Open-vocabulary Phrase Detection

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Abstract

Most existing work that grounds natural language phrases in images starts with the assumption that the phrase in question is relevant to the image. In this paper we address a more realistic version of the natural language grounding task where we must both identify whether the phrase is relevant to an image and localize the phrase. This can also be viewed as a generalization of object detection to an open-ended vocabulary, essentially introducing elements of few- and zero-shot detection. We propose a Phrase R-CNN network for this task that extends Faster R-CNN to relate image regions and phrases. By carefully initializing the classification layers of our network using canonical correlation analysis (CCA), we encourage a solution that is more discerning when reasoning between similar phrases, resulting in over double the performance compared to a naive adaptation on two popular phrase grounding datasets, Flickr30K Entities and ReferIt Game, with test-time phrase vocabulary sizes of 5K and 39K, respectively.

1. Introduction

Grounding natural language phrases in images is a natural evolution from standard object detection to an open-ended scenario with a potentially very large number of recognizable concepts. However, most existing work has approached natural language grounding in constrained settings. These include methods that localize a text query known to be relevant to an image [3, 4, 6, 14, 16, 24, 29, 30, 31, 34, 37, 38, 40], tasks that artificially limit the number of text queries or negative examples [12, 21, 42], or methods that produce region-based descriptions but do not consider the localization performance of specific concepts [1, 9, 15, 32].

In this paper we propose a new task without the restrictions to negative regions or queries in prior work, which we call phrase detection. Given a database of images and a set of query phrases, the goal is to identify which phrases are associated with each image, and localize or ground the phrases within the images.

One of the challenges faced in this task is the high false positive rate, especially from semantically similar concepts. Consider the example in Figure 1. The man and woman are considered distinct even though they are both instances of person. In the standard phrase localization task, where the search is limited only to the phrases present in the image (typically phrases present in reference captions), distinguishing between closely related references is often unnecessary. In vision-language grounding datasets like Flickr30K Entities [31], 60% of test images have a single person reference, and 27% have only two. If we had an oracle person detector and simply assigned person boxes to person phrases at random, we would expect to get 79% of the person references correct. For other phrase types this is even more pronounced: e.g., an oracle vehicle detector would get 95% of vehicle phrases correct. Thus, standard phrase localization often degenerates to simply identifying the basic object category the phrase refers to. In contrast, in phrase detection distinguishing between multiple references is necessary since a detector must decide which phrases are actually relevant to the image in addition to localizing them.

To build a good phrase detector, we not only need to be able to distinguish between semantically similar concepts, but also between visually similar ones. In the bottom part of Figure 1, it is easy to understand why microphone would be predicted for cigar due to their visual similarity. In standard phrase localization, a model needs to find only ground truth phrases, so the number of visual confusions is greatly limited. In addition, while in phrase detection the confidence scores for each phrase need to be comparable across images in order to separate images that contain the phrase from those that do not, in phrase localization the scores need only allow us to rank regions for a phrase within each image. These differences suggest, and our experiments will confirm, that a model that performs well at phrase localization may not actually generalize to the much more challenging phrase detection task.

1Code: https://github.com/VisionLearningGroup/phrase-rcnn
A straightforward approach to phrase detection would be to extend the Faster R-CNN network \cite{ren2015faster} to a Phrase R-CNN relating image regions to phrases (as done for related tasks, e.g. \cite{jin2016phrase,hinami2013negative}). Figure 2 shows the parallels between the major components of Phrase R-CNN and Faster R-CNN. Due to the challenges we have discussed, however, a naive implementation results in a model that is unable to discriminate between similar phrases. Simply altering the training procedure to encourage a more discriminative model is not straightforward. For example, finding hard negative regions is an issue since these models are trained with small batches that rarely contain examples of similar but distinct phrases (e.g., we can rarely find both a microphone and a cigar in the same image).

Rather than mining hard negative regions, Hinami and Satoh \cite{hinami2013negative} performed negative phrase augmentation (NPA), which adds hard-negative phrases to a minibatch using a confusion matrix estimated on validation data. However, as our experiments will show, Phrase-R-CNN trained with NPA does well for common phrases, but it does not generalize favorably to rarer phrases. We find that simpler methods like canonical correlation analysis (CCA) \cite{hotelling1936relations} actually perform much better on phrase detection than a straightforward implementation of Phrase R-CNN or a method trained for standard phrase localization. Nonetheless, we also show that we can beat the CCA baseline by using it to initialize the fully connected layers of the Phrase R-CNN region classifier.

The contributions of our paper are summarized below:

- To address this task, we introduce a Phrase R-CNN network, which extends the Faster R-CNN detector to relate phrases, rather than categories, to image regions.
- We propose a training procedure which enables our network to take advantage of the discriminative power of a CCA-learned embedding, resulting in a model that compares favorably on both the phrase localization and phrase detection tasks.
- We perform an evaluation on two datasets with test set phrase vocabulary sizes of 5K and 39K, respectively, and report mean average precision (mAP) across these entire vocabularies, further broken down by phrase frequencies. We will publicly release our models and evaluation code to encourage other researchers to adopt the same challenging protocol.

Section 3 discusses how we adapt the region proposal network, bounding box regression, and region classification components of Faster R-CNN for phrase detection. Section 4 benchmarks our detection models on the phrase localization task addressed in prior work, where the goal is simply to localize a phrase in an image it is known to exist. Our phrase detection experiments in Section 5 show that by carefully initializing and fine-tuning the classification layers of the network, our approach achieves more than double the performance of the straightforward adaptation of the Faster R-CNN network, and a significant improvement over ablated versions of our model.

2. Related Work

The most relevant phrase grounding methods to our work are those that do not assume that a ground truth image-phrase pair are provided at test time. Zhang et al. \cite{zhang2018phrase} evaluated a scenario in which each query phrase had to be local-
Figure 2. **Model Overview.** Our approach follows the Faster R-CNN paradigm consisting of a region proposal network, a bounding box regressor, and a region classifier. Phrase R-CNN performs an element-wise product of the text embedding and region features as our input to our bounding box regression layer. We propose several variants to our region classification method, but training the text and region features as an embedding using a triplet loss performed best in our experiments. We find careful initialization of our classification layers are key to enable our model to discriminate between related phrases.

Using all its positive images (i.e., images known to contain the phrase) plus a limited number of negative (distractor) images. Johnson et al. [15] trained a model to generate descriptions of image regions, but Zhang et al. [42] have shown this model doesn’t localize phrases as well as models that address the task directly. Hinami and Satoh [12] addressed a simpler version of phrase detection covering just the most common phrases (< 0.001% of the available text queries), effectively ignoring the challenging zero- and few-shot aspects of the phrase detection task. They proposed a Faster R-CNN network which used the text representation to output a (linear) classifier and regressor (a multi-layer perceptron) on image region features. By contrast, we learn a linear embedding on top of the image region and text features which projects them to a shared space where distances are meaningful. This is an important choice, since it enables us to take advantage of CCA to initialize our model, which we found key to good performance.

Much of the prior work on the more constrained phrase localization task has mostly focused on better relating image and text features (e.g., [37, 34, 6, 14, 29]). Others have focused on how regions are selected [40, 4] or incorporated cues from the phrases themselves [23, 30, 38, 22]. However, our experiments show that these phrase localization approaches are not well suited to the open-ended detection task. We find that several straightforward changes to how negatives are sampled, such as the negative phrase augmentation proposed by Hinami and Satoh [12], are insufficient to close the performance gap between recent phrase localization approaches and simpler methods such as CCA.

An often cited alternative to (linear) CCA is Deep CCA [2], which learns a non-linear embedding that maximizes the correlation between the features being compared (in this case, between image regions and phrase features). To identify these correlations, a singular value decomposition is computed over features in a minibatch during training. This requires a relatively large minibatch size that must also increase with the dimensionality of the desired embedding. The resulting GPU memory requirements make it difficult to train an embedding of the same dimensionality as that of the linear CCA baseline. Ultimately, we find that linear CCA still outperforms Deep CCA even when they have the same output dimensions.

3. **Phrase R-CNN**

We will now present our proposed Phrase R-CNN network. It extends Faster R-CNN [33], which consists of three components: a region proposal network (RPN) that generates bounding boxes likely to contain an object; a bounding box regressor that refines the RPN boxes taking into account the object being detected; and a region classifier. We will explain these components below.

3.1. **Region Proposal Network and Phrase-Based Bounding Box Regression**

Rather than using an off-the-shelf category-independent region proposal method like many earlier phrase localization approaches (e.g., [14, 29, 31, 34]), we replace it with a trained RPN followed by phrase-aware bounding box regression. The RPN predicts the proposals most likely to contain objects from a set of reference boxes or anchors. We follow the original RPN formulation et al. [33] for the architecture and loss, which is a weighted linear combination of a log-loss over two labels indicating whether an anchor contains an object or not, along with smooth $L_1$ loss [7].

After proposing a generic set of boxes, each is adapted to the input phrase via bounding box regression. Unlike the RPN, which operates solely on image features, the input representation to this predictor is the initial joint image-text representation, i.e., an element-wise product of image region and phrase features. Our phrase representation is obtained using HGLMM Fisher vectors [17] which are built on top of word2vec [25] after being PCA-reduced to 6,000 dimensions. Our region feature is a concatenation of the standard Region-of-Interest (ROI) feature and the 5-dimensional bounding box feature shown to improve grounding performance in prior work (e.g., [4, 29]). Specifically, for an image of height $H$ and width $W$ and a box with height $h$ and width $w$ the bounding box feature is encoded as $[x_{min}/W, y_{min}/H, x_{max}/W, y_{max}/H, wh/WH]$.

While our feature representation is different, our loss for bounding box regression is the same as in Ren et al. [33]. We train the RPN and bounding box regressor first before initializing the classification layers we shall discuss in the next section and then fine-tune the whole network.
3.2. Region classifier

The region classifier’s task is to output a confidence or compatibility score given a region and a phrase feature. We implement this classifier by training an embedding consisting of two fully connected layers (without a bias term), one layer for each modality, that project the image region and language features into a shared space. No additional activation functions are used (i.e., it learns a simple linear embedding just like methods such as CCA), but the final embeddings are L2 normalized as this has shown to promote stability during training [35]. This embedding is trained with a triplet loss, i.e., given some query phrase \( q \), a positive region \( r_p \) and negative region \( r_n \), our loss is

\[
L_{\text{TQR}}(q, r_p, r_n) = \max[0, m + d(q, r_p) - d(q, r_n)],
\]

where \( d \) is the Euclidean distance and \( m \) is a scalar parameter representing the minimum desired margin between the positive and negative pairs. Given some phrase \( q \), a positive region \( r_p \) is defined as a region with at least 0.5 intersection over union (IOU) with the ground truth. After the embedding network is trained, we define the confidence score for a region and a phrase as the distance between the L2-normalized embedded vectors.

As discussed in the introduction, a straightforward adaptation of the Faster R-CNN network tends to make similar predictions for related words. To help encourage our model to learn how to discriminate between words, we initialize its region classification layers using CCA. After using the learned CCA projections for the mean-subtracted region and phrase features, normalized CCA [8] scales the final embedding by the CCA-learned eigenvalues before L2-normalizing them. When we fine-tune the fully connected layers along with the RPN and bounding box regressor from Section 3, we keep the eigenvalues and mean values for the phrase and region features obtained when training the CCA embedding fixed.

3.3. Negative Phrase Augmentation

Obtaining hard negatives is one of the primary challenges of the phrase detection task due to the sparse nature of the annotations in vision-language datasets. Since hard negative image regions are difficult to obtain from the same image (i.e., a deer and antelope are rarely in the same photo) Hinami and Satoh [12] instead focused on mining hard-negative phrases. During training we obtain hard-negative phrases for every ground truth phrase from a confusion table. This confusion table is computed every three epochs in our experiments, and contains the 500 phrases that are most likely to be confused by the current model. We weight the likelihood of drawing a negative phrase by how often it is being confused with the ground truth. These phrases are used in a triplet loss function between a region \( r \) with ground truth phrase \( q_p \) and hard-negative phrase \( q_n \), i.e.,

\[
L_{\text{TVAUG}}(r, q_p, q_n).
\]

We also tried to filter out hard negative phrases that are not mutually exclusive by identifying parent-child relationships in WordNet [26] (e.g., the phrase a person should not be used as a negative for a man) as done in [12]. Using a similar idea, we also looked into augmenting the dataset by using the parents of a child in the hierarchy as additional positive examples (i.e., a person can also be used as a positive for a man). However, we found that filtering out negatives only improved performance for the most common phrases (consistent with [12]) but made little difference over all the phrases. Augmenting the dataset with additional positives did result in slightly faster convergence rates, but did not affect the final performance of the model either.

3.4. Structure-Preserving Constraints

In addition to encouraging the vision-language inputs to embed into a similar space, Wang et al. [37] included additional constraints which also considered the performance when comparing the vision-vision and language-language inputs. This helped produce a more structured representation which generalized better to new samples. Thus, we take advantage of these same constraints in our work. The total loss function using \( q \) to represent phrases, \( r \) regions, and \( p, n \) for positive and negative pairs, respectively, becomes,

\[
L_{\text{cls}} = L_{\text{TQR}}(q, r_p, r_n) + \lambda_1 L_{\text{TVAUG}}(r, q_p, q_n) + \lambda_2 L_T(q, q_p, q_n) + \lambda_3 L_T(r, r_p, r_n),
\]

where the \( \lambda \)'s are scalar parameters. Here we use the phrase pairs obtained from negative phrase augmentation discussed in Section 3.3.

4. Phrase Localization Experiments

We begin by evaluating our approach on the established task of phrase localization before discussing performance on the phrase detection task in Section 5. Localization assumes we are provided a ground truth image-phrase pair, and the goal is to find the bounding box for the phrase within the image. The localization is deemed successful if the predicted box has at least 0.5 IOU with the ground truth.

4.1. Experimental Setup

Implementation Details. We use a 101-layer ResNet [11] as our base image feature encoder and initialize it with a network that was trained for object detection on MSCOCO [20]. On each epoch we randomly subsample 5 ground truth phrases per image when training our proposed model as we found having more balanced mini-batches improves performance. We set \((\lambda_1, \lambda_2, \lambda_3)\) in Eq. (2) to \((0.7, 0.1, 0.1)\), and used a margin of \( m = 0.2 \) in Eq. (1). We also
experimented with an iterative procedure where we alternated between estimating our classification layer’s weights with CCA and using the new weights to fine-tune the entire network, but found a single iteration was sufficient.

**Datasets.** We use two common phrase grounding datasets in our experiments. Our first dataset is Flickr30K Entities [31] which consists of 276K bounding boxes in 32K images for the noun phrases associated with the image’s descriptive captions (5 per image) from the Flickr30K dataset [41]. We use the splits of Plummer et al. [31] which consist of 30K/1K/1K train/test/validation images. The test set in Flickr30K Entities contains 14.5K instances which can be separated into 5,024 unique phrases. The second dataset evaluate performance on is the ReferIt dataset [16]. This dataset consists of 20K images from the IAPR TC-12 dataset [10] which have been augmented with 120K region descriptions. We use the splits of Hu et al. [14] which splits the train/val and testing sets evenly (i.e. 10K each). The ReferIt test set contains 60K instances which can be separated into 34,930 unique phrases.

**Comparative evaluation.** In addition to reporting results from prior work, we compare the following methods:

- **CITE [29]:** The CITE network trains a set of embeddings, each of which can specialize in identifying useful concepts for finding the phrase. These embeddings are assigned to phrases using what can be seen as a soft attention mechanism over the learned embeddings using the phrase features as input. Our implementation of this paper constructs mini-batches by grouping together all phrases from the same image and feeding them into the network together rather than simply sampling image-phrase pairs. While this does reduce training time significantly since each image is processed only once on each epoch, we found it hurt localization performance by about 1%. The CITE paper also used EdgeBox region proposals [43] rather than the RPN used in this work for CITE. The remainder of the settings we used were the same as the original paper.

- **CCA:** We train a CCA embedding between image region features concatenated with the bounding box features and HGLMM text features. This method can be considered our initial model before fine-tuning using the loss function described by Eq. (2).

- **Deep CCA [2]:** Learns a new image region and text feature representation by training a fully connected layer using a correlation loss with a batch size of 30K and a final feature embedding of 1,024. After the representation is learned, the final embedding is trained using CCA. We also experimented with a multi-layer network (as used in the original paper), but found a single layer worked the best.

- **NPA:** Indicates mining hard negative phrases using the method described in Section 3.3.

- **QA R-CNN (ResNet):** Our implementation of [12].

- **Phrase R-CNN:** Our model trained using the loss function described by Eq. (2).

Each model except the last one (Phrase R-CNN) uses a fixed RPN, features, and bounding box regressors that have been trained on the respective datasets. Thus, they directly compare the classification method and not the underlying feature representation or the quality of region proposals.

### 4.2. Localization Results

Table 1(a) gives reported numbers from other papers on the Flickr30K Entities test set. The last line gives the performance for our implementation of the CITE network with RPN and bounding box regression. We can see that CITE obtains similar performance to the adaptations of the Faster R-CNN network proposed by Hinami and Satoh [12] and Chen et al. [4] without training on outside vision-language datasets (i.e. Visual Genome (VG) [18]), performing online hard example mining (OHEM) [36], or using reinforcement learning to jointly predict multiple phrases in the same image at once [4]. Thus, we can regard CITE as a good representative of the state-of-the-art in phrase localization.

Our experiments comparing classification methods using the ResNet architecture are provided in Table 1(b). We can see that the relative performance of methods using VGG...
Table 2. Phrase localization performance on the ReferIt test set. (a) Published results of methods which fine-tune the visual representation, except for CITE which does no fine-tuning. (b) our compared approaches which use the same RPN and feature representation varying only the trained region classifier, and (c) benefits provided from initializing our classification layers using CCA.

| Methods                                      | Accuracy |
|----------------------------------------------|----------|
| (a) State of the art (VGG)                   |          |
| CITE (w/o RPN, w/o finetuning) [29]          | 34.13    |
| QRC [4]                                      | 40.07    |
| APML [19]                                    | 44.18    |
| CITE (our implementation)                    | 45.19    |
| (b) Region Classification Method (ResNet)    | 50.95    |
| CITE                                         |          |
| Deep CCA                                     | 47.43    |
| CCA                                          | 47.65    |
| QA R-CNN                                     | 47.83    |
| Phrase R-CNN                                 | 48.27    |
| Phrase R-CNN + NPA                           | 46.98    |
| (c) w/CCA Initialization (ResNet)            |          |
| Phrase R-CNN                                 | 49.28    |
| Phrase R-CNN + NPA                           | 48.35    |

and ResNet architectures remain unchanged. NPA still results in a slight decrease in performance, similar to what is observed with QA R-CNN (Table 1(a)). NPA was designed to make the model more discriminative between similar phrases, something that is important to detection, but largely unnecessary in phrase localization since very similar phrases often don’t occur in the same image.

Notably, Deep CCA performs worse than regular CCA in Table 1(b). This is not due to a difference in embedding dimensionality (the CCA model being shown has a final embedding size of 2053). When we reduce the CCA model to the same dimensions as Deep CCA, we get a localization accuracy of 66.00. In addition, since the Deep CCA model requires a batch size of 30K to train its best model, fine-tuning the entire network is impractical (in this experiment most of the network was frozen and only the classification method was trained).

Our full model’s performance is shown in Table 1(c). It slightly outperforms the CITE baseline and is about 4% better than the CCA model which was used for initialization. We show that our approach generalizes to the ReferIt dataset in Table 2, where the results follow a similar pattern to those on Flickr30K Entities. This demonstrates that our approach can compare favorably to the state-of-the-art in phrase localization, but, as our experiments in the next section will show, the relative performance of methods changes considerably on phrase detection.

5. Phrase Detection Experiments

Given a set of phrases and a database of images, our task is to identify which images contain the query phrases and localize them. This makes our task akin to object detection where the phrases can be thought of as categories. Thus, we evaluate this task using mean average precision (mAP) over the phrases. A single prediction per image is made for every query evaluated for it (i.e., every image predicts a single location for each phrase). This helps alleviate the issues with false negatives arising from annotation sparsity, since a full labeling for vision-language datasets is not typically done. Since this metric may be unstable for phrases with few instances (i.e., getting a AP of 0 or 100 is more likely to arise for phrases with a single occurrence), we separate the phrases into three main groups based on the number of test instances: \( \leq 9, 10–29, \geq 30 \). Separating the phrases by occurrence also provides a glimpse of a model’s performance on the zero shot, few shot, and standard object detection components of this task.

5.1. Detection Results

We report performance on the phrase detection task for both the Flickr30K Entities and ReferIt datasets in Table 3. When comparing the different classification methods in Table 3(a), as we did in our phrase localization experiments in Section 4, we see that cross-correlation methods (i.e., CCA and Deep CCA) significantly outperform other approaches. As seen in the second line of Table 3(a), the majority of the improvement seen by NPA is in the common phrases, with much smaller improvement, if any, in the uncommon or rare phrases. Thus, using NPA to obtain hard negatives during training is not enough by itself to compensate for the improved discriminative power of the CCA-based methods. However, we show in the first of line Table 3(b) that fine-tuning the learned CCA weights can still improve performance. Indeed, by incorporating the learned CCA weights into our network we can take advantage of sampling improvements like NPA, which results in total increase of 1 mAP over CCA as shown in the second line of Table 3(b).

We provide qualitative examples comparing the differences our model undergoes before and after using CCA initialization in Figure 3. In the leftmost example, before using CCA to initialize our classification layers our model made similar predictions for the dog and child, while also confusing the child and the man, all of which we correctly identify using CCA initialized layers. Being able to correctly identify similar phrases isn’t restricted to references of “people,” however, as seen in the middle example of Figure 3, where the model before CCA initialization makes the same prediction for the dog and large brown white cow, but gets them correct with our full model. The third example of Figure 3 also makes several correct references with the CCA initialized model, including for the phrase someone even though that person is much less prominent than the woman. This suggests there may be some visual cues that may be useful in resolving pronominal references, and taking into ac-
### Table 3. mAP for phrase detection task split by frequency of test instances. (a) our compared approaches which use the same RPN and feature representation varying only the trained region classifier, and (b) benefits from initializing our classification layers using CCA.

| Method               | #Categories | 1 − 9 | 10 − 29 | ≥ 30 | mean/total | 1 − 9 | 10 − 29 | ≥ 30 | mean/total |
|----------------------|-------------|-------|---------|------|------------|-------|---------|------|------------|
| (a) Region Classification Method |             |       |         |      |            |       |         |      |            |
| CITE                 |             | 3.2   | 8.6     | 16.9 | 9.6        | 1.4   | 6.6     | 18.8| 8.9        |
| Deep CCA             |             | 7.2   | 16.1    | 23.0 | 15.4       | 3.7   | 11.8    | 25.1| 13.5       |
| CCA                  |             | **9.2** | **18.2** | **24.3** | **17.2** | **3.8** | **11.9** | **26.7** | **14.1** |
| QA R-CNN             |             | 2.1   | 6.5     | 15.9 | 8.2        | 0.7   | 5.2     | 15.1| 7.0        |
| Phrase R-CNN         |             | 1.9   | 6.8     | 15.3 | 8.0        | 0.7   | 4.9     | 15.7| 7.1        |
| Phrase R-CNN + NPA   |             | 2.2   | 9.1     | 20.5 | 10.6       | 1.0   | 5.6     | 17.2| 7.9        |
| (b) w/CCA Initialization |           |       |         |      |            |       |         |      |            |
| Phrase R-CNN         |             | **9.6** | **18.8** | **25.2** | **17.9** | **4.1** | **12.7** | **27.3** | **14.7** |
| Phrase R-CNN + NPA   |             | **9.6** | **19.1** | **26.4** | **18.3** | **3.9** | **12.9** | **28.0** | **14.9** |

Count the bias of what and how entities are referenced may improve performance (e.g. taking into account human bias when writing the phrases as done in Misra et al. [27]).

**Analyzing Model Behavior.** In the Introduction we argued straightforward implementations of Phrase R-CNN would be biased towards making similar predictions for similar phrases. To verify our intuition, we measure the entropy in the confidence scores over the 100 most common phrases referring to people in the Flick30K Entities dataset. If a model has high entropy on these phrases, then it would have about the same confidence in each phrase. A model with low entropy would indicate high confidence on a handful of predictions, and low confidence everywhere else.

We begin by converting the confidence scores for the people terms produced by the baseline Phrase R-CNN (no CCA initialization) model and CCA methods in Table 3(a) to probabilities using Platt scaling [28]. The scaling parameters are computed per-phrase for each model. Then, we calculate the entropy over the probability of each phrase for an image and average them. We find baseline Phrase R-CNN has 8% more entropy than CCA. This confirms our hypothesis that CCA is more discriminative than the baseline Phrase R-CNN. If we do the same procedure for 100 phrases taken at random (averaged over 5 sets of random phrases), baseline Phrase R-CNN has only 3% more entropy than CCA, verifying the difference in entropies is more significant for similar phrases. To visualize the behavior of the two models, we provide the confusion matrix for the top 20 person phrases for each method in Figure 4, which shows without initializing Phrase R-CNN with CCA the network tends to make the same prediction for similar phrases.

#### 5.2. Filtering Phrases

At test time, evaluating Phrase R-CNN for the entire phrase vocabulary may be too computationally expensive, and is likely to result in many false positive detections. To
mitigate these issues, we can introduce a filtering step in which we first use a global image representation to predict a short list of phrases likely to be in the image that can then be detected using Phrase R-CNN. To this end, we use the two-branch image-sentence retrieval approach of Wang et al. [37] trained on Flickr30K to retrieve sentences for each image in the test set. Then, for each image we extract phrases from its retrieved sentences and only predict the extracted phrases for that image with our detection models. For the text representation we used the same HGLMM features used by our phrase detectors, while we used a 152-layer ResNet pretrained on ImageNet [5] and averaged over 10 crops for our image representation.

Table 4 reports a consistent improvement provided by pre-filtering phrases on the Flickr30K Entities dataset after retrieving the top 100 sentences from the training set. Notably, we see a significant boost in performance for Phrase R-CNN when it doesn’t use CCA initialization, although using CCA still works best. However, a drawback of this approach is that it requires database sentences from similar a distribution of images. We also tried to generate captions using the Show and Tell [39] approach with ResNet features rather than retrieve them, but we found the captions provided low recall on the phrases in the test set resulting in poor performance.

Retrieving sentences provides at least two constraints the phrase detection models lack. First, it provide some structured information about co-occurrences between phrases (e.g. you likely shouldn’t try to detect “a hand” if you don’t think an image contains a “person”). Second, these sentences give some measure of the prior probability of a phrase, i.e. we are unlikely to retrieve a phrase if it occurs once in the entire dataset unless we are relatively certain it exists. Incorporating such constraints in an end-to-end trainable phrase detection framework is a good potential direction for future work on this task.

6. Conclusion

In this paper we introduced the phrase detection task, which is more challenging and has a broader set of applications than the localization-only problem addressed in prior work. Our experiments show that naive adaptations of prior work tend to have difficulty reasoning about similar phrases compared to methods like CCA, and combining the two achieved better performance than either alone. However, our models still perform relatively poorly compared with tasks like object detection, indicating substantial room for improvement in future work. A significant challenge of phrase detection stems from the long tail of phrases that occur only a few times. As discussed in Section 5.2, improvement could come from jointly predicting multiple phrases at a time while also taking into account how common a phrase is. We also feel improving negative sampling methods has potential to have a significant impact on performance in future work. Last but not least, we need to understand the reasons for the effectiveness of CCA on phrase detection so as to design better objective functions for the task instead of...
resorting to CCA initialization heuristics.

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