated predicate and entity indicators, the predicate-indicator fusion is adopted to refine the association within the predicate node.
query.

We adopt the standard transformer decoder structure in this work, where each decoder layer consists of a multi-head self-attention layer, a multi-head cross-attention layer, and FFN layers. For notation clarity, we focus on the single decoder layer and omit layer number $l$ while introducing the decoder for this section. The detailed notation of the self-attention operation is also omitted. The iterative form will be discussed in the predicate-indicator fusion paragraph.

**Predicate Sub-decoder.** The predicate sub-decoder is designed to decode the predicate representation from the image feature map $Z^p$, which utilizes the spatial context of the image for extracting predicate representation. We implement this decoding process using the cross-attention mechanism: $\hat{Q}_p = A(q = Q_p, k = Z^p, v = Z^p)$. $\hat{Q}_p$ is updated predicate representation.

**Entity Indicator Sub-Decoder** The entity indicator sub-decoders explicitly learn the representation of which entity associates with the predicate. Instead of relying on image features, we leverage more accurate entity information in the given scene to conduct cross-attention between entity indicators of each predicate. $Q_{is}, Q_{io},$ and entity feature $H_e$ from the entity node generator, which explicitly modeling the association between entity and predicate. We denote the updated representation of the entities indicator as $\hat{Q}_{is}, \hat{Q}_{io}$, which are generated with standard cross-attention operation:

$$\hat{Q}_{is} = A(Q_{is}, H_e, H_e), \quad \hat{Q}_{io} = A(Q_{io}, H_e, H_e)$$

(2)

**Predicate-Indicator Fusion** The predicate sub-decoder owns a multi-layer self-attention design for modeling the relationships among all the predicates. However, it is necessary to encode the context between the predicate and its entity indicator for calibrating the features of each component. We explicitly fuse the current $l$-th decoder layer outputs $\hat{Q}_p^l, \hat{Q}_{is}^l, \hat{Q}_{io}^l$ to update each component of as the query for next layer $Q_p^{l+1}, Q_{is}^{l+1}, Q_{io}^{l+1}$. Specifically, we adopt simple fully connected layers for updating the predicate by fusing entity indicators representation as Eq. 3:

$$Q_p^{l+1} = \left(\hat{Q}_p^l + (\hat{Q}_{is}^l + \hat{Q}_{io}^l) \cdot W_i\right) \cdot W_p$$

(3)

where $W_i, W_p \in \mathbb{R}^{d \times d}$ is the transformation parameters for updating. For entity indicator, we implicitly adopt the previous layer output as input: $Q_{is}^{l+1} = \hat{Q}_{is}^l, Q_{io}^{l+1} = \hat{Q}_{io}^l$.

Based on the entity-aware predicate queries, we are able to predict the geometric and semantic predictions of the predicate node and generate the location and category of its associated entity indicator.

$$\mathbf{P}_p = \text{Softmax}(Q_p \cdot W_{cls}) \in \mathbb{R}^{N_e \times (C_p + 1)}$$

(4)

$$\mathbf{B}_p = \sigma(\hat{Q}_p \cdot W_{reg}) = \{(x_c^p, y_c^p, x_c^o, y_c^o)\} \in \mathbb{R}^{N_e \times 4}$$

(5)

where $\mathbf{P}_p$ is classification predictions of predicates, and $\mathbf{B}_p = \{(x_c^p, y_c^p, x_c^o, y_c^o)\}$ is the box center coordinates of its associated subject and object entities. The entity indicators are also translated as location prediction of entities $B_s, B_o \in \mathbb{R}^{N_e \times 4}$ and their classification predictions $P_s, P_o \in \mathbb{R}^{N_e \times (C_s + 1)}$, which are similar to the entity generator. Finally, each predicate decoder layer produces the location and classification prediction of each entity-aware predicate query. The predicate decoder is able to gradually improve the quality of predicate and entity association using this multi-layer structure.

**4.3 Bipartite Graph Assembling**

In the proposed SGIR, we convert the original scene graph into a bipartite graph structure which consists of $N_e$ entity nodes and $N_p$ predicate nodes, as shown in Fig. 3. The main goal of the graph assembling is to link the entity-aware predicate nodes to the proper entity node.

To achieve this, we need to obtain the adjacency matrix between the $N_e$ entity nodes and $N_p$ predicate nodes, which can be encoded into a correspondence matrix $\mathbf{M} \in \mathbb{R}^{N_e \times N_p}$. Concretely, that correspondence matrix is defined by the distance between the entity indicators of predicate nodes and the entity nodes. Taking the subject entity indicator as example, we have: $\mathbf{M}^s = d_{loc}(B_s, B_o) \cdot d_{cls}(P_s, P_o)$, where $d_{loc}(\cdot)$ and $d_{cls}(\cdot)$ are the distance function to measure the matching quality from different perspectives$^3$. The correspondence of object entity $\mathbf{M}^o \in \mathbb{R}^{N_o \times N_e}$ is obtained following the same strategy. The empirical analysis of different distance measurements will be discussed in the experiment section. Based on the correspondence matrix, we keep the top-$K$ links according to the matching score as the edge links for each predicate node:

$$\mathbf{R}^s = \mathcal{F}_{top}(\mathbf{M}^s, K) \in \mathbb{R}^{N_e \times K}$$

(6)

$$\mathbf{R}^o = \mathcal{F}_{top}(\mathbf{M}^o, K) \in \mathbb{R}^{N_o \times K}$$

(7)

where $\mathcal{F}_{top}$ is the top-$K$ index selection operation, $\mathbf{R}^s$ and $\mathbf{R}^o$ are the index matrix of entities kept for each triplet from the two relationship roles of subject and object, respectively.

$^3$e.g., cosine distance between the classification distribution, GIOU and L1 distance between the bounding box predictions, detailed illustration is presented in supplementary details.
Based on the index matrix $R^s$ and $R^o$, we are able to generate the final relationship triplets as $T = \{(b^s_i, p^s_i, b^o_i, p^o_i, m^s_i, m^o_i)\}$. The $b^s_i, b^o_i \in \mathbb{R}^{1 \times 4}$ and $p^s_i, p^o_i \in \mathbb{R}^{1 \times (G_i + 1)}$ are bounding box and classification prediction of subject and object entity respectively. $m^s_i, m^o_i \in \mathbb{R}^{1 \times (G_i + 1)}$ is classification prediction of each predicate $P_p$, and $b_p \in B_p$ is the centers of the predicate’s associated entities. To this end, the graph assembling module generates the final scene graph as the output of SGTR.

### 4.4. Learning and Inference

**Learning** To train our SGTR model, we design a multi-task loss that consists of two components, including $L_{enc}$ for entity generator and $L^{pre}$ for predicate generator. The overall loss function is formulated as:

$$L = L_{enc} + L^{pre}, \quad L^{pre} = L^{pre}_{i} + L^{pre}_{p}$$

As we adopt a DETR-like detector, the $L^{enc}$ follows a similar form with [2], detailed loss equation is reported in the supplementary material. We mainly focus on $L^{pre}$ in the remaining parts of this section.

To calculate the loss for the predicate node generator, we first obtain the matching matrix between the prediction and the ground truth by adopting the Hungarian matching algorithm [17]. We first convert the ground-truth of the visual relationships into a set of triplet representations in the similar form of $T$, denoted as $T^{gt}$. The cost of the set matching is defined as:

$$C = \lambda_p L_p + \lambda_e L_e$$

The two components of the total cost correspond to the cost of the predicate, subject, and object entity, respectively. The matching index $I^{tri}$ between the triplet prediction and the ground truth is produced by: $I^{tri} = \text{argmin}_{T,T^{gt}} \mathcal{C}$, which is used for the following loss calculation of the predicate node generator.

The two terms of $L^{pre}$, that is, $L^{pre}_{i}, L^{pre}_{p}$ are used to supervise two types of sub-decoder in predicate node generator. For the entity indicator sub-decoder, we have $L^{pre}_{i} = L_{box}^{i} + L_{cls}^{i}$, where $L_{box}^{i}$ and $L_{cls}^{i}$ are the localization loss (L1 and GIOU loss) and cross-entropy loss for entities indicator $P_p, B_s, P_s, B_o$. Similarly, for the predicate sub-decoder, we have $L^{pre}_{p} = L_{ent}^{p} + L_{cls}^{p}$. The $L^{p}_{ent}$ is the L1 loss of the location of the predicate’s associated entities $B_p$. The $L^{p}_{cls}$ is the cross entropy of the predicate category $P_p$.

**Inference** During model inference, we generate $K \cdot N_r$ visual relationship predictions after the assembling stage. We further remove the invalid self-connection edges during inference. We adopt a post-process operation to filter the self-connected triplets (subject and object entities are identical). Then, we rank the remaining predictions by the triplet score $\mathcal{S}_t$ and take the top $N$ relationship triplet as final outputs.

We have $\mathcal{S}_t = \{(s^t_i \cdot s^t_o \cdot s^t_p)\}$, where $s^t_i, s^t_o$ and $s^t_p$ are the classification probability of subject entity, object entity and predicate, respectively.

### 5. Experiments

#### 5.1. Experiments Configuration

We evaluate our methods on OpenImage V6 datasets [18] and Visual Genome [16]. We mainly adopt the data splits and evaluation metrics from the previous work [19, 42, 55]. In OpenImage benchmark, the weighted evaluation metrics (wmAP$_{phr}$, wmAP$_{rel}$, score$_{wad}$) are adopted by us for more class-balance evaluation. For Visual Genome dataset, we adopt the evaluation metric recall@K (R@K) and mean recall@K (mR@K) of SGDet, and also report the mR@100 on each long-tail category groups: head, body and tail as same as [19].

We use the ResNet-101 and DETR [2] as backbone networks and entity detector, respectively. To increase the speed of convergence, we first train the entity detector on the target dataset, before doing joint training with the predicate node generator. In our predicate node generator, we use 3 layers for predicate encoders, 6 layers of decoder for predicate and entity indicator sub-decoders, respectively, with $N_r = 150$ queries with $d = 256$ hidden dimensions. We set the $K = 40$ in training time and $K = 3$ in test time for the graph assembling module. More implementation details refer to supplementary.

#### 5.2. Ablation Study

**Model Components** As shown in Tab. 1, we ablate each module to demonstrate the effectiveness of our design on the validation set of Visual Genome.

- We find that using the holistic query for predicate rather than the proposed structural form decreases the performance by a margin of R@100 and mR@100 at 1.9 and 1.4 in line-2.
- Adopting the shared cross-attention between the image features and predicate/entity indicator instead of the structural predicate decoder leads to the sub-optimal performance as

| # | EPN | SPD | GA | mR@50 | mR@100 | R@50 | R@100 |
|---|-----|-----|----|-------|--------|------|-------|
| 1 | ✓   | ✓   | ✓  | 13.9  | 17.3   | 24.2 | 28.2  |
| 2 |   | ✓   | ✓  | 12.0  | 15.9   | 22.9 | 26.3  |
| 3 | ✓ |     | ✓  | 11.4  | 15.1   | 21.9 | 24.9  |
| 4 | ✓ |     | ✓  | 11.3  | 14.8   | 21.2 | 24.1  |
| 5 | ✓ | ✓   |   | 4.6   | 7.0    | 10.6 | 13.3  |

Table 1. Ablation study on model components. EPN: Entity-aware Predicate Node; SPD: Structural Predicate Decoder, GA: Graph Assembling.
reported in line-3
• We further remove both entity indicators and directly decode the predicate node from the image feature. The result is reported in line-4, which decreases the performance by a margin of 4.2 and 2.5 on R@100 and mR@100.
• We also investigate the graph assembling mechanism by directly adopting the prediction of entity indicators as entity nodes for relationship prediction. The poor results shown in line-5 demonstrate that the model struggles to tackle such complex multi-tasks within a single structure, while proposed entity-prediction association modeling and graph assembling reduce the difficulty of optimization.

Graph Assembling Design We further investigate the effectiveness of our graph assembling design. Specifically, we adopt the differentiable entity-predicate pair matching function proposed by recent HOI methods [3, 13], as shown in Tab. 3. Comparison experiments are conducted on the validation set of Visual Genome by using different distance functions for the assembling module. In AS-Net [3], the grouping is conducted based on the distance between entity bounding box and entity center predicted by interaction branch, which lacks the entity semantic information. The HOTR [13] introduces a cosine similarity measurement between the predicate and entity in feature space. We implement this form for calculation the distance between the entity indicator $\bar{Q}_{e}$, $\bar{Q}_{o}$ and entity nodes $H_{e}$. Compared with location-only [3] similarity and feature-based [13] similarity, our proposed assembling mechanism, taking both semantic and spatial information into the similarity measurement, is preferable. We also empirically observe that the feature-based [13] similarity design has a slower and more unstable convergence process.

Model Size To investigate the decoder layers’ number of structural predicate node decoders, we incrementally vary the number layer $L$ of predicate and entity indicator decoder.

| NPD | NED | mR@50 | mR@100 | R@50 | R@100 |
|-----|-----|-------|-------|------|-------|
| 3   | 3   | 10.6  | 13.3  | 23.4 | 27.4  |
| 6   | 6   | 13.9  | 17.3  | 24.2 | 28.2  |
| 12  | 12  | 13.7  | 17.0  | 24.0 | 28.4  |

Table 2. Ablation study on number of predicate decoder layers. NPD: number of predicate sub-decoder layers; NED: number of entity indicator sub-decoder layers;

| GA | mR@50 | mR@100 | R@50 | R@100 |
|----|-------|-------|------|-------|
| S  | 10.6  | 11.8  | 24.4 | 27.7  |
| F  | 13.3  | 16.1  | 23.7 | 27.5  |
| Ours | 13.9 | 17.3 | 24.2 | 28.2 |

Table 3. Ablation study on graph assembling. S: spatial distance between the predicate and entity-based matching function proposed by AS-Net [3]; F: feature similarity-based matching function proposed by HOTR [13].

The quantitative results are shown in Tab. 2. The results indicate that our model achieves the best performance while $L = 6$. We observe that the performance improvement is considerable when increasing the number of decoder layers from 3 to 6, and the performance will be saturated when $L = 12$.

5.3. Comparisons with State-of-the-Art Methods

We conduct experiments on OpenImage-V6 benchmark and VG dataset to demonstrate the effectiveness of our design. We compare our method with several state-of-the-art two-stage(e.g., VCTree-PCPL, VCTree-DLFE, BGNN [19], VCTree-TDE, DT2-ACBS [5]) and one-stage methods(e.g. AS-Net, HOTR, FCSGG) on Visual Genome dataset. Since our backbone is different from what they reported, we reproduced the SOTA methods BGNN and its baseline RelDN with the same ResNet-101 backbone for more fair comparisons. Furthermore, since there are only FCSGG for SGG specifically, we reproduce the result of several strong related one-stage HOI methods with similar entity-predicate pairing mechanisms (AS-Net [3], HOTR [13]) by authors code for a more comprehensive comparison.

OpenImage V6 The performance on the OpenImage V6 dataset is reported in Tab. 4. We re-implement the SOTA one-stage and two-stage methods with the same ResNet-101 backbone. Our method outperforms the two-stage SOTA method BGNN with an improvement of 2.28. Specifically, our design has a significant improvement on weighted mAP metrics of relationship detection (wmAP$_{rel}$) and phrase detection (wmAP$_{phr}$) sub-tasks of 5.83 and 7.36 respectively, which indicates that leveraging the compositional property of the visual relationship is beneficial for the SGG task.

Visual Genome As shown in Tab. 5, with the same ResNet-101 backbone, we compare our method with the two-stage method BGNN [19], and the one-stage methods HOTR [13], AS-Net [3]. It shows that our method outperforms HOTR with a significant margin of 4.9 and 3.2 on mRecall@100.

• Benefitting from the sparse proposal set, SGTR has a more balanced foreground/background proposal distribution...
| B | D | Method                  | mR@50/100 | R@50/100 | Head | Body | Tail | Time/Sec |
|---|---|-------------------------|-----------|----------|------|------|------|----------|
|  |  | FCSGG [24]              | 3.6 / 4.2 | 21.3 / 25.1 | -    | -    | -    | 0.12     |
|  |  | RelDN [19]              | 6.0 / 7.3 | 31.4 / 35.9 | -    | -    | -    | 0.65     |
|  |  | Motifs [32]             | 5.5 / 6.8 | 32.1 / 36.9 | -    | -    | -    | 1.00     |
|  |  | VCTree [32]             | 6.6 / 7.7 | 31.8 / 36.1 | -    | -    | -    | 1.69     |
|  |  | BGNN^{†} [19]           | 10.7 / 12.6 | 31.0 / 35.8 | 34.0 | 12.9 | 6.0  | 1.32     |
| X101-FPN | Faster-RCNN | VCTree-TDE [32]       | 9.3 / 11.1 | 19.4 / 23.2 | -    | -    | -    | -        |
|  |  | VCTree-PCPL^{†} [4]     | 10.8 / 12.6 | 26.6 / 30.1 | -    | -    | -    | -        |
|  |  | VCTree-DLFE [4]         | 11.8 / 13.8 | 22.7 / 26.3 | -    | -    | -    | -        |
|  |  | VCTree-EBM [29]         | 9.7 / 11.6 | 20.5 / 24.7 | -    | -    | -    | -        |
|  |  | VCTree-BPLSA [7]        | 13.5 / 15.7 | 21.7 / 25.5 | -    | -    | -    | -        |
|  |  | VCTree-DLFE [4]         | 9.3 / 11.1 | 19.4 / 23.2 | -    | -    | -    | -        |
|  |  | VCTree-EBM [29]         | 9.7 / 11.6 | 20.5 / 24.7 | -    | -    | -    | -        |
|  |  | VCTree-BPLSA [7]        | 13.5 / 15.7 | 21.7 / 25.5 | -    | -    | -    | -        |
|  |  | BGNN^{†}                | 8.6 / 10.3 | 28.2 / 33.8 | 29.1 | 12.6 | 2.2  | 1.32     |
|  |  | RelDN^{†}               | 4.4 / 5.4  | 30.3 / 34.8 | 31.3 | 2.3  | 0.0  | 0.65     |
|  |  | AS-Net^{†} [3]          | 6.12 / 7.2 | 18.7 / 21.1 | 19.6 | 7.7  | 2.7  | 0.33     |
|  |  | HOTR^{†} [13]           | 9.4 / 12.0 | 23.5 / 27.7 | 26.1 | 16.2 | 3.4  | 0.25     |
|  |  | Ours^{†}                | 12.0 / 14.6 | 25.1 / 26.6 | 27.1 | 17.2 | 6.9  | 0.35     |
|  |  | Ours                    | 12.0 / 15.2 | 24.6 / 28.4 | 28.2 | 18.6 | 7.1  | 0.35     |
|  |  | Ours^{‡}                | 15.8 / 20.1 | 20.6 / 25.0 | 21.7 | 21.6 | 17.1 | 0.35     |

Table 5. The SGDet performance on test set of Visual Genome dataset. † denotes results reproduced with the authors’ code. * denotes the bi-level resampling [19] is applied for this model. ‡ denotes that our model uses the top-1 matching in graph assembling. * denotes the special backbone HRNetW48-5S-FPN\_x24 and entities detector, CenterNet [59].

than the traditional two-stage design, where there exists a large number of negative samples due to exhausted entity pairing. Thus, when equipped with the same backbone and learning strategy as before, our method achieves competitive performance in mean recall. We also list the remaining newly proposed works, which propose various training strategies for long-tailed recognition. Our method achieves higher mR@100 performance with few overall performance drops when using the resampling strategy proposed in [19].

- We also find that the performance of our model in the head category is lower than the two-stage methods with the same backbone. The main reason is that the DETR detector performs weaker on small entities than the traditional Faster-RCNN. Since the visual genome has a large proportion of relationships involving small objects, our method performs sub-optimal in recognizing those relationships. The detailed analysis will be discussed in the supplementary.

- We also compare the efficiency with previous methods according to the inference time (seconds per image) on the NVIDIA GeForce Titan XP GPU with an inference batch size of 1, with an input size of 600 x 1000. Our design obtains comparable inference time-consuming with one-stage methods with the same backbone, which demonstrates the efficiency of our method.

- Moreover, the performance of our model with the most recent long-tailed training strategy [5, 10, 58] is reported in supplementary.

• We also compare the efficiency with previous methods according to the inference time (seconds per image) on the NVIDIA GeForce Titan XP GPU with an inference batch size of 1, with an input size of 600 x 1000. Our design obtains comparable inference time-consuming with one-stage methods with the same backbone, which demonstrates the efficiency of our method.

5.4. Qualitative Results

As shown in Fig. 4, we visualize the attention weight of the predicates sub-decoder and entity sub-decoder from the validation set of the Visual Genome dataset. By comparing the heatmaps shown in Fig. 4 (a) and Fig. 4 (b), For the same triplet prediction, the predicate sub-decoder puts more focus on contextual representation around the entities of triplets. Entity indicator sub-decoders focus on relationship-based entity regions. Thus, our design allows the model to learn compositional information simultaneously and explicitly, improving prediction accuracy. More visualization results are reported in the supplementary (e.g. analysis of graph assembling, comparison between two-stage methods).
6. Conclusions

In this work, we propose a novel end-to-end CNN-Transformer-based scene graph generating approach (SGTR). In comparison to the prior approaches, our major contribution consists of two components: We formulate the SGG as a bipartite graph construction with three steps: entity and predicate nodes generation and directed edges connection. We develop the entity-aware representation for modeling the predicate nodes, which is integrated with the entity indicators by the structural predicate node decoder. Finally, the scene graph is constructed by the graph assembling module in an end-to-end manner. Extensive experimental results show that our SGTR outperforms or is competitive with previous state-of-the-art methods on the Visual Genome and Openimage V6 datasets.

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Overview of Appendixes

In this supplementary material, we present implementation details and more experiments results. First, more experiments and analysis (e.g., analysis of overall recall performance, experiments using stronger long-tail learning strategy, and extra qualitative results) are described in Sec. A. We provide the implementation details in Sec. B. Moreover, we also present the details of the graph assembling mechanism and loss function in Sec. C and Sec. D.

In this supplementary material, we present implementation details and more experimental results. First, more experiments and analysis (e.g., analysis of overall recall performance, experiments using stronger long-tail learning strategies, and extra qualitative results) are described in Sec. A. We provide the implementation details in Sec. B. Moreover, we also present the details of the graph assembling mechanism and loss function in Sec. C and Sec. D.

A. More Experimental Results

A.1. Overall Recall Analysis

![Graph showing overall recall analysis](image)

Figure 5. Left) The statistics of entity sizes in visual relationship based on the training set of Visual Genome. Right) The performance (Recall@100) of relationship detection with respect to different entity sizes. We define an entity as "small" if the area of its box is smaller than 64 × 64 pixels.

First, we analyze why our SGTR achieves lower overall recall performance than the traditional two-stage design. One potential reason is that the SGTR uses an ResNet-101 backbone (like DETR) for entity detection rather than the Faster-RCNN with an ResNet-101 FPN backbone. According to the experimental results of DETR [2], using the ResNet-101 backbone achieves lower performance than Faster-RCNN with the ResNet-101 FPN on small objects (21.9 versus 27.2 APs on the COCO dataset).

To confirm that, we further study how small entities influence visual relationship detection. We categorize the relationship instances in the Visual Genome dataset into three disjoint sets according to their entity sizes, and plot the statistics of the sets in Fig. 5. The result shows that more than half of the relationships consist of small entities. We also compare the performance of our method (R@100) on three relationship sub-sets with the two-stage approach BGNN [19] and report the performance in Fig. 5. The BGNN with the two-stage design outperforms the SGTR on the relationships with small entities by a large margin due to the inherent limitation of DETR on small entity detection.

The issue of recognizing small objects efficiently and effectively is still under active study [25, 40, 49, 61]. With more sophisticated transformer-based detectors, the overall recall of our method can be further improved.

A.2. Experiments with Long-tail Learning Strategy

| Method     | mR@50/100 | R@50/100 | Head | Body | Tail |
|------------|-----------|----------|------|------|------|
| Ours       | 12.0 / 15.2 | 24.6 / 28.4 | 28.2 | 18.6 | 7.1  |
| Ours*      | 15.8 / 20.1 | 20.6 / 25.0 | 21.7 | 21.6 | 17.1 |
| OursDisAlign | 13.7 / 16.8 | 24.1 / 28.0 | 26.8 | 21.7 | 8.9  |
| OursACBS   | 16.5 / 19.8 | 20.8 / 23.6 | 23.4 | 21.6 | 17.5 |
| OurscRT    | 18.8 / 21.6 | 22.0 / 24.8 | 24.1 | 22.1 | 18.1 |

Table 6. The performance of SGTR by adopting the advanced long-tail learning strategy on the VG dataset. "*" denotes the bi-level sampling proposed in [19]; the "cRT" denotes the decoupled retraining strategy on predicate classifier proposed by [10]; the "DisAlign" denotes the retraining strategy for logits adjustment proposed by [58]; the "ACBS" refers to the alternative class balanced retraining strategy proposed by [5].

Long-tail data distribution is a challenging issue in the SGG. To achieve better performance on the SGG task, we further apply several recent long-tail learning strategies in our model. [5, 10, 58], and report the performance in Tab. 6. We find that there exists a trade-off between overall and mean recall in the comprehensive experimental results. The advanced learning strategies enable our model to either achieve a higher mean recall or maintain a better trade-off between overall and mean recall.
Figure 7. **Comparison of entity indicator of predicate node and entity node.** We use the different colored bounding boxes of entities to distinguish between the entity node (red) and the entity indicator (pink). The yellow arrow indicates the predicate between the entities. (best viewed in color)

Figure 8. **Qualitative comparison between our method and BGNN† in SGG.** Both methods predict many reasonable relationships which are not annotated in GT. We mark the relationships of rare semantic predicate categories retrieved by SGTR in red (best viewed in color).

**Learning**

- We adopt the retraining strategy, DisAlign [58], to adjust the predicate prediction logits via loss re-weighting with respect to the instance distribution of relationships. This method improves the performance trade-off between mR@100 and R@100 by increasing mean recall by 1.6 and achieving only a 0.4 performance drop on R@100.
- Moreover, we re-implement the alternative class-balanced retraining strategy (ACBS) [5], which achieves the SOTA on mean recall with the two-stage SGG model. The ACBS re-trains both entity and predicate classifiers using class-based sampling. This method achieves high mean recall performance while sacrificing the performance of the overall performance.
- Finally, we apply the decoupled retraining strategy [10] on the predicate classifier of SGTR. We observe that using additional balanced-sampling retraining results in 6.4 performance gain on mR@100 with a 3.6 drop on R@100. This strategy outperforms the aforementioned methods in terms of mean recall performance.

We also observe that using the re-balance idea on entity classifier does not bring too much performance benefit. To investigate this phenomenon, we report the relationship between the per-class instance frequency and the performance of entity detection in Fig. 6. Despite the fact that the distribution of entity instances obeys the long-tail distribution, SGTR’s entity detection performance is quite balanced, which means that the transformer-based detector is capable of tackling the data imbalanced scenario to some degree, and the additional re-balancing strategy is unnecessary.

**A.3. Qualitative Results**

**Visualization of Entity Indicator and Entity Node** To demonstrate the effectiveness of our proposed graph assembling mechanism, we visualize predictions of entity indica-
tors of our predicate representation and entity nodes after the graph assembling. As shown in Fig. 7, the entity indicator only provides a rough localization and classification of entities rather than precise bounding boxes. This information can be refined into more accurate entity results with graph assembling, which significantly improves the quality of the generated scene graph.

**Prediction Comparison between Different Design** We compare different method (e.g., BGNN [19]) by visualizing the relationship predictions. In Fig. 8, we mark the different relationship predictions between BGNN and SGTR with red color. It shows that SGTR retrieves more relationships of less frequent semantic categories than BGNN.

**B. Implementation Details**

We implement our method based on the PyTorch 1.8 [26] and cvpods [60]. Our training process consists of two phases: 1) entity detector pre-training and 2) SGTR joint training.

**Entity Detector Pre-training Phase:** We follow the DETR training configuration to learn the entity detector on Visual Genome and OpenImage datasets. We train the entity detector with the AdamW optimizer with a learning rate of 1e-5, a batch size of 16, and the model takes 100 epochs for convergence on 4 TITAN V GPUs. We use the same scale augmentation with DETR, resizing the input images such that the shortest side is at least 480 and at most 600 pixels, while the longest is at most 1000. The hyper-parameters of Transformer (e.g., number of attention heads, drop-out rate) are also kept the same with the DETR.

**Joint Learning Phase:** In the joint training phase, we adopt the same optimizer, learning rate, and batch size configuration as in the entity detector pre-training stage. In contrast with the two-stage SGG model, we refine the parameters of the detector in the joint learning rather than freezing the detector. We empirically observe that this refinement further improves the performance of entity detection. We train the SGTR for the Visual Genome dataset for 8,39e4 iterations without learning rate decay by using an early-stopping strategy. For the Openimage dataset, we train the model with 1.5e5 iterations, and the learning rate is decreased by 0.1x after 1e5 iterations.

We re-implement the previous two-stage methods (BGNN [19] and RelDN [57]) in our codebase by using the same configuration as the released codes. For fair comparison, we replace the ResNet-101 FPN backbone with the ResNet-101 backbone to learn the model. We also apply the one-stage HOI works (AS-Net [3] and HOTR [13]) on the SGG. We use the hyper-parameters of the models reported by the authors. All experiments are conducted by training the model until convergence.

**C. Correspondence Matrix for Assembling**

For clarity, we will use the correspondence matrix between the subject entity and predicate $M_s$ to introduce the details. The correspondence matrix is determined by the distance function, which takes the semantic outputs (e.g. bounding boxes $B$, classification $P$ of the entity detector and entity indicator of the predicate structural decoder) as input. Specifically, the distance function consists of two parts: spatial matching distance $d_{loc} \in \mathbb{R}^{N_s \times N_e}$ and category matching distance $d_{cls} \in \mathbb{R}^{N_s \times N_e}$, as shown in Eq. 10:

$$M = d_{loc}(B_s, B_e) \cdot d_{cls}(P_s, P_e)$$

Each element in the correspondence matrix $M_s$ is calculated by pairing the $N_s$ predicate predictions with $N_e$ entity predictions, as shown in the following equations:

$$M_{s,i,j} = d_{loc}(B_s(i), B_e(j)) \cdot d_{cls}(P_s(i), P_e(j))$$

where $i \in [0, N_s], j \in [0, N_e]$ for enumerating each pair between the predicate proposal and entity set.

Then we present the two components of the distance function, $d_{loc}$ and $d_{cls}$. Specifically, the $d_{loc}$ consists of the $d_{giou} \in \mathbb{R}^{N_s \times N_e}$ and $d_{center} \in \mathbb{R}^{N_s \times N_e}$, as show in Eq. 13.

$$d_{loc}(b_s, b_e) = \frac{d_{giou}(b_s, b_e)}{d_{center}(b_s, b_e)}$$

Concretely, the $d_{giou}$ is the clipped GIOU of the entity and the indicator’s bounding boxes, and $d_{center}$ is the L1 distance between the bounding boxes’ centers in Eq. 14, 15. The center points-based matching has also been adopted in HOI methods [3, 22, 57].

$$d_{giou}(b_s, b_e) = \max(\min(GIOU(b_s, b_e), 0), 1)$$

$$d_{center}(b_s, b_e) = ||[x_c, y_c]^c - [x_e, y_e]^e||_1$$

Here $[x, y]^c$ and $[x, y]^e$ are the normalized center coordinates of the bounding box in $b_s$ and $b_e$ respectively. For the $d_{cls}$, we use the cosine distance to calculate the similarity of the classification distribution between two entity predictions, as shown in following equation:

$$d_{cls}(p_s, p_e) = \frac{p_s \cdot p_e^T}{||p_s|| \cdot ||p_e||}$$

**D. Matching Cost and Loss Function**

**D.1. Triplets Matching Cost**

We use the set-matching strategy to supervise the relationship predictions $T = \{b_i, p_s^i, p_e^i, p_p, b_p\}$. To obtain
the matches, we need to calculate and minimize the matching cost \( C \in \mathbb{R}^{N_r \times N_{gt}} \) between the \( N_r \) relationship predictions and the \( N_{gt} \) GT relationships. Concretely, the matching cost \( C \) includes two parts: the predicate cost \( C_p \) and the entity cost \( C_e \), as:

\[
C = \lambda_p C_p + \lambda_e C_e
\]

(17)

where \( \lambda_p, \lambda_e \) is the coefficients of two cost terms.

The predicate cost, \( C_p(i,j) \) between the \( i \)-th predicate prediction and the \( j \)-th ground-truth relationship is computed according to the predicate classification distribution and location prediction in Eq. 18:

\[
C_p(i,j) = \exp \left(-p^g_{p,j} \cdot p^\top_{p,i}\right) + \|b_{p,i} - b^g_{p,j}\|_1
\]

(18)

where \( p^g_{p,j} \in \mathbb{R}^{1 \times c_p} \) is the \( i \)-th \( p \)-th predicate label and \( b^g_{p,j} \in \mathbb{R}^{1 \times 4} \) is the one-hot predicate label of the \( j \)-thGT relationship. Similarly, \( b_{p,i} \in \mathbb{R}^{1 \times 4} \) and \( b^g_{p,j} \in \mathbb{R}^{1 \times 4} \) are the center coordinates of the entity pair from the \( i \)-th relationship prediction and the \( j \)-th ground-truth relationship, respectively.

The entity cost \( C_e(i,j) \) between the \( i \)-th predicted relationship and \( j \)-th ground-truth relationship is given by:

\[
C_e(i,j) = \omega_{giou} \cdot \prod_{s=\{s,o\}} \exp \left(-d_{giou}(b^*_e,i, b^*_g{j})\right) + \omega_{tri} \cdot \sum_{s=\{s,o\}} \|b^*_e - b^*_g\|_1
\]

(19)

\[
+ \omega_{cls} \cdot \prod_{s=\{s,o\}} \exp \left(-p^g_{r,j} \cdot p^*_{e,i}\right)
\]

(20)

where the \( b^*_e \) and \( p^*_e \) are the \( i \)-th subject/object entity box and category distribution of relationship \( \mathcal{R} \) after graph assembling, respectively. The \( b^*_g{j}, p^g_{r,j} \) is the subject/object bounding boxes and one-hot entity category label from \( j \)-th ground truth relationships.

D.2. Loss Calculation

Our total loss \( L \) is composed of entity detector loss \( L_{ent} \) and predicate node generator loss \( L_{pre} \):

\[
L = L_{enc} + L_{pre}
\]

(22)

The entity detector loss \( L_{enc} \) is calculated independently by following the same design in DETR [2].

The loss of predicate node generator \( L_{pre} \) is determined by the prediction and ground-the relationships according to the matching index \( I^{tri} \in \mathbb{N}^{N_{gt}} \). The \( I^{tri} \) stores the index of matched predictions for each GT relationship. Specifically, the predicate node generator loss consists of entity indicator loss \( L_{ent} \) and predicate sub-decoder loss \( L_{p} \):

\[
L_{pre} = L_{ent} + L_{p}
\]

(23)

For loss of predicate sub-decoder loss \( L_{p} \), we have:

\[
L_{p} = \sum_{i}^{N_{gt}} \left(\|b_{p,1^{tri}(i)} - b^g_{p,i}\|_1 + CE(p_{p,1^{tri}(i)}, p^g_{p,i})\right)
\]

(24)

where \( b_{p,i} \) and \( p_{p,1^{tri}(i)} \) is the entity center coordinates of the GT relationship and prediction, respectively. The CE denotes the cross entropy loss between the predicate classification \( b_{p,1^{tri}(i)} \) and the GT predicate category one-hot vector \( p^g_{p,i} \).

For the entity indicator loss \( L_{ent} \):

\[
L_{ent} = \sum_{s=\{s,o\}} (L_{ent, loc} + L_{ent, cls})
\]

(25)

where \( s = \{s,o\} \) indicates the subject/object role of an entity in relationships. The indicator loss is composed of two factors, \( L_{ent, loc} \) and \( L_{ent, cls} \), for two types of semantic representation: bounding boxes \( b_s, b_o \) and classification \( p_s, p_o \).

\[
L_{ent, loc} = \sum_{i}^{N_{gt}} \left(\|b_s,1^{tri}(i) - b^g_{s,i}\|_1 + 1 - GIOUT(b_s,1^{tri}(i), b^g_{s,i})\right)
\]

(26)

\[
L_{ent, cls} = \sum_{i}^{N_{gt}} CE(p_s,1^{tri}(i), p^g_{s,i})
\]

(27)

The \( L_{ent, loc} \) is computed by the \( L1 \) distance and GloU loss between the bounding box outputs \( b_s,1^{tri}(i) \) and ground-truth entity boxes \( b^g_{s,i} \). The \( L_{ent, cls} \) is calculated from the cross entropy loss of classification prediction \( p_s,1^{tri}(i) \) according to ground-truth entities’ category \( p^g_{s,i} \).