Object-Centric Unsupervised Image Captioning

Zihang Meng\textsuperscript{1}, David yang\textsuperscript{2}, Xuefei Cao\textsuperscript{2}, Ashish Shah\textsuperscript{2} and Ser-Nam Lim\textsuperscript{2}

\textsuperscript{1}University of Wisconsin-Madison, \textsuperscript{2}Meta AI

zmeng29@wisc.edu, xuefeicao01@gmail.com, \{dzyang, ashishbshah, sernamlim\}@fb.com

Abstract

Training an image captioning model in an unsupervised manner without utilizing annotated image-caption pairs is an important step towards tapping into a wider corpus of text and images. In the supervised setting, image-caption pairs are “well-matched”, where all objects mentioned in the sentence appear in the corresponding image. These pairings are, however, not available in the unsupervised setting. To overcome this, a main school of research that has been shown to be effective in overcoming this is to construct pairs from the images and texts in the training set according to their overlap of objects. Unlike in the supervised setting, these constructed pairings are however not guaranteed to have fully overlapping set of objects. Our work in this paper overcomes this by harvesting objects corresponding to a given sentence from the training set, even if they don’t belong to the same image. When used as input to a transformer, such mixture of objects enable larger if not full object coverage, and when supervised by the corresponding sentence, produced results that outperform current state of the art unsupervised methods by a significant margin. Building upon this finding, we further show that (1) additional information on relationship between objects and attributes of objects also helps in boosting performance; and (2) our method also extends well to non-English image captioning, which usually suffers from a scarcer level of annotations. Our findings are supported by strong empirical results.

1. Introduction

Image captioning is an important task standing at the crossroad of computer vision (CV) and natural language processing (NLP) that has been widely studied for many years. In the deep learning era, with the advent of transformer models [5,27,43], significant advances in image captioning have been made since its “humble” beginning from the early use of Convolutional Neural Networks in combination with Recurrent Neural Networks [18]. Since then, various attention mechanisms [2,40] and transformer based models [8] have been proposed with great effect. The current success has however been predicated on the availability of large amount of image-caption annotations, which is quite expensive to obtain. As a matter of fact, in [29], it was revealed that it costs 144.7 seconds on average for a professional full-time annotator to provide a high-quality caption for just a single image.

This has led researchers to propose methods that do not require image-caption pairings, but instead train their models on separate image and text datasets. This line of work precipitates the onset of unsupervised image captioning, with [11] making an early attempt here by utilizing policy gradient to encourage visual concepts in the predicted captions. This approach, however, only encourages the appearance of visual object words, but ignore how they should
properly fit into the sentence. Later on, [22] proposed to mine pseudo image-caption pairs to train the model. Given a sentence, the algorithm searches and pairs the sentence with an image in the training set which contains overlapping visual concepts. Building on this, [16] makes further improvements by introducing a new gate function that tells the model which word in the sentence is irrelevant to the image to form higher quality pseudo image-caption pairs.

While these advances have produced state of the art performance, we found that it has a fundamental limitation. Since the image and text datasets are unpaired, it is more likely that the quality of the image-caption pairs could be sub par as measured by the number of objects in the sentence that are actually captured in the image (see Table 4 and 5 on how object coverage affects performance). Our work in this paper tries to solve this problem with a simple yet effective approach. Given a sentence in the text dataset, instead of trying to find a candidate from the image dataset, we harvest objects corresponding to the sentence. Because we do not require these objects to be from the same image, we significantly increase the chance of fully covering all the objects that appear in the sentence. Specifically, the harvested objects are fed into a transformer, which is then supervised by the corresponding sentence during training. “Surprisingly”, experiments show that our approach outperforms the state-of-the-art methods by a clear margin.

To further boost performance, we note that the harvested objects do not really respect spatial relationships (e.g., the phrase “person riding a bike” requires the “person” to be above “bike”). However, when a relationship detector also becomes available, our approach naturally enables the utilization of such relationship information by feeding such information together with the objects into the transformer. Most previous works [11, 14, 16, 22] would find the incorporation of such information challenging without making significant change to their model or training procedure.

Finally, we explore the possibility of going beyond English to generate captions in other languages. Non-English captioning tasks are expected to be one of the largest beneficiaries of unsupervised image captioning, simply because paired image-captions annotations are scarcely available in languages other than English, and really speaks to the importance of making advances in unsupervised image captioning. We demonstrate our proposed approach on non-English captioning with convincing empirical results.

2. Related Work

**Supervised Image Captioning.** Supervised image captioning traditionally relies on paired image-caption data to train a generative model which creates a text description given an input image. In recent years, the research community has significantly raised the level of performance for the image captioning task [35]. Some earlier work such as [18] adopts Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) with global image feature as input, while others such as [3, 40] proposed to add attention over the grid of CNN features. [2] further adds attention over visual regions to learn better feature representations. More recently, transformer-based models have been utilized with great success [8]. Other notable advances include personalized image captioning [42] that is conditioned on the learned representation of a certain user, dense image captioning [17] which localizes and describes salient image regions, and the generation of captions in a controllable way guided by speech [9], a set of bounding boxes [7] or human attention traces [27].

**Towards Unsupervised Image Captioning.** Paired image-caption datasets are usually very expensive to obtain. To deal with this challenge, some studies have been conducted to explore the possibility of reducing the amount of paired information needed or utilizing unpaired images and sentences. [15, 38] explored learning simultaneously from multiple data sources with auxiliary objectives to describe a variety of objects unseen in paired image-caption data. [12] leverages the paired information in a pivot language to train the generative model and translate the generated captions into the target language. More relevant to our work is the recent line of work in [11, 13, 14, 16, 22, 26], which utilize unpaired image and text information. They assume that a pretrained object detector is available for extracting visual concepts from an image which act as the link between visual and language domain. Some of them utilize adversarial training to align the visual and language domain. [11] relies on discrete rewards to help the model generate high-quality captions. [14] trains a generator which generates a sentence from discrete words. They discard the visual information in detected object regions and only keep the visual concept words as the input to the model. [13] assumes that a pretrained scene graph detector is available, and trains a captioning model using scene graph decomposition. [22] mines pseudo image-caption pairs from existing but unpaired image and text datasets to train the captioning model. [16] improves on it by removing spurious alignments. Our work in this paper follows the same line of thoughts to mine pseudo image-caption pairs. However, unlike these existing approaches which when given a sentence look for an image that contains as many of the objects occurring in the sentence as possible, our method explore the possibility of harvesting these objects from different images.

**Non-English Captioning.** Most current work on image captioning focus on the English language. To extend captioning technology to non-English languages, we are starting to see some studies being reported. Some researchers have attempted to directly propose a captioning model on a target language while utilizing a pivot language, typically English, in which paired information is readily avail-
able [12, 23, 34, 39]. Nevertheless, the straightforward approach remains to collect image-caption pairs in the target language (e.g., French [30], German [10], or Chinese [24]). These efforts have not been as extensive as hoped, and advances in unsupervised image captioning could have strong impact here. In this paper, we provide benchmarks showing that even in non-English captioning tasks, our proposed method surpasses or is on par with the state of the art unsupervised image captioning methods.

3. Method

Given a set of images $\mathcal{I} = \{I_1, ..., I_N\}$, and a set of sentences $\mathcal{S} = \{S_1, ..., S_N\}$, our goal is to train a model which takes an image as input and generates a caption that well describes the input image. We follow previous work on unsupervised image captioning [11] in assuming that we do not have information about the pairing between $\mathcal{I}$ and $\mathcal{S}$, but have access to a pretrained object detector (a pretrained Faster R-CNN) to detect the regions and extract the visual features given as $\mathcal{S}$.

We can utilize these artificially constructed $\mathcal{R}$–$\mathcal{S}$ pairs to train the captioning model using Cross Entropy (CE) loss:

$$L = \text{CE}(f(\mathcal{R}_i), S_i),$$

where $f$ represents the captioning model which predicts the caption from a set of object region features. In this work, we adopt the transformer model described in [36] as $f$.

3.1. Utilizing Additional Information

The flexibility of a transformer architecture means that we can also include additional information as input together with the object information. In our method described so far, we note that a part of the information is lost, being that we used the original locations of the object regions, which may be incorrect in relation to other objects as well as losing fine-grained information when we replaced the objects (e.g., face attributes). In this regard, our experiments also show that losing such information causes a drop in performance (see Table 3). To this end, we describe how we take a pretrained relationship detector and attribute detector as examples of additional information that we can add to our method.

Consider that for a given $I_i$, the relationship detector can detect triplets in the form of subject-relation-object,

$$\mathcal{T}_i^r = \{\text{sub}_1 \text{-rel}_1 \text{-obj}_1, ..., \text{sub}_{N_r}^i \text{-rel}_{N_r}^i \text{-obj}_{N_r}^i\},$$

and for a sentence $S_i$, the relationship parser can detect triplets in the same form,

$$\mathcal{T}_i^s = \{\text{sub}_1 \text{-rel}_1 \text{-obj}_1, ..., \text{sub}_{N_s}^i \text{-rel}_{N_s}^i \text{-obj}_{N_s}^i\}. \tag{5}$$

Then for a given sentence $S_i$, we can similarly obtain $\mathcal{R}_i$ using the same strategy as that in Eqn. 2. However, instead of only selecting image regions which match the visual concepts in $S_i$, we also add to $\mathcal{R}_i$ pairs of image regions (subject–object), which match the triplets (subject–relation–object) in $\mathcal{T}_i^r$:

$$\mathcal{R}_i = \{r_1, ..., r_k, \text{pair}_1, ..., \text{pair}_l\}. \tag{6}$$

where each $r$ refers to one image region and each pair refers to a pair of image regions formed by the subject–object and the object region from one triplet. $k$ is the number of visual concepts in $S_i$ and $l$ is the number of triplets in $S_i$ detected by the language relationship detector. The subsequent steps to construct pairs for training are the same as that in Sec. 3.

To utilize the pretrained attribute detector, we basically perform the same steps. The only difference is that instead of detecting triplets subject–relation–object, the attribute detector detects pairs in the form of attribute–object. Then when we see a certain attribute–object pair in the sentence $S_i$, we look for an image region that matches this attribute–object, and add this image region into $\mathcal{R}_i$. Similar procedure could be conducted when other pretrained models such as scene detector, facial expression detector, etc., are available. In this paper, we will focus on leveraging relationship and attribute detectors in addition to the objects, and leave the study of adding other detectors to future work.

3.2. Extension to Other Languages

We can also easily adapt our work to train a non-English image captioning model in an unsupervised way. Consider the same object detector pretrained on English vocabulary. We denote the English vocabulary of the object detector as

$$\text{voc}_{\text{English}} = \{\text{word}_1, ..., \text{word}_{N_{\text{English}}}\}. \tag{7}$$
Then we translate each word in the English vocabulary into the target language denoted as “Target” (although translating a whole sentence into a different language is a challenging task, translating a single word can be easily done using language dictionaries) given as

\[ \text{voc}_{\text{Target}} = \{ \text{word}_1, \ldots, \text{word}_{N_{\text{Target}}} \}, \]

where \( N_{\text{English}} \) may not equal to \( N_{\text{Target}} \). Considering it is possible that multiple words in English are translated into the same word in the target language and vice versa. After this, we can follow the same steps in Sec. 3 to construct pairs to train a model directly in the target language.

4. Experiments

Our experiments are designed to empirically establish: (i) that our proposed method outperforms state of the art unsupervised image captioning methods, (ii) that our proposed method can easily incorporate additional information, in this case object relationships and attributes to help boost performance, (iii) the effects of swapping in objects from different images to generate training pairs, and, (iv) that our proposed method outperforms state of the art in non-English captioning tasks. We will provide the implementation details next so that we have a common ground for discussing the results.

Implementation Details. We tokenize the text datasets and delete sentences which are shorter than 5 words or longer than a certain length, 20 for Google Conceptual Captions (GCC) [33] and Shutterstock (SS) [11], and 100 for Localized Narratives (LN) [29]) and build a language vocabulary. Then we match the object words of the object detector with the language vocabulary. Our object detector is a Faster R-CNN [31] pretrained on Visual Genome [20], whose vocabulary contains 1600 object words. Next, we build a dictionary that maps an object word to a set of images which contain this object word. Finally, during training, for a randomly picked sentence, we first find all object words it contains, and for each object word, we randomly pick one image that contains this object word and crop this object region using its bounding box location. In this way, for each sentence \( S_i \) we can have a set of object regions \( R_i \). Our captioning model is a one layer transformer [36]. The size of the hidden attention layers is 512 and that of the feed-forward layers is 2048. The input object features are extracted by the Faster R-CNN mentioned above. We train the network with a batch size of 100 using the Adam optimizer [19]. The initial learning rate is 5e-4, which decays by 0.8 every 3 epochs, for a total of 30 epochs. The same training setup is used for all experiments in this paper. Note that these hyperparameters are directly borrowed from [27] (except that we increased the batch size from 30 to 100 for faster training), and we did not utilize the validation set to further finetune the hyperparameters to ensure that we do not utilize any pairing information during training (the validation set contains pairing information).

Evaluation Datasets. For images, we follow previous work [11, 16] to use the MS COCO dataset and the train/validation/test split provided by [18], and report the performance on the test split (except in Sec. 4.3.1, where we follow [27] to use COCO-2017 official splits). For the text, we choose the recently released Localized Narratives (LN) [29] which provides captions for four public datasets including COCO, ADE20k, Flickr30k and Open Images. We choose LN-COCO instead of COCO captions [6] because the captions in LN are longer, contain more verbs, and the overall quality is better (see our supplement or Table 2 in [29] for a comparison between LN-COCO and COCO captions). We use LN-COCO for all experiments except those on non-English languages in Sec 4.4, where we use the annotations provided by COCO-CN [24] and Multi30k [10].

Evaluating Metrics. We use the official COCO caption evaluation tool and report the performance in terms of BLEU-1 [28], BLEU-4, METEOR [4], ROUGE [25], CIDEr [37], SPICE [1] and WMD [21].

4.1. Comparisons With State-of-the-Art Methods

[11,16] are two state of the art methods in unsupervised image captioning. We compare our method with them using COCO images together with GCC and SS as the text datasets respectively. We use the code released by the authors to produce results on these datasets for benchmarking. It is important to note that both GCC and SS are web-crawled text datasets and help to showcase unsupervised methods’ flexibility in exploiting large scale data by breaking the chain of pairing. We further note that these state of the art methods are also not transformer based.

Quantitative results are presented in Table 1. We can see that our method outperforms all baseline methods on both text datasets by a clear margin. The qualitative results are in Fig. 2. The captions generated by [11] tend to contain verbs describing the objects but make mistakes frequently (e.g., in “a person is sitting on a motorbike” the verb “sitting” matches with object “motorbike” but does not match the input image). [16] generated mostly correct captions but the captions are mainly concatenations of object names (nouns) without verbs describing the action of the objects or the relationships between objects (e.g., “a young man in a white skies”). Our method generates more comprehensive captions with mostly correct nouns and verbs and the captions are aware of the interaction between objects for most part (e.g., “female skier wearing red jacket”, “standing with skis on snow mountain slope”).

We can also see that all methods fail to identify any color attributes, and this is a limitation of only having a pretrained object detector with no color attribute detector. If
Table 1. The performance of our method and baseline methods [11, 16] trained using COCO images and SS/GCC text datasets, evaluated using test split of COCO images and LN-COCO caption annotations as ground truth.

| Text dataset | Method       | BLEU-1 | BLEU-4 | METEOR | ROUGE$_L$ | CIDEr  | SPICE   | WMD  |
|--------------|--------------|--------|--------|--------|-----------|--------|---------|------|
| SS [11]      | 0.016        | 0.001  | 0.037  | 0.109  | 0.018     | 0.073  | 0.045   |      |
| SS [16]      | 0.022        | 0.001  | 0.043  | 0.126  | 0.025     | 0.078  | 0.042   |      |
| SS Ours      | **0.056**    | **0.003** | **0.060** | **0.127** | **0.038** | **0.102** | **0.060** |      |
| GCC [16]     | 0.006        | 0.000  | 0.035  | 0.115  | 0.017     | 0.075  | 0.040   |      |
| GCC Ours     | **0.062**    | **0.004** | **0.062** | **0.146** | **0.032** | **0.104** | **0.055** |      |

Table 2. The performance of utilizing only object detector and that of utilizing object detector plus relationship/attribute detector. The models are trained using COCO images and LN-OpenImages captions, and evaluated using the test split of COCO images and LN-COCO caption annotations as ground truth.

| Pretrained models | BLEU-1 | BLEU-4 | METEOR | ROUGE$_L$ | CIDEr  | SPICE   | WMD  |
|-------------------|--------|--------|--------|-----------|--------|---------|------|
| object            | 0.327  | 0.059  | 0.140  | 0.262     | 0.109  | 0.181   | 0.079|
| object + attribute| **0.332** | 0.059  | 0.136  | 0.266     | 0.124  | 0.181   | 0.079|
| object + relationship | 0.329 | 0.061  | 0.140  | 0.268     | 0.120  | 0.188   | 0.080|
| object + relationship + attribute | 0.329 | **0.062** | **0.141** | **0.274** | **0.138** | **0.193** | **0.083**|

a pre-trained color detector becomes available, our method naturally enables the utilization of this information as described in Sec. 3.1.

4.2. Utilizing Object Relationships and Attributes

In Sec. 3.1, we described how our framework naturally enables utilizing additional pretrained models when they become available. Here, we provide empirical results from adding both a relationship and attribute detector. We use the relationship and attribute detector pretrained on Visual Genome [41] for images, and the semantic parser provided by [1], which is built on [32], to find relationship triplets from sentences. Note that we only need the pretrained relationship detectors during training to construct $(R_i, S_i)$ pairs, not test time. We train the model on COCO images, and choose LN-OpenImages as the text dataset since it contains rich semantic relationship information. Ideally, when given a pair of triplets, we would like to completely match the subject-relation-object, but we found that such complete matches are rare because the relationship detector is not 100% accurate and discrepancies between the image and sentence relationship detectors exist. So, instead, we consider two triplets a match as long as the subject-object matches between them.

The quantitative results are presented in Table 2. Row 2 shows results when a attribute detector is added while row 3 gives the results for when only a relationship detector is added. Results from row 4 come from adding both a relationship and attribute detector. We can see that adding either a relationship or attribute detector is beneficial. Interestingly, row 4 shows a slight improvement over row 3 but a much larger boost over row 2. Qualitatively, we can refer to the last row of Fig. 2. We can see that the captions are comprehensive and contain many relationship triplets in the generated captions (e.g., “he-holding-ski sticks”, “he-wearing-helmet”, “man-standing on-land”).

4.3. Ablations

4.3.1 Effects of Object Mining

In the set of experiments depicted in Table 3, we attempt to understand the effect of our proposal to use objects from different images. Our experiments involve a state of the art supervised image captioning method described in [27], which is a transformer based model. We adopt the same experiment settings but deleted the head for trace in their model, which the authors of [27] utilized in addition to captions and images. We took the code provided, and trained a captioning model with COCO images and LN-COCO. The resulting performance is provided in the first row of Table 3. Then, for each image-caption pair in the training set, we detect all object regions in the image and replace each object region with another one of the same category mined from other images in the dataset. During training, we feed the visual features of the substitute objects, together with the 5-D location vectors of the replaced objects into the transformer. The performance of this second model is given in the second row of Table 3. The third model is trained similarly as the second but with the locations taken from the images where the substitute objects come from. The result is in the third row of Table 3. Finally, we run our unsupervised method, which performed as given in the last row of Table 3. To better understand the effects of our proposed method, we highlight the difference between these four models in the following. (i) Row 1, which is the supervised model, is a transformer model as mentioned. Similar to our method, objects are fed into the model, but the key differences are, given an image-caption pair, (1) the objects are all from a single image, and (2) the objects include those that are not in the given caption, which can include back-
Table 3. The performance of supervised training, before and after replacing the objects with randomly mined objects of the same category (the supervised training was conducted following [27] using their provided code). Detailed interpretation of each row is in Sec. 4.3.1.

| Methods                        | BLEU-1 | BLEU-4 | METEOR | ROUGE_L | CIDEr | SPICE | WMD  |
|--------------------------------|--------|--------|--------|---------|-------|-------|------|
| Supervised training            | 0.306  | 0.082  | 0.151  | 0.306   | 0.263 | 0.238 | 0.113|
| After replacing objects        | 0.297  | 0.078  | 0.145  | 0.298   | 0.227 | 0.232 | 0.109|
| After replacing objects and location | 0.298 | 0.080  | 0.146  | 0.300   | 0.239 | 0.234 | 0.108|
| Ours                           | 0.298  | 0.071  | 0.159  | 0.264   | 0.125 | 0.164 | 0.083|

4.3.2 Object Coverage

While [16] and our method all assume a pretrained object detector, a key difference is that the former mines images while our method mines objects. To demonstrate the benefit of our approach more clearly, we construct a baseline method (“Ours-baseline1”) which shares all experimental settings with our method but instead of constructing \((R_i, S_i)\) pairs, it follows [16, 22] to mine pseudo pairs \((I_i, S_i)\) from the training set. The results are in Table 4. We observe here that the practice of mining pseudo pairs performs significantly worse than our method, primarily due to the resulting lower object coverage, given as the percentage of object words in the sentence that appear in the corresponding image during training. Our method has a 100% object coverage by virtue of mining objects, while for Ours-baseline1, there is on average at least a third of the objects that are missing. To further confirm, we artificially drop half of the object coverage from our approach, and the re-
4.4. Non-English Image Captioning

Due to the scarcity of annotated image-caption pairs in non-English languages, we expect unsupervised image captioning methods to have a fairly large impact in bridging the gap here. To understand how well our proposed method works for non-English image captioning, we chose Chinese and French to benchmark our method. Our aim is to demonstrate the unpairing that is made possible by our method. To do so, for the experiments in this section, we construct training pairs that are not part of any annotated pairs.

For Chinese, we use the COCO-CN [24], which provides Chinese captions on 20,342 images in COCO. We unpair the training set by training with the train split of COCO-CN captions but in conjunction with the COCO images that are not included in the 20,342 (COCO has a total of ≈123k images). Evaluation is then conducted on the test split of COCO-CN captions and the corresponding COCO images. For French, we use Multi30k [10] that provides French captions for all of Flickr30k images and 1k images from COCO. Similarly, to achieve the effect of unpairing, the model is trained on just the Flickr30k captions together with the COCO images that are not included in the 1k COCO images. Testing is subsequently conducted on the 1k image-caption COCO pairs.

Three baselines are used here. The first baseline, “Baseline-translate”, is our method trained to produce English captions, which are then translated. The second baseline, “Baseline-existing”, follows the same procedure of our method but instead of constructing \((R_i, S_i)\) pairs, it mines pseudo image-caption pairs \((I_i, S_i)\) from existing image and text datasets (similar to the “baseline1” in Sec. 3.3.2, but extended to non-English datasets as described in Sec. 3.2). The last baseline is the current state of the art, [16], which is extended to mine pseudo non-English image-caption pairs (Sec. 3.2). For all these baselines, we apply the same principle to unpair the training set while ensuring that the training sets for the baselines and our method are apple to apple. Therefore, all the baselines adopt the same training set described in the previous paragraph, except for “Baseline-translate”, which uses the English version of the same training captions.

We present the quantitative results in Table 6. We can see that our method when trained directly on the target language performs better than “Baseline-translate”, most likely because translating a full sentence accurately is much harder than translating a single object word. “Baseline-existing” performs much better but still lag behind our method as expected based on results presented in the earlier section. [16] (extended by us to non-English) performs worse than our method on French but has a smaller gap or on par to our method on Chinese. This may be because that the training images and sentences are from the same paired dataset (COCO-CN), thus mining pairs from existing images and sentences are relatively easy. We have also observed in both the English and Chinese datasets that the captions generated by [16] usually cover most needed object words although being semantically less meaningful and comprehensive compared with our method, and the captions in COCO-CN are mostly short (like COCO captions), which favors

| Text dataset | Method         | BLEU-1 | BLEU-4 | METEOR | ROUGE_L | CIDEr | SPICE | WMD  | Overlap | Object Coverage |
|--------------|----------------|--------|--------|--------|--------|-------|-------|------|---------|----------------|
| SS           | Ours           | 0.058  | 0.003  | 0.060  | 0.126  | 0.039 | 0.102 | 0.060| 100%    | 50.0%          |
| SS           | Ours-half-obj  | 0.056  | 0.002  | 0.055  | 0.117  | 0.036 | 0.082 | 0.055| 50.0%   | 47.5%          |
| SS           | Ours-baseline1 | 0.040  | 0.002  | 0.045  | 0.104  | 0.021 | 0.068 | 0.049| 57.4%   |                |
| GCC          | Ours           | 0.062  | 0.004  | 0.062  | 0.146  | 0.032 | 0.104 | 0.055| 100%    | 50.0%          |
| GCC          | Ours-half-obj  | 0.057  | 0.003  | 0.054  | 0.140  | 0.025 | 0.080 | 0.050| 50.0%   |                |
| GCC          | Ours-baseline1 | 0.046  | 0.002  | 0.048  | 0.131  | 0.025 | 0.073 | 0.047| 68.8%   |                |

Table 4. Importance of object coverage. Baseline1 is the model trained with pseudo \((I_i, S_i)\) pairs. Object Coverage refers to the percent of objects in a given sentence that are captured by the corresponding image during training, averaged over all used training pairs. Our method has 100% object coverage by construction.

| BLEU-1 | BLEU-4 | METEOR | ROUGE_L | CIDEr | SPICE | WMD | Overlap | Object Coverage |
|--------|--------|--------|--------|-------|-------|-----|---------|----------------|
| 0.022  | 0.001  | 0.042  | 0.134  | 0.026 | 0.075 | 0.042| ≥ 2     | 47.5%          |
| 0.020  | 0.001  | 0.035  | 0.117  | 0.051 | 0.042 | 0.042| ≥ 0     | 4.2%           |

Table 5. We test the importance of object coverage by doing experiments using [16] on COCO images and SS text dataset. We change the object coverage of their method by changing the criterion of selecting training pseudo pairs from existing images and sentences. “Overlap” refers to how many objects the image and the sentence in a training pair share in common. See our supplement for the detailed explanation of how we change the object coverage. The number in the parenthesis refers to the relative performance drop compared with the first row.
Table 6. Quantitative results of our method on COCO images and two text datasets of different languages (Chinese and French). “Baseline-translate” and “Baseline-existing” are defined in Sec. 4.4.

| Training text          | Test text          | Method            | BLEU-1 | BLEU-4 | METEOR | ROUGE-L | CIDEr  | SPICE  | WMD   |
|------------------------|--------------------|-------------------|--------|--------|--------|---------|--------|--------|-------|
| COCO-CN (Chinese)      | COCO-CN (Chinese)  | Ours              | 0.256  | 0.039  | 0.121  | 0.228   | 0.349  | 0.117  | 0.272 |
| COCO-CN (Chinese)      | COCO-CN (Chinese)  | [16]              | 0.240  | 0.026  | 0.128  | 0.234   | 0.197  | 0.110  | 0.304 |
| COCO caption (English) | COCO-CN (Chinese)  | Baseline-translate| 0.111  | 0.000  | 0.072  | 0.097   | 0.059  | 0.003  | 0.185 |
| COCO-CN (Chinese)      | COCO-CN (Chinese)  | Baseline-existing | 0.176  | 0.020  | 0.119  | 0.189   | 0.198  | 0.047  | 0.259 |
| Multi30k (French)      | Multi30k (French)  | Ours              | 0.174  | 0.010  | 0.094  | 0.173   | 0.120  | 0.014  | 0.079 |
| Multi30k (French)      | Multi30k (French)  | [16]              | 0.143  | 0.007  | 0.083  | 0.156   | 0.053  | 0.014  | 0.072 |
| Multi30k (English)     | Multi30k (French)  | Baseline-translate| 0.104  | 0.000  | 0.053  | 0.092   | 0.099  | 0.006  | 0.056 |
| Multi30k (French)      | Multi30k (French)  | Baseline-existing | 0.126  | 0.008  | 0.086  | 0.154   | 0.059  | 0.013  | 0.078 |

[16] when used as the evaluation set. Qualitative results are also provided in Fig. 3 (Chinese) and Fig. 4 (French).

5. Limitations and Discussions

Unsupervised image captioning is an important research area that has the potential of truly scaling up image captioning in the wild. As progress is made, the hope is that image captioning will soon take a departure from the need to laboriously annotate image-caption pairs, allowing researchers to “simply” scrape unpaired images and text from different sources, including the internet. Our work in this paper takes a step towards this goal by showing how one can mine objects from multiple images to improve object coverage. The results we presented in this paper is encouraging, perhaps even surprising that “unrelated objects” mined can produce results that surpass current state of the art. By employing a transformer architecture, we also show that our proposed approach is flexible enough to ingest additional information such as object relationships and attributes that we have shown could be immensely useful. The work is not completed yet. Unsupervised performance still lags that of supervised models, but even in that we see some encouraging signs (Table 3). Further, the current line of work in unsupervised image captioning including ours depends heavily on a pretrained object detector. One way to overcome this is to employ zero-shot object detection, which still has some way to go in terms of maturity. Another more promising direction is for the community to continue to strengthen the performance of supervised object detection as well as broaden the classes of objects covered. Our code will be made publicly available.

Potential negative societal impact. Unsupervised image captioning has the potential to learn a wide spectrum of languages and images on the internet. It is important that practitioners of our proposed approach be cognizant of the potential for learning illicit captions such as hate speech, misinformation, etc. Practitioners of our technology are advised to put in place appropriate filters to avoid such issues.
References

[1] Peter Anderson, Basura Fernando, Mark Johnson, and Stephen Gould. Spic: Semantic propositional image caption evaluation. In European conference on computer vision, pages 382–398. Springer, 2016. 4, 5

[2] Peter Anderson, Xiaodong He, Chris Buehler, Damien Teney, Mark Johnson, Stephen Gould, and Lei Zhang. Bottom-up and top-down attention for image captioning and visual question answering. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 6077–6086, 2018. 1, 2, 3

[3] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473, 2014. 2

[4] Satanjeev Banerjee and Alon Lavie. Meteor: An automatic metric for mt evaluation with improved correlation with human judgments. In Proceedings of the acl workshop on intrinsic and extrinsic evaluation measures for machine translation and/or summarization, pages 65–72, 2005. 4

[5] Soravit Changpinyo, Bo Pang, Piyush Sharma, and Radu Soricut. Decoupled box proposal and featureization with ultratine-grained semantic labels improve image captioning and visual question answering. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 1468–1474, 2019. 1

[6] Xinlei Chen, Hao Fang, Tsung-Yi Lin, Ramakrishna Vedantam, Saurabh Gupta, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco captions: Data collection and evaluation server. arXiv preprint arXiv:1504.00325, 2015. 4

[7] Marcella Cornia, Lorenzo Baraldi, and Rita Cucchiara. Show, control and tell: A framework for generating controllable and grounded captions. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 8307–8316, 2019. 2

[8] Marcella Cornia, Matteo Stefanini, Lorenzo Baraldi, and Rita Cucchiara. Meshed-memory transformer for image captioning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 10578–10587, 2020. 1, 2

[9] Aditya Deshpande, Jyoti Aneja, Liwei Wang, Alexander G Schwing, and David Forsyth. Fast, diverse and accurate image captioning guided by part-of-speech. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 10695–10704, 2019. 2

[10] Desmond Elliott, Stella Frank, Khalit Sima’an, and Lucia Specia. Multi30k: Multilingual english-german image descriptions. arXiv preprint arXiv:1605.00459, 2016. 3, 4, 7

[11] Yang Feng, Lin Ma, Wei Liu, and Jiebo Luo. Unsupervised image captioning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 4125–4134, 2019. 1, 2, 3, 4, 5

[12] Jiuxiang Gu, Shafiq Joty, Jianfei Cai, and Gang Wang. Unpaired image captioning by language pivoting. In Proceedings of the European Conference on Computer Vision (ECCV), pages 503–519, 2018. 2, 3

[13] Jiuxiang Gu, Shafiq Joty, Jianfei Cai, Handong Zhao, Xu Yang, and Gang Wang. Unpaired image captioning via scene graph alignments. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 10323–10332, 2019. 2

[14] Dan Guo, Yang Wang, Peipei Song, and Meng Wang. Recurrent relational memory network for unsupervised image captioning. arXiv preprint arXiv:2006.13611, 2020. 2

[15] Lisa Anne Hendricks, Subhashini Venugopalan, Marcus Rohrbach, Raymond Mooney, Kate Saenko, and Trevor Darrell. Deep compositional captioning: Describing novel object categories without paired training data. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1–10, 2016. 2

[16] Ukyo Honda, Yoshitaka Ushiku, Atsushi Hashimoto, Taro Watanabe, and Yuji Matsumoto. Removing word-level spurious alignment between images and pseudo-captions in unsupervised image captioning. arXiv preprint arXiv:2104.13872, 2021. 2, 4, 5, 6, 7, 8

[17] Justin Johnson, Andrej Karpathy, and Li Fei-Fei. Denselycap: Fully convolutional localization networks for dense captioning. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4565–4574, 2016. 2

[18] Andrej Karpathy and Li Fei-Fei. Deep visual-semantic alignments for generating image descriptions. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3128–3137, 2015. 1, 2, 4

[19] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014. 4

[20] Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David 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. 4

[21] Matt Kusner, Yu Sun, Nicholas Kolkin, and Kilian Weinberger. From word embeddings to document distances. In International conference on machine learning, pages 957–966. PMLR, 2015. 4

[22] Iro Laina, Christian Rupprecht, and Nassir Navab. Towards unsupervised image captioning with shared multimodal embeddings. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 7414–7424, 2019. 2, 6

[23] Weiyu Lan, Xirong Li, and Jianfeng Dong. Fluency-guided cross-lingual image captioning. In Proceedings of the 25th ACM international conference on Multimedia, pages 1549–1557, 2017. 3

[24] Xirong Li, Chaoxi Xu, Xiaoxu Wang, Weiyu Lan, Zhengxiong Jia, Gang Yang, and Jieping Xu. Coco-cn for cross-lingual image tagging, captioning, and retrieval. IEEE Transactions on Multimedia, 21(9):2347–2360, 2019. 3, 4, 7

[25] Chin-Yew Lin. Rouge: A package for automatic evaluation of summaries. In Text summarization branches out, pages 74–81, 2004. 4
[26] Fenglin Liu, Meng Gao, Tianhao Zhang, and Yuexian Zou. Exploring semantic relationships for unpaired image captioning. *arXiv preprint arXiv:2106.10658*, 2021. 2

[27] Zihang Meng, Licheng Yu, Ning Zhang, Tamara L Berg, Babak Damavandi, Vikas Singh, and Amy Bearman. Connecting what to say with where to look by modeling human attention traces. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12679–12688, 2021. 1, 2, 4, 5, 6

[28] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting of the Association for Computational Linguistics*, pages 311–318, 2002. 4

[29] Jordi Pont-Tuset, Jasper Uijlings, Soravit Changpinyo, Radu Soricut, and Vittorio Ferrari. Connecting vision and language with localized narratives. In *European Conference on Computer Vision*, pages 647–664. Springer, 2020. 1, 4

[30] Janarthanan Rajendran, Mitesh M Khapra, Sarath Chandar, and Balaraman Ravindran. Bridge correlational neural networks for multilingual multimodal representation learning. *arXiv preprint arXiv:1510.03519*, 2015. 3

[31] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. *Advances in neural information processing systems*, 28:91–99, 2015. 4

[32] Sebastian Schuster, Ranjay Krishna, Angel Chang, Li Fei-Fei, and Christopher D Manning. Generating semantically precise scene graphs from textual descriptions for improved image retrieval. In *Proceedings of the fourth workshop on vision and language*, pages 70–80, 2015. 5

[33] Priyush Sharma, Nan Ding, Sebastian Goodman, and Radu Soricut. Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning. In *Proceedings of ACL*, 2018. 4

[34] Yuqing Song, Shizhe Chen, Yida Zhao, and Qin Jin. Unpaired cross-lingual image caption generation with self-supervised rewards. In *Proceedings of the 27th ACM International Conference on Multimedia*, pages 784–792, 2019. 3

[35] Matteo Stefanini, Marcella Cornia, Lorenzo Baraldi, Silvia Ciscianelli, Giuseppe Fiameni, and Rita Cucchiara. From show to tell: A survey on image captioning. *arXiv preprint arXiv:2107.06912*, 2021. 2

[36] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008, 2017. 3, 4

[37] Ramakrishna Vedantam, C Lawrence Zitnick, and Devi Parikh. Cider: Consensus-based image description evaluation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4566–4575, 2015. 4

[38] Subhashini Venugopalan, Lisa Anne Hendricks, Marcus Rohrbach, Raymond Mooney, Trevor Darrell, and Kate Saenko. Captioning images with diverse objects. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5753–5761, 2017. 2

[39] Yike Wu, Shiwan Zhao, Jia Chen, Ying Zhang, Xiaojie Yuan, and Zhong Su. Improving captioning for low-resource languages by cycle consistency. In *2019 IEEE International Conference on Multimedia and Expo (ICME)*, pages 362–367. IEEE, 2019. 3

[40] Kelvin Xu, Jimmy Ba, Ryan Kiros, Kyunghyun Cho, Aaron Courville, Ruslan Salakhudinov, Rich Zemel, and Yoshua Bengio. Show, attend and tell: Neural image caption generation with visual attention. In *International conference on machine learning*, pages 2048–2057. PMLR, 2015. 1, 2

[41] Rowan Zellers, Mark Yatskar, Sam Thomson, and Yejin 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. 5

[42] Wei Zhang, Yue Ying, Pan Lu, and Hongyuan Zha. Learning long-and short-term user literal-preference with multilingual hierarchical transformer network for personalized image caption. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 9571–9578, 2020. 2

[43] Luowei Zhou, Hamid Palangi, Lei Zhang, Houdong Hu, Jason Corso, and Jianfeng Gao. Unified vision-language pre-training for image captioning and vqa. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 13041–13049, 2020. 1