Cascaded Revision Network for Novel Object Captioning
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Abstract—Image captioning, a challenging task where the machine automatically describes an image by sentences, has drawn significant attention in recent years. Despite the remarkable improvements of recent approaches, however, these methods are built upon a large set of training image-sentence pairs. The expensive labor efforts hence limit the captioning model to describe the wider world. In this paper, we present a novel network structure, Cascaded Revision Network, which aims at relieving the problem by equipping the model with out-of-domain knowledge. CRN first tries its best to describe an image using the existing vocabulary from in-domain knowledge. Due to the lack of out-of-domain knowledge, the caption may be inaccurate or include ambiguous words for the image with unknown (novel) objects. We propose to re-edit the primary captioning sentence by a series of cascaded operations. We introduce a perplexity predictor to find out which words are most likely to be inaccurate given the input image. Thereafter, we utilize external knowledge from a pre-trained object detection model and select more accurate words from detection results by the visual matching module. In the last step, we design a semantic matching module to ensure that the novel object is fit in the right position. By this novel cascaded captioning-revising mechanism, CRN can accurately describe images with unseen objects. We validate the proposed method with state-of-the-art performance on the held-out MSCOCO dataset as well as scale to ImageNet, demonstrating the effectiveness of this method.

Index Terms—Captioning, novel object, visual matching, semantic matching.

I. INTRODUCTION

Image captioning has become a promising direction in the research for computer vision and language [1], [2], [3], [4], [5], [6], [7], [8]. This task aims to automatically generate a natural and concrete description of an image. Recent approaches based on the encoder-decoder structure have achieved encouraging performances on the image captioning task. However, existing models could only describe the objects shown in the training image-caption pairs, which hinders the generalization of these models in real-world scenarios. How to describe images with unseen objects is still a challenge for image captioning [9], [10], [11].

In this paper, we aim to alleviate this problem by equipping the image captioning model with out-of-domain knowledge. Naturally, when seeing an unknown object, human search their memory and find the most similar object to describe it. For example, when seeing a “zebra”, humans tend to project the features and the environment of the “zebra” and deduce: “It is something like a horse.” If an additional knowledge database is available, e.g., picture flashcards or an internet search engine, human could look up similar objects and select the correct “word” to better describe the unknown object. With out-of-domain knowledge, it is possible to learn the similarity and difference between a “horse” and a “zebra” and describe the unseen “zebra” with its correct name.

In this paper, we introduce a novel framework called Cascaded Revision Network (CRN) for novel object captioning. When describing an image with novel objects, the image captioner is first asked to try its best to characterize the image...
using existing in-domain knowledge. To this end, the agent could choose synonyms or similar words in its vocabulary to describe unknown objects. These synonyms or similar words can be ambiguous and even inaccurate due to the lack of out-of-domain knowledge. We define a sentence generated by the image captioner with only in-domain vocabulary as a primary caption.

Imitating human-style describing an image with unseen objects, we design three cascaded operations to better revise the primary caption: 1) estimating the uncertainty of each word; 2) searching the external knowledge database for a better description; 3) embedding the out-of-domain object into the caption without breaking the grammar. In our CRN framework, the above sub-tasks are executed by the perplexity predictor, the visual matching module and the semantic matching module, respectively. The perplexity predictor is designed to figure out the ambiguous words in the primary caption. Specifically, the perplexity predictor checks each word in the primary caption and predicts a perplexity score for each word. If a perplexity score is greater than the perplexity threshold, the corresponding word is considered as a candidate to be revised. When predicting a word with high perplexity, the agent probably meets an object it is not familiar with or not sure about. Thus, the agent needs to ask for help from external knowledge to generate more accurate words. Besides, there are also cases when the agent is capable to caption the image based on its own knowledge. The agent can handle these cases with high confidence which means it does not need additional help.

Next, we leverage the external knowledge to find more accurate noun words for the cases with high perplexity. In CRN, a pre-trained object detector is used to obtain all objects with their names in the image. We then design the visual matching module to match the inaccurate words with detected objects. We adopt the key-value memory mechanism to construct the communication between the captioning agent and the object detector. Specifically, the agent uses the substitutes to query the memory according to the visual information of objects. Then, the word corresponding to the object with the highest probability is selected to replace the substitute. To this end, the visual matching module exploits an external object detector [12] as out-of-domain knowledge. In this way, the corresponding name of the selected object becomes a candidate to revise the primary caption.

However, the object detector is not always reliable to detect all the objects accurately. In this case, the visual matching module would generate a wrong matching proposal. The semantic matching module is responsible for eliminating such incorrect visual match proposals. Specifically, the semantic matching module measures the similarity between the ambiguous word and the object name with an out-of-domain word embedding. The incorrect visual match could result in a small similarity and therefore be ignored. By this cascaded captioning-revising mechanism, novel objects are described accurately in the final caption sentence. An example of novel object captioning by CRN is illustrated in Figure 1.

Our proposed method turns out with results competitive with the current state-of-the-art performance on the held-out MSCOCO on the novel object captioning task. We also scale CRN to a larger dataset: ImageNet [13]. With more analysis, we reveal that our approach not only improves captioning with novel objects as well as images without novel objects. Finally, the main contributions of this paper are summarized as follows:

- We propose a novel cascaded framework for novel object captioning by imitating how we human describe an image with an unseen object. At first, the model tries its best to generate a primary caption based on in-domain knowledge. We propose to gradually revise the primary captioning sentence by a series of cascaded operations.
- In the cascaded network, we develop a perplexity predictor, a visual matching module and a semantic matching module to revise the primary captioning.
- To our knowledge, we are the first to match the out-of-domain knowledge both visually and semantically to better combine it with the in-domain captions.

II. RELATED WORK

Deep Image Captioning. Given an image, the goal of image captioning is to generate a natural and accurate sentence to describe the image. Early approaches [14], [15] composed image captions via slot filling which separate the object recognition and the language template generation. These approaches may generate natural sentences but less related to the visual contents. Deep Learning has elevated the performance of captioning models with images and videos. Most of related work [16], [17], [18], [19], [20], [21], [22], [23], [24], [25] follow a multimodal framework which combines CNN [26], [27] and RNN like Long Short-Term Memory (LSTM) [28] and Gated Recurrent Unit (GRU) [29]. Visual features in high-level with semantic information are first extracted by the CNN encoder, while the RNN decoder predicts the description word by word according to visual features. However, these methods do not consider the situation where a large number of unseen objects exist in the images.

Zero-shot Learning. With the booming development of techniques in computer vision, lack of well-labeled data becomes the bottleneck of performance. Image-paired sentences is in large scarcity and the label tagging of captioning costs much more than other tasks. Zero-shot learning is a good solution to resolve the out-of-domain adaptation for models with limited knowledge. There has been a recent surge on the zero-shot tasks [30], [31], [32] which aims to recognize objects unseen during the training stage. Many two-stage approaches [33] are proposed to first capture the attributes of the unseen objects, then infer the class label with the most similar set of features.

Novel Object Captioning. The novel object captioning task attracts increasing attention recently. The problem exists in how to leverage the unpaired image and semantic data [34] to better describe the unseen objects. A few works are carried out to address this captioning task. The Deep Compositional Captioner (DCC) is proposed by [9], a pilot work to put forward the task of novel objects captioning. DCC [9] combine visual groundings of lexical units to generate descriptions.
about objects which are not present in caption corpora (paired image-sentence data), but are present in object recognition datasets (unpaired image data) and text corpora (unpaired text data). Novel Object Captioner (NOC) [35] is introduced as an end-to-end framework training the object classification, language model and the captioning jointly. The detection model is integrated with the language sequence model by copying detection results into the prediction out of the RNN-based decoder model to alleviate the gap between novel objects with the captioning model in [36]. An approach is proposed in [10] to generate language template along with slots and the corresponding region in the image at first. Then objects are fit into the slots by recognizing the region with a detection model. But they have to manually define the category of the novel object with an existing one when captioning. What is more, the categories are still not well defined and limit the concepts to similar visual looking which is too idealized. For example, “man” and “woman” are classified as “person”, while “car”, “bus” and “truck” belong to three different classes. A placeholder is used in [11] to take place of the novel objects which generalize the concept of novel object but also lost information of the current object. These methods rely too much on visual detection. The results are limited to the detection model and less likely to select small objects. They neglected the original lexical context information. To the best of our knowledge, our model is the first captioning model with self-awareness and two-way revision mechanism.

**Summary.** In a nutshell, the proposed method focuses on generating accurate caption of images with novel objects. With the cascaded revision mechanism, CRN exploits the out-of-domain knowledge provided by the object detector and better embeds the novel object with the in-domain captions. With the setting of pseudo objects, CRN is able to distinguish unknown objects from correct ones. What’s more, the cascaded visual matching and semantic matching ensures the combination of out-of-domain objects with the in-domain descriptions.

### III. The Proposed Approach

The Cascaded Revision Network (CRN) is designed to better embed the out-of-domain objects into the in-domain captions. In this section, we first introduce the traditional image captioning model in Section III-A. We then show how CRN describes images with novel objects in Section III-B. The full framework of CRN is illustrated in Figure 2.

#### A. Image Captioning Model

The main task of an image captioning model is to generate a natural language sentence to describe the image, while maintaining the semantic grammar of the sentence. Given an image \( I \) and the ground truth caption \( w = \{ w_1, w_2, ..., w_T \} \), the objective of the captioning model is to minimize

\[
L = -\log p(y|I) = -\log p(w_1, w_2, ..., w_T|I) \\
= -\log \prod_{t=1}^{T} p(w_t|w_1, w_2, ..., w_{t-1}, I) \\
= -\sum_{t=1}^{T} \log p(w_t|w_1, w_2, ..., w_{t-1}, I). \tag{1}
\]

Eq. 1 aims to maximize the likelihood of each word in the ground-truth caption. Usually, the term \( p(w_t|w_1, ..., w_{t-1}, I) \) is modeled by a Long Short-Term Memory (LSTM) [28] that takes \( I \) as its initial state \( h_0 \):

\[
p(\cdot|w_1, w_2, ..., w_{t-1}, h_0), h_t = \text{LSTM}(w_{t-1}, h_{t-1}), \tag{2}
\]

where \( w_0 \) is the start symbol \(<\text{START}>\). What’s more, the distribution \( p(\cdot|w_1, w_2, ..., w_{t-1}, h_0) \) is a parametric function of \( h_t \). LSTM first generates the current hidden state \( h_t \) and then emits the distribution by a fully-connected layer according to \( h_t \). For simplicity, we use \( \pi(\cdot|h_t) \) to denote this distribution:

\[
\pi(\cdot|h_t) = p(\cdot|w_1, w_2, ..., w_{t-1}, h_0). \tag{3}
\]

The current word is generated by

\[
w_t = \arg \max_w \pi(\cdot|h_t). \tag{4}
\]

During training, the previous ground-truth words are given. When conducting the evaluation, the previous ground-truth words are unavailable and are generated by maximum likelihood estimation (MLE).

#### B. Cascaded Revision Network

CRN aims to alleviate the problem of novel object captioning by equipping the model with out-of-domain knowledge. To exploit out-of-domain knowledge, CRN adopts a captioning-revising mechanism. Following [10], [11], in this paper, we use the out-of-domain knowledge provided by an object detector and a word embedding look-up table. CRN contains four cascaded modules: a primary image captioner, a perplexity predictor, a visual matching module and a semantic matching module. With the setting of pseudo objects, CRN learns to distinguish ambiguous words inconsistent with the images.

1) **Image Captioner:** The main challenge of this task is that the model has no prior knowledge of novel objects. In this case, the captioning model will predict a word based on the visual looking or the semantic context. Specifically, the captioner describes an image with its existing vocabulary to generate a primary caption. Ambiguous or even inaccurate words may be used when describing unknown objects. Several words are assigned as novel objects during the training of captioner based on the encoder-decoder framework described in III-A. Here, we denote words in the vocabulary of the image-paired captions as \( V_c \). The objects neither in the images nor the captions are novel objects denoted as \( O_u \). To simulate the existence of novel objects, objects are selected from the vocabulary \( V_c \) to be replaced in the captions which are denoted as \( O_t \). Objects \( \in O_t \) act as the role of novel objects during training which the model has never seen. We replace objects \( \in O_t \) with pseudo objects. With the open-source pretrained embeddings, each object \( \in O_t \) is paired with its most similar word \( \in V_c \) which acts as pseudo object. The pseudo object and its corresponding object \( \in O_t \) form a pair of inaccurate description of an object. The word similarity is measured with the cosine metric between the word embeddings. Furthermore, in order to inform the captioner about the existence of pseudo
object, we design an additional novel label \( \hat{n} \) of each word \( w \) to indicate whether it is a novel object or not:

\[
\hat{n} = \begin{cases} 1, & w \in O_t \\ 0, & \text{otherwise} \end{cases}
\]  

(5)

Another embedding function \( \phi_{\hat{n}} \) is adopted to embed the novel label into the input of captioner. At time step \( t \), the input vector of the captioner \( x_t \) is the concatenation of the embedding of \( w_{t-1} \) and its novel label \( \hat{n}_{t-1} \):

\[
x_t = \phi_{x}(w_{t-1}, \phi_n(\hat{n}_{t-1})) = [W_e I_{t-1}^w, W_n I_{t-1}^\hat{n}],
\]

(6)

where \( W_e \in \mathbb{R}^{N_e \times D_e} \) is the word embedding matrix of the vocabulary \( V_c \). \( N_e \) is the number of the vocabulary. \( D_e \) denotes the dimension of embedding. \( W_n \in \mathbb{R}^{2 \times D_e} \) denotes learnable weight matrix of the novel label \( \hat{n} \). \( I_{t-1}^w \) and \( I_{t-1}^\hat{n} \) are the corresponding one-hot encoding of \( w_{t-1} \) and \( \hat{n}_{t-1} \). With the input vector \( x_t \), the output hidden state of captioner is given by:

\[
h_t = w_h^T \tanh(W_s x_t + W_z h_{t-1}),
\]

(7)

where \( w_h^T, W_s, W_z \) are weights to be learned. At each time step, the distribution of the conditional probabilities over all possible words \( \in V_c \) is:

\[
p_t = \text{softmax}(W_p h_t + b_p),
\]

(8)

where \( W_p, b_p \) are learned weights and biases.

2) Perplexity Predictor: To revise the primary caption, the perplexity predictor is designed to figure out the ambiguous words in it. The intuition behind the proposed method is to enable the captioner to justify whether the word is consistent with the image or not. Thus, it is aware of the ambiguity of its outputs. We here define the level of ambiguity as semantic perplexity. In information theory, perplexity is a measurement of how well a model predicts a sample. The perplexity of the current output of captioner is calculated using the hidden state of captioner. The function of the perplexity predictor is designed as:

\[
m_t = \sigma(W_m h_t + b_m),
\]

(9)

where \( W_m, b_m \) are learned weights and biases for this layer. \( \sigma \) is the sigmoid activation of confidence probability. A threshold \( \tau_p \) is adopted here. If \( m_t \) surpasses \( \tau_p \), it indicates that the current prediction is not with enough confidence. All outputs with high perplexity will become regarded as inaccurate words and will probably be replaced with a matched object in the next revision steps.

With the image captioner and the perplexity predictor introduced above, the corresponding objective cross entropy loss function is:

\[
L_{\text{corr}}(w_{1:t-1}, I; \theta) = -\frac{1}{T} \sum_{t=1}^{T} \log p(w_t | w_{1:t-1}) + \sum_{t=1}^{T} \log p(m_t | w_{1:t-1}).
\]

(10)

3) Visual Matching Module: The visual matching module is responsible for acquiring objects in the image with the knowledge of the detector and generate replacement proposals based on visual similarity. To introduce novel objects out-of-domain into the image captioner, we employ an freely available pretrained object detection model \( M_d \). Thus, we can take advantage of \( M_d \) to detect objects in the image which are further used to revise the inaccurate words in the primary
caption. The extracted visual features $V_d \in \mathbb{R}^{N_o \times D_v}$. $N_o$ is the number of detected objects. $D_v$ is the dimension of visual feature. The predicted class labels $O_d \in \mathbb{R}^{1 \times N_d}$ of the objects can also be obtained from $M_d$. $N_d$ is the number of target classes of $M_d$. We extract the visual features of objects from the ROI pooling layer of $M_d$ following [2]. The objects are chosen according to the prediction scores given by the object detection model. With the hidden state $h_t$ of captioner at time step $t$, the visual similarity between the current feature and features of all detected objects can be calculated as:

$$S_t = V_d h_t.$$  \hspace{1cm} (11)

Then we address the probabilities over all classes of $M_d$ at time $t$:

$$O_t = S_t O_d,$$  \hspace{1cm} (12)

Each inaccurate word will be matched with a detected object which is regarded as a candidate to be put in the final caption. For the matching between the output of captioner and the feature of detected objects, the objective for training this module is defined as:

$$L_{det}(h_t; \theta) = -\frac{1}{N_d} \sum_{i=1}^{N_d} n_t \log p(o_i | h_t),$$  \hspace{1cm} (13)

where $N_d$ is the number of detected objects at time step $t$, $n_t$ is used as the mask of the current ground truth word which is defined in Eq (5). These three modules of CRN are jointly trained during the training of CRN.

4) Semantic Matching Module: Simply replacing the inaccurate words with the visually matched objects may break the semantic structure of the sentences. Besides, due to the limitation of the compressed features, objects with salient features tend to be matched with a high frequency. It is observed that many ambiguous words are matched with the same detected object while some are not relative semantically. Therefore, we elevate the quality of revision by employing the semantic matching as the last step.

With the selected objects from the detection model, the word similarity is calculated with the pretrained word embedding look-up. It is noticed that there are some words which are composed of two words cannot be found in the Glove embedding, e.g., “hot dog”, “hair drier”, etc. In this case, to prevent manual intervention, we simply average the embeddings of the two words. The cosine similarity is used to measure the distance between the novel objects and the caption words. The word with the largest word similarity is replaced by the detected object.

Finally, the full framework of CRN is proposed to deal with the captioning of images with novel objects. With the different modules cascaded in the model, each module is optimized with a sub-goal. The gap between the novel object and the existing knowledge is represented by the perplexity of the prediction which simulates the process of thinking before the description.

IV. EXPERIMENTS

We start by describing the setups of this task and our experiments. Then, the results of our methods and the state-of-the-art methods in history are compared on the held-out MSCOCO dataset. Furthermore, several ablation studies are carried out with competitive results to prove the effectiveness and reliability of our proposed method.

A. Experimental Settings

MSCOCO is a widely used benchmark for many tasks including image captioning [34]. The held-out subset of the MSCOCO dataset following [9], [35], [36] are used as the training set in our experiments. In [9], eight classes of MSCOCO objects are chosen. None of the 8 classes is included in the captioning in the training split set, but all of them are in the evaluation split set. We follow the same setting of training, validation and test split in [9] in order to generate comparable captioning results.

**Pseudo object processing**. All classes except the eight held-out classes in MSCOCO are chosen as novel objects $O_t$ in the train set which are replaced with pseudo objects in the in-domain vocabulary. To select pseudo object of each novel object $O_t$, we employ the open source pretrained embedding weights of Glove following [9], [36] with the dimension of 300. For example, “umbrella” \(\rightarrow\) “parasol”, “zebra” \(\rightarrow\) “horse”, “sandwich” \(\rightarrow\) “burger”, etc. We stress that we have not used any other semantic data or description for these objects, neither do we manually change any word. The detail of the replacement is shown in Figure 3. It comes out the plural format of the word tends to be the most similar word to itself, e.g., “sandwiches” to “sandwich”. It is meaningless if we use word “sandwiches” to take place of “sandwich”, as they refer to the same object.

**Experiment details**. We apply a 16-layer VGG pretrained on ImageNet following [9], [35], [36] as the image encoder in our model. Parameters of the encoder are frozen during the training. The features output by layer fc7 are used as the
representation of the image and fed into the language decoder. The dimension of the image feature is 4,096. In order to introduce the novel objects into the final captions, a popular open-source pre-trained Faster-RCNN model [12] is adopted to detect and crop the objects in an image following [37], [10], [11]. Then, we reuse the VGG Net mentioned above to extract visual features of the detected objects. The pre-trained detection model is released by [38], which is trained on all the 80 classes of objects in the MSCOCO detection dataset. We adopt the LSTM as the decoder with one layer and its dimension is 1024.

**Compared approaches.** To evaluate on the held-out MSCOCO, results of our proposed method are compared with DCC [9], NOC* [35], LSTM-C [36], Base+T4 [37], NTB+G [10] and DNOC [11] to demonstrate the competitiveness. During the methods, NTB+G and DNOC do not use the additional semantic data. We follow the same zero-shot setting in our experiments. Furthermore, the results of several ablation versions of the proposed model are compared and discussed. In order to prove the advantage of CRN not only exists in the context of the known objects than objects never seen before. It is explainable that captioning model can better describe the existence of the pseudo novel object. Thus, the F1 score is 0. The perplexity predictor adds the second task: predicting the perplexity of each word. If the perplexity

| Method  | METEOR | \( F_{\text{beau}} \) | \( F_{\text{hae}} \) | \( F_{\text{lich}} \) | \( F_{\text{micro}} \) | \( F_{\text{piza}} \) | \( F_{\text{cket}} \) | \( F_{\text{tcase}} \) | \( F_{\text{bra}} \) | \( F_{\text{veage}} \) |
|---------|--------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| DCC [9] | 21     | 4.63           | 29.79          | 45.87          | 28.09          | 64.59          | 52.24          | 13.16          | 79.88          | 39.78          |
| NOC* [35] | 21.32 | 17.78          | 68.79          | 25.55          | 24.72          | 69.33          | 55.31          | 39.86          | 48.79          | 39.78          |
| LSTM-C [36] | 22    | 29.07          | 64.38          | 26.01          | 26.04          | 75.57          | 66.54          | 55.54          | 92.03          | 54.40          |
| LSTM-C* | 23    | 29.68          | 74.42          | 38.77          | 27.81          | 68.17          | 70.27          | 44.76          | 91.40          | 55.66          |
| Base+T4† [37] | 23.6  | 16.3           | 67.8           | 48.2           | 29.7           | 77.2           | 57.1           | 49.9           | 85.7           | 54.0           |
| NBT+G† [10] | 22.8  | 7.1            | 73.7           | 34.4           | 61.9           | 59.9           | 20.2           | 42.3           | 88.5           | 48.5           |
| DNOC [11] | 21.57 | 33.04          | 76.87          | 53.97          | 46.57          | 75.82          | 32.98          | 59.48          | 84.58          | 57.92          |
| CRN (ours) | 21.31 | 38.05          | 78.40          | 55.93          | 53.76          | 81.43          | 62.02          | 57.69          | 85.38          | 64.08          |

| Method  | \( F_{\text{bear}} \) | \( F_{\text{cat}} \) | \( F_{\text{dog}} \) | \( F_{\text{ephant}} \) | \( F_{\text{horse}} \) | \( F_{\text{microwave}} \) | \( F_{\text{average}} \) |
|---------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| LRCN [39] | 66.23          | 75.73          | 53.62          | 65.49          | 55.20          | 71.45          | 64.62          |
| DNOC [11] | 62.86          | 87.28          | 71.57          | 77.46          | 71.20          | 77.59          | 74.66          |
| CRN     | 60.38          | 86.74          | 74.04          | 81.41          | 75.36          | 78.39          | 76.05          |

| Method  | METEOR | \( F_{\text{average}} \) |
|---------|--------|----------------|
| LRCN [39] | 19.33  | 0              |
| CRN I   | 18.24  | 0              |
| CRN I + II | 19.65  | 45.30          |
| CRN w/o II | 19.26  | 53.31          |
| CRN w/o IV | 20.85  | 56.32          |
| CRN w/o III | 21.01  | 62.08          |

| Method  | Novel | \( F_{\text{average}} \) | Acc |
|---------|-------|----------------|-----|
| NOC [35] | 69.08 | 15.63          | 10.04          |
| LSTM-C [36] | 72.08 | 16.39          | 11.83          |
| CRN     | 77.92 | 19.5           | 16.34          |
goes beyond the threshold \( \tau_p \), the word will be replaced by a detected object randomly selected from the results of the detection model. It brings a significant rise in the F1 score. The METEOR also increases from 18.12 to 19.65. The threshold \( \tau_p \) is set as 0.15 in our experiments learned by the model. **CRN w/o II** is CRN without the perplexity predictor. As the average number of words above the perplexity threshold in the training stage is 1.7 per sentence, we choose two positions in the sentence to replace the detected object matched with the two-way matching of visual similarity and word similarity. It shows that **CRN I+II** is better on METEOR than **CRN w/o II** which indicates the value of the perplexity predictor. The average F1 score of **CRN w/o II** is 53.31\%, 8.01\% higher than **CRN I+II**. **CRN w/o IV** (semantic matching) is CRN without the matching of word similarity. Objects are matched only with the features from the language decoder and visual features of objects detected. The F1 average score increases from 45.30\% to 56.32\%. **CRN w/o III** (visual matching) objects are matched only with word similarity which outperforms **CRN w/o IV** by 5.76\% on F1 score. With full stages, our model is able to capture features of the unknown objects on visual outlook and semantic context which composes more accurate captions about the image. Furthermore, in order to show the advantage of the proposed model not only exist in the novel object captioning, we also evaluate F1 scores of other words in \( W_s \). Our model is also able to generate accurate descriptions of known objects. F1 scores on a different group of known objects are listed in Table II. It turns out that the performance on these objects is also quite qualitative. Figure 4 shows some examples of image captioning results with novel objects.

**Threshold of Perplexity.** We present the performance of F1 score and METEOR along with the change of threshold of perplexity in Figure 5. When the threshold is 0, the F1 score achieves quite high but with a low meteor. It indicates that the objects detected by the detection model in the image are replaced into the caption while it destroys the grammar and structure of the sentence. When the threshold is between (0, 0.15), METEOR both get higher, while F1 score drops slightly. It indicates that the threshold limits the ambiguous words area while the number of objects replaced into the sentence decreased. After that, the F1 score goes down when the threshold is larger than 0.15. The METEOR score also decreases and drops more when threshold goes beyond 0.5.

**Scale to Larger Dataset.** The proposed CRN takes advantage of an expertised detector to introduce novel objects. Considering the out-of-MSCOCO objects, a detector with
By applying the two-way matching, CRN better integrates the mechanism, the unknown object can be better matched or unknown to itself. Furthermore, with a two-way matching, the captioner in CRN is able to be aware of what is ambiguous between existing knowledge and objects out-of-domain, to deal with captioning with novel objects. To overcome the gap, experiments are reported in Table IV.

V. CONCLUSION

In this paper, we present a novel cascaded framework CRN to deal with captioning with novel objects. To overcome the gap between existing knowledge and objects out-of-domain, the captioner in CRN is able to be aware of what is ambiguous or unknown to itself. Furthermore, with a two-way matching mechanism, the unknown object can be better matched and fit in the caption. At a higher level, our proposed method decouples the captioning of novel objects to two sub-tasks: what is the novel object and where to put the novel object. By applying the two-way matching, CRN better integrates the out-of-domain knowledge both visually and semantically.

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