Importance Weighted Structure Learning for Scene Graph Generation

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Abstract—Scene graph generation is a structured prediction task aiming to explicitly model objects and their relationships via constructing a visually-grounded scene graph for an input image. Currently, the message passing neural network based mean field variational Bayesian methodology is the ubiquitous solution for such a task, in which the variational inference objective is often assumed to be the classical evidence lower bound. However, the variational approximation inferred from such a loose objective generally underestimates the underlying posterior, which often leads to inferior generation performance. In this paper, we propose a novel importance weighted structure learning method aiming to approximate the underlying log-partition function with a tighter importance weighted lower bound, which is computed from multiple samples drawn from a reparameterizable Gumbel-Softmax sampler. A generic entropic mirror descent algorithm is applied to solve the resulting constrained variational inference task. The proposed method achieves the state-of-the-art performance on various popular scene graph generation benchmarks.

Index Terms—Importance weighted variational inference, message passing neural network, scene graph generation, structured prediction.

I. INTRODUCTION

A structured prediction task, scene graph generation (SGG) aims to construct a visually-grounded scene graph for an input image, in which its potential objects as well as their relevant relationships are explicitly modelled. Such fundamental scene understanding task could potentially facilitate the downstream computer vision tasks, such as image captioning [1], [2], [3] and visual question answering [4], [5], [6]. Given an input image \( x \), SGG aims to infer the optimum interpretations \( \theta^* \) by a max a posteriori (MAP) estimation \( \theta^* = \arg \max_{\theta} p_{\theta}(z|x) \), where \( \theta \) is applied to parameterize the underlying posterior \( p(z|x) \) over the entangled dependencies among the output variables, it is often computationally intractable to directly compute \( p_{\theta}(z|x) \).

To this end, current SGG models generally follow a variational Bayesian (VB) [7], [8] framework, in which the variational inference step aims to approximate \( p_{\theta}(z|x) \) with a computationally tractable variational distribution \( q(z) \), while the variational learning step tries to fit the underlying posterior \( p_{\theta}(z|x) \) for the ground-truth training samples via a cross entropy loss. To estimate the optimum \( q^*(z) \) and \( \theta^* \), one needs to alternate the above variational inference and learning steps. For tractability, in current SGG models [9], [10], [11], [12], [13], [14], [15], [16], the variational distribution \( q(z) \) is often assumed to be fully decomposed as \( q(z_1, z_2, \ldots, z_n) = \prod_{i=1}^{n} q_i(z_i) \), where \( z_i \) is the interpretation of one of the potential \( n \) object and relationship region proposals and \( q_i(z_i) \) represents the corresponding local variational approximation. The resulting VB framework is also known as the mean field variational Bayesian (MFVB) [7], [8], and the associated variational inference step is also called mean field variational inference (MFVI) [7], [8].

The above MFVI step in current SGG tasks is often formulated using message passing neural network (MPNN) models [15], [16], [17], [18], [19], which require two fundamental modules to be constructed: visual perception and visual context reasoning [20]. Such formulation combines the superior feature representation learning capability of the deep neural networks and the inference capability of the classical MFVI. As a result, the above MPNN-based MFVI methodology has become the ubiquitous solution for current SGG tasks [15], [16], [17], [18], [19]. In the above formulation, a classical evidence lower bound (ELBO) [21] is often implicitly (since the message passing optimization method does not need to explicitly maximize it) chosen as the variational inference objective.

However, the variational approximation inferred from such loose ELBO objective generally underestimates the underlying complex posterior [21], which often leads to inferior generation performance. In other words, the classical ELBO objective does not achieve a balanced bias-variance trade-off, since it generates overly simplified representations which fail to use the entire modeling capability of the network [22]. This perhaps partly explains the fact that the detection performance of the current SGG models fall short of our expectations.

To solve the above issue, in this paper, we propose a novel importance weighted structure learning (IWSL) method, which employs a tighter importance weighted lower bound [22] to replace the classical loose ELBO [21] as the variational inference objective. Such importance weighted approximation is essentially a lower bound of the underlying log-partition function [22],

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which is estimated from the multiple samples drawn from a reparameterizable Gumbel-Softmax sampler [23, 24]. Unlike the classical MPNN-based SGG models, the proposed IWSL method requires to solve a constrained variational inference step. Basically, it aims to explicitly maximize the importance weighted lower bound objective, subject to the constraint that the categorical probability approximated by a Gumbel-Softmax variational distribution resides in a probability simplex. To this end, a generic constrained optimization algorithm - entropic mirror descent [25] - is applied to infer the optimum interpretation from the input image. The proposed IWSL method achieves the state-of-the-art performance on two popular scene graph generation benchmarks: Visual Genome and Open Images V6.

This paper is organized as follows: Section II presents the related works while Section III demonstrates the proposed importance weighted structure learning methodology. The experimental results and the corresponding analysis are elaborated in Section IV. Finally, the conclusions are drawn in Section V.

II. RELATED WORKS

Current SGG models follow two main research directions: pursuing a superior feature extracting structure or implementing an unbiased relationship prediction. The former aims to improve the feature representation learning capabilities of the neural network models, while the latter focuses on overcoming the problem of bias (which mainly detects the dominant relationship categories with abundant training samples and largely ignores the informative ones with fewer training samples) in the learnt relationship prediction, caused by a long-tail data distribution.

For the first direction, [3], [11], [17], [26], [27] devise novel MPNN models while [26], [13], [15], [12], [19] embed the relevant contextual structural information into the current MPNN models. For the second direction, various debiasing methodologies have been proposed to solve the biased relationship prediction problem. For instance, dataset resampling [28], [29], [30], instance-level resampling [31], [32], bi-level data resampling [16], knowledge transfer learning [33], [34], [35] and loss reweighting based on instance frequency [36], [37] are the various remedies suggested in the literature. Unlike the above traditional debiasing methods, [38] removes the harmful bias from the good context bias based on the counterfactual causality (via calculating the Total Direct Effect with the help of a causal graph).

Most of the above SGG models [39], [27], [13], [10], [19], [16] tend to rely on a unified MPNN-based MFVB methodology. Such formulation generally employs the ELBO as the variational inference objective, in which the resulting variational approximation derived from ELBO often underestimates the underlying complex posterior [22]. In contrast, we use a tighter importance weighted lower bound as the variational inference objective in the proposed IWSL method, and solve the resulting constrained variational inference task via a generic entropic mirror descent strategy, rather than the traditional message passing technique. Specifically, various samples drawn from a reparameterizable Gumbel-Softmax sampler [23], [24] are applied to compute the above importance weighted lower bound.

The above strictly tighter importance weighted lower bound is first introduced in the importance weighted autoencoder (IWAE) [22], which is a generative model with the same architecture as the classical variational autoencoder (VAE). In particular, the recognition network in IWAE relies on multiple samples to approximate the posterior, which increases the flexibility to model complex posteriors that do not fit the VAE modeling assumptions. Moreover, due to the inability to backpropagate through samples, the output categorical latent variables in SGG tasks are rarely employed in the stochastic neural networks. To this end, in this paper, instead of producing non-differentiable samples from a categorical distribution, Gumbel-Softmax sampler is utilized to draw differentiable samples from a novel Gumbel-Softmax distribution [23], [24]. Due to the applied explicit reparameterization function, it is quite easy to construct an efficient gradient estimator.

III. PROPOSED METHODOLOGY

In this section, we first present the problem formulation, followed by the proposed scoring function and the relevant Gumbel-Softmax sampler. Finally, the importance weighted structure learning and the adopted entropic mirror descent inference strategy are also discussed in the last two subsections. Fig. 1 demonstrates the overview of the proposed IWSL method.

A. Problem Formulation

As a structured prediction task, scene graph generation aims to build a visually-grounded scene graph for an input image by explicitly identifying the scene objects and their relevant relationships. In the current SGG settings, the scene graph includes a list of intertwined semantic triplet structures, in which each triplet consists of three components: a subject, a predicate and an object. Specifically, the current SGG tasks only focus on inferring the pairwise relationships, where the relationship between two interacting instances (subject and object) in an input image is termed as a predicate.

Generally, SGG task aims to infer the optimum interpretations \( z^* \) from the input image \( x \) via a MAP estimation \( z^* = \arg\max_z p_\theta(z|x) \), in which the underlying posterior \( p_\theta(z|x) \) can be computed as follows:

\[
p_\theta(z|x) = \frac{s_\theta(x, z)}{\sum_z s_\theta(x, z)} = \frac{s_\theta(x, z)}{s_\theta(x)}
\]

where \( s_\theta(x, z) \) is a scoring function of the probabilistic graphical model (e.g. conditional random field [41]) of the SGG task, which is used to measure the similarity/compatibility between the input variable \( x \) and the output variable \( z \). \( s_\theta(x) \) is the relevant partition function or normalizing constant. Due to the exponential combinatorial dependencies between the variables, \( s_\theta(x) \) is generally computationally intractable, which implies that it can only be estimated by certain approximation strategies.

To this end, a classical variational inference (VI) [7], [8] technique is generally employed to estimate the computationally intractable log-partition function \( \log s_\theta(x) \) in current SGG models. For tractability, the computationally tractable variational
distribution is often assumed to be fully decomposable, and the resulting inference technique is known as mean field variational inference (MFVI) [7], [8]. Besides the above variational inference step, one still requires another variational learning step to fit the underlying posterior with the ground-truth training samples. Such formulation is also known as mean field variational Bayesian (MFVB) [7], [8] framework, in which the optimum \(q^*(z)\) and \(\theta^*\) are obtained by alternating the above inference and learning steps. More importantly, for MFVI, the original MAP inference in SGG task can be transformed into a corresponding marginal inference task, which is not the case for other VI techniques [42].

In the current SGG modelling approaches, a classical cross-entropy loss is generally employed to solve the variational learning step, while the above MFVI step is commonly formulated using a message passing neural network (MPNN) [43], [44], [45], [46] model, in which the traditional ELBO is invariably implicitly chosen as the variational inference objective. As a result, the MPNN-based MFVB formulation has became the de facto solution for current SGG tasks. In this MPNN-based MFVB framework, two fundamental modules are required, namely, visual perception and visual context reasoning. The former aims to locate and instantiate the objects and predicates within the input image, while the latter tries to infer their consistent interpretation. Specifically, given an input image \(x\), a visual perception module aims to generate a set of object region proposals \(b_{o,i}^g \in \mathbb{R}^4, i = 1, \ldots, m\), as well as a set of predicate region proposals \(b_{p,j}^g \in \mathbb{R}^4, j = 1, \ldots, n\), where \(m\) and \(n\) represent the number of objects and predicates detected in the input image, respectively. Correspondingly, the input image \(x\) can be divided into two sets of image patches \(x_{o,i}^g\) and \(x_{p,j}^g\).

However, the variational distribution derived from the above loose ELBO objective often underestimates the underlying posterior [21], which leads to inferior generation performance. To this end, in this paper, we propose a novel importance weighted structure learning (IWSL) method, which employs an MFVI framework (with the entropic mirror descent inference method) to infer the optimum categorical probability, which is then used to update the Gumbel-Softmax sampler. The associated surrogate logit set is computed from the above optimum categorical probability, as well as the log marginal scoring set, and eventually transformed into the resulting log marginal set via the LogSumExp trick. Finally, the output scene graph is generated via the corresponding arg max operation. A cross-entropy loss is employed in the variational learning step.
B. Scoring Function

As a structured prediction task, scene graph generation can generally be formulated using a probabilistic graphical model, e.g., a conditional random field (CRF) [41]. With such probabilistic graphical models, one can model the conditional dependencies among the relevant variables by devising a non-negative scoring function \( s_\theta(x, z) \), where \( \theta \) is used to parameterize the scoring function.

Basically, \( s_\theta(x, z) \) measures the similarity or compatibility between the input image \( x \) and the output interpretations \( z \), which is often defined as follows:

\[
s_\theta(x, z) = \prod_{r \in R} f_r(x_r, z_r) \tag{2}
\]

where \( r \) is a clique within a clique set \( R \) (which is defined by the corresponding graph structure), \( f_r \) is a non-negative factor function, which models the dependencies between \( x_r \) and \( z_r \). Generally, the underlying posterior \( p_\theta(z|x) \) related to \( s_\theta(x, z) \) is often assumed to be a Gibbs distribution in the traditional VB framework [7]. Correspondingly, \( f_r \) often takes the exponential form and the log scoring function is computed as follows:

\[
\log s_\theta(x, z) = -\sum_{r \in R} \log f_r(x_r, z_r) \tag{3}
\]

where \( \psi_r \) is also known as a potential function. In current SGG models, we have two types of potential functions: the unary potential function \( \psi_u \) and the pairwise/binary potential function \( \psi_b \).

Currently, only pairwise dependencies are considered in most previous SGG models, while the higher order dependencies are largely ignored. In this paper, we aim to compute a latent global feature representation \( g^\theta \in \mathbb{R}^d \) from the global region proposal \( b^\theta \), where \( b^\theta \) is obtained by the union of all the associated object/predicate region proposals in the input image. Correspondingly, \( x^\theta \) is the relevant global image patch of \( b^\theta \), and \( z^\theta \) is its interpretation.

With the above definitions, by adding two types of pairwise potential terms \( \psi_b^u(x^\theta_i, x^\theta_j, z^\theta_i, z^\theta_j) \) and \( \psi_b^p(x^\theta_i, x^\theta_j, z^\theta_i, z^\theta_j) \), one can implicitly incorporate higher order dependencies into the log scoring function as follows:

\[
\log s_\theta(x, z) = -\sum_{i=1}^{m} \left[ \psi_b^u(x^\theta_i, z^\theta_i) + \sum_{j \in N(i)} \psi_b^p(x^\theta_i, x^\theta_j, z^\theta_i, z^\theta_j) \right] \\
+ \sum_{i \in N(i)} \psi_b^p(x^\theta_i, x^\theta_j, z^\theta_i, z^\theta_j) + \psi_b^p(x^\theta_i, x^\theta_j, z^\theta_i, z^\theta_j)
\]

where the superscripts \( o, p, g \) represent the object, the predicate and the global context, respectively. \( N(i) \) is the set of neighbouring nodes around the target \( i \). It is worth to note the latent feature representations \( y \) are implicitly embedded in the above formulation.

C. Gumbel-Softmax Sampler

In SGG tasks, the output variables \( z \) are generally assumed as categorical variables, which are rarely applied in stochastic neural networks due to the inability to compute and backpropagate the gradients of the associated discrete distributions [23], [24]. To this end, instead of generating non-differentiable samples from a categorical distribution, a Gumbel-Softmax sampler [23], [24] is employed to produce differentiable samples drawn from a novel Gumbel-Softmax distribution. Such sampler is generally reparameterizable, in which an efficient gradient estimator can be easily implemented.

Suppose \( z \) be the interpretation of a potential region proposal. It can be modelled as a categorical variable with the class probabilities \( \pi^1, \ldots, \pi^v \) (where \( v \) is the number of hypotheses for \( z \), and the output categorical variables in SGG are encoded as \( v \)-dimensional one-hot vectors located on the corners of the \((v-1)\)-dimensional simplex, \( \Delta^{v-1} \). The reparameterization function \( g_\pi \) in Gumbel-Softmax sampler is defined as follows:

\[
g_\pi(\sigma) = z \tag{5}
\]

where \( \sigma \) represents a \( v \)-dimensional Gumbel noise, \( z \in \Delta^{v-1} \) is the output \( v \)-dimensional sample vector and its \( i \)-th element \( z^i \) is computed as follows:

\[
z^i = \frac{\exp((\log(\pi^i) + \sigma^i)/\tau)}{\sum_{j=1}^{v} \exp((\log(\pi^j) + \sigma^j)/\tau)}, \text{ for } i = 1, \ldots, v \tag{6}
\]

where \( \tau \) is the softmax temperature. The samples drawn from the Gumbel-Softmax sampler become one-hot vectors when annealing the softmax temperature \( \tau \) to zero. In reality, \( \tau \) is often annealed to a relatively low temperature instead of zero.

D. Importance Weighted Structure Learning

In the traditional VB framework, ELBO is generally employed as the variational inference objective and the resulting maximization of ELBO is used to approximate the computationally intractable log-partition function [21]. Given a scoring function \( s_\theta(x, z) \) and a computationally tractable variational distribution \( q(z) \), one can easily derive the following:

\[
\log s_\theta(x) = \mathbb{E}_{q(z)}[\log s_\theta(x, z)/q(z)] + \mathbb{E}_{q(z)}[\log q(z)/p_\theta(z|x)] \tag{7}
\]

where, on the right-hand side of the equation, the first term is the so-called ELBO and the second term is the Kullback–Leibler (KL) divergence between the variational distribution \( q(z) \) and the underlying posterior \( p_\theta(z|x) \). Clearly, ELBO is lower bound of \( \log s_\theta(x) \) since the KL divergence term is non-negative. However, such loose ELBO objective often leads to overly simplified model, which may not capture the complicated multi-modal structure of the underlying posterior [22].

To this end, a tighter lower bound \( L_s \) based on \( s \)-sample importance weighting [22] is employed to replace the classical ELBO in this paper. Such lower bound is also known as
importance weighted lower bound, which is defined as follows:

\[
\mathcal{L}_s = \mathbb{E}_{z_1, \ldots, z_s \sim q(z)} \left[ \log \frac{1}{s} \sum_{i=1}^{s} s \theta(x, z_i) - q(z_i) \right] \leq \log \theta(x) \tag{8}
\]

where \(s\) represents the number of samples, in which each \(z_i\) is an i.i.d. random sample drawn from the variational distribution \(q(z_i) = \frac{1}{N} \sum_{i=1}^{N} \delta(z_i)\) is also known as the importance weight, and \(\mathcal{L}_s\) is the importance weighted lower bound of \(\log \theta(x)\) when \(s\) is a relatively small value. Essentially, \(\mathcal{L}_s\) becomes an unbiased estimator of \(\log \theta(x)\) when \(s\) reaches infinity. In particular, the traditional ELBO is just a special case of the importance weighted lower bound \(\mathcal{L}_s\) (when setting \(s = 1\)). Using more samples could only improve the tightness of the bound [22]. Therefore, compared with the traditional ELBO, \(\mathcal{L}_s\) is a much tighter lower bound of the log partition function \(\log \theta(x)\).

For tractability, the above variational distribution \(q(z)\) is often assumed to be fully decomposed as:

\[
q(z) = \prod_{i=1}^{m} q_i(z_i) \prod_{j=1}^{n} q_j(z_j) \tag{9}
\]

where \(q_i(z_i) \in \Delta^{v_1-1}\) and \(q_j(z_j) \in \Delta^{v_2-1}\) are local variational approximations for the objects and predicates in the output scene graph, respectively. \(v_o\) and \(v_p\) are the sizes of vocabularies for the objects and predicates, respectively. Such inference procedure is also known as mean field variational inference (MFVI) [7], [8]. In MFVI, the MAP inference formulated in the first subsection can be transformed into a corresponding marginal inference task, which may not be the case in general [42].

Given a potential region proposal \(b_i\), the corresponding log marginal posterior \(\log \theta_b(z_i|x_i)\) is computed as follows:

\[
\log \theta_b(z_i|x_i) = \log \theta_b(x_i, z_i) - \log \theta_b(x_i) \tag{10}
\]

where \(\log \theta_b(x_i)\) is the computationally intractable log partition function, and \(\log \theta_b(x_i, z_i) = \sum_{z_j \backslash z_i} \log \theta_b(x_i, z)\) (where \(z_j \backslash z_i\) represents marginalization over all nodes except the node \(i\)) is the local log marginal scoring function of \(b_i\), which is generally obtained by a variable elimination technique.

Specifically, for a potential object region proposal \(b_i\), it is computed as follows:

\[
\log \theta_b(x_i, z_i) = \psi_u(x_i, z_i) + \sum_{j \in N(i)} m_{j \rightarrow i}^{op} + \sum_{l \in N(i)} m_{l \rightarrow i}^{oo} + m_{g \rightarrow i}^{oo} \tag{11}
\]

while for a potential predicate region proposal \(b_j\), it is obtained by:

\[
\log \theta_b(x_j, z_j) = \psi_u(x_j, z_j) + \sum_{i \in N(j)} m_{j \rightarrow i}^{po} + m_{g \rightarrow j}^{po} \tag{12}
\]

In the above two equations, \(\cdot\) means an inner product, \(z_i^o\) and \(z_j^p\) are the output variables for an object and a predicate, which are generated by a Gumbel-Softmax sampler. \(G\) is a region proposal interpretation set. The feature representation \(\theta\) of \(x_i\), \(z_i\), \(z_j\), \(x_j\) is set to \(\sigma_{x_i} \times \sigma_{z_i} \times \sigma_{z_j} \times \sigma_{x_j}\) and \(\psi_u\) is reparameterizable, based on the Gumbel-Softmax distribution prescribed in Equations (11) and (12). The resulting log score is essentially the inner product of the above \(v\)-dimensional feature vector and the corresponding \(v\)-dimensional vector \(z\).

To approximate the computationally intractable \(\log \theta_b(z_i)\), in this paper, we employ the following constrained variational inference objective \(\mathcal{L}_i^s\):

\[
\log \theta_b(z_i) \overset{\Delta}{=} \max_{\pi_i} \mathcal{L}_i^s = \max_{\pi_i} \mathbb{E}_{z_{1}, \ldots, z_s \sim q_{\pi_i}(z_i)} \left[ \log \frac{1}{s} \sum_{j=1}^{s} s \theta_b(x_i, z_{ij}) - q_{\pi_i}(z_{ij}) \right] \text{ s.t. } \pi_i \in \Delta^{v-1} \tag{13}
\]

where \(\mathcal{L}_i^s\) represents the \(s\)-sample importance weighted lower bound, and the local variational approximation \(q_{\pi_i}(z_i)\) is set to a Gumbel-Softmax distribution with a categorical probability \(\pi_i \in \Delta^{v-1}\), \(z_{i1}, \ldots, z_{is}\) represent the \(s\) i.i.d samples drawn from \(q_{\pi_i}(z_i)\). Since the local Gumbel-Softmax variational distribution \(q_{\pi_i}(z_i)\) is reparameterizable, based on the Gumbel-Softmax sampler in the above subsection, \(\mathcal{L}_i^s\) can be formulated as follows:

\[
\mathcal{L}_i^s = \mathbb{E}_{\sigma_{x_i}, \ldots, \sigma_{x_s} \sim u(\sigma_i)} \left[ \log \frac{1}{s} \sum_{j=1}^{s} s \theta_b(x_i, z_{ij}) - q_{\pi_i}(z_{ij}) \right]_{z_{ij} = g_{\pi_i}(\sigma_{ij})} \tag{14}
\]
where $\sigma_{ij}$ is $v$-dimensional Gumbel noise drawn from a Gumbel distribution $u(\sigma)$, which is fed into the Gumbel-Softmax reparameterization function $g_{\pi}$, to explicitly compute the corresponding output sample $z_{ij}$.

As a result, the above expectation $\mathcal{L}_s^i$ can be approximated using a Monte Carlo estimator as follows:

$$L_s^i = \left[ \frac{1}{s} \sum_{j=1}^{s} \log \frac{q_{\pi_i}(z_{ij})}{s_{\theta_i}(x_i, z_{ij})} \right]_{z_{ij} = \text{argmax}_{\sigma_i} (\sigma_{ij}), \sigma_{ij} \sim u(\sigma)} \tag{15}$$

where the efficient computation of the log importance weight $\log q_{\pi_i}(z_{ij}) = \log s_{\theta_i}(x_i, z_{ij}) - \log p_{\theta_i}(z_{ij})$ is essential for computing the above $L_s^i$. Specifically, $\log s_{\theta_i}(x_i, z_{ij})$ can be easily computed based on (11) and (12), while the above log probability $\log q_{\pi_i}(z_{ij})$ is approximated as follows:

$$\log q_{\pi_i}(z_{ij}) \triangleq \left\| \pi_i \cdot z_{ij} \right\|_1 - \text{max}(\pi_i) - \log \left\| e^{\pi_i \cdot \text{max}(\pi_i)} \right\|_1 \tag{16}$$

where $\| . \|_1$ represents the $L_1$ norm, while $\text{max}(\pi_i)$ is the maximum value of $\pi_i$.

With the above $\mathcal{L}_s^i$, one can compute the target log marginal posterior $\log p_{\theta}(z_i|x_i)$ via a corresponding surrogate logit $\phi$:

$$\log p_{\theta}(z_i|x_i) \triangleq \phi + C \tag{17}$$

where $C$ is a relevant constant w.r.t. $x_i$ and $z_i$. According to the LogSumExp trick, one can compute $\log p_{\theta}(z_i|x_i)$ by ignoring the above constant $C$:

$$\log p_{\theta}(z_i|x_i) \triangleq \phi - \log \left\| e^{\phi} \right\|_1 \tag{18}$$

where the optimum interpretation $z_i^*$ of the input region proposal $b_i$ is computed as $z_i^* = \text{arg max}_{z_i} \log p_{\theta}(z_i|x_i)$.

Moreover, a classical cross-entropy loss is employed in the relevant variational learning step to fit the above $p_{\theta}(z|x)$ with the ground-truth training samples:

$$\theta^* = \text{arg min}_{\theta} L(\theta) = \text{arg min}_{\theta} - \left[ \frac{1}{c} \sum_{k=1}^{c} \log p_{\theta}(z_k|x_k) \right] \tag{19}$$

where $L(\theta)$ represents the variational learning objective, $c$ is the number of training images in a mini-batch, $z_k$ is the ground-truth scene graph of the input image $x_k$.

Finally, to better illustrate the proposed IWSL method, we summarize it in Algorithm 1. As a MFVB framework, the proposed IWSL method consists of two procedures: variational inference and variational learning. In particular, the variational inference procedure includes steps 3-7, while steps 8-9 represent the variational learning procedure. The temperature annealing process is accomplished in step 10. For computational efficiency, the number of samples $s$ in variational inference is often smaller than the one applied in variational learning.

Specifically, in variational inference, one first randomly initialize a categorical probability $\pi$ for a potential region proposal $b$, and then draw $s$ Gumbel noise samples $\sigma_1, \ldots, \sigma_s$ from a Gumbel noise distribution $u(\sigma)$. The output samples $z_1, \ldots, z_s$ are explicitly computed by feeding the above Gumbel noises $\sigma_1, \ldots, \sigma_s$ into a Gumbel-Softmax reparameterization function $g_{\pi}$, with $\pi = \text{arg max}(\pi_i)$. Finally, we compute the variational learning by feeding $s_{\theta}$ output samples $z_1, \ldots, z_s$ by feeding $\sigma_1, \ldots, \sigma_s$ into $g_{\pi}$.

Algorithm 1: Importance Weighted Structure Learning.

**Input** region proposal $b$, categorical probability $\pi$, number of samples $s$, Gumbel noise distribution $u(\sigma)$, Gumbel-Softmax reparameterization function $g_{\pi}$, learning rate $\alpha$, softmax temperature $\tau$, minimum temperature $T\_{min}$, temperature annealing rate $\beta$, number of iterations $T$.

**Output** $\theta$, $\tau$.

1: randomly initialize $\theta$
2: for iteration $t = 1$ to $T$ do
3: randomly initialize $\pi$ for $b$
4: draw $s$ Gumbel noise samples $\sigma_1, \ldots, \sigma_s$ from $u(\sigma)$
5: compute $s$ output samples $z_1, \ldots, z_s$ by feeding $\sigma_1, \ldots, \sigma_s$ into $g_{\pi}$
6: compute log importance weight $\log g_{\pi}(x,z)$ and approximate $\mathcal{L}_s$ via Monte Carlo estimation
7: employ EMD to solve (13) and update $\pi$
8: compute the surrogate logit $\phi$ as well as the resulting $\log p_{\theta}(z|x)$ using the updated $\pi$
9: compute $L(\theta)$ and update $\theta \leftarrow \theta - \alpha \cdot \nabla_{\theta} L(\theta)$
10: update $\tau \leftarrow \max(\tau \cdot e^{-\beta t}, T\_{min})$
11: end for

**E. Entropic Mirror Descent**

As demonstrated in (13), the variational inference procedure in the proposed method requires us to solve a constrained optimization problem. Specifically, to approximate the computationally intractable log partition function $\log q_{\pi_i}(x_i)$, one needs to maximize the $s$-sample importance weighted lower bound $\mathcal{L}_s^i$, subject to the constraint that the categorical probability $\pi_i$ resides in $(v - 1)$-simplex.

Among the existing constrained optimization algorithms, entropic mirror descent (EMD) [25] method is chosen as the applied variational inference methodology, as demonstrated in Algorithm 2. To solve the constrained optimization problem, the...
Algorithm 2: Entropic Mirror Descent.

Input \( \text{variational distribution } \pi, \text{importance weighted lower bound } L_s, \text{number of iterations } M, \text{an initial learning rate } \gamma, \text{a predefined objective } L^p, \text{a small positive value } \epsilon \)

Output optimum \( \pi^∗ \)

1: \( \text{for iteration } i = 1 \text{ to } M \text{ do} \)
2: \( \text{compute the derivative } \nabla_\pi L_s \)
3: \( \text{set learning rate } \gamma = \frac{2}{\sqrt{i}} \)
4: \( \text{end the loop if } |L_s - L^p| < \epsilon \)
5: \( \text{set } L^p = L_s \)
6: \( \text{compute } r = \gamma \cdot \nabla_\pi L_s \)
7: \( \text{compute } r = \pi \cdot e^{r - \max(r)} \)
8: \( \text{set } \pi = \frac{r}{\|r\|_1} \)
9: \( \text{end for} \)

Projected gradient descent method adds a \( \|_{L_2} \) regularization term in the weight update step, aiming to project the updated weight to a valid set defined by the constraints. As a generalized projected gradient descent method, mirror descent algorithm (EMD) [25] applies a general Bregman distance [47] to replace the above \( \|_{L_2} \) euclidean distance. Entropic mirror descent method is a special mirror descent algorithm, in which the negative entropy is used as a specific function to construct the corresponding Bregman distance. Due to the utilization of the geometry of the optimization problem, compared with the projected gradient method, it improves the convergence and has a faster convergence rate [48], [49].

IV. EXPERIMENTS

In this section, we first validate the proposed IWSL method by comparing it with various state-of-the-art SGG models on two popular benchmarks: Visual Genome [50] and Open Images V6 [51], respectively. Finally, the ablation study and the visualization results are presented and discussed in the last two subsections.

A. Visual Genome

1) Experiment Configuration: Benchmark: Visual Genome [50] is the most common scene graph generation benchmark, which consists of 108,077 images with an average of 38 objects and 22 relationships per image. In this experiment, we employ the data split protocol as in [9], in which the most frequent 150 object categories and 50 predicate classes are selected. Furthermore, we split the Visual Genome into a training set (70%) and a test set (30%). For validation, an evaluation set (5k) is randomly selected from the training set. Following [52], according to the number of objects in training split, the relevant categories are divided into three disjoint sets: \( \text{head} \) (more than 10k), \( \text{body} \) (0.5k to 10k) and \( \text{tail} \) (less than 0.5k), as demonstrated in Fig. 2.

Evaluation Metrics: Due to the reporting bias caused by the data imbalance, the mean Recall@K \( (mR@K) \) rather than the common Recall@K \( (R@K) \) is chosen as the main evaluation metric in this experiment. Compared with \( R@K \) which only concentrates on common predicates (e.g. on) with abundant training samples, \( mR@K \) focuses on the informative predicate categories (e.g. parked on) with much less training samples. Three tasks are applied to validate the proposed method, namely, Predicate Classification (PredCls), Scene Graph Classification (SGCls) and Scene Graph Detection (SGDet). Specifically, PredCls aims to predict the predicate labels, given the input image, the ground-truth bounding boxes and object labels; SCGs tries to predict the labels for objects and predicates, given the input image and the ground-truth bounding boxes; SGDet constructs the output scene graph from the input image.

Implementation Details: Following [38], ResNeXt-101-FPN [53] and Faster-RCNN [40] are chosen as the backbone and the object detector, respectively. Like previous methods, we choose the step training strategy and freeze the above visual perception models during training. As in [16], a bi-level data resampling strategy is adopted to achieve an effective trade-off between the head and the tail categories, which consists of image-level over-sampling and instance-level under-sampling. The former creates a random permutation of images, repeating each image according to its repeat factor \( t \) in each epoch, while the latter achieves under-sampling according to a drop-out probability for instances of different predicate classes in each image. Specifically, we set the repeat factor \( t = 0.07 \) and the instance drop rate \( \gamma_d = 0.7 \). The batch size \( bs \) is set to 12, and an SGD optimizer with a learning rate of \( 0.008 \times bs \) is applied in this experiment. The number of samples \( s \) is set to 50 in the variational inference step. For the variational learning step, \( s \) is set to 8000 in the SGDet task and 5000 in the PredCls and SCGs tasks.

2) Comparisons With State-of-the-Art Methods: As demonstrated in Table 1, besides achieving comparable performance
TABLE I
PERFORMANCE COMPARISON ON VISUAL GENOME DATASET

| Method   | PredCls | SGCls | SGDet | SGDet(R@100) |
|----------|---------|-------|-------|--------------|
|          | mR@50  | mR@100 | mR@50 | mR@100 | Head | Body | Tail | Mean |
| RelDN[^39] | 15.8  | 17.2  | 9.3  | 9.6  | 6.0  | 7.3  | 34.1 | 6.6  | 1.1  | 13.9 |
| Motifs[^27] | 14.6  | 15.8  | 8.0  | 8.5  | 5.5  | 6.8  | 36.1 | 7.0  | 0.0  | 14.4 |
| Motifs[^+27] | 18.5  | 20.0  | 11.1 | 11.8 | 8.2  | 9.7  | 34.2 | 8.6  | 2.1  | 15.0 |
| G-RCNN[^13] | 16.4  | 17.2  | 9.0  | 9.5  | 5.8  | 6.6  | 28.6 | 6.5  | 0.1  | 11.7 |
| MSDN[^10] | 15.9  | 17.5  | 9.3  | 9.7  | 6.1  | 7.2  | 35.1 | 5.5  | 0.0  | 13.5 |
| GPS-Net[^19] | 15.2  | 16.6  | 8.5  | 9.1  | 6.7  | 8.6  | 34.5 | 7.0  | 1.0  | 14.2 |
| GPS-Net[^+19] | 19.2  | 21.4  | 11.7 | 12.5 | 7.4  | 9.5  | 30.4 | 8.5  | 3.8  | 14.2 |
| VCTree-TDE[^38] | 25.4  | 28.7  | 12.2 | 14.0 | 9.3  | 11.1 | 24.5 | 13.9 | 0.1  | 12.8 |
| BGNN[^16] | 30.4  | 32.9  | 14.3 | 16.5 | 10.7 | 12.6 | 33.4 | 13.4 | 6.4  | 17.7 |
| IWSL     | 30.0  | 32.1  | 17.4 | 18.9 | 13.7 | 15.9 | 30.6 | 16.5 | 10.7 | 19.3 |
| IWSL+BA  | 36.9  | 39.2  | 20.7 | 22.2 | 16.1 | 18.6 | 16.2 | 25.2 | 13.0 | 18.1 |

* Note: All the above methods apply ResNet[10][10]-FPN as the backbone. + means the re-sampling strategy [31] is applied in this method, and | depicts the reproduced results with the latest code from the authors.

Fig. 3. Performance comparison (R@100 metric) of the baseline BGNN model with the proposed IWSL method and the derived IWSL+BA algorithm on the SGDet task involving all predicate categories. The predicate categories are divided into three disjoint sets: head (red area), body (green area) and tail (blue area).

with the latest BGNN algorithm in the PredCls task, the proposed IWSL method outperforms the previous state-of-the-art SGG models by a large margin in the remaining SGCls and SGDet tasks. For instance, for the most difficult yet representative SGDet task, the proposed IWSL method outperforms the state-of-the-art BGNN model by 3 and 3.3, respectively. By adopting a generic balance adjustment (BA) strategy [35] in the proposed IWSL method, the resulting IWSL+BA algorithm improves the informative predicate detection capability further.

Moreover, we also compare the SGDet performance (R@100) on the long-tail categorical groups in Table I, in which the proposed IWSL method archives the best mean performance. For the informative body and tail category groups, the proposed IWSL method outperforms the state-of-the-art SGG models by a large margin. Unlike the previous models, which focus on detecting the common predicate categories, the proposed IWSL method aims to improve the informative predicate detection capability. In other words, the proposed IWSL method is able to mitigate the intrinsic biased predicate prediction problem, caused by the long-tail data distribution exhibited in Visual Genome. Furthermore, a SGDet performance comparison (R@100) for each predicate category is also reported in Fig. 3.

For a comprehensive comparison, we also compare the SGDet performance using other popular evaluation metrics in Table II. It can be seen that the proposed IWSL method can efficiently achieve the current mean recall performance, without sacrificing too much on recall performance. In particular, it achieves the current detection performance with the speed of 0.13 s per image, and by only using a quite small number of training iterations (which is usually set to 4000). This is mainly because the applied
Fig. 4. Visualization of the qualitative results of the ground-truth (GT), the baseline BGNN model, the proposed IWSL method and the derived IWSL+BA algorithm in the SGDet task. The black, orange and green arrows represent the triplets in the head, body or tail predicate categories, and the arguably reasonable triplets detected by the models, that are not included in GT, respectively. Compared with the baseline BGNN model, the scene graphs generated by the proposed IWSL method and the derived IWSL+BA algorithm are much closer to the ground-truth scene graph GT.

TABLE II
SGDet Performance Comparison on the Visual Genome Dataset Using Popular Evaluation Metrics

| Method   | R@20 | R@50 | R@100 | zR@20 | zR@50 | zR@100 | mR@20 | mR@50 | mR@100 | Speed |
|----------|------|------|-------|-------|-------|--------|-------|-------|--------|-------|
| ReIDN\[39\]  | –    | 31.4 | 35.9  | –     | –     | –      | –     | 6.0   | 7.3    | –     |
| Motifs [27]| 25.1 | 32.1 | 36.9  | –     | 0.1   | 0.2    | 4.1   | 5.5   | 6.8    | 0.45  |
| G-RCNN\[13\] | –    | 29.7 | 32.8  | –     | –     | –      | –     | 5.8   | 6.6    | –     |
| GPS-Net\[19\] | –    | 31.1 | 35.9  | –     | –     | –      | –     | 6.7   | 8.6    | –     |
| BGNN [16]  | –    | 31.0 | 35.8  | –     | –     | –      | –     | 10.7  | 12.6   | –     |
| IWSL      | 20.2 | 27.3 | 32.0  | 0.2   | 0.5   | 0.8    | 10.6  | 13.7  | 15.9   | 0.13  |

* Note: All the above methods apply ResNet-101-FPN as the backbone. I depicts the reproduced results with the latest code from the authors. The speed unit is second per image.

generic entropic mirror descent method converges faster than the classical message passing strategy.

To further mitigate the biased predicate prediction problem, two main debiasing techniques are commonly employed in the literature, namely, logit adjustment (LA) \[56\] and data resampling \[54\], \[55\]. In Table III, we compare the SGDet performance on the Visual Genome dataset with different advanced debiasing techniques. Essentially, the debiasing strategies improve the mean recall performance at the cost of lowering the recall performance. Specifically, the DT2-ACBS \[55\] algorithm achieves the best mean recall performance at the cost of a really low recall performance. In contrast, the proposed IWSL+LA method is able to strike a balanced trade-off.

B. Open Images V6

1) Experiment Configuration: Benchmark: With its superior annotation quality, Open Images V6 \[51\], constructed by Google, is another popular scene graph generation benchmark. It includes 126,368 training images, 5322 test images and 1813 validation images. In this experiment, we adopt the same data processing protocols as in \[19\], \[39\], \[51\].

Evaluation Metrics: According to the evaluation protocols in \[19\], \[39\], \[51\], in this experiment, we choose the following evaluation metrics: the mean Recall@50 (mR@50), the regular Recall@50 (R@50), the weighted mean AP of relationships (wmAP_rel) and the weighted mean AP of phrase
TABLE III
SGDet Performance Comparison on the Visual Genome Dataset With Advanced Debiasing Techniques

| Method         | R@50 | R@100 | mR@50 | mR@100 | Speed |
|----------------|------|-------|-------|--------|-------|
| R101 DETR       | 20.6 | 25.0  | 15.8  | 20.1   | 0.35  |
| ResNeXt-101-FPN Faster-RCNN | 15.0 | 16.3  | 22.0  | 24.4   | 0.63  |
| ResNeXt-101-FPN - | 23.7 | 27.3  | 18.6  | 22.5   | 0.32  |
| ResNeXt-101-FPN Faster-RCNN | 24.0 | 27.5  | 17.1  | 20.7   | 0.13  |

* Note: B and D stand for backbone and detector, respectively. The speed unit is second per image.

TABLE IV
Performance Comparison on the Open Images V6 Dataset

| Method          | mR@50 | mR@50 | wmAP_rel | wmAP_phr | score_wtd |
|-----------------|-------|-------|----------|----------|-----------|
| ResNet [39]     | 33.98 | 73.08 | 32.16    | 33.39    | 40.84     |
| ResNet [39]     | 37.20 | 75.34 | 33.21    | 34.31    | 41.67     |
| VCC [15]        | 33.91 | 74.08 | 34.16    | 33.11    | 40.21     |
| G-RNN [13]      | 34.04 | 74.51 | 33.15    | 34.21    | 41.84     |
| Menils [27]     | 32.68 | 71.63 | 32.91    | 31.59    | 38.93     |
| VFCNN-TDE [38]  | 35.47 | 69.30 | 30.74    | 32.80    | 39.27     |
| G-PN [19]       | 35.26 | 74.41 | 32.85    | 33.98    | 41.69     |
| G-PN [19]       | 38.93 | 74.74 | 32.77    | 33.87    | 41.60     |
| BCNN [16]       | 40.45 | 74.98 | 33.51    | 34.15    | 42.06     |
| IWSL            | 42.18 | 74.68 | 33.11    | 34.33    | 41.87     |

* Note: All the above methods apply ResNet-101-FPN as the backbone. † means the resampling method [31] is applied in this method, and * depicts the results reproduced with the latest code from the authors.

Like [19], [51], [39], the weighted metric score is defined as: score_wtd = 0.2 × R@50 + 0.4 × wmAP_rel + 0.4 × wmAP_phr.

Implementation Details: Similar to the previous experiment on the Visual Genome dataset, we choose ResNet-101-FPN [53] and Faster-RCNN [40] as the backbone and the object detector, respectively. We employ the step training strategy and freeze the above visual perception models. The same bi-level data resampling strategy is adopted as in the previous experiment. We set the batch size bs = 12 and utilize an Adam optimizer with the learning rate of 0.0001. For the variational inference step, the number of samples s is set to 50. For the variational learning step, s is set to 5000.

2) Comparisons With State-of-the-Art Methods: To verify the effectiveness of the proposed IWSL method further, in this experiment, we compare it with various state-of-the-art SGG models in Table IV. Some of the methods (with †) are reproduced with the latest code from the authors, while the other methods (with *) employ an additional re-sampling strategy [31]. As demonstrated in Table IV, the proposed IWSL method outperforms the state-of-the-art SGG models on the most representative mR@50 evaluation metric by a large margin. It achieves a comparable performance with the latest BGN algorithm on the remaining evaluation metrics. This is because the main aim of the proposed IWSL method is to improve the most representative mean recall evaluation metric. Such choice would inevitably impact the recall performance, since it is biased towards the body and tail predicate categories.

TABLE V
Ablation Study of the Impact of the Number of Samples Used in the Variational Inference Step

| Number of Samples S | mR@20 | mR@50 | mR@100 |
|---------------------|-------|-------|--------|
| 1                   | 8.8   | 11.9  | 14.3   |
| 10                  | 9.9   | 13.1  | 15.5   |
| 30                  | 10.7  | 13.5  | 15.6   |
| 50                  | 10.6  | 13.7  | 15.9   |

* Note: We compare the SGDDet performance in this ablation study.

TABLE VI
Ablation Study of the Different Types of Scoring Functions (By Comparing the SGDDet Performance)

| Method | Scoring Function | mR@20 | mR@50 | mR@100 |
|--------|-----------------|-------|-------|--------|
| IWSL   | without GF      | 9.7   | 12.9  | 15.1   |
| IWSL   | with GF         | 10.6  | 13.7  | 15.9   |

* Note: GF stands for global feature.

C. Ablation Study

The importance weighted lower bound becomes an unbiased estimator, when the number of samples reaches infinity. However, it is impossible to achieve the above learning scenario in reality, due to the high computational complexity and the huge computational resources. In practice, for computational efficiency, the number of samples is often set to a relatively small number. To investigate the detection performance dependency of the proposed IWSL method on the number of samples, in this section, we choose four settings and compare their impact on the SGDDet performance, as shown in Table V. It can be seen that the SGDDet performance gradually increases with the number of samples. More importantly, compared with the ablation without using importance sampling (s = 1), the ablations with importance sampling (s = 10, 30, 50) achieve much better performance. The performance gain obtained from a larger number of samples (s > 50) is not that obvious, while its corresponding computation time increases dramatically. To pursue a balanced trade-off between the detection performance and the computational complexity, in this paper, the number of samples s used in the variational inference step is set to 50.

Furthermore, another ablation study is conducted to investigate the impact of using the global feature in the scoring function. As demonstrated in Table VI, with the global feature,
the SGDet performance achieved by the proposed IWSL method is constantly improved over all the evaluation metrics.

D. Visualization Results

To visually demonstrate the superiority of the proposed methods, in Fig. 4, we compare the visualization of the qualitative results of the ground-truth (GT), the baseline BGN model, the proposed IWSL method and the derived IWSL+BA algorithm in the SGDet task. Compared with the baseline BGN model, the proposed IWSL method is capable of detecting more informative body and tail predicates. For example, the proposed IWSL could detect an additional <laying on> predicate for the top image, and an additional <standing on> predicate for the middle image. Besides, the spatial informative predicates such as <on back of> can also be detected. Moreover, the derived IWSL+BA method further improves the above capability. For example, it could detect an additional triplet <cat in front of window> for the top image, and even the completely new, semantically meaningful triplet, <wing of airplane>, (which is not included in the ground-truth scene graph GT) for the bottom image. In summary, compared with the baseline BGN model, the scene graphs generated by the proposed IWSL method and the derived IWSL+BA algorithm are much closer to the ground-truth scene graph GT.

V. CONCLUSION

To achieve a balanced bias-variance trade-off, in this paper, we proposed a novel importance weighted structure learning (IWSL) method, which employs a tighter importance weighted lower bound to replace the classical ELBO as the variational inference objective. This is because the variational approximation derived from the ELBO often underestimates the underlying posterior. A generic entropic mirror descent algorithm, rather than the traditional message passing strategy, is employed to accomplish the resulting constrained variational inference task. We validate the proposed IWSL method on two popular scene graph generation benchmarks: Visual Genome and Open Images V6, showing it outperforms the state-of-the-art models by a large margin. In the future, we plan to extend the proposed methodology in two directions: by adapting it to the single-stage end-to-end SGG paradigm, and by enhancing it with the advanced class balanced sampling strategy.

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