Caption Generation on Scenes with Seen and Unseen Object Categories

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Abstract

Image caption generation is one of the most challenging problems at the intersection of vision and language domains. In this work, we propose a realistic captioning task where the input scenes may incorporate visual objects with no corresponding visual or textual training examples. For this problem, we propose a detection-driven approach that consists of a single-stage generalized zero-shot detection model to recognize and localize instances of both seen and unseen classes, and a template-based captioning model that transforms detections into sentences. To improve the generalized zero-shot detection model, which provides essential information for captioning, we define effective class representations in terms of class-to-class semantic similarities, and leverage their special structure to construct an effective unseen/seen class confidence score calibration mechanism. We also propose a novel evaluation metric that provides additional insights for the captioning outputs by separately measuring the visual and non-visual contents of generated sentences. Our experiments highlight the importance of studying captioning in the proposed zero-shot setting, and verify the effectiveness of the proposed detection-driven zero-shot captioning approach.

Keywords: zero-shot learning, zero-shot image captioning

1. Introduction

The problem of generating a concise textual summary of a given image, known as image captioning, is one of the most challenging problems that require joint vision and
lingual modeling. With ever-increasing recognition rates in object detection models, pioneered by [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11], there has been a recent interest in generating visually grounded captions via constructing detection-driven captioning models, e.g. [12, 13, 14, 15]. However, the success of such approaches is inherently limited by the set of classes spanned by the detector training set, which is typically too small to construct a visually comprehensive model. Therefore, such models are prone to synthesizing irrelevant captions in realistic, uncontrolled settings where input images may contain instances of classes unseen during training.

In the context of image classification, zero-shot learning (ZSL) has emerged as a promising alternative towards overcoming the practical limits in collecting labeled image datasets and constructing image classifiers with very large object vocabularies. In a similar manner, zero-shot image captioning (ZSC), aims to develop methods towards overcoming the data collection bottleneck in image captioning. However, we observe that there is no prior work directly tailored to study captioning in a truly zero-shot setting, except the preliminary conference version of this paper to the best of our knowledge: recent works on ZSC [15, 16] study the ZSC problem only in the language domain, presuming the availability of a pre-trained fully-supervised object detector covering all object classes of interest. We refer to these methods as partial zero-shot image captioning.
Following these observations, we propose the problem of true zero-shot captioning, where test images contain instances of unseen object categories with no supervised visual or textual examples, in addition to the seen categories. We believe that this change constitutes a more direct problem definition towards (i) developing semantically scalable captioning methods, and, (ii) evaluating captioning approaches in a realistic setting where not all object classes have training examples. The difference between the partial versus true ZSC problems is illustrated in Figure 1.

To tackle the true ZSC problem, we propose an approach that consists of a novel generalized zero-shot detection (GZSD) model, which aims to generate detections in scenes with both seen and unseen class instances, and a template-based [15] caption generator. A high-level summary of our ZSC approach can be found in Figure 2. In order to address the GZSD problem, we propose a scaling scheme and incorporate uncertainty calibration [17] to make seen and unseen class scores comparable. We also show out that using class-to-class similarities obtained over word embeddings [18] as class embeddings improves the GZSD results, compared to using class name embeddings directly. On the MS-COCO dataset [19], we present a detailed evaluation of both GZSD and ZSC models. For a more accurate evaluation of the ZSC results, we propose a new evaluation metric called V(visual)-METEOR, which adapts and improves the widely used METEOR metric for ZSC evaluation purposes.

A preliminary version of this work has previously appeared in [20]. In addition to provide more detailed related work discussions and method explanations, this paper extends the conference version by introducing uncertainty calibration loss for class confi-
dence calibration, evaluating the impact of various model decisions and score calibration, introducing a comparison to the recent GZSD methods on the benchmark MS-COCO dataset, quantitatively demonstrating the advantage of using class-to-class similarities as the class embeddings, and analyzing the GZSD failure patterns, which are all directly relevant for the captioning quality. The journal version also proposes the V-METEOR metric, and uses the new metric for a more detailed analysis of the ZSC model.

2. Related Work

Below, we provide an overview of the related work on zero-shot classification, detection and captioning.

2.1. Zero-shot classification

Early work on ZSL focused on directly using attribute based probabilistic models for transferring knowledge from seen to unseen classes [21]. More recent works explore other knowledge transfer mediums and predictive models, e.g. [22, 23, 24, 25, 26, 27, 28, 29, 30]. A comparative survey of discriminative ZSL models can be found in Xian et al. [31], which introduces the problem of generalized zero-shot learning (GZSL) problem in an image classification context. Alternatively, the development of generative models that can synthesize training examples of unseen classes has received significant interest in recent years, e.g. [32, 33, 34, 35, 36, 37, 38, 39, 40].

One of the challenges in GZSL is keeping the seen and unseen class scores comparable. A prominent idea in addressing this problem is reducing the prediction bias towards seen classes. For this purpose, Liu et al. [41] proposes to increase unseen class prediction confidence by minimizing the entropy of unseen class scores during training. Jian et al. [42] promotes higher confidence scores for the familiar unseen classes during training based on unseen-to-seen class similarity estimates. Chao et al. [43] uses an empirically chosen seen class score scaling coefficient. We utilize a similar strategy for GZSD, except that instead of manually choosing the scaling coefficient, we learn it during training.

2.2. Zero-shot object detection

ZSD is a relatively new problem, pioneered by [44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57]. These approaches typically extend supervised detection models to ZSD.
Among these studies, Bansal et al. [46] proposes a two-step approach that first locates object proposals from low-level features [58] and then classifies the resulting candidate regions using a ZSL model. Rahman et al. [44] proposes a region proposal-based approach and uses a semantic clustering-based loss term to bring similar classes closer to each other. Demirel et al. [45] proposes a regression-based ZSD model that jointly incorporates convex combinations of semantic embeddings [59] and bi-linear compatibility models [22]. Rahman et al. [47] proposes a polarity loss term that is based on the focal loss approach, to tackle better alignment between visual and semantic domains. Hence, the semantic representations of visually similar classes get closer to each other. Li et al. [49] uses natural language descriptions of classes for ZSD. Shao et al. [60] focuses on the candidate proposal generation problem of unseen classes in the ZSD. Gupta et al. [52] learns a joint embedding space to obtain more discriminative visual and textual embeddings. Li et al. [53] uses a dual-path method to fuse side analogy information and knowledge transfer between the visual and textual sides. Yan et al. [57] uses semantics-guided network to improve conventional embeddings.

The model closest to the ZSD component of our ZSC approach is the one proposed by Demirel et al. [45]. Our approach differs by (i) leveraging class-to-class similarities measured in the word embedding space as class embeddings, as opposed to directly using the word embeddings, (ii) learning a class score scaling coefficient that reduces the seen class bias and improves GZSD accuracy, and (iii) exploring the use of uncertainty calibration [17] in GZSD.

There exist alternative learning paradigms that also aim to reduce the dependency on fully-supervised training examples for object detection. To this end, methods for transforming image classifiers into object detectors, e.g., [60, 61, 1], and image-level label based weakly supervised learning approaches, e.g., [62, 63, 64], stand out as closely related directions. However, such approaches still require labeled training images for all classes of interest, which can be a major obstacle in building models with the semantic richness needed for captioning.

### 2.3. Image captioning

State-of-the-art captioning approaches are based on deep neural networks [65, 66, 67, 68, 69, 12, 15]. Mainstream methods can be categorized as (i) template-based tech-
Techniques [12, 70, 15] and (ii) retrieval-based ones [71, 72, 73, 68]. Template-based approaches generate templates with empty slots, and fill those slots using attributes or detected objects. Kulkarni et al. [12] builds conditional random field models to push tight connections between the image content and sentence generation process before filling the empty slots. Farhadi et al. [70] uses triplets of scene elements for filling the empty slots in generated templates. Lu et al. [15] uses a recurrent neural network to generate sentence templates for slot filling. Retrieval-based image captioning methods, in contrast, rely on retrieving captions from the set of training examples. More specifically, a set of training images similar to the test example are retrieved and the captioning is performed over their captions.

Dense captioning [74, 75, 76] appears to be similar to ZSC, but the focus is significantly different: while dense captioning aims to generate rich descriptions, our goal in ZSC is to achieve captioning over the novel object classes. Some captioning methods go beyond training with fully supervised captioning data and allow learning with a captioning dataset that covers only some of the object classes plus additional supervised examples for training object detectors and/or classifiers for all classes of interest [13, 77, 16, 78, 79]. Since these methods presume that all necessary visual information can be obtained from some pre-trained object recognition models, we believe they cannot be seen as true ZSC approaches.

Recently, the generation of fine-grained captions has attracted interest [80, 81, 82, 83]. Chen et al. [80] proposes to use scene graphs to control caption detail level according to user intentions. Khan et al. [81] uses Bahdanau attention [84] to enrich visual embeddings. Yuan et al. [82] proposes gating mechanisms to weight global and local cues. Cheng et al. [83] adjusts attention weights of visual feature vectors and semantic feature embeddings in a decoder cell sequence to obtain rich fine-grained image captions. Unlike ZSC, these methods do not target generating captions with objects unavailable in the training set.

We additionally study the problem of evaluating ZSC results. While various metrics such as METEOR [85] and SPICE [86] are widely used, the captioning evaluation is still an open problem, e.g. [87]. We propose a ZSC-focused metric that evaluates the visual and linguistic caption quality separately for the unseen and seen classes.
3. Method

In this section, we first explain our main ZSD model component, and its GZSD extensions. We then explain how we build the ZSC model. Finally, we discuss the evaluation difficulties and define the V-METEOR metric.

3.1. Main zero-shot detection model

In ZSD, the goal is to learn a detection model over the examples given for the seen classes ($Y_s$) such that the detector can recognize and localize the bounding boxes of the unseen classes $Y_u$. For this purpose, we adapt the YOLO [2] architecture to the ZSD problem.

In the original YOLO approach, the loss function consists of three components: (i) the localization loss, which measures the error between ground truth locations and predicted bounding boxes, (ii) the objectness loss, and (iii) the recognition loss, over a prediction grid of size $S \times S$. Following our prior work in [45], we adapt the YOLO model to the ZSD problem by replacing per-cell class probability predictions with cell embeddings and re-defining the prediction function as a compatibility estimator between the cell and class embeddings:

$$f(x, c, i) = \frac{\Omega(x, i)^T \Psi(c)}{\|\Omega(x, i)\| \|\Psi(c)\|}$$

Here, $f(x, c, i)$ is the prediction score corresponding to the class $c$ and cell $i$, for image $x$, $\Psi(c)$ represents the $c$-th class embedding, and $\Omega(x, i)$ denotes the predicted cell embedding as shown in Figure 3. The resulting model, therefore, allows making detection predictions for samples of novel classes purely based on their class embeddings.

**Class embeddings.** In principle, one can use attributes or word embeddings of class names directly as class embeddings, e.g. [45]. Attributes can provide powerful visual descriptions of classes, however, they tend to be domain-specific and typically difficult to define for a large variety of object classes, as needed in ZSC. Word embeddings of class names are much easier to collect, however, they typically contain indirect information about the visual characteristics of classes, and therefore, known to provide significantly weaker prior knowledge for visual recognition [23].

To use the word embeddings more effectively, we propose to define class embeddings in terms of class-to-class similarities computed over word embeddings: we define the class
c embedding in terms of the similarity with each seen class \( \bar{c} \):

\[
Ψ(c) = [\varphi(c)^T \varphi(\bar{c}) + 1]_{c \in Y_s}
\]  

where \( \varphi(c) \) denotes the c-th class name’s word embedding. Since semantic relations across classes tend to correlate with their visual characteristics, this embedding can provide a valuable implicit visual description defined through a series of inter-class similarities. The ZSL method, therefore, can make predictions based collectively on these similarity values. We empirically demonstrate the advantage of this scheme in Section 4.

3.2. Generalized zero-shot detection extensions

There can be a significant bias towards the seen classes as the GZSD model is trained to predict seen class instances. We use the following two extensions to reduce this bias.

**Alpha scaling.** In this technique, we aim to reduce the bias towards the training classes by making the unseen and seen class scores more comparable through a score scaling scheme. For this purpose, we introduce the \( \alpha \) coefficient for the unseen test classes, and redefine \( f(x, c, i) \) as follows:

\[
f(x, c, i) = \begin{cases} 
\alpha \frac{\Omega(x_i)^T \Psi(c)}{\|\Omega(x_i)\| \|\Psi(c)\|}, & \text{if } c \in Y_u \\
\frac{\Omega(x_i)^T \Psi(c)}{\|\Omega(x_i)\| \|\Psi(c)\|}, & \text{otherwise}
\end{cases}
\]

(3)

To make the \( \alpha \) estimation practical, we want to avoid requiring additional training examples. For this reason, we first train the ZSD model over all training classes without \( \alpha \). We then designate a subset of seen classes as *unseen-imitation* classes. To obtain
unseen-like confidence scores for these classes, we temporarily set all entries corresponding to unseen-imitation classes in Eq. 2 to zeros and treat unseen-imitation classes as unseen classes in Eq. 3. These modifications allow us to obtain classification scores as if the model was trained without using the samples of unseen-imitation classes. We then train \( \alpha \) only, keeping the rest of the network frozen, as shown in Figure 4.

Overall, the proposed \( \alpha \) coefficient estimation scheme leverages the special structure of our class embeddings to efficiently approximate the unseen class scores. While the approximation can possibly be coarse, we experimentally show in Section 4 that the proposed scheme is effective for learning the \( \alpha \) coefficient, at a negligible extra training cost.

Uncertainty calibration. The second unbiasing technique that we explore is uncertainty calibration, adapted from the zero-shot classification approach of Liu et al. The idea is to minimize the uncertainty over unseen class predictions during training, based on the observation that a prediction model learned over seen class samples tends to yield lower confidence scores for unseen classes, resulting in misdetections.

The uncertainty in confidence scores is quantified via entropy over unseen class probabilities. We adapt the uncertainty calibration loss \( \ell_h \) to our ZSD model as a loss over per-cell predictions:

\[
\ell_h(x) = - \sum_{i=0}^{S^2} \sum_{c \in Y_u} p_u(c|x,i) \log p_u(c|x,i)
\]  

(4)
Here, \( p_u(\cdot) \) corresponds to \( f(x, c, i) \)-driven unseen class likelihoods:

\[
p_u(c|x, i) = \frac{\exp(f(x, c, i)/\tau)}{\sum_{c' \in Y_u} \exp(f(x, c', i)/\tau)}
\]

(5)

where \( \tau \) denotes the softmax temperature coefficient. \( \tau \) is empirically determined as in Liu et al. [17]. The loss encourages more confident unseen class score estimates, as less ambiguous prediction results in smaller entropy values. In order to adapt the uncertainty calibration to the detection model, we first train the ZSD model over all training classes as in the alpha scaling optimization process. We also use the same designated unseen-imitation subset as unseen classes. In the second training stage, we temporarily set all entries corresponding to unseen-imitation classes to zeros and then fine-tune the whole model without freezing any layers, unlike alpha scaling coefficient learning.

3.3. Zero-shot captioning model

Our goal is the construction of an image captioning model that can accurately summarize scenes potentially with seen and unseen class instances. For this purpose, we opt to use a template-based captioning method which provides the sentence templates with visual word slots to be filled based on the outputs of an object detection model.

We adapt the slotted sentence template generation model of Neural Baby Talk (NBT) [15]. The NBT method generates sentence templates which consist of the empty word slots by using a recurrent neural network. To obtain a content-based attention mechanism over the grounding regions, NBT embraces pointer networks [88]. The NBT model is trained by optimizing the model parameters \( \omega \) such that the log-likelihood of each ground-truth caption \( q \) conditioned on the corresponding image \( x \) is maximized:

\[
\omega^* = \arg \max_\omega \sum_{(x,q)} \log p(q|x; \omega).
\]

(6)

Here, the conditional caption likelihood \( p(q|x; \omega) \) of \( |q| \) words is measured auto-regressively, using a recurrent network:

\[
p(q|x; \omega) = \prod_{t=1}^{|q|} p(q_t|q_{1:t-1}, x; \omega).
\]

(7)

The NBT method additionally incorporates a latent variable \( r_t \) to represent the specific image region, so the probability of a word \( q_t \) is modeled as follows:

\[
p(q_t|q_{1:t-1}, x; \omega) = p(q_t|r_t, q_{1:t-1}, x; \omega)p(r_t|q_{1:t-1}, x; \omega).
\]

(8)
The NBT defines two word types for \( q_t \), corresponding to *textual* and *visual* words. Textual words are not directly related to any image region or specific visual object instance, therefore the model provides only dummy grounding for them. The template generation network uses the object detection outputs to fill empty visual word slots, where we utilize the outputs of our GZSD model.

We train both the GZSD model and the sentence template generation component of NBT over examples containing only the seen class instance annotations, as required by the *true* ZSC protocol. At test time, we use the GZSD outputs over all classes as inputs to the NBT sentence generator.

### 3.4. Measuring zero-shot captioning quality

*Partial zero-shot image captioning* approaches use existing captioning metrics, such as METEOR [85], SPICE [86] and F1 score, for evaluation purposes. While these generic textual similarity based metrics provide useful information about the quality of captioning results, they do not explicitly handle the problem of capturing visual content within the generated sentence. Therefore, such metrics can possibly be heavily influenced by structural and syntactic similarities across generated and ground-truth sentences. Exceptionally, F1 score differs in this regard by completely ignoring the sentence structure and measuring only the coverage of (unseen) class names within captions. However, F1 score fails to measure the overall quality or accuracy of the generated sentences, which is also clearly important.

We observe that, based on our experiments in Section 4, the explicit handling of visual and non-visual content in the evaluation of sentences is particularly necessary for *true* zero-shot image captioning. In this setting, the problem of generating sentences that summarize the visual content accurately, including visual entities that are completely unseen during training, is fundamentally challenging, especially in comparison to partial ZSC with fully-supervised visual recognition models. Therefore, we propose a new captioning evaluation metric as a step towards formalizing better metrics for true ZSC.

We develop our metric based on METEOR, which is known to be a simple yet effective metric that yields a strong correlation with human judgment [89]. The original METEOR
metric is defined by the following formula:

\[
\text{METEOR} = F_{\text{mean}}(1 - p)
\]  

(9)

where \(F_{\text{mean}}\) aims to capture correctness in terms of unigram precision and recall values and \(p\) is a penalty term for evaluating the overall sentence compatibility. More specifically, \(F_{\text{mean}}\) is given by:

\[
F_{\text{mean}} = \frac{10PR}{R + 9P}
\]  

(10)

where \(P\) and \(R\) are the unigram precision and unigram recall values, respectively. These are calculated as:

\[
P = \frac{m}{w_t}
\]  

(11)

\[
R = \frac{m}{w_r}
\]  

(12)

where \(m\) is the number of unigrams in both reference and generated captions, \(w_t\) is the number of unigrams in the candidate caption and \(w_r\) is the number of unigrams in the reference caption. The \(p\) penalty term checks how well textual chunks match between a pair of reference and generated captions, using the following definition:

\[
p = 0.5 \left( \frac{c}{u_m} \right)^3
\]  

(13)

where \(c\) is number of maximally long matching subsequences, and \(u_m\) is number of mapped unigrams.

We extend the METEOR metric by defining two separate \(F_{\text{mean}}\) metrics for the visual and non-visual entities. For this purpose, we compute \(F_{\text{mean}}^v\) and \(F_{\text{mean}}^n\), similar to Eq. (10) separately over only visual words and only non-visual words, respectively. We, then, define the proposed metric V-METEOR based on their harmonic mean, as follows:

\[
\text{V-METEOR} = \frac{2F_{\text{mean}}^vF_{\text{mean}}^n}{F_{\text{mean}}^v + F_{\text{mean}}^n}(1 - p)
\]  

(14)

In this manner, the proposed V-METEOR metric explicitly measures the joint visual or non-visual accuracy of a sentence, through the harmonic mean of the \(F_{\text{mean}}^v\) and \(F_{\text{mean}}^n\) terms. It also incorporates the overall sentence similarity by keeping the penalty term \((p)\) as in METEOR.
To be able to measure per-class captioning quality, which is particularly valuable in the ZSC context, we separately compute V-METEOR for each class. In the calculation of the V-METEOR score of a sentence for a class, the words corresponding to the class name are considered as the visual words, and the words that are not corresponding to any one of the class names are considered as non-visual words. The overall V-METEOR score is obtained by averaging per-class scores.

Finally, we additionally define the following two variations for separately measuring the visual and non-visual quality of the generated sentences, respectively:

\[
\text{V-METEOR}_{\text{vis}} = F_{\text{mean}}^v (1 - p) \tag{15}
\]

\[
\text{V-METEOR}_{\text{nvis}} = F_{\text{mean}}^n (1 - p) \tag{16}
\]

We use V-METEOR_{vis} and V-METEOR_{nvis} to gain additional insights.

4. Experiments

In this section, we explain our experimental setup, present the GZSD and ZSC results, discuss the V-METEOR evaluations, and provide additional analyses.

4.1. Experimental setup

ZSD and (partial) ZSC works use different splits of the MS-COCO dataset for historical reasons. To make our results comparable to related works, we use the same splits as in the related works, separately for GZSD and ZSC as explained below.

**GZSD evaluation.** We use MS-COCO [19] dataset in our experiments. In our main GZSD experiments, we use the same dataset splits and settings as in the recent work [52, 53, 54, 55, 56, 57, 51, 48, 45], where 15 of 80 MS-COCO classes are used as unseen classes. There also exist different ZSD methods (e.g. SB [46] and DSES [46]), but they use only 48/17 seen-unseen class distribution or do not share GZSD results with 65/15, so we do not report any comparisons with these methods.

**ZSC evaluation.** For the ZSC approach, we compare the proposed approach with selected upper-bound methods from [13, 77, 16, 78, 15]. We again use the same dataset splits and settings as in these works, where 8 of 80 MS-COCO classes are used as the unseen classes.
Word embeddings. For the GZSD model, we use 300-dimensional word2vec [90] class name embeddings. For the names containing more than one word, e.g. tennis racket, we take the average of the per-word embeddings. We use 300-dimensional GloVe vector embeddings [91] in the template generation component of the ZSC, following the NBT approach [15].

4.2. Generalized zero-shot object detection

In this section, we report and discuss experimental results for the GZSD model. We train the model for 160 epochs with a learning rate of 0.001, and a batch size of 32. Once the model is trained, we select 8 out of 65 seen classes as unseen-imitation classes for alpha scaling optimization and uncertainty calibration purposes, and continue training for 10 more epochs.

Main results. We present the experimental results in Table 1. The upper part of the table presents results of the two-stage object detection techniques, and the lower part presents the single-stage techniques and our approach, which we call SimEmb. In the lower part, SimEmb-base, which represents the model without score calibration, obtains 28.54% mAP on seen classes, 12.45% mAP on unseen classes and 17.34 harmonic mean (HM). SimEmb, which represents the version with learned $\alpha$ scaling coefficient, obtains 28.91% mAP on seen classes, 15.78% mAP on unseen classes and 20.41% HM. Finally, SimEmb* represents an upper-bound reference model, where alpha scaling coefficient is empirically tuned on the test set to maximize the HM score by evaluating for a range of $\alpha$ values. This upper-bound model obtains 28.87% mAP on seen classes, 16.00% mAP on unseen classes, and 20.59 HM value.

From the results, we first observe that our single-stage approach improves the state-of-the-art among single-stage GZSD models. We also observe that SimEmb performs similar to or better than many two-stage GZSD models, with the only exception being the very recently published two-stage approach ContrastZSD [57]. Second, the improvements obtained by SimEmb show that alpha scaling coefficient is crucial for obtaining higher accuracy on unseen class detections and alpha scaling does not disrupt the seen class performance. Finally, the comparison between SimEmb and the SimEmb* upper-bound shows that the proposed alpha scaling learning scheme is effective as it yields results
Table 1: mAP results on MS-COCO dataset with GZSD (65/15) settings. SimEmb-base, SimEmb and SimEmb* correspond to our model without confidence calibration, with learned $\alpha$, and with optimal $\alpha$ (upper-bound), respectively.

| Category | Method       | seen  | unseen | HM    |
|----------|--------------|-------|--------|-------|
| two-stage| MS-Zero [52] | 42.40 | 12.90  | 19.79 |
|          | MS-Zero++ [52]| 35.00 | 13.80  | 19.78 |
|          | DPIF-S [53]  | 32.72 | 13.95  | 19.56 |
|          | DPIF-M [53]  | 29.33 | 16.36  | 21.00 |
|          | BLC [54]     | 36.00 | 13.10  | 19.20 |
|          | VL-SZSD [55] | 39.45 | 13.18  | 19.76 |
|          | FNG [56]     | 38.10 | 13.90  | 20.40 |
|          | ContrastZSD [57]| 40.20 | 16.50  | 23.40 |
| single-stage| TL [58]   | 28.79 | 14.05  | 18.89 |
|           | PL [51]      | 34.07 | 12.40  | 18.18 |
|           | HRE [45]     | 28.40 | 12.80  | 17.65 |
|           | SimEmb-base  | 28.54 | 12.45  | 17.34 |
|           | SimEmb       | 28.91 | 15.78  | 20.41 |
|           | SimEmb*      | 28.87 | 16.00  | 20.59 |

Comparable to directly tuning $\alpha$ on the test set.

We also observe that the proposed model achieves results comparable to those of two-stage approaches. While single-stage and two-stage detectors are built on very different design principles and trade-offs, the overall competitiveness is noteworthy since the work on other low-shot detection problems show that two-stage models typically yield higher AP scores [92].

Qualitative detection results using the proposed SimEmb model can be found in Figure 5.

Correctness of $\alpha$ estimation. We present the evaluation results as a function of $\alpha$ in Figure 6. We observe that the best empirical $\alpha$ coefficient value (in HM) among the tested ones is 1.4. The proposed $\alpha$ estimator, which in contrast uses only training
Figure 5: GZSD results on scenes containing various seen and unseen class instances. (Best viewed in color.)

Figure 6: The accuracy values of the proposed method in the GZSD test splits of MS-COCO according to different alpha scaling factors.
Table 2: mAP results on MS-COCO dataset in the 65/15 GZSD setting, using the base model with and without alpha scaling and uncertainty calibration (uc-calib).

| Exp. Type | Test | bottle | bus | couch | microwave | pizza | racket | suitcase | zebras | U-mAP(%) | S-mAP(%) | HM |
|-----------|------|--------|-----|-------|-----------|-------|--------|----------|--------|---------|----------|-----|
| ZSD       | U    | 5.2    | 53.3| 35.1  | 23.9      | 44.4  | 36.4   | 9.1      | 43.7   | 31.4    | -        | -    |
| GZSD w/o α| S+U  | 0      | 0   | 2.7   | 0         | 0     | 0      | 0        | 0      | 0.3     | 27.4     | 0.7 |
| GZSD      | S+U  | 0.8    | 21.4| 4.9   | 1.2       | 4.8   | 0.7    | 9.1      | 15.8   | 7.3     | 19.2     | 10.6|

Table 3: Our results on ZSD and GZSD (72/8). The first row represents the experimental results where we only use images belonging to the unseen classes and unseen class embeddings, the remaining rows represent the GZSD results where we use all class embeddings on the MS-COCO val5k split.

examples, results in $\alpha = 1.28$, which is both value-wise and performance score-wise close to the optimal choice.

**Alpha scaling versus uncertainty calibration.** As an alternative to alpha scaling for GZSD, we evaluate the uncertainty calibration technique, as explained in Section 3.2. We present the results in Table 2 with the following combinations from top to the bottom: base model, uncertainty calibration (uc-calib) only, alpha scaling only, and their combination. We observe that uncertainty calibration alone performs poorly probably due to the difficulty of correcting class bias purely based on fine-tuning. Our alpha scaling technique yields a much better result in terms of HM score, with an improvement from 17.34 to 20.41. The combination of the two techniques slightly improves the HM score to 20.46. This proves that the alpha scaling scheme is effective in comparison to a state-of-the-art calibration technique. For the sake of simplicity, we keep using only alpha scaling in our following experiments.

**GZSD results on ZSC splits.** In our experiments presented so far, we have used the 65/15 COCO split. In our ZSC experiments, however, we need to use the alternative 72/8 split of [13] to make comparisons to the related work. Therefore, here we report
the results of our GZSD model on the 72/8 split. We train the model using the same hyper-parameters as before. We select 8 out of 72 seen classes as unseen-imitation classes for alpha scaling optimization.

We evaluate the detection model under the ZSD and GZSD scenarios. For the ZSD experiments, we use the MS-COCO validation images consisting of unseen class instances. For the GZSD experiments, we use the whole MS-COCO val5k split. We present the results on Table 3. In the ZSD case, we observe an unseen class mAP of 31.4%. In the GZSD case, we observe a much lower 0.3% mAP without alpha scaling, and 0.7 HM. Alpha scaling improves the unseen class mAP to 7.3% and the HM score to 10.6. We note that prior works on GZSD do not use this ZSC (72/8) split, therefore, we do not report any comparisons to the state-of-the-art in this split. We also note that our primary interest in GZSD is to build a strong method to serve as a crucial component of ZSC, therefore, these results highlight one of the major difficulties in building accurate captioning models in the realistic ZSC setting.

4.3. Zero-Shot image captioning

For the ZSC experiments, we use the same experimental setup described in [15], and exclude the image-sentence pairs containing unseen class instances during training. We consider the partial ZSC approaches proposed in [13, 77, 16, 78, 15] as upper-bound baselines for our true ZSC setting. We also define and evaluate a baseline method based on NBT, where we train the NBT captioning model based solely on the training classes without integrating our GZSD model. We refer to this model as NBT-baseline.

To establish a fair comparison, we follow the practices of the NBT [15] approach. We evaluate the ZSC model on the selected validation subset of the MS-COCO caption dataset. To obtain per-class evaluation scores, we use the F1 metric [13], where a visual class is considered as relevant in an image if that class name appears in any one of the human generated reference captions for that image, and irrelevant otherwise. Similarly, on a test image, a model-generated caption is considered as correct for a visual class if the generated caption includes (excludes) the corresponding word for that relevant (irrelevant) class. The per-class F1 score is then defined as the ratio of correctly captioned test images. We additionally use the well-established METEOR [85] and SPICE [86] metrics, in addition to averaging the per-class F1 scores (referred to as Avg. F1). We
Table 4: Zero-shot captioning results with comparison to captioning models involving visually fully-supervised models.

| Method          | bottle | bus  | couch | microwave | pizza | racket | suitcase | zebra | Avg. F1 | METEOR | SPICE |
|-----------------|--------|------|-------|-----------|-------|--------|----------|-------|---------|--------|-------|
| True zero-shot captioning |        |      |       |           |       |        |          |       |         |        |       |
| NBT-baseline    | 0      | 0    | 0     | 0         | 0     | 0      | 0        | 0     | 0       | 18.2  | 12.7 |
| Our method      | 2.4    | 75.2 | 26.6  | 24.6      | 29.8  | 3.6    | 0.6      | 75.4  | 29.8    | 21.9  | 14.2 |

Partial zero-shot captioning (upper-bounds)

| Method          | bottle | bus  | couch | microwave | pizza | racket | suitcase | zebra | Avg. F1 | METEOR | SPICE |
|-----------------|--------|------|-------|-----------|-------|--------|----------|-------|---------|--------|-------|
| DCC [13]        | 4.6    | 29.8 | 45.9  | 28.1      | 64.6  | 52.2   | 13.2     | 79.9  | 39.8    | 21.0  | 14.4 |
| NOC [77]        | 17.8   | 68.8 | 25.6  | 24.7      | 69.3  | 68.1   | 39.9     | 89.0  | 49.1    | 21.4  | -    |
| C-LSTM [16]     | 29.7   | 74.4 | 38.8  | 27.8      | 68.2  | 70.3   | 44.8     | 91.4  | 55.7    | 23.0  | -    |
| Base+T4 [78]    | 16.3   | 67.8 | 48.2  | 29.7      | 77.2  | 57.1   | 49.9     | 85.7  | 54.0    | 23.3  | 15.9 |
| NBT+G [15]      | 14.0   | 74.8 | 42.8  | 63.7      | 74.4  | 19.0   | 44.5     | 92.0  | 53.2    | 23.9  | 16.6 |
| DNOC [79]       | 33.0   | 77.0 | 54.0  | 46.6      | 75.8  | 33.0   | 59.5     | 84.6  | 57.9    | 21.6  | -    |

We separately discuss the evaluation results in terms of the proposed V-METEOR metric in the next section.

We present the results in Table 4. First, we observe that the proposed approach greatly outperforms the NBT-baseline with clear improvements in terms of Avg. F1 (0 to 29.8), METEOR (18.2 to 21.9) and SPICE (12.7 to 14.2) scores. This shows the value of explicitly handling the GZSD task as part of the captioning process. In comparison to the upper-bound partial-ZSC captioning approaches, which involve supervised visual training in both seen and unseen classes, our approach yields comparable results in terms of METEOR and SPICE metrics. In particular, we observe that the ZSC model yields better results compared to the DCC [13] and NOC [77] methods. This is most probably due to the fact that our sentence template generation method provides accurate locations for visual words, enabling the generation of more natural and visually grounded captions. We observe relatively lower scores for the ZSC model, compared to the remaining supervised models.

Noticeably, the performance gap between true ZSC and (visually) supervised partial ZSC is larger in terms of the Avg. F1 metric. This is mostly an expected result as the F1 metric directly measures the ability to incorporate visual classes during captioning, akin to a visual recognition metric. Here, supervised methods are known to perform much better than the state-of-the-art ZSL models in most cases, which turns out to also be the
Figure 7: Image captioning results on images with **seen** and **unseen** class instances. (Best viewed in color.)

For qualitative examination, we present visual output examples in Figure 7 along with the corresponding GZSD detection results. It can be observed that the ZSC model is able to generate semantically sound captions in a variety of challenging scenes involving both seen and unseen class instances.

### 4.4. V-METEOR experiments

We now evaluate the baseline and proposed models using the V-METEOR metric. We present the overall average V-METEOR scores in Table 5. These summary results show that the proposed approach greatly improves the visual captioning score from 0.0 to 12.63 and also increases the non-visual V-METEOR scores from 20.50 to 22.26. The final V-METEOR score improves from 0.0 to 13.19. These results show that the integration of an (accurate) GZSD can not only help with visual coverage of the captioning results but also improve the non-visual parts of the generated captions thanks to the better visual information from the detector to the language model. In these results, we also observe the main advantage of the proposed V-METEOR metric by being able to separately discuss the visual and non-visual quality of the generated captions.

To better understand the captioning results, we present per-class V-METEOR scores
| Method     | V-METEOR\(\text{vis}\) | V-METEOR\(\text{nvis}\) | V-METEOR     |
|------------|-------------------------|--------------------------|--------------|
| NBT-Baseline | 0.0                     | 20.50                    | 0.0          |
| Our Method  | 12.63                   | 22.26                    | 13.19        |

Table 5: V-METEOR comparison results. V-METEOR\(\text{vis}\) represents a sub-metric that only includes results for visual words, and V-METEOR\(\text{nvis}\) represents another sub-metric that only includes non-visual words.

Figure 8: V-METEOR results of each unseen classes. visual-bs represents the visual meteor scores of the NBT-Baseline, non-visual-bs represents the non-visual meteor scores of the NBT-Baseline and hm-bs represents the V-METEOR scores of the NBT-Baseline method. Similarly, visual, non-visual and hm bars correspond to our method. (Best viewed in color.)

Figure 9: Image captioning results of NBT-baseline and our methods. ♦ represents the NBT-baseline results, and ★ represents the results of the proposed method. **Bold** type words represent visual words from detectors.
for the unseen classes in Figure 8. In these results, we again observe both the most significant improvements are in V-METEOR$_{vis}$ scores with still noticeable improvements in non-visual scores. The complementary qualitative captioning comparisons presented in Figure 9 supports these quantitative observations: in the person and bus examples, the whole sentence changes and improves with the correction in visual details. In the bus and zebra examples, we observe that the NBT-baseline method produces coarsely plausible sentences, however, with incorrect visual coverage due to confusions across visually similar classes.

4.5. Additional analyses

In this section, we present a quantitative analysis on the error patterns and an ablative study on the importance of proposed similarity embeddings in GZSD.

4.5.1. Diagnosing errors

The experimental results show that GZSD plays a central role in achieving accurate captioning results. Therefore, it is potentially valuable to understand the typical detection errors of our GZSD model, towards building better GZSD and ZSC approaches. For this purpose, we embrace the detector analysis approach by Hoiem et al. [93], which is originally proposed for analyzing false positives in supervised detectors. The original analysis approach defines semantic categories for the PASCAL VOC dataset. To utilize this technique in the GZSD setting, we use the MS-COCO superclasses, namely vehicle, outdoor, animal, accessory, sports, kitchen, food, furniture, electronic, appliance and indoor, as defined in [19]. Following [93], we additionally define a separate singleton superclass for the person class, as it contains a greatly larger number of instances and its overall distinct visual characteristics.

The following four misdetection categories are examined for each superclass: (i) localization errors, corresponding to detections considered as false positive due to poor localization, (ii) confusion with background, counting false positive detections located in the background, (iii) class confusion within superclass members, and (iv) class confusion across superclasses. The corresponding error distributions are shown in Figure 10.

The obtained error distribution results show that the false positives are mainly occurred due to the within superclass confusions for the vehicle, animal, accessory, sports,
kitchen and food superclasses. The dominant misdetection type for the furniture, appliance and indoor superclasses is confusion with other classes. In contrast, most person misdetections correspond to localization errors. Finally, we observe that most problematic detections for outdoor and electronic superclasses correspond to background detections. Overall, these results show that there is no single error pattern dominating the GZSD outputs, and errors vary greatly across the classes.

4.5.2. Impact of using similarity embeddings

One of the advantages of using the proposed class-to-class similarity vectors is that each dimension of the embedding explicitly corresponds to a class relevance value. We additionally utilize its structure in the design of our alpha scaling training scheme. To better understand the value of the proposed class embeddings for GZSD, we present a direct comparison between using the proposed class embeddings versus the original class name word embeddings.

We present the results based on both embeddings in Table 6. The results show that the standard word embedding scheme obtains 28.41% mAP on seen classes, 14.36% mAP on unseen classes and a harmonic mean score of 19.08. In contrast, the proposed embedding yields 28.91% 15.78% and 20.41 unseen mAP, seen mAP and harmonic mean scores, respectively. These results show that using class-to-class similarity vectors also provides a relative performance advantage in terms of model performance, while also
enabling our effective alpha coefficient learning procedure.

5. Conclusion

An important shortcoming of current image captioning methods that aim training through non-paired datasets is that they do not work in a fully ZSL setting. These methods generate captions for images which consist of classes not seen in captioning datasets, but they assume that there is a ready-to-use fully supervised visual recognition model. To this end, we define the ZSC problem, propose a novel GZSD model and a ZSC approach based on it. We additionally introduce a practical class embedding scheme, a technique to improve GZSD performance via score scaling, and a novel evaluation method that provides insights into the ZSC results. Our qualitative and quantitative experimental results show that our method yields promising results towards achieving our ZSC goals. We believe that ZSC is an important research direction towards building captioning models that are more suitable to use in realistic, in-the-wild settings.

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