A Baseline for Detecting Out-of-Distribution Examples in Image Captioning

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ABSTRACT

Image captioning research achieved breakthroughs in recent years by developing neural models that can generate diverse and high-quality descriptions for images drawn from the same distribution as training images. However, when facing out-of-distribution (OOD) images, such as corrupted images, or images containing unknown objects, the models fail in generating relevant captions.

In this paper, we consider the problem of OOD detection in image captioning. We formulate the problem and suggest an evaluation setup for assessing the model’s performance on the task. Then, we analyze and show the effectiveness of the caption’s likelihood score at detecting and rejecting OOD images, which implies that the relatedness between the input image and the generated caption is encapsulated within the score.

CCS CONCEPTS

• Computing methodologies → Computer vision tasks.

KEYWORDS

out-of-distribution detection, image captioning, uncertainty estimation, anomaly detection

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1 INTRODUCTION

Deep Neural Networks (DNNs) have gained lots of success after enabling several breakthroughs in notably challenging problems such as image classification, object detection, and language generation. However, despite the tremendous progress driven by DNNs, they were found as vulnerable to OOD inputs. For example, image classification models were shown to fail by predicting the wrong class with high confidence when given images containing unknown objects [31]. Another example would be in the image captioning (IC) task, where the models are able to output high-quality and diverse sentences when given images drawn from the same distribution as the training set; however, when facing images in the wild, these models are shown to generalize poorly [40].

OOD detection task has been formulated as the task of detecting whether input data is drawn from a distribution different from the training distribution. The task has been studied for a long, and recently, a baseline for detecting OOD images by neural image classification models has been proposed in [12]. The authors
investigated the OOD detection rate of image classification models by considering the confidence of the predicted class and set baseline results for the task. The baseline became widely adopted, and many advanced approaches have been suggested for the task [17, 20, 24, 26, 37]. Yet, despite the field’s progress, detecting OOD images remains a difficult problem, as they are not limited to some particular type of images. Instead, OOD images can have infinite forms, such as images of objects that do not appear in the training set (unknown objects), corrupted images of known objects, or even random noise images.

We focus on detecting OOD instances in image captioning (IC). While in the image classification task, a model is given an image and is expected to correctly classify it to one of $K$ possible classes, in IC, the model is expected to generate a sentence that describes the scene in the image. Since most OOD image detection research works considered the detection in an image classification task environment, adopting these methods to IC is not straightforward. A possible way to reject OOD images in the IC task environment is by designing a two-phase system. First, a pre-trained image classifier is applied to reject OOD images, and then, if the image was not rejected, it is fed into the IC model to generate a caption. However, such a method has several caveats: (1) It requires training and maintaining two separate models, which adds to the time and space complexity. (2) When the training data is composed of only images and their corresponding captions, training an image classifier can be difficult as it requires heuristics for generating a ground-truth class. But while these caveats are manageable, there is a bigger question of whether image-classification-based models are applicable to images used to train image captioning models, as the images are different from those used to train image classification models. For example, while image classification models are given images containing a single main dominant object, IC models are given images containing complex scenes with multiple objects interacting with each other.

This paper proposes a simple yet effective method for detecting OOD instances by IC systems. Using an empirical study on several widespread IC models, we show that the generated caption’s likelihood score can capture the relatedness between the image and the generated caption and effectively allow the rejection of OOD images. Furthermore, we find that while image-classification-based methods express their uncertainty using a single score (such as the predicted class probability), IC models express their uncertainty majorly in visually grounded tokens (such as Nouns, Verbs, and Adjectives) and outperform in detecting OOD images with a complex scene. Moreover, to facilitate OOD detection research in IC, we construct benchmarks on top of widely used image datasets and set baseline results for this task.

As the research in IC achieved breakthroughs in the field by developing end-to-end IC models that are able to output high-quality and diverse sentences, an increasing number of industrial companies integrated IC models into their applications [6, 34]. However, in real-world scenarios, it is most likely that input instances will contain objects that the model did not see during training, which will result in unexpected behavior by the model. A research work [30], explored how blind and visually impaired people experience generated image captions. The authors showed that people trust incorrect AI-generated captions, filling in details to reconcile incongruencies rather than suspecting the caption may be wrong. Therefore, with the increasing adoption of IC models in real-life applications, it is crucial to focus on rejecting OOD inputs without outputting the generated captions for these instances.

Neural generative IC models are encoder-decoder networks, trained end-to-end, and achieve state-of-the-art results in the field. Training the models is commonly done by maximum likelihood estimation (MLE), which maximizes the probability of a ground-truth sentence given its corresponding training image. During inference time, a decoding strategy is applied to search and output the most probable describing sentence for the input image. These training and inference procedures allow models to have rich image descriptiveness ability and achieve high scores in IC metrics (such as Cider [41] and BLEU [32]) when given in-distribution images, but their ability of “expressing” their uncertainty for OOD images is yet unknown.

In Fig-1 we show captions generated by Top-Down model [2] for several different types of OOD images. The figure shows that the sentences are vibrant and natural but also loosely related to the given image. Ideally, when the IC model is facing an OOD image that it cannot describe, the decoded sentence should be assigned with a low probability to allow the rejection of the instance. However, MLE training does not guarantee to capture the relatedness between the generated caption and the given image. Here, we explore the effectiveness of the captions’ likelihood at expressing uncertainty in the caption when given OOD images.

In summary, the contribution of this paper is as follows:

- We define the task of out-of-distribution detection in image captioning and explore the performance of several top-performing image captioning models.
- We construct benchmarks that include multiple types of out-of-distribution image sets and suggest evaluation metrics.
- We demonstrate the efficiency of the generated captions’ likelihood at detecting out-of-distribution images without requiring any additional data or external knowledge and show that the uncertainty is expressed through the probability of the visually grounded tokens.

2 RELATED WORK

Out-of-distribution detection. Since DNNs are ubiquitous, present in nearly all segments of the technology industry, from search engines [35] to critical applications such as self-driving cars [5] and healthcare [9, 36], it becomes critical to design models that can express uncertainty when predicting OOD inputs. OOD detection task has been studied for a long, and recently, a baseline for detecting OOD images by neural image classification models has been proposed in [12]. The authors examined the OOD detection performance of image classification models using a confidence score derived from the network (max softmax probability). Later, several studies proposed improving the baseline by modifying the model’s architecture [20, 37], inference procedure [17, 27] and training criterion [23, 24].

OOD detection methods were also developed for safety-critical image applications [42], and also into other modalities such as natural language processing (NLP) and speech processing. [13] explored
the task of OOD text detection in NLP classification tasks (sentiment analysis and textual entailment). The authors showed that the output confidence scores of pre-trained Transformers can effectively indicate whether the sample is OOD. They also concluded that pre-trained Transformers have an improved OOD detection rate compared to RNN and convolution-based text classification models. More recently, [26] suggested improving the OOD detection by combining a self-supervised training method with an ensemble of text classifiers, and the method sets the state-of-the-art results.

**Novel object description.** Some of the first attempts at IC [8, 22] relied heavily on the outputs of object detectors and attribute classifiers to describe images. Since then, a large amount of end-to-end IC models have been developed, eliminating the need for external object detector [2, 4, 14, 18, 25, 39, 43]. However, several works [1, 29, 40] also leveraged the output of a pre-trained object detector to tackle the task of novel object description. In this task, the IC model is given an image containing an unknown object, and a caption describing the object with the presented scene should be generated. Most commonly, external knowledge from a pre-trained object detector is facilitated for describing the unknown objects.

The task of novel object description overlaps with the task of OOD detection in the sense that both tasks need to deal with unknown objects. However, OOD image definition is not limited to images containing unknown objects but rather to a broad range of types such as corrupted and low-quality images or even images containing random noise. Moreover, in OOD detection, the model is expected to express its uncertainty in the caption to allow the rejection of the instance. In contrast, in novel object description, the generated caption is expected to include the unknown object.

While the proposed methods for novel object description gained success at describing images containing unknown objects, they mainly rely on the output of an object detector. Detecting whether an image is OOD [12] or contains novel objects [1] based on the outputs of the object detector is not sufficient for real-world applications since the number of classes that can be detected by the object detector is finite and limited, even when trained on massive image classification datasets. Additionally, object detectors include in their mechanism a classification module which by itself is vulnerable to OOD examples [12], causing the entire process to be error-prone to both classification and detection errors made by the external detection model. Therefore, we find the task of OOD detection in IC an important complementary task to the novel object detection task.

### 3 NOTATIONS AND DEFINITIONS

IC is the task of generating a natural language sentence that accurately describes a given image. Neural generative IC models typically consist of a CNN or visual Transformer, which is responsible for encoding the input image, and an RNN or Transformer that decodes descriptive sentences word-by-word conditioned on the image encoding.

Commonly, the models trained as follows: assume a training dataset, \( D_{\text{train}} = \{(I_i, S_i)\}_{i=1}^N \) composed of image-sentence pairs, where \( I_i \) is the \( i \)-th image and \( S_i \) is the corresponding descriptive sentence. The parameters of the model, denoted by \( \theta \), are found by MLE, which directly maximizes the log-likelihood of the ground-truth description given the image, formally:

\[
\theta^* = \arg\max_{\theta} \sum_{(S_i, I_i) \in D_{\text{train}}} \log P(S_i|I_i; \theta)
\]

Since \( S_i \) composed of a sequence of words \( S_{i1}, \ldots, S_{ij} \), where \( j \) is the length of \( S_i \), a chain rule is applied to model the joint probability over the sentence words (we omit \( \theta \) for simplicity):

\[
\log P(S_i|I_i) = \sum_{z=j} \log P(S_{iz}|S_{iz-1}, \ldots, S_{i1})
\]

This optimization requires assigning the highest probability to the ground-truth sentence, which is the sum of the log probabilities of its composing words.

At inference, a decoding strategy is applied, searching for the best describing sentence. A greedy decoding is the one that, at each decoding step, chooses the most probable next word. Another widely spread heuristic decoding strategy is **Beam-search-K (BS-K)**, which maintains the \( K \) most probable partial sentences until each decoding step. Notice that the greedy decoding is a special case of BS-K, where \( K = 1 \). The BS-K does not guarantee finding the most probable sentence and leads to degenerated sentences when \( K \) is large [16]. Several sampling-based decoding algorithms have been proposed. **Top-K decoding** [7], is a method that samples at each timestamp a word from the \( K \) most probable next words. Later, **Nucleus sampling (NS-p)** decoding strategy has been proposed [16]. NS-p suggests sampling from the top \( p \) portion of the probability mass instead of relying on a fixed top \( K \) candidate pool.

### 4 PROBLEM FORMULATION

In this paper, we are interested in the problem of out-of-distribution detection in IC: can we detect whether the given image is from a different distribution than the training data? Does the generated caption relate to the OOD image? Denote by \( S \) the infinite set of all possible sentences and by \( I \) the infinite set of all possible images. Assume each training example, \( (S_i, I_i) \in S \times I \), is drawn from a fixed but unknown distribution \( \rho \). In OOD detection, a model is expected to perform well on unseen images drawn from the same distribution \( \rho \) (in-distribution images) and identify images drawn from a different distribution, \( \mu \), to prevent the generation of unrelated captions. Since we train the model to maximize the probability of the ground-truth captions for images drawn from \( \rho \), its behavior on images drawn from \( \mu \) is unexpected. Therefore, we are interested in exploring whether MLE training allows models to capture the relatedness between the generated caption and the given image. If the model learned to factor in the relatedness, it would be reasonable to assume that in-distribution images will result in higher likelihood captions than the OOD images. Meaning:

\[
\log P(S_{i\rho}|I_{i\rho}) > \log P(S_{i\mu}|I_{i\mu})
\]

Where \( I_{i\rho}, I_{i\mu} \) are in- and out- of-distribution images, respectively, and \( S_{i\rho}, S_{i\mu} \) are the corresponding generated captions.

In- and out-of-distribution images are not a strict dichotomy. There are various types of OOD images, such as images containing unknown objects (that are not appearing in the training set) or random noise. Identifying images containing unknown objects,
We start by describing the models in section 5.1. Then, in section which the model cannot accurately describe, is more challenging As our captioning models, we trained two of the most widespread (GODIN)[17]. Notice that the classification and the captioning mod-
ods: (1) Max probability score (MSP) [12] (2) Generalized ODIN score at OOD detection by evaluating the performance of six wide-
sessment. In the proposed setup, models are required to distinguish between a set of in-distribution samples and multiple OOD sets in the following setup: First, a model is trained over a training dataset \( D_{\text{train}}^I \) (without the exposure to OOD instances). Afterward, the model is evaluated over the test set \( D_{\text{test}}^I \), and the predicted probability for each sample is recorded. Then, to assess the detection ability, the model is evaluated over several OOD datasets, denoted as \( D_{\text{test}}^O \), ..., \( D_{\text{test}}^m \), and the predicted probability for each sample in the sets is recorded. Lastly, a measure of the separation between the recorded probabilities for \( D_{\text{test}}^I \) and each of the OOD sets \( D_{\text{test}}^O \) is calculated.

We follow this setup and conduct several experiments wherein we create two groups. The first group contains the likelihood scores of captions generated for in-distribution images. This group is shared across all the experiments. The second group contains the likelihood scores of captions generated for OOD images. We consider eight types of OOD image sets in various degrees of difficulty, described later in this section. We compare each of the groups created from the OOD sets with the group created from the in-distribution set and measure the separation between the two using the evaluation metrics described in section 5.3. An IC model with a perfect OOD detection ability will allow setting a fixed threshold of \( T \), where all captions generated for in-distribution images will have higher likelihood scores, and captions for OOD images will be assigned with lower scores.

For evaluating the OOD detection methods by the classification model, we follow the same setup but consider the predicted model’s confidence as described in the original papers.

5.2 Experimental Setup

For evaluating OOD detection in IC, we adopt the popular experimental settings of OOD detection in image [12] and text [13] classification. In the proposed setup, models are required to distinguish between a set of in-distribution samples and multiple OOD sets in the following setup: First, a model is trained over a training dataset \( D_{\text{train}}^I \) (without the exposure to OOD instances). Afterward, the model is evaluated over the test set \( D_{\text{test}}^I \), and the predicted probability for each sample is recorded. Then, to assess the detection ability, the model is evaluated over several OOD datasets, denoted as \( D_{\text{test}}^O \), ..., \( D_{\text{test}}^m \), and the predicted probability for each sample in the sets is recorded. Lastly, a measure of the separation between the recorded probabilities for \( D_{\text{test}}^I \) and each of the OOD sets \( D_{\text{test}}^O \) is calculated.

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For evaluating the OOD detection methods by the classification model, we follow the same setup but consider the predicted model’s confidence as described in the original papers.

5.2.1 Out-of-Distribution Image Sets. We evaluate the performance on eight different OOD image sets. Two of the sets composed of images with no object appearing in them. Additional two sets composed of images containing unknown objects (samples can be seen in Fig-1 and Fig-2). The last four sets are composed of algorithmically corrupted in-distribution images. The details of the sets are as follows:

**Unknown objects:** For creating this set we collected images containing a scene with objects that are not appearing the training sets. The images are sourced from the Open Images V4 [21], which is a publicly available human-annotated object detection dataset, containing 14.6M bounding boxes of 600 objects in ~1.7M images. From this set, we manually collected 38 objects which are not appearing in the COCO set and constructed a set of 4067 images containing unknown objects in natural scenes. The full list of the extracted objects can be found in the appendix.

**Cropped unknown objects:** Since Open images V4 composed of natural images where the unknown objects are appearing with a scene in the background, we isolate the objects from the presented scene and create a set of images containing a single object only. For creating this set, we consider images from the Unknown objects set, and crop the unknown objects using the corresponding ground-truth bounding boxes. Examples can be seen in Fig-2
Google's cartoon set: A publicly available dataset of 10K 2D cartoon avatar images. The cartoons vary in 10 artwork categories, 4 color categories, and 4 proportion categories, with a total of ~$10^{13}$ possible combinations.

Random noise: We generate 5K random noise images by randomly drawing each pixel’s value.

Corrupted image sets: Since COCO and Flickr training sets contain high-quality images, we apply on the corresponding test sets four types of algorithmically generated corruptions to create the following OOD sets: (1) **JPEG corruption**: consisting of images corrupted by JPEG compression. (2) **Salt-and-pepper corruption**: consisting of images added with salt-and-pepper noise. (3) **Snow corruption**: consisting of images added with white noise, imitating images taken in snowy weather (4) **Cartoon corruption**: consisting of images converted to cartoon style. In Fig-3 we demonstrate the considered corruptions.

These corruptions are a subset of the corruptions used to benchmark models’ robustness to common corruptions and perturbations [11, 38]. The corruptions are generated using ImgAug [19] library. We normalize the OOD images using the same normalization parameters used for normalizing the training set.

### 5.3 Evaluation Metrics

For evaluating the detection rate, we compare the likelihood scores of the generated sentences for the in-distribution image with the scores of the generated sentences for each of the OOD sets and measure how well they can be separated. For measuring the separation, we use the following metrics:

**Area under the Receiver Operating Characteristic curve (AUROC):** The metric was adopted by [12] for OOD detection in image classification task. The ROC curve depicts the relationship between *true positive rate* and *false positive rate*. The metric is a threshold-independent performance evaluation that can be interpreted as the probability that a positive example has a greater detector score/value than a negative example. A perfect detector corresponds to AUROC of 1.

**Area under the Precision-Recall curve:** As the AUROC is not ideal when the positive and negative classes have greatly differing base rates, another threshold independent metric was proposed for OOD detection [12]. The PR curve is a graph showing the precision and recall against each other. The metrics PRin and PRout in Tables denote the area under the precision-recall curve where in- and out-of-distribution images are specified as positives, respectively. A perfect detector has an AUPR of 1.

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1 [https://google.github.io/cartoonset/]
We start by aggregating all the OOD image sets and evaluating the aggregation of the OOD sets. (COCO as an in-distribution set) We evaluate each metric on (from left to right): distance (BD) measures the similarity of two discrete or continuous distributions. Bhattacharyya distance: The distance metric was introduced by [3] and later adopted by [33] for feature selection. Bhattacharyya Distance (BD) measures the similarity of two discrete or continuous distributions.

Table 2: Results for in- and out-of-distribution detection over the aggregation of the OOD sets. (COCO as an in-distribution set)

| Model  | Cider          | BLEU-4 | ROUGE-L          |
|--------|----------------|--------|------------------|
| Top-Down | 1.16/ 0.09/ 0.18/ 0.41/ 0.33 | 0.35/ 0.05/ 0.09/ 0.17/ 0.13 | 0.53/ 0.29/ 0.33/ 0.36/ 0.37 |
| Show-Tell | 0.98/ 0.17/ 0.19/ 0.36/ 0.37 | 0.31/ 0.07/ 0.06/ 0.13/ 0.14 | 0.51/ 0.30/ 0.31/ 0.38/ 0.39 |
| ORT     | 1.28/ 0.08/ 0.16/ 0.42/ 0.38 | 0.38/ 0.06/ 0.06/ 0.11/ 0.12 | 0.58/ 0.27/ 0.31/ 0.36/ 0.37 |
| ETA     | 1.6/ 0.13/ 0.17/ 0.39/ 0.38 | 0.38/ 0.06/ 0.06/ 0.12/ 0.13 | 0.58/ 0.29/ 0.32/ 0.36/ 0.37 |
| M2      | 1.20/ 0.14/ 0.18/ 0.38/ 0.37 | 0.38/ 0.07/ 0.08/ 0.13/ 0.13 | 0.58/ 0.30/ 0.31/ 0.36/ 0.37 |
| GET     | 1.30/ 0.14/ 0.19/ 0.39/ 0.38 | 0.38/ 0.08/ 0.06/ 0.12/ 0.13 | 0.58/ 0.30/ 0.31/ 0.36/ 0.38 |

5.4 Results

We start by aggregating all the OOD image sets and evaluating the detection rate. Tables 2 and 3 summarize the results for models trained on COCO and Flickr-8k datasets, respectively. As results indicate, the generated captions’ likelihood scores can detect OOD instances significantly better than the methods based on image-classification models. Since the captions generated for the OOD images are assigned with a lower likelihood than unseen in-distribution images, they can be rejected with high rates by thresholding the likelihood score. Meaning that instead of applying two separate models where the first decide whether an image is OOD or not, and the second is the IC model responsible for generating a relevant caption, a single IC model can be applied. We also notice that Transformer-based IC models can detect OOD instances with higher rates than RNN-based models. These results are aligned with [13] that showed that Transformer-based models used for text classification are better OOD detectors. Next, we analyze the detection of each OOD set independently. We start by examining the corrupted image sets, and afterward, we analyze the unknown object, random noise, and cartoon image sets.

Corrupted image sets: recall that these sets consist of corrupted in-distribution images taken from the corresponding test sets. To demonstrate the severity of the corruptions, we generate captions for each of the corrupted sets and measure the standard IC evaluation metrics against the corresponding ground-truth captions. Results, summarized in Table-1, show a significant drop in all metrics when models are evaluated over the corrupted sets since the generated captions are irrelevant to the given images. For comparison, randomly generated captions (created by randomly drawing tokens from the vocabulary without considering the image) achieve the following scores: a Cider of 0.06, BLEU-4 of 0.04, and ROUGE-L of 0.24. However, despite the severe drop caused by these sets, we find that the corrupted images can be effectively detected by considering the captions’ likelihood scores. The detection results of the models trained on the COCO dataset appear in Table-4 (results for Flickr data sets are consistent).
In Fig-4, we demonstrate the likelihood of the JPEG compression set against COCO’s test set. The ROC curve for the JPEG compression set shows that when 80% of the compressed images are rejected, less than 3% of in-distribution images are falsely rejected (at the point where the TPR and FPR are 97%, 20% respectively). For comparison, a random detector that randomly assigns a score for a caption would reject only 3% of the OOD images while falsely rejecting 3% of the in-distribution images (at the point where the TPR and FPR are both 97%).

Table 4: Results for in- and out-of-distribution detection over the corrupted OOD image sets.

| Model  | OOD set         | ROC↑ | PRin↑ | PRout↑ | BD↑ |
|--------|-----------------|------|-------|--------|-----|
| ORT    | Salt-and-pepper | 0.924| 0.915 | 0.918  | 0.523|
|        | JPEG compression| 0.931| 0.937 | 0.929  | 0.503|
|        | Snow flakes     | 0.829| 0.801 | 0.842  | 0.184|
|        | Cartoon corruption| 0.836| 0.822 | 0.851  | 0.210|
| ETA    | Salt-and-pepper | 0.909| 0.922 | 0.900  | 0.511|
|        | JPEG compression| 0.939| 0.944 | 0.923  | 0.555|
|        | Snow flakes     | 0.801| 0.789 | 0.832  | 0.134|
|        | Cartoon corruption| 0.833| 0.813 | 0.836  | 0.202|
| Top-Down| Salt-and-pepper | 0.911| 0.910 | 0.909  | 0.455|
|        | JPEG compression| 0.961| 0.962 | 0.968  | 0.797|
|        | Snow flakes     | 0.778| 0.739 | 0.791  | 0.111|
|        | Cartoon corruption| 0.803| 0.785 | 0.809  | 0.149|
| Show-Tell| Salt-and-pepper | 0.863| 0.849 | 0.851  | 0.292|
|        | JPEG compression| 0.870| 0.868 | 0.851  | 0.321|
|        | Snow flakes     | 0.752| 0.693 | 0.772  | 0.103|
|        | Cartoon corruption| 0.725| 0.682 | 0.712  | 0.053|
| MSP    | Salt-and-pepper | 0.891| 0.901 | 0.854  | 0.498|
|        | JPEG compression| 0.822| 0.854 | 0.812  | 0.349|
|        | Snow flakes     | 0.712| 0.735 | 0.701  | 0.118|
|        | Cartoon corruption| 0.852| 0.856 | 0.829  | 0.219|
| GODIN  | Salt-and-pepper | 0.843| 0.810 | 0.866  | 0.432|
|        | JPEG compression| 0.849| 0.841 | 0.850  | 0.422|
|        | Snow flakes     | 0.739| 0.726 | 0.744  | 0.127|
|        | Cartoon corruption| 0.741| 0.765 | 0.704  | 0.089|

**Non-corrupted image sets:** moving forward to the next four OOD sets. These sets, composed of images containing unknown objects, cartoons, and noise, can also be detected at high rates using the likelihood score. Table-5 summarizes the detection rates of the models. As can be seen, unsurprisingly, images containing random noise or cartoons are the easiest to detect, while images containing unknown objects are the hardest due to their visual closeness to in-distribution images.

Table 5: Results for in- and out-of-distribution detection over the non-corrupted OOD image sets.

| Model  | OOD set            | ROC↑ | PRin↑ | PRout↑ | BD↑ |
|--------|--------------------|------|-------|--------|-----|
| ORT    | Unknown objects    | 0.769| 0.771 | 0.763  | 0.132|
|        | Random noise       | 0.985| 0.971 | 0.992  | 1.691|
|        | Google’s cartoon set| 0.986| 0.988 | 0.979  | 1.198|
|        | Cropped unknown objects| 0.767| 0.764 | 0.782  | 0.131|
| ETA    | Unknown objects    | 0.755| 0.764 | 0.701  | 0.119|
|        | Random noise       | 0.981| 0.976 | 0.984  | 1.531|
|        | Google’s cartoon set| 0.978| 0.969 | 0.984  | 1.101|
|        | Cropped unknown objects| 0.781| 0.771 | 0.793  | 0.163|
| Top-Down| Unknown objects    | 0.736| 0.737 | 0.716  | 0.115|
|        | Random noise       | 0.965| 0.981 | 0.899  | 1.682|
|        | Google’s cartoon set| 0.980| 0.985 | 0.964  | 1.181|
|        | Cropped unknown objects| 0.759| 0.762 | 0.732  | 0.128|
| Show-Tell| Unknown objects    | 0.727| 0.722 | 0.704  | 0.097|
|        | Random noise       | 0.954| 0.969 | 0.921  | 0.995|
|        | Google’s cartoon set| 0.930| 0.943 | 0.910  | 0.595|
|        | Cropped unknown objects| 0.722| 0.721 | 0.699  | 0.092|
| MSP    | Unknown objects    | 0.641| 0.656 | 0.629  | 0.099|
|        | Random noise       | 0.899| 0.903 | 0.886  | 0.349|
|        | Google’s cartoon set| 0.912| 0.922 | 0.909  | 0.498|
|        | Cropped unknown objects| 0.702| 0.689 | 0.711  | 0.094|
| GODIN  | Unknown objects    | 0.706| 0.699 | 0.711  | 0.102|
|        | Random noise       | 0.969| 0.984 | 0.973  | 1.544|
|        | Google’s cartoon set| 0.963| 0.977 | 0.965  | 1.001|
|        | Cropped unknown objects| 0.786| 0.782 | 0.789  | 0.171|

**Figure 5:** Comparison between the average predicted probability for noun, verb, and adjective tokens. On the left panel we show the results of Show-Tell model with NS-0.8. On the right panel we show the results of Top-Down model with BS-10.

Here as before, we find the Transformer-based models outperform. In all tested sets, the models outperform a random detector.\(^2\)

\(^2\)AUROC is equal to 0.5, BD is equal to 0, and AUPR is equal to the precision
and the classification-based models. To gain an intuition for why the classification models achieve lower results, we checked their confidence scores and found that they tend to be high even for objects that are not part of the training object (overconfidence when wrong). This was also observed in previous works [10].

Recall that training the captioning models is done by MLE, which does not guarantee to produce less likely captions for OOD images. To better understand why exactly the generated captions for OOD images tend to have a lower confidence, we extract the predicted probabilities of their visual counterpart tokens. More specifically, we consider the part-of-speech of each token in the generated caption and focus on the predicted probabilities of noun, verb, and adjective tokens, as they should be visually grounded in the given image. Interestingly, in all models, the noun, verb, and adjective tokens are predicted with lower probabilities for OOD images compared to in-distribution images (see Fig-5). In contrast, tokens from other part-of-speech groups such as determiner (a, an, the, etc.), adverbs (very, there, where, etc.), and adposition (in, to, during, etc.) are predicted with the same average probability for both in- and out-of-distribution images. Our intuition is that since the predicted visual tokens should match the image and fit the textual context, the model can learn the in-distribution from a richer signal compared to the classification model. We also noticed, in preliminary results, that as we increased the weight of the loss of visually grounded tokens during training (by multiplying the loss with a constant), the OOD detection rates increased while at the same time, the performance on in-distribution remained unchanged. We leave the exploration of this direction to future work.

Table 6: Results for in- and out-of-distribution detection of Top-Down model using different decoding strategies.

| OOD set       | decoding   | ROC↑ | PRin↑ | PRout↑ | BD↑ |
|---------------|------------|------|-------|--------|-----|
| Salt-and-pepper corruption | Greedy     | 0.831 | 0.842 | 0.809 | 0.230 |
|               | Top-10     | 0.597 | 0.614 | 0.562 | 0.025 |
|               | N-0.8      | 0.837 | 0.833 | 0.826 | 0.238 |
| Snow          | Greedy     | 0.706 | 0.678 | 0.703 | 0.091 |
| flake         | Top-10     | 0.603 | 0.610 | 0.574 | 0.013 |
|               | N-0.8      | 0.696 | 0.675 | 0.685 | 0.076 |
| Unknown       | Greedy     | 0.691 | 0.690 | 0.670 | 0.068 |
| objects       | Top-10     | 0.553 | 0.566 | 0.531 | 0.013 |
|               | N-0.8      | 0.676 | 0.669 | 0.659 | 0.057 |
| Random        | Greedy     | 0.809 | 0.863 | 0.766 | 0.720 |
| noise         | Top-10     | 0.657 | 0.685 | 0.610 | 0.058 |
|               | N-0.8      | 0.911 | 0.924 | 0.891 | 0.470 |
| Google’s      | Greedy     | 0.892 | 0.922 | 0.842 | 0.515 |
| cartoon       | Top-10     | 0.566 | 0.609 | 0.531 | 0.028 |
|               | N-0.8      | 0.865 | 0.884 | 0.830 | 0.336 |
| Cropped       | Greedy     | 0.708 | 0.713 | 0.679 | 0.082 |
| unknown       | Top-10     | 0.549 | 0.559 | 0.525 | 0.012 |
|               | N-0.8      | 0.760 | 0.761 | 0.734 | 0.130 |

Decoding strategies: lastly, we investigate the influence of the decoding strategy on the OOD detection rates. We compare three additional types of decoding strategies: (1) greedy, (2) top-10 sampling, (3) nucleus sampling (N-0.8). Results presented in Table-6 and Table-7 indicate that the influence of the decoding strategy has a high impact on the overall results and that beam search is the most effective for this task. We find Top-K as the least effective decoding method for this task, as it has higher chances of choosing low confidence tokens even for in-distribution samples. As some decoding strategies yield significantly superior results for OOD detection than others, we think that developing new techniques that consider the relatedness might boost the results further.

6 CONCLUSIONS AND FUTURE WORK

To conclude, we formulated the task of OOD detection in image captioning and presented evaluation datasets and metrics. We demonstrated that IC models are able to express their uncertainty when facing OOD images by generating low probability captions. While the captions’ likelihood is effective for detecting OOD images and is able to capture the image-caption relatedness, results indicate there is still room for improvement. We hope to inspire future work on developing new models, training methods, and decoding strategies for tackling the important task of “knowing” when the model cannot describe the given image.

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1 Unknown Objects

For creating the unknown object and the cropped unknown object sets we collected images containing 35 objects which are not appearing in COCO training sets. The objects we fetched are: bomb, camel, calculator, dolphin, lion, beetle, chime, dumbbell, hammer, belt, alpaca, dice, balloon, frog, cheetah, hippopotamus, fork, fox, kangaroo, flute, cart, binoculars, insect, armadillo, helicopter, grape, coin, handgun, otter, beaker, bat, bee, lizard, hamster, cello, axe, barrel, egg. Examples can be seen in Fig-2. Images are sourced from open V4 images.
2 Baseline Model

The baseline model was trained on COCO dataset labels: person, umbrella, tie, backpack, handbag, suitcase, bicycle, motorcycle, bus, truck, airplane, train, boat, bench, stop sign, traffic light, fire hydrant, parking meter, zebra, elephant, sheep, dog, bird, cat, horse, cow, bear, giraffe, surfboard, baseball glove, kite, snowboard, frisbee, skis, sports ball, baseball bat, skateboard, tennis racket, bowl, knife, cup, bottle, wine glass, fork, spoon, donut, hot dog, broccoli, sandwich, banana, apple, orange, carrot, pizza, cake, dining table, potted plant, chair, couch, bed, toilet, keyboard, mouse, tv, laptop, remote, cell phone, refrigerator, toaster, microwave, oven, sink, toothbrush, teddy bear, vase, book, clock, scissors, and hair drier.