Unsupervised Cross-lingual Image Captioning

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Abstract

Most recent image captioning works are conducted in English as the majority of image-caption datasets are in English. However, there are a large amount of non-native English speakers worldwide. Generating image captions in different languages is worth exploring. In this paper, we present a novel unsupervised method to generate image captions without using any caption corpus. Our method relies on 1) a cross-lingual auto-encoding, which learns the scene graph mapping function along with the scene graph encoders and sentence decoders on machine translation parallel corpora, and 2) an unsupervised feature mapping, which seeks to map the encoded scene graph features from image modality to sentence modality. By leveraging cross-lingual auto-encoding, cross-modal feature mapping, and adversarial learning, our method can learn an image captioner to generate captions in different languages. We verify the effectiveness of our proposed method on the Chinese image caption generation. The comparisons against several baseline methods demonstrate the effectiveness of our approach.

1 Introduction

Image captioning has attracted a lot of attention in recent years. Most of state-of-the-art image captioning models are following the popular encoder-decoder framework, which encodes the image with a convolutional neural network (CNN) (Gu et al., 2017) and decodes the image description with a recurrent neural network (RNN)-based decoder (Vinyals et al., 2015; Rennie et al., 2017; Anderson et al., 2018; Zhou et al., 2020; Chen and Jin, 2020). Those approaches are trained in a supervised manner, relying on paired image-caption datasets. Despite the impressive results achieved by those methods, most of the existing image captioning models focus on English. However, the image captioning techniques should be expanded to different languages since there are a lot of non-English speakers in our world.

Some studies have explored the image captioning in other languages by relaxing the data requirement of image-caption pairs (Gu et al., 2018; Song et al., 2019). These methods can generate captions based on paired training data in a pivot language, without relying on paired data in target language. However, using pivot language to generate captions in another language is still deficient due to the limited scale of image-caption datasets in pivot language. Recently, some works further investigate the unsupervised image captioning problem (Feng et al., 2019; Gu et al., 2019; Laina et al., 2019). However, all these methods are partially trained on the caption corpus. For example, (Gu et al., 2019) train their model based on a shuffled image-caption pairs collected from MS-COCO and (Feng et al., 2019) use the image description corpus crawled from Shutterstock. The training data used in (Laina et al., 2019) is created by sampling the unpaired images and captions from different image-caption datasets. Although their results are quite promising, their methods still highly depend on the collected image captions. This issue makes those methods hardly be applied to resource-scarce languages due to the following reasons. First, even though recent unsupervised image captioning methods argue that their model can be trained in unsupervised manner, their methods still depend on caption corpus during training. Besides, in many low-resource languages, collecting a large scale image caption corpus is difficult and expensive. To the best of our knowledge, there is yet no work that investigates the image caption generation without relying on any caption corpus.
Our approach is based on two motivations: (1) the scene graphs (Johnson et al., 2018; Wang et al., 2018) can provide rich semantic information of images and sentences, and can effectively bridge the gap between the images and sentence modalities (Yang et al., 2019); (2) we can learn a scene graph mapping across different languages by taking advantage of large-scale machine translation (MT) parallel corpus. In this paper, we propose a novel framework that can generate image captions in different languages, addressing above problems of current unsupervised image captioning task. The key concepts of our framework include a cross-lingual auto-encoding and an unsupervised feature mapping. Specifically, we first train the cross-lingual auto-encoding on the MT parallel corpus. Then, a joint training mechanism is introduced to train the scene graph encoders and sentence decoders in different languages. Finally, an unsupervised cross-modal feature mapping function is learned to align the image scene graph features from image modality to sentence modality, which is subsequently fed to sentence decoder to generate image captions in the target language.

The contributions of this paper are threefold. First, we incorporate the cross-lingual auto-encoding process into image captioning, which is able to learn the language generation across different languages. Second, we propose a hierarchical graph mapping (HGM) module which can effectively map the scene graph from one language to another language. Third, our unsupervised cross-modal feature mapping network can align the encoded image scene graph features from image modality to sentence modality, without relying on any paired data. We conduct extensive experiments to demonstrate that our unsupervised image captioning method can generate quite promising results without using any caption annotations.

2 Related Work

Supervised Image captioning. Recent works on supervised image captioning follow the popular encoder-decoder framework (Vinyals et al., 2015; You et al., 2016; Rennie et al., 2017; Anderson et al., 2018; Yang et al., 2019). Most of those state-of-the-art works focus on generating image captions in English since neural image captioning models require a large-scale of annotated image-caption pairs to achieve good performance. In Miyazaki and Shimizu, 2016, they create a Japanese image captioning dataset with CrowdSourcing and utilize a pre-trained CNN as the image encoder and LSTM network as the sentence decoder. Jaffe, 2017 learn a German captioner based on a training corpus in both English and German. To relax the requirement of human effort on caption annotation, Lan et al., 2017 propose a fluency-guided learning framework to generate Chinese captions based on pseudo captions, which are translated from English captions. Our work is related to Yang et al., 2019, which adopts the scene graph as the structured representation for the image, and connect the images and captions with scene graph encoder and RNN-based decoder. Their work is based on paired data, while our model does not rely on any caption corpus and is learned under the unsupervised manner.

Unsupervised Image Captioning. The main challenge in unsupervised image captioning is to learn the captioner without any image-caption pairs. The pioneering work in this area is the pivot-based method proposed by Gu et al., 2018. They obviate the requirements of paired image-caption data in the target language but still rely on paired image-caption data in pivot language. Feng et al., 2019 use a concept-to-sentence model to generate pseudo-image-caption pairs, and align image features and text features in an adversarial manner. The recent work in Song et al., 2019 introduce a self-supervised reward to train the pivot-based captioning model on pseudo image-caption pairs to generate both English and Chinese captions. Gu et al., 2019 propose a scene graph-based method for unpaired image captioning. They adopt the adversarial training to learn the mapping from image to text. While several attempts have been made for the unsupervised image captioning task, this problem is far from mature. More importantly, all those methods highly rely on the caption-like training corpus, i.e., the language corpus in Feng et al., 2019 is collected from Shutterstock image descriptions and Gu et al., 2019 train their model based on disordered images and captions. Such kind of issues make these works hardly be applied to different languages. In this paper, we propose an unsupervised image captioning method that can generate captions in the different language without relying on any caption corpus.
3 Methods

In this section, we first revisit the supervised image captioning in Sec. 3.1 and then describe our unsupervised cross-lingual image captioning framework in Sec. 3.2.

3.1 Supervised Image Captioning Revisited

Supervised image captioning aims to learn a captioner \( P(S | I; \theta_{S \leftarrow I}) \) which can generate an image caption \( S \) from a given image \( I \) such that \( S \) is similar to the ground-truth (GT) caption \( S^* \), where \( \theta_{S \leftarrow I} \) are the learned parameters. In the supervised setting, we have a dataset \( \{(I_i, S^*_i)\}_{i=1}^{N_I} \) with \( N_I \) image-caption pairs. For notational simplicity, we use \( I \) and \( S \) to represent image modality and sentence modality respectively, use \( I_i \) to denote the image instance, and use \( S_i^* \) to denote the corresponding image description in language \( x \). The encoder-decoder framework for supervised image captioning can be formulated as:

\[
S \leftarrow I : \hat{S}_i^x \leftarrow v_i \leftarrow I_i
\]  

(1)

where \( v_i \) denotes the encoded image feature, and \( \hat{S}_i^x \) is the predicted image caption based on \( v_i \). The most common training objective is to maximize the probability of words in the GT caption given the previous GT words and the image. In practice, we optimize this model with the cross-entropy (XE) loss.

3.2 Unsupervised Cross-lingual Image Captioning

In our setting, we aim to learn a captioner that can generate captions in different languages without using any caption corpus. We assume that we have an image dataset \( \{I_i\}_{i=1}^{N_I} \) and another paired source-target machine translation dataset \( \{(S_i^x, S_i^y)\}_{i=1}^{N_S} \), where \( N_S \) is the number of source-target sentence pairs. Our goal is to learn a mapping function to describe an image \( I \) with a caption \( \hat{S}^y \) in the target language \( y \) (Chinese) with the help of the source language \( x \) (English). Fig. 1 shows our proposed unsupervised cross-lingual image captioning framework. We decompose our method into the following submodules:

\[
S^x \leftarrow \hat{S}^x \leftarrow z^x \leftarrow G^x \leftarrow S^x
\]  

(2)

\[
S^y \leftarrow \hat{S}^y \leftarrow z^y \leftarrow G^y \leftarrow S^x
\]  

(3)

\[
S^y \leftarrow I : \hat{S}^y \leftarrow z^y \leftarrow G^y \leftarrow G^x \leftarrow I
\]  

(4)

Figure 1: Overview of our unsupervised cross-lingual image captioning method. It can be divided into two stages: cross-lingual auto-encoding and unsupervised feature mapping. The scene graph mapping in the first stage (Top) is designed to map the scene graph from the source language (English) to the target language (Chinese). The unsupervised feature mapping in the second stage (Bottom) is designed to align the image modality to sentence modality. We mark the object, relationship, and attribute nodes in the scene graph in yellow, blue and grey, respectively. The English sentences (marked in gray) in parentheses are translated by google translator for better understanding.
Scene Graphs. Given a set of nodes \( V \) and edges \( E \), we can build a scene graph as \( G = (V, E) \). As illustrated in Fig. 1, a scene graph contains three kinds of nodes: object, relationship and attribute nodes. Let object \( o_i \) denote the \( i \)-th object. The triplet \( \langle o_i, r_{i,j}, o_j \rangle \) in \( G \) is composed of two objects: \( o_i \) (as subject role) and \( o_j \) (as object role), along with their relation \( r_{i,j} \). Each object may have a set of attributes, we denote \( a_{l} \) as the \( l \)-th attribute of object \( o_i \). To generate image scene graph \( G^I \), we follow (Gu et al., 2019) to build the image scene graph generator based on Faster-RCNN (Ren et al., 2015) and MOTIFS (Zellers et al., 2018). To generate sentence scene graph \( G^S \), we first convert each sentence into a dependency tree with syntactic parser (Anderson et al., 2016), and then apply the rule-based method (Schuster et al., 2015) to build a graph. The \( G^S \) is mapped from \( G^I \) through our scene graph mapping module.

Cross-lingual Hierarchical Graph Mapping. Fig. 2 illustrates our HGM method. Let \( \langle e_{o_i}^l, e_{r_{i,j}}^l, e_{o_j}^l \rangle \in G^l \) denote the triplet for relation \( r_{i,j} \) in \( l \)-language domain, where \( e_{o_i}^l \), \( e_{o_j}^l \) and \( e_{r_{i,j}}^l \) are the embeddings representing subject \( o_i \), object \( o_j \), and relationship \( r_{i,j} \). Our hierarchical mapping lies in three aspects: word-level mapping, sub-graph mapping, and full-graph mapping. The scene graph mapping from language \( x \) to language \( y \) can be formatted as:

\[
\langle e_{o_i}^y, e_{r_{i,j}}^y, e_{o_j}^y \rangle = \langle f_{\text{HGM}}(e_{o_i}^x, G^x), f_{\text{Word}}(e_{r_{i,j}}^x), f_{\text{HGM}}(e_{o_j}^x, G^x) \rangle
\]

\[
f_{\text{HGM}}(e_{o_i}^y, G^x) = f_{\text{FC}}([f_{\text{Word}}(e_{o_i}^x), f_{\text{Sub}}(e_{o_i}^x, G^x), f_{\text{Full}}(e_{o_i}^x, G^x)])
\]

where \( e_{o_i}^y \), \( e_{r_{i,j}}^y \) and \( e_{o_j}^y \) are the mapped embeddings (subject, object, relationship) in target language \( y \), \( f_{\text{FC}}(\cdot) \) is a fully-connected (FC) layer which maps the concatenated embeddings to a lower dimension. Here, we only consider graph-level mapping for object nodes since relationship only exists between object nodes. For relationship and attribute nodes, the cross-lingual mapping is still word-level mapping.

Fig. 2(a) illustrates the word-level mapping. It is achieved by retrieving the most similar word embedding in language \( y \) based on a cross-lingual word embedding space, which is aligned using the relaxed cross-domain similarity local scaling method (Joulin et al., 2018). In practice, we first map the word embedding in language \( x \) to a common space and then retrieve the closest word in language \( y \) through the cosine similarity. The word-level mapping for relationship embedding \( e_{r_{i,j}}^x \) and attribute embedding \( e_{a_{l}}^x \) are similarly defined.

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1For notational simplicity, we also use \( G^x \) and \( G^y \) to represent the image scene graph \( G^I \) in language \( x \) and \( y \), respectively.
Since each node in the scene graph is associated with a set of surrounding nodes, we also consider the mapping in graph-level: sub-graph mapping and full-graph mapping, which are illustrated by Fig. 2(b) and (c), respectively. For sub-graph mapping, \( f_{\text{Sub}}(e^x_{\text{o}}, G^x) \) is computed by: \( \sum_{k=1}^{N^o} f_{\text{Sub}}(e^x_{\text{o}_k}, e^x_{\text{o}_k})/N^o \), where \( N^o \) is the total number of directly connected nodes that node \( o_k \) has, and \( f_{\text{Sub}}(\cdot) \) is the spatial convolution operation. For full-graph mapping, \( f_{\text{Full}}(e^x_{\text{o}}, G^x) \) is calculated by an attention module: \( \sum_{k=1}^{N^o} \alpha_k e^x_{\text{o}_k} \), where \( \alpha_k \) is calculated by the softmax operation over the object embeddings \( e^x_{\text{o}_k} \).

**Scene Graph Encoder.** Following (Yang et al., 2019), we encode the \( G^x \) and \( G^y \) with two scene graph encoders \( G^x_{\text{Enc}}(\cdot) \) and \( G^y_{\text{Enc}}(\cdot) \), separately. The output of each scene graph encoder can be formulated as:

\[
f^l_{\text{Sub}, N^o}, f^l_{\text{Sub}, N^o}, f^l_{\text{Sub}, N^o} = G^l_{\text{Enc}}(G^l), \quad l \in [x, y]
\]  

where \( f^l_{\text{Sub}, N^o}, f^l_{\text{Sub}, N^o}, f^l_{\text{Sub}, N^o} \) denote the set of encoded object embeddings, relationship embeddings, and attribute embeddings, separately. Each object embedding \( f^l_{\text{Sub}, N^o} \) is calculated by considering relationship triplets \( (e^l_{\text{Sub}, N^o}, e^l_{\text{Sub}, N^o}, e^l_{\text{Sub}, N^o}) \). \( \text{Sub}(o_i) \) represent the subjects when \( o_i \) represents as object, and \( \text{obj}(o_i) \) represent the objects when \( o_i \) represents as subject. \( f^l_{\text{Sub}, N^o} \) is calculated based on relationship triplet \( (e^l_{\text{Sub}, N^o}, e^l_{\text{Sub}, N^o}, e^l_{\text{Sub}, N^o}) \). \( f^l_{\text{Sub}, N^o} \) is the attribute embedding calculated by object \( o_i \) and its associated attributes.

**Sentence Decoder.** As shown in Fig. 1, we have two sentence decoders: \( G^x_{\text{Dec}}(\cdot) \) and \( G^y_{\text{Dec}}(\cdot) \). Each decoder is composed of three attention modules and a LSTM-based decoder. It takes the encoded scene graph features as input, and generates the captions. The decoding process can be described as:

\[
\alpha^l_{t}, h^l_t = G^l_{\text{Dec}}(f_{\text{Triplet}}([z^l_{o_i}, z^l_{r}, z^l_{a_i}]), h^l_{t-1}, s^l_{t-1}) \quad l \in [x, y]
\]

\[
s^l_t \sim \text{softmax}(W_var \alpha^l_t)
\]

where \( s^l_t \) is the t-th decoded word drawn from the dictionary according to the softmax probability, \( W_var \) is a learnable weight matrix, \( \alpha^l_t \) is the cell output of the decoder, and \( h^l_t \) is the hidden state. \( f_{\text{Triplet}}(\cdot) \) is a non-linear mapping function that takes the concatenated features as input and outputs the triplet level feature. \( z^l_{o_i} \) is calculated by the attention module defined as:

\[
\sum_{k=1}^{N^o} \alpha^l_{o_i} f^l_{o_i}, \quad \alpha^l_{o_i} \text{ is the attention weight calculated by the softmax operation over the encoded scene graph embeddings } f^l_{o_i}, \quad z^l_{o_i} \text{ and } z^l_{a_i} \text{ are similarity calculated by the attention modules like } z^l_{o_i}.
\]

### 3.3 Learning

We have two learning stages in our method. In the first stage, we train the scene graph encoders (\( G^x_{\text{Enc}} \) and \( G^y_{\text{Enc}} \)), sentence decoders (\( G^x_{\text{Dec}} \) and \( G^y_{\text{Dec}} \)), and the cross-lingual scene graph mapping module (\( G^x \leftrightarrow G^y \)), supervised by parallel MT corpus. In the second stage, we freeze the cross-lingual mapping module (\( G^y \leftrightarrow G^x \)), the scene graph encoder (\( G^y_{\text{Enc}} \)) and sentence decoder (\( G^y_{\text{Dec}} \)), and train the cross-modal feature mapping (\( G^y \leftrightarrow G^x \)) under the unsupervised setting.

**Stage 1: cross-lingual auto-encoding.** In this stage, the two graph encoders encode \( G^x \) and \( G^y \) into feature representations and predict sentences (\( \hat{S}^x \) and \( \hat{S}^y \)). We minimize the following loss:

\[
L_{\text{XE}} = - \sum_t \log P_{\theta_{x \rightarrow y} \rightarrow G^x}(s^x_t | s^x_{0:t-1}, G^x) - \sum_t \log P_{\theta_{y \rightarrow x} \rightarrow G^y}(s^y_t | s^y_{0:t-1}, G^y) \quad l \in [x, y]
\]

where the \( s^x_t \) and \( s^y_t \) are the GT words, \( G^x \) and \( G^y \) are sentence scene graphs in different languages, \( \theta_{x \rightarrow y} \rightarrow G^x \) and \( \theta_{y \rightarrow x} \rightarrow G^y \) are the parameters of two encoder-decoder models.

We also add an additional loss to perform the feature-level mapping between encoded scene graph features \{\( z^x_{o_i}, z^x_{r}, z^x_{a_i} \)\} and \{\( z^y_{o_i}, z^y_{r}, z^y_{a_i} \)\}. Specifically, we enforce the scene graph features in different languages to be close through a KL-divergence-based loss:

\[
L_{\text{KL}} = \exp(\text{KL}(p(z^x_{o_i})|p(z^y_{o_i}))) + \exp(\text{KL}(p(z^x_{r})|p(z^y_{r}))) + \exp(\text{KL}(p(z^x_{a_i})|p(z^y_{a_i})))
\]
where KL refers to the Kullback–Leibler divergence loss, \( p(\cdot) \) is composed of a fully-connected mapping function that maps the input features to a low-dimension \( d_g \), followed by a softmax function. The exponential operations are adopted to amplify the effect of divergence between scene graph features.

The overall objective for stage 1 becomes: \( \mathcal{L}_{\text{Stage 1}} = \mathcal{L}_{\text{XE}} + \mathcal{L}_{\text{KL}} \).

**Stage 2: unsupervised cross-modal feature mapping.** To adapt the learned model from sentence modality to image modality, we adopt the CycleGAN (Zhu et al., 2017) to learn the feature mapping across domains. For each type (\( p \in \{o, r, a\} \)) of triplet embedding in Eq. (8), we have two mapping functions: \( g_{p\rightarrow y}^o(\cdot) \) and \( g_{p\rightarrow y}^r(\cdot) \), where \( g_{p\rightarrow y}^o(\cdot) \) maps the features from image modality to the sentence modality, and \( g_{p\rightarrow y}^r(\cdot) \) maps the sentence modality to the image modality. The training objective for cross-modal feature mapping is defined as:

\[
\mathcal{L}_{\text{CycleGAN}}^p = \mathcal{L}_{\text{GAN}}^{I\rightarrow y} + \mathcal{L}_{\text{GAN}}^{y\rightarrow I} + \lambda \mathcal{L}_{\text{cyc}}^{I\rightarrow y}
\]

where \( \mathcal{L}_{\text{cyc}}^{I\rightarrow y} \) is a cycle consistency loss, \( \mathcal{L}_{\text{GAN}}^{I\rightarrow y} \) and \( \mathcal{L}_{\text{GAN}}^{y\rightarrow I} \) are the adversarial loss (Goodfellow et al., 2014) for the mapping functions and discriminators.

Specifically, for mapping function \( g_{p\rightarrow y}^o(\cdot) \) and its discriminator \( D_y^o \), the objective is to fool the \( D_y^o \) through adversarial learning. The objective function for image to sentence mapping is formulated as:

\[
\mathcal{L}_{\text{GAN}}^{I\rightarrow y} = E_S[\log D_y^o(z_p)] + E_r[\log(1 - D_y^o(g_{p\rightarrow y}^o(z_p)))]
\]

where \( z_p^y \) and \( z_p^I \) are the encoded embeddings for sentence scene graph \( G^y \) and image scene graph \( G^I \), respectively. We also have the adversarial loss \( \mathcal{L}_{\text{GAN}}^{y\rightarrow I} \) for sentence to image mapping. The cycle-consistent loss \( \mathcal{L}_{\text{cyc}}^{I\rightarrow y} \) is designed to regularize the training and make the mapping functions cycle-consistent:

\[
\mathcal{L}_{\text{cyc}}^{I\rightarrow y} = E_I[\|g_{y\rightarrow I}^o(g_{p\rightarrow y}^o(z_p^I)) - z_p^I\|_1] + E_y[\|g_{p\rightarrow y}^o(g_{y\rightarrow I}^o(z_p^y)) - z_p^y\|_1]
\]

The overall training objective for stage 2 becomes: \( \mathcal{L}_{\text{Stage 2}} = \mathcal{L}_{\text{CycleGAN}}^o + \mathcal{L}_{\text{CycleGAN}}^r + \mathcal{L}_{\text{CycleGAN}}^o \).

During inference, given an image \( I \), we first extract the image scene graph \( G^I \) with pre-trained image scene graph generator and then map \( G^I \) in language \( x \) to \( G^y \) in language \( y \) through the trained cross-lingual scene graph mapping module. After that, we encode \( G^y \) with \( G_{\text{Enc}}^y(\cdot) \) and map the output embeddings to the language domain through \( g_{y\rightarrow I}^o(\cdot) \). The mapped features are then fed to the LSTM-based sentence decoder \( G_{\text{Dec}}^o(\cdot) \) to generate the image caption \( \hat{S}^y \) in the target language \( y \).

### 4 Experiments

#### 4.1 Datasets and Setting

**Datasets.** In our experiments, we set Chinese as the target language and English as the source language. For cross-lingual auto-encoding, we collect the paired English-Chinese corpus based on existing machine translation datasets, including WMT19 (Barrault et al., 2019), AIC-MT (Wu et al., 2017), UM (Tran et al., 2014), and Trans-zh (Xu, 2019). Since the language style in the collected MT corpus is quite different from the dictionary of caption corpus. More specifically, we first build the caption-style Chinese dictionary based on the COCO-CN (Li et al., 2019). We use Jieba\(^2\) a Chinese word segmentation module, for word segmentation. All the captions longer than 16 or smaller than 10 are dropped. We further filter the Chinese sentences in MT corpus by retraining those sentences with 90% of words in the sentence appeared in the COCO-style Chinese dictionary, resulting in a filtered MT corpus of 161,613 sentence pairs. For cross-lingual auto-encoding, we use 151,613 sentence pairs for training, 5,000 sentence pairs for validation, and 5,000 pairs for testing. For unsupervised cross-modal feature mapping, following the split in (Li et al., 2019), we collect 18,341 images from MS-COCO and randomly select 18,341 Chinese sentences from the training split of MT corpus. The validation set and testing set both contain 1,000 images. Each image in validation split has one corresponding GT Chinese caption. Each image in testing split has six GT Chinese captions.

\(^2\)https://github.com/fxsjy/jieba
**Preprocessing.** During prepossessing, we tokenize the English sentences and convert all the tokens to lowercase. Those tokens that appear less than five times are replaced with UNK, resulting in a English vocabulary with 13,194 words. We segment the Chinese sentences with Jieba and drop words with a frequency of less than five, resulting in a Chinese vocabulary with 11,731 words. The English sentence scene graphs are extracted with the parser in (Anderson et al., 2016). We also enrich the English sentences through the pre-trained back-translators (Ng et al., 2019), resulting in 808,065 augmented English sentences in total. Given augmented sentences, we can generate enriched English sentence scene graph can be increased. We extract the image scene graph with the MOTIFS (Zellers et al., 2018) which is pretrained on VG (Krishna et al., 2017).

| Corpus       | 0 Object/Graph      | 1 Object/Graph      | 2 Object/Graph      | >3 Object/Graph   |
|--------------|---------------------|---------------------|---------------------|------------------|
| Raw          | 28,599 (17.7%)      | 68,830 (42.6%)      | 39,370 (24.4%)      | 24,814 (15.4%)   |
| Back-Trans.  | 19,821 (12.3%)      | 21,551 (13.3%)      | 24,342 (15.1%)      | 95,899 (59.3%)   |

Table 1: Statistics of the English sentence scene graphs used in our experiments, where n Object/Graph denotes the number of nodes/object in a scene graph, >3 means larger than 3.

### 4.2 Implementation Details

We set the dimension of scene graph embeddings to 1,000 and \(d_c\) to 100. The sentence decoders share the same architecture. Each decoder has two LSTM layers. We set the number of hidden size for each LSTM to 1,000. During cross-lingual auto-encoding on MT parallel corpus, we first train the cross-lingual encoder-decoder with \(L_{XE}\) for 80 epochs. Then, we jointly train the cross-lingual encoder-decoder with \(L_{Stage\ 1}\) for 20 epochs. We use Adam (Kingma and Ba, 2015) optimizer with a batch size of 50 and a learning rate of 5e-5. During the learning of unsupervised cross-modal feature mapping on unpaired images and MT sentences, we set the output dimension of the discriminator to 1,000, and \(\lambda\) to 10. During stage 2, we learn the cross-modal feature mapping on the unpaid MS-COCO images and translation corpus. Specifically, we freeze parameters of the Chinese scene graph encoder, cross-lingual scene graph mapping module, and Chinese sentence decoder, and only learn the cross-modal mapping functions and discriminators with \(L_{Stage\ 2}\). We optimize the model with Adam, a batch size of 50, and an initial learning rate of 5e-4. During inference, we use beam search with beams size of 5. The widely used BLEU (Papineni et al., 2002), CIDEr (Vedantam et al., 2015), METEOR (Denkowski and Lavie, 2014) and ROUGE (Lin, 2004) are used to evaluate the quality of generated sentences.

To gain insights into the effectiveness of our method, we have several baselines:

- **GM (Trans.).** This baseline maps the English scene graph to scene graph in target language (Chinese) with Google’s MT system (Wu et al., 2016). It translates all the object, relationship, and attribute nodes in scene graphs from English to Chinese. This model is trained with \(L_{XE}\).

- **GM (Word):** This model obtains the scene graph in Chinese through word-level cross-lingual mapping. We train GM (Word) to generate Chinese captions with \(L_{XE}\). To exploit the knowledge obtained from English scene graphs, GM* (Word) jointly train the encoders and decoders in both English and Chinese with \(L_{Stage\ 1}\). GM (Word, GAN) is initialized with the trained parameters from GM* (Word), and then learns the unsupervised cross-modal feature mapping use \(L_{Stage\ 2}\). During adversarial training, we freeze the parameters of cross-lingual graph mapping module, \(G_{Enc}^E(\cdot)\) and \(G_{Dec}^E(\cdot)\), and only optimize the mapping functions using adversarial training.

- **GM (Word+Sub.):** This model considers the sub-graph information during the cross-lingual scene graph mapping. We train GM (Word+Sub.) with \(L_{XE}\). Variants GM* (Word+Sub.) and GM (Word+Sub., GAN) are trained with \(L_{Stage\ 1}\) and \(L_{Stage\ 2}\), separately.

- **HGM:** Apart from word-level mapping and sub-graph mapping, this model also considers the full-graph mapping. Like other baselines, we have three kinds of variants for this baseline. HGM is trained with \(L_{XE}\). HGM* is jointly trained with \(L_{Stage\ 1}\). HGM (GAN) is initialized with the trained parameters from HGM* and trained with \(L_{Stage\ 2}\).
4.3 Results and Analysis

**Investigation on Data Augmentation.** We investigate the effectiveness of the data augmentation in Table 2. For the ‘Raw’ setting, we train the GM (Trans.) with the original MT corpus, while in the ‘Back-Trans.’ setting, we train the GM (Trans.) with the augmented MT corpus. We can see that ‘Back-Trans.’ achieves better performance than ‘Raw’. This is reasonable since the sentence scene graph generated from five sentences (original sentence and four augmented sentences) contains richer information than the original sentence scene graph. This finding is also supported by the examples shown in Fig. 5.

| Method   | B@1 | B@2 | B@3 | B@4 | M   | R   |
|----------|-----|-----|-----|-----|-----|-----|
| Raw      | 22.5| 12.3| 7.5 | 5.1 | 12.8| 24.6|
| Back-Trans. | 26.6| 15.4| 10.0| 7.3 | 15.1| 28.1|

Table 2: Results of generated Chinese sentences of GM (Trans.) on the test split of MT corpus. B@n is short for BLEU-n, M is short for METEOR and R is short for ROUGE.

**Investigation on Cross-lingual Scene Graph Mapping.** Table 3 shows the comparisons among different baselines. We first consider the incorporation of different scene graph mapping methods into the cross-lingual auto-encoding process. We can see that, compared with GM (Trans.), GM (Word) achieves better performance on the Chinese sentence generation. Moreover, by considering the sub-graph information and full-graph information, GM (Word+Sub.) and HGM further improve the performances. This suggests the effectiveness of our proposed HGM module, which helps to map the sentence scene graph from English to Chinese. Then, we train the above baseline models using joint loss $L_{Stage 1}$, where $L_{KL}$ enforces the distribution of the latent encoded scene graph embeddings to be close. It can be seen from Table 3 that the baselines with joint-training achieve better performance than baselines without joint-training.

| Method               | $L_{XE}$ | $L_{KL}$ | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | METEOR | ROUGE |
|----------------------|----------|----------|--------|--------|--------|--------|--------|--------|
| GM (Trans)           | ✓        | ×        | 26.6   | 15.4   | 10.0   | 7.3    | 15.1   | 28.1   |
| GM (Word)            | ✓        | ×        | 27.7   | 15.8   | 10.4   | 7.7    | 15.3   | 28.3   |
| GM (Word+Sub.)       | ✓        | ×        | 28.9   | 17.6   | 12.3   | 9.5    | 16.1   | 30.1   |
| HGM                  | ✓        | ×        | 29.2   | 17.9   | 12.6   | 9.8    | 16.3   | 30.3   |
| GM* (Word)           | ✓        | ✓        | 28.1   | 16.2   | 10.7   | 8.0    | 15.4   | 28.2   |
| GM* (Word+Sub.)      | ✓        | ✓        | 29.2   | 17.9   | 12.6   | 9.9    | 16.3   | 30.2   |
| HGM*                 | ✓        | ✓        | 29.6   | 18.1   | 12.8   | 9.9    | 16.5   | 30.4   |

Table 3: Performance compassion of the Chinese sentence generation on the test split of MT corpus.

**Investigation on CycleGAN.** To bridge the gap between image modality and text modality, we use CycleGAN to learn the cross-modal feature mapping functions in the unsupervised manner. During testing, we feed the predicted image scene graphs into $G_{Enc}^x(\cdot)$ and decode the sentence with $G_{Dec}^x(\cdot)$. Table 4 shows the comparison of the baselines on the test split of COCO-CN. The left part of Table 4 shows the performance of Chinese image captions generated by baseline models without cross-modal feature mapping. The right part of Table 4 shows the results of baselines with CycleGAN. We can see that CycleGAN can improve the performance of those models. Note that, it is interesting that the performance of HGM (GAN) on the COCO-CN is worse than GM (Word, GAN) and GM (Word+Sub., GAN), which is different from the results in Table 3. The main reason is that the generated image scene graphs are biased and contain a lot of noise, which makes the sub-graph encoding and full-graph encoding less discriminative.

| Method               | B@1 | B@4 | M   | R   | C   | Method               | B@1 | B@4 | M   | R   | C   |
|----------------------|-----|-----|-----|-----|-----|----------------------|-----|-----|-----|-----|-----|
| GM* (Word)           | 40.1| 2.2 | 15.6| 28.4| 9.5 | GM (Word, GAN)       | 43.1| 3.0 | 16.5| 29.4| 12.6|
| GM* (Word+Sub.)      | 37.7| 2.5 | 14.3| 27.0| 7.9 | GM (Word+Sub., GAN)  | 40.6| 2.8 | 15.2| 28.3| 10.8|
| HGM*                 | 38.0| 2.4 | 14.4| 27.3| 8.0 | HGM (GAN)           | 39.8| 2.6 | 14.8| 27.7| 10.2|

Table 4: Performance comparisions on the test split of COCO-CN. C is short for CIDEr.
### 4.4 Qualitative Results

Fig. 3 visualizes some examples of generated captions. Generally, compared with the raw English (En) sentence scene graph, the augmented English sentence scene graphs are richer than raw sentence scene graphs. Also, the HGM model can generate more accurate and descriptive sentences than other baselines, demonstrating that our hierarchical graph mapping can better map the scene graph from one language to another language. We also provide some Chinese (Zh) captioning examples for MS-COCO images in Fig. 4. From these results, we can see that our method can generate reasonable image descriptions without using any paired image-caption data. Also, we observe that the image scene graphs generated by the pre-trained model are quite noisy. This observation potentially explains why the performance GM (Word+Sub., GAN) and HGM(GAN) are worse than GM (Word, GAN).

![Image 1](image1.png)

**Figure 3:** Qualitative results of models trained on different sentence scene graphs. ‘Raw’ represents that model is trained on the original corpus. ‘Aug’ represents that model is trained on the augmented corpus. * represents English translation translated by google translator, provided for non-Chinese readers.

![Image 2](image2.png)

**Figure 4:** Qualitative results of different unsupervised cross-lingual caption generation models.

### 5 Conclusion

In this paper, we propose a novel framework to learn a cross-lingual image captioning model in an unsupervised manner. Specifically, we design a hierarchical scene graph mapping module to map the scene graphs across different languages, and design a cross-lingual joint training mechanism to better encode sentence scene graphs for sentence generation in the target language. The unsupervised cross-modal feature mapping further bridges the gap between image modality and sentence modality. The extensive experiments demonstrate that our proposed methods can achieve promising results for caption generation in the other language without using any caption corpus.
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