Learning Visual Relation Priors for Image-Text Matching and Image Captioning with Neural Scene Graph Generators

Kuang-Huei Lee∗† Hamid Palangi† Xi Chen Houdong Hu Jianfeng Gao
Microsoft AI and Research
{kualee,hpalangi,chnxi,houhu,jfgao@microsoft.com

Abstract

Grounding language to visual relations is critical to various language-and-vision applications. In this work, we tackle two fundamental language-and-vision tasks: image-text matching and image captioning, and demonstrate that neural scene graph generators can learn effective visual relation features to facilitate grounding language to visual relations and subsequently improve the two end applications. By combining relation features with the state-of-the-art models, our experiments show significant improvement on the standard Flickr30K and MSCOCO benchmarks. Our experimental results and analysis show that relation features improve downstream models’ capability of capturing visual relations in end vision-and-language applications. We also demonstrate the importance of learning scene graph generators with visually relevant relations to the effectiveness of relation features.

1. Introduction

Vision-and-language refers to a range of tasks that bridge vision and natural language, e.g. automatically describing visual content with text. Early neural approaches to vision-and-language [22, 46, 35, 49, 10] often encode visual information with pre-trained classification networks like VGG-Net [43] and ResNet [13]. Recently, Anderson et al. [2] demonstrated that image understanding at instance-level can provide valuable prior knowledge to help language-and-vision models focus on salient objects and stuffs. This “bottom-up attention” approach (as the attention on salient objects and stuffs comes bottom-up from perceptual priors instead of textual context) has proven to be very successful across various tasks including visual question answering, caption generation, image-text matching, and text-to-image synthesis [2, 25, 27].

Despite these progress, vision-and-language remains challenging partly due to the fact that interplay between objects and stuffs is not taken into account. Unlike attributes and actions (of single objects) that may be inferred from individual object/region features, visual relations are not considered at all in many state of the art models (e.g. the top-down captioner [2] and the SCAN model for image-text matching [25]). To understand the crux of the matter, we present two examples in Fig. 1 where “a baseball player swinging a bat” and “a baseball player holding a bat” are captions of two different images. However, say image-text matching models that do not consider visual relations (“holding” and “swinging”) could score both captions equally good for both images, thus fail to align the captions to their corresponding images. The same issue can be found in models for other applications such as caption generation and visual question answering [52].

Detecting visual relations between objects and stuffs is an emerging research problem that has drawn significant attention recently [50, 54, 6, 29, 34, 40, 48, 28, 30, 36, 39, 55, 56, 58] after the release of several large-scale visual-relation-labeled datasets such as visual genome [24] and HICO [4]. In particular, researchers have developed scene
graph generators by combining region and relationship detection models. Given an image, scene graph generators predict relation triplets \(<subject, predicate, object>\). We hypothesize that training neural scene graph generators for relation detection, by necessity, would also learn embedding features with rich semantics of visual relations. Assuming this is true, potentially these embedding features could provide prior knowledge of visual relations for various language-and-vision applications. To empirically verify this hypothesis, we incorporate the scene graph generator features into state of the art models for image-text matching and image caption generation. For image-text matching, we propose a new relation-based Stacked Cross Attention Network (R-SCAN) based on SCAN [25]. R-SCAN additionally encodes visual relations and employs a gating mechanism to adaptively select region and relation features. Similarly, we extend the top-down captioner [2] with an additional attention component for relation features.

Previous scene graph generators are usually trained and evaluated on Visual Genome [24] splits that consists of the most common visual relationships (e.g. VG150 dataset [48]). However, such datasets are problematic in that they mainly contain common relations whose corresponding predicates can be easily detected using statistical counting based on the text context without the need of truly understanding visual relations [54, 31]. For example, they would predict that the relation between “a baseball player” and “a bat” is most likely “swing” rather than “throw”, because “swing” co-occurs more often with “baseball player” and “bat” in data. In another word, scene graph generators learn to take the easy way out with such datasets. In light of this, Liang et al. [31], in parallel to this work, created VrR-VG dataset which contain much richer categories of relations that cannot be easily detected based solely on statistical counting. We therefore also resort to VrR-VG for training scene graph generators.

The experimental results show that R-SCAN significantly improves bi-directional retrieval metrics compared with SCAN which is the current state of the art (e.g. it improves recall@1 of image retrieval on Flickr30K [53] by 12.2% relatively). Our relation-based top-down captioner [2] also improves CIDEr score [44] from 113.5 to 114.9 and SPICE score [1] from 20.3 to 20.9 on MSCOCO [32].

A major difference between this work and recent works [52, 14, 51] that also explore visual relations for vision-and-language is in that we do NOT use graph convolution networks (GCN). For example, Yao et al. [52] drew connections between regions with scene graph generators or proximity-based heuristics (whereas no semantic information attached to these connections) and built complicated graph convolution to implicitly capture visual relations from caption data. We argue that directly transferring knowledge of visual relations from scene graph generators instead of discarding them is a much simpler and is an equivalently effective alternative to GCN. We show that our approach is generic and applicable to metric learning (image-text matching) and sequence prediction (image caption generation) tasks.

2. Related Work

Image-Text Matching. The goal of image-text matching is learning similarity between images and text descriptions, and is usually evaluated on bi-directional image and text retrieval tasks. There has been an extensive line of work addressing image-text matching using neural networks [22, 45, 3, 47, 23, 26, 57, 10, 38, 12, 9, 7, 11, 19, 37, 16, 15, 35, 25]. In particular, R-SCAN model proposed in this paper is built on Stacked Cross Attention Network (SCAN) [25] that uses a two-stage attention mechanism to discover fine-grained correspondence between objects/stuffs and words. R-SCAN additionally encodes visual relations and employs a gating mechanism to select between region and relation features.

Image Captioning. Image captioning refers to automatic image description generation and has also been widely studied over the years [46, 11, 49, 41, 33]. Recently, Anderson et al. [2] proposed “bottom-up attention”, which refers to extracting and encoding salient regions of object and stuff bottom-up from perceptional priors that region detectors (e.g. Faster R-CNN) learn through pre-training. Bottom-up attention dramatically improve various vision-and-language tasks including image captioning [2]. We extend the top-down captioner proposed by Anderson et al. [2], adding relation features from scene graph generators along with region features from bottom-up attention to help the captioning model capture visual relations.

Scene Graph Generation. The scene graph generation task has recently attracted significant interest from the vision community [42, 8, 50, 54, 6, 29, 34, 40, 48, 28, 30, 36, 39, 55, 56, 58]. In most of these works, visual relationships are treated as edges between two objects in the scene graph, and many previously proposed approaches have used context propagation mechanism. Xu et al. [48] presented an iterative message passing framework to predict object and their relationships jointly by using two separate networks, one for edge and one for nodes. In [54], Zellers et al. designed Stacked Motif Network to capture higher order substructures in scene graphs. Stacked Motif Network encodes each relation triplet \(<subject, predicate, object>\) into an embedding vector which we use in this work as a source of visual relation prior for downstream applications.

Scene graph generators are usually trained and evaluated on Visual Genome [24] splits dominated with the most common visual relationships (e.g. VG150 dataset [48]). It is pointed out in [54, 31] that such relation data would lead scene graph generators fitting to statistical counting based
on textual context instead of truly understanding visual relations. This finding implies existing scene graph generation benchmarks are potentially not ideal.

**Bringing Visual Relations to Vision-and-Language.** Johnson et al. [18] proposed a framework using ground-truth scene graph as the query for image retrieval, but in practice it is still very difficult to construct accurate scene graphs from either text or images. Several recent works proposed GCN-based models for image captioning and visual question answering [14, 51, 52]. For example, Yao et al. [52] designed a GCN-based captioning model that employs either heuristics of spatial proximity or scene graph generators to propose possible connections between objects (whereas no semantic information attached to these connections). These approaches discard semantic labels and representations of visual relations coming from scene graph generators, and instead implicitly infer relationships from caption data. Directly utilizing scene graph generator features avoids expensive graph convolution, and we argue it is still effective in capturing visual relations. On the other hand, Liang et al. [31] show that additional visual relation prediction objective enriches region features and improves downstream image captioning and visual question answering models, but their proposal does not actually model visual relations and thus is lack of explainability.

### 3. Methods

Sec. 3.1 describes R-SCAN model which leverages visual relation features from scene graph generators to improve the image-text matching. In Sec. 3.2, we present the proposed relation-based top-down captioneer which extends the top-down captioneer from Anderson et al. [2]. Sec 3.3 explains how we pre-train scene graph generators to learn effective relation features.

#### 3.1. R-SCAN for Image-Text Matching

The architecture of R-SCAN is presented in Fig. 2. R-SCAN consists of three components: (1) a text encoder, (2) a visual encoder for features of image region and visual relation, and (3) an attention module for aligning image regions and visual relations to words and calculating image-text similarity.

**Text encoder.** The text encoder is identical to SCAN [25]. It takes as input a sequence of \( n \) words, each being represented as a one-hot vector, and maps each word into a 300-dimensional vector as

\[
x_i = W_e \hat{w}_i
\]

where \( i \in \{1, 2, \ldots, n\} \). \( W_e \) is a randomly initialized embedding matrix and \( \hat{w}_i \) is the one-hot representation of the \( i \)-th word. We then use a bi-directional GRU to generate for each word \( x_i \) a contextual embedding vector by infusing contextual information from both sides of the word in the text. The bi-directional GRU contains a forward GRU which reads the word sequence \( T \) from left to right to produce the hidden states:

\[
\overset{\rightarrow}{h}_i = GRU^\rightarrow(x_i)
\]

and similarly a backward GRU which reads \( T \) from right to left to produce the hidden states \( \overset{\leftarrow}{h}_i \). The contextual embedding vector of word \( w_i \) is obtained by averaging the forward hidden state \( \overset{\rightarrow}{h}_i \) and backward hidden state \( \overset{\leftarrow}{h}_i \):

\[
w_i = \frac{\overset{\rightarrow}{h}_i + \overset{\leftarrow}{h}_i}{2}
\]
**Visual encoder.** We use a pre-trained Faster R-CNN (identical to SCAN [25]) for extracting representations of object and stuff, denoted as \( \{ \mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k \} \) where \( k \) is number of regions detected in an image. On the other hand, we use a pre-trained Stacked Motif Networks (a scene graph generator proposed by Zellers et al. [54]) for extracting representations of visual relations <subject, predicate, object>, denoted as \( \{ \mathbf{r}_1, \mathbf{r}_2, \ldots, \mathbf{r}_m \} \) where \( m \) is number of visual relations detected in an image. \( \mathbf{v}_1 \) and \( \mathbf{r}_1 \) are subsequently transformed to \( h \)-dimensional vectors:

\[
\mathbf{v}_1 = W_v \mathbf{v}_1 + b_v \tag{4}
\]

\[
\mathbf{r}_1 = W_r \mathbf{r}_1 + b_r \tag{5}
\]

**Attention module for similarity inference.** The attention module generalizes the previously proposed SCAN t-i model [25] and softly aligns' representations of region and relation in image with words in text and infer the similarity between image and text.

Given feature vector of regions \( \mathbf{v} \), relations \( r \) and words \( w \), attention weights \( \text{att}^{rel} \) and \( \text{att}^{rgn} \) are computed as

\[
\text{att}^{rel}_{ij} = \frac{\exp(\lambda^{rel} \mathbf{s}^{rel}_{ij})}{\sum_{l=1}^m \exp(\lambda^{rel} \mathbf{s}^{rel}_{lj})} \tag{6}
\]

\[
\text{att}^{rgn}_{ij} = \frac{\exp(\lambda^{rgn} \mathbf{s}^{rgn}_{ij})}{\sum_{l=1}^k \exp(\lambda^{rgn} \mathbf{s}^{rgn}_{lj})} \tag{7}
\]

where \( \lambda^{rgn} \) and \( \lambda^{rel} \) are temperature hyper-parameters [5].

Following [25], the similarity between \( l \)-th relation and \( j \)-th word \( \mathbf{s}^{rel}_{ij} \) is computed as

\[
\mathbf{s}^{rel}_{ij} = \frac{\mathbf{r}_1^T \mathbf{w}_j}{\| \mathbf{r}_1 \| \| \mathbf{w}_j \|} \tag{8}
\]

\[
\mathbf{s}^{rgn}_{ij} = \frac{[s^{rel}_{ij}]_+}{\sqrt{\sum_{l=1}^m [s^{rel}_{ij}]_+^2}} \tag{9}
\]

where \( [x]_+ = \max(x, 0) \). The similarity between \( i \)-th region and \( j \)-th word \( \mathbf{s}^{rgn}_{ij} \) is computed as

\[
\mathbf{s}^{rgn}_{ij} = \frac{\mathbf{v}_1^T \mathbf{w}_j}{\| \mathbf{v}_1 \| \| \mathbf{w}_j \|} \tag{10}
\]

\[
\mathbf{s}^{rgn}_{ij} = \frac{s^{rgn}_{ij} + \beta_{rgn}}{\sqrt{\sum_{i=1}^k [s^{rgn}_{ij}]_+^2}} \tag{11}
\]

1 Attention on visual representations (of region or relation) w.r.t. a word in text fuses visual representations deferentially based on their relevance to the word. Such process can be considered as a soft alignment of relevant visual representations w.r.t. the word. We further introduce a "visual feature fusion gate" conditioned on the word to fuse the attended region and relation representation deferentially. This process is considered as a soft decision of whether to align region or relation w.r.t. the word.

Given attention weights \( \text{att}^{rel}_{ij} \), the attended relation representation of the image w.r.t. word \( \mathbf{w}_j \) is defined as

\[
\mathbf{a}_j^{rel} = \sum_{l=1}^m \text{att}^{rel}_{ij} \mathbf{r}_1 \tag{12}
\]

where \( \mathbf{a}_j^{rel} \) can be viewed as a summarized relation vector of the image generated using a fusing process where all the relation vectors are weighted by their attention weights of equation (6) w.r.t. \( \mathbf{w}_j \) and aggregated. \( \mathbf{a}_j^{rel} \) can also be considered representing the soft alignment between \( \mathbf{w}_j \) and the relations in the image. A special case of the soft alignment is hard alignment where there is only one relation that has a non-zero attention weight w.r.t. \( \mathbf{w}_j \).

Similarly, given attention weights \( \text{att}^{rgn}_{ij} \), the attended region representation of the image w.r.t. word \( \mathbf{w}_j \) is defined as:

\[
\mathbf{a}_j^{rgn} = \sum_{i=1}^k \text{att}^{rgn}_{ij} \mathbf{v}_1 \tag{13}
\]

We now define the attended representation of the image w.r.t. word \( \mathbf{w}_j \), denoted as \( \mathbf{a}_j \), which combines \( \mathbf{a}_j^{rel} \) and \( \mathbf{a}_j^{rgn} \). Considering that while entities/nouns often attend to objects and stuffs in an image, predicates to relations, we introduce a visual feature fusion gate that conditions on each word (type) to fuse \( \mathbf{a}_j^{rel} \) and \( \mathbf{a}_j^{rgn} \) using a mixture model:

\[
g_{vf}(\mathbf{w}_j) = \sigma(\omega_{vf}^T \mathbf{w}_j + \beta_{vf}) \tag{14}
\]

\[
\mathbf{a}_j = g_{vf}(\mathbf{w}_j) \mathbf{a}_j^{rel} + (1 - g_{vf}(\mathbf{w}_j)) \mathbf{a}_j^{rgn} \tag{15}
\]

where \( \sigma(.) \) is the sigmoid function, \( \beta_{vf} \) is bias and \( \omega_{vf} \) is a trainable projection vector with the same dimension as \( \mathbf{w}_j \). The similarity between the whole image and \( j \)-th word is computed as:

\[
R(\mathbf{a}_j, \mathbf{w}_j) = \frac{\mathbf{a}_j^T \mathbf{w}_j}{\| \mathbf{a}_j \| \| \mathbf{w}_j \|} \tag{16}
\]

Finally, we need to compute the similarity between the image and the text which consists of a set of words. In SCAN t-i [25], this is achieved by averaging or LogSum-Exp pooling the word-image similarity over all the words in the text. In R-SCAN, we assign each word an importance weight using a machine-learned importance gate, similar to the visual feature fusion gate of equation (14):

\[
g_{impt}(\mathbf{w}_j) = \sigma(\omega_{impt}^T \mathbf{w}_j + \beta_{impt}) \tag{17}
\]

The similarity between image \( V \) and text \( T \) is defined as the sum of the \( \ell_1 \) norm of the weighted word-image similarity over all the words in the text:

\[
sim(V, T) = \sum_{j=1}^n \| R(\mathbf{a}_j, \mathbf{w}_j) \|_1 \tag{18}
\]
3.3. Scene Graph Generator as Feature Learner

In our framework, relation features are extracted from neural scene graph generators. Specifically, we use Stacked Motif Network [54] as the default scene graph generator for all the experiments. Stacked Motif Networks predict graph elements by staging bounding box predictions, object classifications, and relationships such that the global context encoding of all previous stages establishes rich context for predicting subsequent stages. We take the 4096-d relation representation before applying the final projection and softmax function to represent relation triplets <subject, predicate, object> (see Sec. 4.3 of [54]).

Previous scene graph generators are usually trained and evaluated on Visual Genome [24] splits that consists of the most frequent visual relationships in Visual Genome. VG150 dataset is one of the most used benchmark [48], but this data could be problematic because it consists of most frequent 50 relation predicates and 150 object categories in Visual Genome, and these common relation predicates in VG150 can often be detected statistical counting without understanding of the images [54, 31]. As a result, although the scene graph generators developed on VG150 are often reported to perform well on the VG150 test set, the high performance does not translate to visible gains in end applications such as captioning and visual question answering, as reported in Sec. 4 and in [31]. Other similar benchmarks also suffer from the same cause.

In light of this, we resort to training Stacked Motif Networks with VrR-VG dataset [31]. VrR-VG was created by choosing a subset of Visual Genome and removing the predicates that can be easily predicted solely using language models. We carefully avoid training data contamination, excluding any images that are in MSCOCO validation and test sets (created by Karpathy et al. [19]) from our training split.

In this work, we do not draw relations between visual relation detection results and numbers on end applications, although we did find that features from [54] lead to better results than [48] whose results on VG150 is inferior. First of all, as mentioned in Sec. 2, it has been found that VG150 and similar benchmarks might not be ideal for visual relations [54, 31]. Secondly, the common mAP metric becomes problematic with datasets like VrR-VG that contain large number of object and/or relation classes. As most of the classes are in tail of distributions, they can barely be accurately predicted yet mAP takes average of per-class precision.

We would also like to clarify that using additional relation features do not mean including additional training images. We pre-train Stacked Motif Networks with VrR-VG or VG150 which are subsets of Visual Genome, whereas the baseline methods SCAN [25] and top-down captioner [2] also use Visual Genome for pre-training of bottom-up attention Faster R-CNN models.
4. Experiments

Datasets. We evaluate R-SCAN on the MSCOCO [32] and Flickr30K [53] datasets. Relation-based top-down captioner is only evaluated on MSCOCO following prior work. Flickr30K contains 31,000 images collected from Flickr with five captions each. Following the MSCOCO splits that Andrej Karpathy created [19, 10], we use 1,000 images for validation and 1,000 images for testing and the rest for training. MSCOCO contains 123,287 images, and each image is annotated with five text descriptions. In [19], the dataset is split into 82,783 training images, 5,000 validation images and 5,000 test images. We follow [10, 25] to add 30,504 images that were originally in the validation set of MSCOCO but have been left out in this split into the training set. Each image comes with 5 captions. The results are reported on full 5K test images or averaging over 5 folds of 1K test images. As is common in information retrieval, we measure performance of sentence retrieval (image query) and image retrieval (sentence query) by recall at $K$ ($r@K$) defined as the fraction of queries for which the correct item is retrieved in the closest $K$ points to the query. Also following prior work, we evaluate captioning with CIDEr score [44] which captures the syntactic correctness and SPICE score [1] which reflects whether our models generate right descriptions of scene.

Implementation details. As mentioned in Sec. 3.3, we use Stacked Motif Networks to learn relation features. Top $m$ relation features are chosen based on the triplet confidence score following [54]. We fix $m$ to 36 for the following experiments but using $m = 18$ can result in similar performance in most of the cases. Increasing $m$ to 72 results in performance degradation due to noisy information. Stacked Motif Networks pre-trained with VG150 that we used in experiments is available publicly$^2$. We train Stacked Motif Networks on VrR-VG and matches the results reported in [31] for object detector, scene graph classification and scene graph detection. The object detector for Stacked Motif Networks is selected to be Faster R-CNN with VGG backbone [43]. We have also experimented with ResNet-101 backbone [13] but did not observe difference in performance.

To detect and encode image regions, we adopt the same Faster R-CNN model from [2] as our bottom-up attention model. Top 36 regions were selected per image following the same criterion in [2, 25]. Although region features from Stacked Motif Networks can also be used, we choose the bottom-up attention model for fair comparison with SCAN [25] and top-down captioner [2].

For R-SCAN, softmax temperature $\lambda^{rel}$ and $\lambda^{gen}$ are selected on the validation set. We use Adam optimizer [20] to train the models. R-SCAN models are trained with a learning rate of 0.0005 for 10 epochs and then 0.00005 for another 10 epochs, following SCAN [25]. For captioning, we follow the training and evaluation configurations [2].

| Model                  | text-to-image | image-to-text |
|------------------------|---------------|---------------|
|                         | $r@1$         | $r@5$         | $r@10$        | $r@1$       | $r@5$         | $r@10$        |
| SCAN-t-i AVG            | 37.9          | 69.4          | 80.8          | 38.5        | 70.7          | 82.5          |
| R-SCAN-VG150            | 39.8          | 70.6          | 82.0          | 38.1        | 71.0          | 83.5          |
| R-SCAN-VrR               | 40.1          | 70.5          | 81.8          | 39.6        | 72.7          | 83.7          |

Table 1. Comparison of the cross-model retrieval results in terms of recall@K ($r@K$) on COCO-test-VrR. ‘text-to-image’ denotes image retrieval given text query. ‘image-to-text’ denotes text retrieval given image query.

4.1. The Effectiveness of Visual Relations

In the following analysis, we investigate the quality of image-text matching specifically on captions that describe visual relations and corresponding images, and compare Stacked Motif Network features pre-trained on VrR-VG and VG150. The motivation is to focus only on relation-relevant predicts to best quantify the improvements coming from relation features. Zellers et al. [54] analyzed Visual Genome and concluded that the predominant relations are geometric (above, behind, under) and possessive (has, part of, wearing). Such relations are often obvious, e.g., houses tend to have windows. VrR-VG dataset rules out relations that could be easily predicted with language prior, and clusters the remaining high frequency relations based on semantic similarity to 117 predicates [31]. By comparing VrR-VG and the original Visual Genome, those 117 relations can be mapped back to 259 relation predicates in Visual Genome, where 164 of them are identified by us as semantic relations (leaning on, walking towards, jumping on) which correspond to activities, are less frequent and less obvious (definition of semantic visual relations can be found in [54]). We found that there are 3,403 images in MSCOCO 5K test set with at least one ground truth caption that has one of the 164 semantic predicates. We use those images and randomly sample one corresponding caption that describes visual relations to construct a new COCO caption test split with visually relevant relations (COCO-test-VrR) which allows us to focus on improvements of image-text matching that involves visual relations.

In Table 1, we report the results of the baseline SCAN t-i AVG model and R-SCAN trained on MSCOCO and evaluated on COCO-test-VrR. We consider R-SCAN models with relation features pre-trained on VG150 and VrR-VG. Comparing to the SCAN t-i baseline, it can be observed that improvements on bi-directional retrieval with R-SCAN-VG150 is limited. Pre-training with VrR-VG (R-SCAN-VrR) leads to significant improvements. The hypothesis is that VG150 majorly contains relations whose corresponding predicts can be easily predicted with statistical counting and thus does not require

$^2$https://github.com/rowanz/neural-motifs
Figure 4. (a)(b) are qualitative examples of image retrieval given text queries using R-SCAN and SCAN t-i AVG on (COCO-test-VrR). We show the top-1 ranked images. In (a) it can be observed that the predicate “attached to the front of” makes the difference between R-SCAN and SCAN’s results as objects “bike” and “bus” present in both images. Similarly, in (b) both “cat” and “bench” present in image, but SCAN does not capture the relation “sitting on top of”. (c) is an example of text retrieval given image query, where SCAN incorrectly ignores “eating” and R-SCAN captures the relation “laying on”.

| Method                  | Flickr30K 1K Test Images | MSCOCO 5-fold 1K Test Images |
|-------------------------|--------------------------|-------------------------------|
|                         | text-to-image            | image-to-text                 | text-to-image            | image-to-text                 |
|                         | r@1         | r@5  | r@10 | r@1         | r@5  | r@10 | r@1         | r@5  | r@10 | r@1         | r@5  | r@10 |
| UVS [22]                | 16.8 [22]  | 40.0 | 56.5 | 23.0 [22]  | 50.7 | 62.9 | -           | -    | -    | -           | -    | -    |
| DVSA [19]               | 15.2 [19]  | 37.7 | 50.5 | 22.2 [19]  | 48.2 | 61.4 | 27.4 [19]  | 60.2 | 74.8 | 38.4 [19]  | 69.9 | 80.5 |
| HM-LSTM [37]            | 27.7 [37]  | -    | 68.8 | 38.1 [37]  | -    | 76.5 | -           | -    | -    | -           | -    | -    |
| DAN [35]                | 39.4 [35]  | 69.2 | 79.1 | 55.0 [35]  | 81.8 | 89.0 | -           | -    | -    | -           | -    | -    |
| VSE++ [10]              | 39.6 [10]  | 70.1 | 79.5 | 52.9 [10]  | 80.5 | 87.2 | 52.0 [10]  | 84.3 | 92.0 | 64.6 [10]  | 90.0 | 95.7 |
| Picturebook [21]        | -           | -    | -    | -           | -    | -    | -           | -    | -    | -           | -    | -    |
| GXN [12]                | 41.5 [12]  | 80.1 | 56.8 | -           | 89.6 | -    | 56.6 [12]  | 94.5 | 68.5 | -           | 97.9 |    |
| SCO [16]                | 41.1 [16]  | 70.5 | 80.1 | 55.5 [16]  | 82.0 | 89.3 | 56.7 [16]  | 87.5 | 94.8 | 69.9 [16]  | 92.9 | 97.5 |

SCAN:
- SCAN ensemble† [25] 48.6 77.7 85.2 67.4 90.3 95.8 58.2 80.8 94.8 72.7 94.8 98.4
- SCAN t-i AVG [25] 44.0 74.2 82.6 67.7 88.9 94.0 54.4 86.0 93.6 69.2 93.2 97.5
- SCAN i-t AVG [25] 45.8 74.4 83.0 61.8 87.5 93.7 56.4 87.0 93.9 70.9 94.5 97.8

Ours:
- R-SCAN (VrR-VG) 51.4 77.8 84.9 66.3 90.6 96.0 57.6 87.3 93.7 70.3 94.5 98.1

Table 2. The cross-modal retrieval results of R-SCAN in terms of recall@K for Flickr30K 1K test set and MSCOCO 5-fold 1K test set comparing to the baseline SCAN i-t model and other prior works. ‘text-to-image’ denotes image retrieval given text query. ‘image-to-text’ denotes text retrieval given image query. Best numbers with single model are bolded. †: The SCAN ensemble is listed here only as a reference.

4.2. Cross-Modal Retrieval Results

In Table 2, we compare R-SCAN with the baseline SCAN i-t AVG model as well as other state of the art methods on Flickr30K and MSCOCO (tested on 5-fold 1K test set). On Flickr30K, R-SCAN achieves the best single model image retrieval with recall@1 at 51.4. Comparing to SCAN i-t AVG, the relative improvement is 12.2%. The R-SCAN model even outperforms SCAN ensemble on Flickr30K. On MSCOCO 5-fold test set, R-SCAN achieves the best recall@1 at 57.6 for image retrieval (single model). Table 3 presents the results on the full MSCOCO 5K test set. R-SCAN achieves the better performance than all previous single model on most metrics of cross-modal retrieval.

It can be observed that the relative improvement on image retrieval is more significant than on text retrieval. We hypothesize that the underlying causes are the composition of Flickr30K and MSCOCO test sets and the recall@K metric definition: as opposed to image retrieval where only genuine visual understanding, while VrR-VG preserves semantically valuable relations that cannot be inferred solely from counting and therefore learning on VR-VG requires forming features that are truly embedded with visually relevant information. Based on this finding, we choose VrR-VG to train relation features for all the following experiments in this work. In Fig. 4, we present qualitative examples of image-text bi-directional retrievals using R-SCAN and the baseline SCAN i-t AVG model.
one ground truth image exists for each text query, in text retrieval each image query corresponds to five ground truth captions. Any of them could count as a correctly retrieved item. However, not all of the five captions describe visual relations in the image. For example, “a male in a blue shirt and a laptop and couch” and “a man is sitting on a couch with a dog using a laptop” are both ground truth captions for an image in MSCOCO, but the former caption can be retrieved without understanding of semantic visual relations between the man and other major objects (e.g. sitting in a couch). In MSCOCO 5K test set, 68.0% of the images correspond to at least one caption that has one of the 164 COCO-test-VrR predicates. Nonetheless, only 2.8% of the images have five of such captions, despite that predicates could be rephrased in other captions and may not fall in the range of COCO-test-VrR predicates. Another observation that supports our hypothesis is that R-SCAN actually shows similar improvements on image and text retrieval on COCO-test-VrR (as shown in Table 1) where there is only one ground truth caption per image.

### 4.3. Image Captioning on MSCOCO

Table 4 shows the image captioning results of the proposed relation-based top-down captioner and baseline top-down captioner [2] on MSCOCO. We report our results of optimizing the model for cross-entropy loss and subsequent policy gradient fine-tuning using CIDEr scores as rewards, following [2]. Compared with the top-down captioner, our cross entropy model improves CIDEr score [44] from 113.5 to 114.9 and SPICE score [1] from 20.3 to 20.9. We also present the results reported by Yao et al. (GCN-LSTM) [52] which exploits complicated GCN.

Interestingly, we found fine-tuning the original top-down captioner [2] with self-critical CIDEr optimization for 120 epochs (several days on single GPU), rather than training for less than one hour as reported in the original paper, can significantly boost CIDEr from 120.1 to 126.9 and SPICE from 21.4 to 21.8 (as on-policy reinforcement learning algorithms can take many epochs to converge). This finding suggests that the documented results of the baseline in [2] are not comparable with the models whose training takes much more epochs. For example, the performance gap between [2] and [52] might not be as large as indicated by the results reported in the two original papers, respectively. For the sake of fairness, we compare the bottom-up baseline with our models, with both being optimized for CIDEr after 30 epochs. It can be observed in Table 4 that using relation features improves CIDEr score from 125.5 to 126.1 and SPICE score from 21.6 to 21.8. The corresponding qualitative examples are presented in appendix (Fig. 9). The results show that, without GCN, our method is still effective in capturing visual relationships and improving image captioning.

### 5. Conclusion

In this study, we explored learning visual relation features for image-text matching and image caption generation with neural scene graph generators. By additionally capturing interplay between objects and stuffs, the proposed R-SCAN model achieves new state of the art result on the task of image-text cross-modal retrieval on the Flickr30K and MSCOCO benchmarks. Similarly, relation-based top-down captioner also significantly improves image captioning. The scene graph generator features are indeed effective in helping downstream models ground language to visual relations, but the crux of matters lies in pre-training scene graph generators with visually relevant relation data. We hope this work would shed lights on the connection between scene graph generators and vision-and-language, and facilitate future research.

### Acknowledgement

The authors thank Arun Sacheti and Pengchuan Zhang for their thoughtful feedback and discussions.
Appendix Overview

The supplementary material is structured as follows. Sec. A presents in details how the COCO-test-VrR test set is constructed. Sec. B presents additional qualitative examples of cross-modal retrieval between image and text to demonstrate the effectiveness of R-SCAN and the use of visual relations for image-text matching. We also present image captioning examples to qualitatively demonstrate the effectiveness of using visual relations for the task.

A. COCO-test-VrR

COCO-test-VrR is a subset of MSCOCO Karpathy 5K test split [19] introduced in Sec. 4.1 of the main paper. COCO-test-VrR focuses the evaluation of image-text matching on the captions that describe semantic visual relations [54] and the corresponding images. We describe in detail how COCO-test-VrR is constructed in this section.

Zellers et al. [54] and Liang et al. [31] have shown that a majority of the prevalent visual relations in Visual Genome [24] could be predicted without visual information. Liang et al. [31] constructed the Visually-Reliable Relationship Dataset (Vr-R-VG) which excludes the relations that could be easily predicted using language models and positional information. They clustered the remaining high-frequency relations into 117 relation predicates based on semantic similarities. By comparing visual relation triplets in Vr-R-VG and the original Visual Genome metadata, those 117 predicates can be mapped back to 259 relation predicates in the original Visual Genome.

On the other hand, Zellers et al. [54] analyzed visual relations in Visual Genome and grouped them into four categories: geometric (e.g. above, behind, under), possessive (e.g. has, part of, wearing), semantic (e.g. carrying, eating, using), and miscellaneous (e.g. for, from, made of) (see more details in Sec. 3.1 and Table 1 of [54]). The majority of the high-frequency relations in Visual Genome are geometric and possessive [54]. Many of those relations can be easily predicted without visual information [54, 31]. In contrast, semantic relations corresponding to activities are less frequent and hard to predict without visual information [54]. In the aforementioned 259 relation predicates, 164 of them are identified by us as semantic relations: adorning, appearing in, approaching, are attached to, are sitting on, attached, attached to, attached to a, balancing on, biting, boarding, bordering, built into, catching, chasing, coming out of, crashing on, decorating, displayed on, displaying, draped over, drawn on, dressed in, drinking from, driving, driving down, driving on, eating from, entering, filled with, floating in, flying on, flying a, flying above, flying in, flying over, flying through, going down, grabbing, grazing, grazing in, grazing on, gripping, hanging, hanging above, hanging from, hanging in, hanging off, hanging on, hanging on a, hanging out of, hanging over, hangs from, hangs on, hits, hitting, hung on, jumping, jumping on, laying, laying in, laying on, laying on a, leaning on, leaning over, looking at, looking at, looking in, lying in, lying inside, lying next to, lying on, lying on top of, marking, mounted on, mounted to, moving, overlooking, painted, painted on, petting, playing, playing in, playing on, playing with, playing, pointing, printed on, reflected in, reflecting in, reflecting off, reflecting on, resting on, running in, running on, securing, selling, served on, serving, served on, sits in, sits on, sitting, sitting at, sitting behind, sitting in, sitting in a, sitting inside, sitting near, sitting next to, sitting on, sitting on a, sitting with, skiing, skiing down, skiing in, skiing on, sleeping on, sniffing, stacked on, standing inside, standing near, standing with, sticking out, sticking out of, stopped at, stuck in, stuck on, supporting, supports, surfing, surfing in, surfing on, swimming in, swinging, swinging a, swings, talking on, talking to, tied around, tied to, touching, waiting at, waiting on, walking, walking across, walking along, walking behind, walking down, walking in, walking near, walking next to, walking on, walking on a, walking through, walking to, walking up, walking with, working on, wrapped around, wrapped in, written on.

COCO-test-VrR focuses on the semantic relations. We select 3,403 images from MSCOCO Karpathy 5K test split [19] where each image has at least one ground truth caption that contains at least one of the 164 semantic relation predicates. One ground truth caption that describes semantic relations is randomly sampled for each image.

B. Additional Qualitative Examples

In this section, we present additional cross-modal retrieval examples to qualitatively demonstrate the effectiveness of incorporating visual relations for image-text matching. In Figure 5, we present the examples of image retrieval given text queries using R-SCAN and the baseline SCAN t-i AVG model [25]. In Figure 6, we show the examples of text retrieval given image queries using R-SCAN and the baseline SCAN t-i AVG model. In Figure 7, we show the examples of top-5 ranked images given text queries on MSCOCO using R-SCAN. Similarly, in Figure 8, we show the examples of top-5 ranked sentences given image queries.

We also present qualitative examples of image captioning in Figure 9. The top-down captioner baseline [2] is compared with our image captioning model using visual relation features (introduced in Sec 4.4 of the main paper).
Figure 5. Additional qualitative examples of image retrieval given text queries on COCO-test-VrR using R-SCAN and SCAN t-i [25] (both trained on MSCOCO). We show the top-1 ranked images for both models. Correctly retrieved images are marked with green check marks; incorrectly retrieved images are marked with red x. In (a) R-SCAN recognizes the frisbee is held by a person. In (b) R-SCAN recognizes the predicate “decorating” between the subject “girls” and the object “cake”. In (c) R-SCAN is able to tell the cat is “hiding” on top of the refrigerator. (d) is an example where both R-SCAN and SCAN fail when image-text matching requires the ability of counting (of the number of girls). This is relevant to the model’s capability of visual reasoning [17] and remains to be addressed in future research works. In (e) R-SCAN identifies the activity “touching noses” and “standing on rocks”, whereas SCAN t-i only gets the objects (bears, noses) and stuffs (rocks) right. (f) is an example where R-SCAN considers that two birds are “touching” each other’s head, whereas SCAN t-i does not.
Figure 6. Additional qualitative examples of sentence retrieval given image queries on COCO-test-VrR using R-SCAN and SCAN t-i [25] (both trained on MSCOCO). Image query is shown on the left of each example; top-1 ranked images are shown on the right. Correctly retrieved sentences are marked with green check marks; incorrectly retrieved sentences are marked with red x. In (a) the SCAN-retrieved caption incorrectly describes that the dog is “sitting on” grass. In (b) the SCAN result does not correctly describe the relation between “woman” and “frisbee”. (c) is a tricky example where the lady and the little girl “trying to fly” a kite. (d) is an example where both R-SCAN and SCAN fail to retrieve the sentence that correctly describes emotion of the woman. This issue remains to be addressed in future research works. (e) is an example where the both R-SCAN and SCAN t-i recognize the object “giraffe” and stuff “fenced area” but SCAN fails to consider the semantic relation “sitting down in”. In (f), although the SCAN result correctly matches the objects in image and text but the relations between the motorcycle and street or traffic are not correct. The motorcycle is not moving, but the SCAN-retrieved caption describes that it is “driving in” traffic.
(a) Q: there is a man that is running in the sand on a beach

(b) Q: a boy in yellow shirt swinging a baseball bat

(c) Q: a picture of a giraffe drinking some water

(d) Q: one person rides a skateboard, while another person walks alongside, carrying a skateboard

Figure 7. Qualitative examples of image retrieval given text queries on MSCOCO using R-SCAN. Each sentence description corresponds to one ground-truth image. For each sentence query, we show the top-5 ranked images, ranking from left to right. We outline the true matches in green and false matches in red. It can be observed that in these examples visual relations play important roles in ranking. For instance, in (c) the difference between the first and second place is the visual relation “drinking” as the subject “giraffe” and the object “water” present in both images.
Figure 8. Qualitative examples of text retrieval given image queries on MSCOCO using R-SCAN. Correctly retrieved sentences are marked with green check marks; incorrectly retrieved sentences are marked with red x. Sentences are ordered by ranks in each example. These are examples where R-SCAN ranks most of the sentences that correctly describe visual relations higher than the incorrect descriptions.
Figure 9. Qualitative examples of image captioning. We compare our captioning model using visual relations (introduced in Sec 4.4 of the main paper) with the bottom-up captioning model from [2] (both trained on MSCOCO). We show examples where our model predicts correct or more precise visual relations comparing to the bottom-up captioning model. For instance, in (b) our model is able to recognize the woman is “looking at” her cell phone instead of “talking on” it.
References

[1] P. Anderson, B. Fernando, M. Johnson, and S. Gould. Spice: Semantic propositional image caption evaluation. In European Conference on Computer Vision, pages 382–398. Springer, 2016. 2, 6, 8

[2] P. Anderson, X. He, C. Buehler, D. Teney, M. Johnson, S. Gould, and L. Zhang. Bottom-up and top-down attention for image captioning and VQA. In CVPR, 2018. 1, 2, 3, 5, 6, 8, 9, 14

[3] J. L. Ba, J. R. Kiros, and G. E. Hinton. Layer normalization. arXiv preprint arXiv:1607.06450, 2016. 2

[4] Y.-W. Chao, Z. Wang, C. Buehler, D. Teney, M. Johnson, S. Gould, and L. Zhang. Bottom-up and top-down attention for image captioning and VQA. In CVPR, 2018. 1, 2, 3, 5, 6, 8, 9, 14

[5] J. K. Chorowski, D. Bahdanau, D. Serdyuk, K. Cho, and Y. Bengio. Attention-based models for speech recognition. In NIPS, 2015. 4

[6] B. Dai, Y. Zhang, and D. Lin. Detecting visual relationships with deep relational networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3076–3086, 2017. 1, 2

[7] J. Devlin, H. Cheng, H. Fang, S. Gupta, L. Deng, X. He, G. Zweig, and M. Mitchell. Language models for image captioning: The quirks and what works. In ACL, 2015. 2

[8] S. K. Divvala, A. Farhadi, and C. Guestrin. Learning everything about anything: Weakly-supervised visual concept learning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3270–3277, 2014. 2

[9] A. Eisenschtalt and L. Wolf. Linking image and text with 2-way nets. In CVPR, 2017. 2

[10] F. Faghri, D. J. Fleet, J. R. Kiros, and S. Fidler. VSE++: Improved visual-semantic embeddings. arXiv preprint arXiv:1707.05612, 2017. 1, 2, 5, 6, 7, 8

[11] H. Fang, S. Gupta, P. Landola, R. Srivastava, L. Deng, P. Dollár, J. Gao, X. He, M. Mitchell, J. Platt, et al. From captions to visual concepts and back. In CVPR, 2015. 2

[12] J. Gu, J. Cai, S. Joty, L. Niu, and G. Wang. Look, imagine and match: Improving textual-visual cross-modal retrieval with generative models. In CVPR, 2018. 2, 7, 8

[13] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016. 1, 6

[14] J. Hou, X. Wu, Y. Qi, W. Zhao, J. Luo, and Y. Jia. Relational reasoning using prior knowledge for visual captioning. arXiv preprint arXiv:1906.01290, 2019. 2, 3

[15] Y. Huang, W. Wang, and L. Wang. Instance-aware image and sentence matching with selective multimodal LSTM. In CVPR, 2017. 2

[16] Y. Huang, Q. Wu, and L. Wang. Learning semantic concepts and order for image and sentence matching. In CVPR, 2018. 2, 7, 8

[17] J. Johnson, B. Hariharan, L. van der Maaten, L. Fei-Fei, C. Lawrence Zitnick, and R. Girshick. CLEVR: A diagnostic dataset for compositional language and elementary visual reasoning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2901–2910, 2017. 10

[18] J. Johnson, R. Krishna, M. Stark, L.-J. Li, D. Shamma, M. Bernstein, and L. Fei-Fei. Image retrieval using scene graphs. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3668–3678, 2015. 3

[19] A. Karpathy and L. Fei-Fei. Deep visual-semantic alignments for generating image descriptions. In CVPR, 2015. 2, 5, 6, 7, 8, 9

[20] D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014. 6

[21] J. Kiros, W. Chan, and G. Hinton. Illustrative language understanding: Large-scale visual grounding with image search. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), volume 1, pages 922–933, 2018. 7

[22] R. Kiros, R. Salakhutdinov, and R. S. Zemel. Unifying visual-semantic embeddings with multimodal neural language models. arXiv preprint arXiv:1411.2539, 2014. 1, 2, 7

[23] B. Klein, G. Lev, G. Sadeh, and L. Wolf. Associating neural word embeddings with deep image representations using Fisher vectors. In CVPR, 2015. 2

[24] R. Krishna, Y. Zhu, O. Groth, J. Johnson, K. Hata, J. Kravitz, S. Chen, Y. Kalantidis, L.-J. Li, D. A. Shamma, et al. Visual genome: Connecting language and vision using crowdsourced dense image annotations. International Journal of Computer Vision, 123(1):32–73, 2017. 1, 2, 5, 9

[25] K.-H. Lee, X. Chen, G. Hua, H. Hu, and X. He. Stacked cross attention for image-text matching. In Proceedings of the European Conference on Computer Vision (ECCV), pages 201–216, 2018. 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11

[26] G. Lev, G. Sadeh, B. Klein, and L. Wolf. RNN fisher vectors for action recognition and image annotation. In ECCV, 2016. 2

[27] W. Li, P. Zhang, L. Zhang, Q. Huang, X. He, S. Lyu, and J. Gao. Object-driven text-to-image synthesis via adversarial training. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 12174–12182, 2019. 1

[28] Y. Li, W. Ouyang, X. Wang, and X. Tang. Vip-cnn: Visual phrase guided convolutional neural network. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 1347–1356, 2017. 1, 2

[29] Y. Li, W. Ouyang, B. Zhou, K. Wang, and X. Wang. Scene graph generation from objects, phrases and region captions. In Proceedings of the IEEE International Conference on Computer Vision, pages 1261–1270, 2017. 1, 2

[30] X. Liang, L. Lee, and E. P. Xing. Deep variation-structured visual-semantic embeddings. arXiv preprint arXiv:1411.2539, 2014. 1, 2, 7

[31] Y. Liang, Y. Bai, W. Zhang, X. Qian, L. Zhu, and T. Mei. Rethinking visual relationships for high-level image understanding. arXiv preprint arXiv:1902.00313, 2019. 2, 3, 5, 6, 9
[32] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick. Microsoft coco: Common objects in context. In European conference on computer vision, pages 740–755. Springer, 2014. 2, 6
[33] S. Liu, Z. Zhu, N. Ye, S. Guadarrama, and K. Murphy. Improved image captioning via policy gradient optimization of spider. In Proceedings of the IEEE international conference on computer vision, pages 873–881, 2017. 2
[34] C. Lu, R. Krishna, M. Bernstein, and L. Fei-Fei. Visual relationship detection with language priors. In European Conference on Computer Vision, pages 852–869. Springer, 2016. 1, 2
[35] H. Nam, J.-W. Ha, and J. Kim. Dual attention networks for multimodal reasoning and matching. In CVPR, 2017. 1, 2, 7
[36] A. Newell and J. Deng. Pixels to graphs by associative embedding. In Advances in neural information processing systems, pages 2171–2180, 2017. 1, 2
[37] Z. Niu, M. Zhou, L. Wang, X. Gao, and G. Hua. Hierarchical multimodal LSTM for dense visual-semantic embedding. In ICCV, 2017. 2, 7
[38] Y. Peng, J. Qi, and Y. Yuan. CM-GANs: Cross-modal generative adversarial networks for common representation learning. arXiv preprint arXiv:1710.05106, 2017. 2
[39] J. Peyre, J. Sivic, I. Laptev, and C. Schmid. Weakly-supervised learning of visual relations. In Proceedings of the IEEE International Conference on Computer Vision, pages 5179–5188, 2017. 1, 2
[40] B. A. Plummer, A. Mallya, C. M. Cervantes, J. Hockenmaier, and S. Lazebnik. Phrase localization and visual relationship detection with comprehensive image-language cues. In Proceedings of the IEEE International Conference on Computer Vision, pages 1928–1937, 2017. 1, 2
[41] S. J. Remnie, E. Marcheret, Y. Mroueh, J. Ross, and V. Goel. Self-critical sequence training for image captioning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 7008–7024, 2017. 2, 5
[42] M. A. Sadeghi and A. Farhadi. Recognition using visual phrases. In CVPR 2011, pages 1745–1752. IEEE, 2011. 2
[43] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014. 1, 6
[44] R. Vedantam, C. Lawrence Zitnick, and D. Parikh. Cider: Consensus-based image description evaluation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4566–4575, 2015. 2, 6, 8
[45] I. Vendrov, R. Kiros, S. Fidler, and R. Urtasun. Order-embeddings of images and language. In ICLR, 2016. 2
[46] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan. Show and tell: A neural image caption generator. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3156–3164, 2015. 1, 2
[47] L. Wang, Y. Li, and S. Lazebnik. Learning deep structure-preserving image-text embeddings. In CVPR, 2016. 2
[48] D. Xu, Y. Zhu, C. B. Choy, and L. Fei-Fei. Scene graph generation by iterative message passing. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 5410–5419, 2017. 1, 2, 5
[49] K. Xu, J. Ba, R. Kiros, K. Cho, A. Courville, R. Salakhudinov, R. Zemel, and Y. Bengio. Show, attend and tell: Neural image caption generation with visual attention. In International conference on machine learning, pages 2048–2057, 2015. 1, 2
[50] J. Yang, J. Lu, S. Lee, D. Batra, and D. Parikh. Graph r-cnn for scene graph generation. In Proceedings of the European Conference on Computer Vision (ECCV), pages 670–685, 2018. 1, 2
[51] Z. Yang, J. Yu, C. Yang, Z. Qin, and Y. Hu. Scene graph reasoning with prior visual relationship for visual question answering. arXiv preprint arXiv:1812.09681, 2018. 2, 3
[52] T. Yao, Y. Pan, Y. Li, and T. Mei. Exploring visual relationship for image captioning. In Proceedings of the European Conference on Computer Vision (ECCV), pages 684–699, 2018. 1, 2, 3, 8
[53] P. Young, A. Lai, M. Hodosh, and J. Hockenmaier. From image descriptions to visual denotations: New similarity metrics for semantic inference over event descriptions. Transactions of the Association for Computational Linguistics, 2:67–78, 2014. 2, 6
[54] R. Zellers, M. Yateskar, S. Thomson, and Y. Choi. Neural motifs: Scene graph parsing with global context. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 5831–5840, 2018. 1, 2, 4, 5, 6, 9
[55] H. Zhang, Z. Kyaw, S.-F. Chang, and T.-S. Chua. Visual translation embedding network for visual relation detection. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 5532–5540, 2017. 1, 2
[56] H. Zhang, Z. Kyaw, J. Yu, and S.-F. Chang. Ppr-fcn: weakly supervised visual relation detection via parallel pairwise r-fcn. In Proceedings of the IEEE International Conference on Computer Vision, pages 4233–4241, 2017. 1, 2
[57] Z. Zheng, L. Zheng, M. Garrett, Y. Yang, and Y.-D. Shen. Dual-path convolutional image-text embedding. arXiv preprint arXiv:1711.05535, 2017. 2
[58] B. Zhuang, L. Liu, C. Shen, and I. Reid. Towards context-aware interaction recognition for visual relationship detection. In Proceedings of the IEEE International Conference on Computer Vision, pages 589–598, 2017. 1, 2