Improving Weakly Supervised Visual Grounding by Contrastive Knowledge Distillation

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Abstract

Weakly supervised phrase grounding aims at learning region-phrase correspondences using only image-sentence pairs. A major challenge thus lies in the missing links between image regions and sentence phrases during training. To address this challenge, we leverage a generic object detector at training time, and propose a contrastive learning framework that accounts for both region-phrase and image-sentence matching. Our core innovation is the learning of a region-phrase score function, based on which an image-sentence score function is further constructed. Importantly, our region-phrase score function is learned by distilling from soft matching scores between the detected object class names and candidate phrases within an image-sentence pair, while the image-sentence score function is supervised by ground-truth image-sentence pairs. The design of such score functions removes the need of object detection at test time, thereby significantly reducing the inference cost. Without bells and whistles, our approach achieves state-of-the-art results on the task of visual phrase grounding, surpassing previous methods that require expensive object detectors at test time.

1 Introduction

Visual phrase grounding—finding image regions associated with phrases in a sentence description of the image, is an important problem at the intersection of computer vision and natural language processing. Most of existing approaches [11, 32, 38] follow a fully supervised paradigm that requires the labeling of bounding boxes for each phrase. This fine-grained annotation is unfortunately expensive to obtain and thus difficult to scale. Consequently, weakly supervised grounding has recently received considerable attention [34, 41, 40, 46, 4, 33, 44, 10, 37]. In this setting, only images and their sentence descriptions are given at training time, and a method has to link image regions to sentence phrases at test time.

A major challenge of weakly supervised grounding is to distinguish among many “concurrent” visual concepts. For example, the region of a dog and that of its head are likely to co-occur in images associated with the phrase “a running puppy.” Without knowing the ground-truth region-phrase matching, learning to link the region of dog (but not dog head) to its corresponding phrase becomes very challenging. To address this challenge, recent methods [4, 10, 37] leverage generic object

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detectors during training and inference. Object detection provides high quality object regions, as well as their object names that can be further matched to candidate phrases, thereby bringing in external knowledge about region-phrase matching and thus helping to disambiguate those “concurrent” concepts.

In this paper, we focus on developing a principled approach to distill knowledge from a generic object detector for weakly supervised grounding. To this end, we present a simple method under the framework of contrastive learning. Specifically, our model learns a score function between region-phrase pairs, guided by two levels of similarity constraints in the form of noise-contrastive estimation (NCE) loss during training. The first level of region-phrase similarity is distilled from object detection outputs. This is done by aligning predicted region-phrase scores to a set of soft targets, computed by matching object names and candidate phrases. The second level of image-sentence similarity is computed from a greedy matching between all region-phrase pairs, and supervised by ground-truth image-sentence pairs. During inference, our method compares each image region to candidate phrases using the learned score function. Thanks to knowledge distillation, our method does not require an object detector during inference and thus significantly reduces inference time.

To evaluate our method, we systematically vary the components of our model and demonstrate several best practices for weakly supervised phrase grounding. Moreover, we conduct extensive experiments on Flickr30K Entities and ReferItGame datasets, and compare our results to the latest methods of weakly supervised phrase grounding. Our experiments show that our method establishes new state-of-the-art results and outperforms the latest methods, including those that use object detectors at test time, and remains very efficient during inference without using object detectors. For example, on Flickr30K Entities, our method improves the result from [10] by 2.3% and even outperforms the latest method [37] that combines multiple strong object detectors during inference. We hope that our simple yet strong method will shed light on new ideas and practices for weakly supervised image-text grounding.

2 Related Work

We discuss relevant work on weakly supervised phrase grounding and provide a brief review of contrastive learning and knowledge distillation—the two main pillars of our method.

Weakly Supervised Phrase Grounding

Grounding of textual phrases, also referred to as phrase localization, has received considerable attention recently. Several new datasets, e.g., Flickr30K Entities and Visual Genome, have been constructed to capture dense phrase-region correspondences. Building on these datasets, recent approaches learn a similarity function between regions and phrases by using the ground-truth region-phrase pairs. This fully supervised paradigm has shown impressive results, yet requires labor-intensive annotations of bounding boxes for all phrases.

Recent work explores a weakly supervised setting. Specifically, these methods learn from only images and their paired sentence descriptions, without explicit region-to-phrase correspondence. For example, Rohrbach et al. learn visual phrase grounding by reconstructing the input phrases using an attention module over image regions. Recent works show that weakly supervised phrase localization can benefit from side information, such as object segmentation or detection. UTG links words in text and detection classes using co-occurrence statistics from paired captions. Moreover, Xiao et al. look into the linguistic structure of the sentences. They proposed a structure loss to model the compositionality of the phrases and their attention masks. Zhao et al. jointly learns to propose object regions and matches the regions to phrases. Fang et al. explores the weakly supervised grounding by decomposing the problem into several modules and taking additional information, like the color module, to improve the performance. A more recent work of WPT makes use of off-the-shelf models to detect objects, scenes and colors in images, and achieves the goal of grounding via measuring semantic similarity between the categories of detected visual elements and the sentence phrases.

Our method shares the key idea behind these previous works—we seek an explicit alignment between regions and phrases given image-sentence pairs. Our method differs from previous works by explicitly modeling the knowledge distillation from external off-the-shelf object detectors into the unified contrastive learning framework. Our method is also different from WPT though we both need to
use object detectors: our approach learns the distillation in the training stage which makes our model
free of detectors in the testing stage, while WPT requires using detectors during inference.

A concurrent work [14] also proposed to use contrastive loss for weakly supervised phrase grounding.
Different from [14], our work moves beyond the contrastive loss and focuses on knowledge distillation
from an external object detector under a contrastive learning framework.

Contrastive Learning There is recently a trend of exploring contrastive learning approaches in
various tasks recently. Among them, Contrastive Predictive Coding (CPC) [29] learns representations
for sequential data. Deep InfoMax [17] achieved the goal of unsupervised learning by maximizing
the mutual information between the input and output of networks. SimCLR [5] is proposed for image
classification with only a limited amount of data with class labels via contrastive learning. Multiview
coding [36] extends the input to more than two views. These methods are all based on the similar
objectives of contrastive learning related to Noise Contrastive Estimation (NCE) [15], but differ in
various performed tasks. Our work is relevant to these works since our mathematical framework is
also built upon the general idea of infoNCE [29] and NCE [15]. However, as far as we know, we are
the first to extend this framework by integrating knowledge distillation into the cross-view weakly
supervised grounding task.

Knowledge Distillation Knowledge distillation was proposed and popularized by [3,16,1,35,42].
Several recent works [13,26,24] have explored knowledge distillation for multiple modalities.
Knowledge distillation has also shown its effectiveness in various vision-language tasks, such as
VQA [28,8], grounded image captioning [48], video caption [30,45], etc. Different from previous
approaches, we consider knowledge distillation for region-phrase grounding by matching the outputs
of a region-phrase score function to soft targets computed from object detection results.

3 Approach

Consider $X = [X_1, \ldots, X_i, \ldots, X_N]$ as the set of images and $Y = [Y_1, \ldots, Y_j, \ldots, Y_M]$ as the set
of sentences. Each image $i$ consists of a set of regions with their features $X_i = \{x_{i1}, \ldots, x_{in}\}$. Similarly,
each sentence $j$ includes multiple phrase features $Y_j = \{y_{j1}, \ldots, y_{jm}\}$. Thus, $i, j$ index images and
sentences, and $l, k$ index regions and phrases. Oftentimes, we have multiple sentences
describing the same image and many more image regions than sentence phrases. Moreover, with
minor abuse of notations, we denote $p(X_i, Y_j)$ as the probability of a valid image-sentence pair
$(X_i, Y_j)$, i.e., $p(X_i, Y_j) = 1$ if and only if $Y_j$ can be used to describe $X_i$. Similarly, we use $p(x_{il}, y_{jk})$
as the probability of a valid region-phrase pair $(x_{il}, y_{jk})$.

Our goal is to learn a score function that measures the similarity between region features $x_{il}$ and phrase
features $y_{jk}$. However, the learning of this function only has access to ground-truth image-sentence
pairs $p(X_i, Y_j)$ without knowing the matching between regions and phrases $p(x_{il}, y_{jk})$. To address this
challenge of weakly supervised grounding, we leverage a generic object detector $D$ to label candidate
image regions, based on which “pseudo” labels of region-phrase correspondence can be generated by
matching the region object labels to the sentence phrases. Therefore, our key innovation is the design
of a contrastive loss that learns to distill from object detection outputs. A major advantage of using
knowledge distillation is that our method no longer requires object detection at inference time and
thus is very efficient during inference. Fig. 1 presents an overview of our method.

We now present the details of our method by first introducing the design of our score functions for
image-text matching, followed by our contrastive learning loss using knowledge distillation.

3.1 Score Functions for Image-Text Matching

Our model builds on a two-branch network [38] for image-text matching at both region-phrase
and image-sentence levels. The key idea is learning a score function to match region-phrase pairs.
Based on the region-phrase matching scores, we further construct an image-sentence similarity
score. Specifically, our network has two branches $f$ and $g$ that take the inputs of region and phrase
features $x_{il}$ and $y_{jk}$, respectively. Each branch is realized by a deep network by stacking multiple
fully connected layers with ReLU activation in-between, followed by a L2 normalization at the end.
We define the similarity between a region-phrase pair \((x^i_l, y^k_j)\) as the cosine similarity between the transformed features \(f(x^i_l)\) and \(g(y^k_j)\), given by

\[
    s(x^i_l, y^k_j) = f(x^i_l)^T g(y^k_j). \tag{1}
\]

We further aggregate the region-phrase matching scores \(s(x^i_l, y^k_j)\) into a similarity score between a image-sentence pair \((X_i, Y_j)\), defined as

\[
    S(X_i, Y_j) = \sum_{k=1}^{m} \max_{l} s(x^i_l, y^k_j). \tag{2}
\]

This image-sentence score \(S(X_i, Y_j)\) is computed using greedy matching. Concretely, for each phrase \(k\) in the sentence \(j\), we find its best matching region among all candidates. The scores of the best matching regions are further summed across all phrases. Note that phrases and regions are not interchangeable in this score function, i.e., \(S(X_i, Y_j) \neq S(Y_j, X_i)\). This is because that each phrase must be matched to at least one regions, while a region, e.g., a background region, might not be matched to any phrase. A similar image-sentence score function was also discussed in [19, 47] for image-sentence retrieval.

### 3.2 Contrastive Learning with Knowledge Distillation

A major challenge of weakly supervised grounding is the lack of ground-truth region-phrase pairs. Our key idea is to make use of an object detector during training that can provide “pseudo” labels for learning region-phrase matching. We now describe how we generate the pseudo labels and how we supervise the learning of region-phrase matching.

**Pseudo Labels for Region-Phrase Matching**

An object detector \(D\) predicts a distribution of object label \(z^i_l\) in the form of nouns (including “background”) for each candidate region, i.e., \(p(z^i_l|x^i_l) = D(x^i_l)\). \(z^i_l\) can be further matched to phrase \(y^k_j\), e.g., using similarity scores between object noun and the headnoun of the phrase. Let \(p(y^k_j, z^i_l)\) be the matching probability between \(y^k_j\) and \(z^i_l\). We propose to approximate the unknown region-phrase matching ground-truth \(p(x^i_l, y^k_j)\) by soft “pseudo”
We now present our experiments and results. We first discuss our datasets and implementation details, where

\[ \hat{p}(x_i^l, y_j^k) \] can be considered as a soft target distribution given by the matching between object detection outputs and the candidate phrases.

**Distilling Knowledge from Pseudo Labels** We propose to distill from the pseudo label \( \hat{p}(x_i^l, y_j^k) \) by aligning the region-phrase matching scores \( s(x_i^l, y_j^k) \) to the soft pseudo label \( \hat{p}(x_i^l, y_j^k) \). Specifically, given a matching image-sentence pair \((X_i, Y_j)\), we propose the following distillation loss function for region-phrase matching

\[
L_{RP}(X_i, Y_j) = - \sum_{y_j^k \in Y_j} \sum_{x_i^l \in R^l_i} \hat{p}(x_i^l, y_j^k) \log \left( \frac{\exp(s(x_i^l, y_j^k) / \tau)}{\exp(s(x_i^l, y_j^k) / \tau) + \sum_{x_i^l' \in R^l_i} \exp(s(x_i^l', y_j^k) / \tau)} \right),
\]

where \( \tau \) is the temperature scale factor (0.5 in all our experiments). \( R^l_i \) controls how we select \( x_i^l \). A simple choice is to use all regions in \( X_i \) except \( x_i^l \), e.g., \( R^l_i = X_i \setminus \{x_i^l\} \). In this case, our loss can be interpreted as the cross entropy loss, where the normalized output of the score function \( s(x_i^l, y_j^k) \) is trained to mimic the soft target \( \hat{p}(x_i^l, y_j^k) \) given by object detection outputs, thereby resembling the same idea as knowledge distillation [10].

**Contrastive Learning for Image Sentence Matching** Moving beyond region-phrase matching, we enforce additional constraints for image-sentence matching scores \( S(X_i, Y_j) \), where the ground truth pairs \( p(X_i, Y_j) \) is readily available. To this end, we make use of the noise contrastive estimation loss [15] to contrast samples from data distribution (matched pairs) and noise distribution (non-matched pairs). The NCE loss for image-sentence matching is thus given by

\[
L_{IS}(X_i, Y_j) = -\mathbb{E}_{X_i \in X} \left[ p(X_i, Y_j) \log \left( \frac{\exp(S(X_i, Y_j) / \tau)}{\exp(S(X_i, Y_j) / \tau) + \sum_{y_j^k' \in \mathcal{N}(X_i)} \exp(S(X_i, y_j^k') / \tau)} \right) \right],
\]

where \( \tau \) is again the temperature scale factor (0.5). \( p(X_i, Y_j) \) is reduced to binary values during training, i.e., \( p(X_i, Y_j) = 1 \) if and only if \( (X_i, Y_j) \) is a ground-truth image-sentence pair. \( \mathcal{N}(X_i) \) includes a set of negative samples, i.e., those images not matched to the current sentence \( Y_j \), sampled from the set of images \( X \). In practice, we always sample a fixed number of negative pairs from the current mini-batch.

We note that Eq. 4 and Eq. 5 share a similar form and can be both considered as a variant of contrastive loss. Concretely, the two loss functions seek to align the normalized scores in the form of NCE to a target distribution. The difference is how the target distribution is defined and how the samples are selected for normalization. For region-phrase matching, the target distribution is pseudo labels from object detection and local image regions are used for normalization. For image-sentence matching, the target distribution is defined by ground-truth image-sentence pairs and non-matched image-sentence pairs are sampled for normalization.

**Training and Inference** For training, our final loss function is a summation of the region-phrase matching loss \( L_{RP}(X_i, Y_j) \) and the image-sentence matching loss \( L_{IS}(X_i, Y_j) \), given by

\[
L(X_i, Y_j) = L_{IS}(X_i, Y_j) + \lambda L_{RP}(X_i, Y_j),
\]

where \( \lambda \) is the coefficient balance the two loss terms. During training, we gradually increase the coefficient \( \lambda \), such that our model learns to optimize image-sentence matching during the early stage of training, and to focus on region-phrase matching during the late stage of training.

During inference, given an input image-sentence pair, we apply the learned region-phrase score function \( s(x_i^l, y_j^k) \) between every region-phrase pair. The image region with the highest score to each phrase is then selected as the grounding results. We must point out that the inference of our model does not require running object detection, therefore our method is very efficient at test time.

## 4 Experiments

We now present our experiments and results. We first discuss our datasets and implementation details, followed by an ablation study of our model, and finally a comparison of our results to latest methods.
Datasets and Experiment Setup  Our experiments are conducted in two major visual grounding datasets: Flickr30K Entities [32] and the ReferItGame dataset [20]. Flickr30K Entities [32] includes around 30K images. Each image is associated with five sentences. We follow the same train/val/test splits from [32]. For the ReferItGame dataset, we follow the standard split of [34]. We follow the setting of weakly supervised grounding, and do not use the region-phrase annotations of both datasets during training. Following standard evaluation protocols in [4, 34, 37], we report the accuracy as the evaluation metric. The accuracy is defined as the fraction of query phrases whose predicted bounding box overlaps ground-truth box with $\text{IoU}>0.5$. For methods that select the predicted bounding box from a set of region proposals, the metric is equivalent to top-1 recall.

4.1 Implementation Details

We now describe our implementation details, including the features and object detectors, the network architecture and training scheme, and the details of object-phrase matching.

Features and Object Detectors  To establish a fair comparison to previous work using region features extracted from different backbones, we benchmark our methods by varying the backbone networks. We follow the same settings in [4, 37] to extract activations from the last layer before the classification head in Faster R-CNN [33] with VGG16 and ResNet-101 backbones pre-trained on PASCAL VOC (PV) [9] or MS COCO (CC) [25]. To further compare with the recent work of WPT [37] using object detectors trained on Open Images Dataset [22], we also extract classifier logits from Faster R-CNN with Inception-ResNet-V2 (IRV2) backbone pre-trained on Open Images Dataset (OI). We denote these feature choices as “VGG16”, “Res101”, “IRV2” respectively plus the object data set when reporting our results. For example, “IRV2 OI” means that the backbone is Inception-ResNet-V2 (IRV2) pre-trained on the Open Images (OI) Dataset.

Network Architecture  We normalized the last layer activations to zero-mean and unit-variance using stats estimated on training samples. We find this normalization helps our model to converge faster. For phrase representation, we used the LSTM [18] encoder with the GloVe embeddings [31]. The embedding vocabulary contains the most frequent 13K tokens from the Flickr30K Entities training split. The same vocabulary is used for ReferItGame. The LSTM has two layers, with both embedding and hidden space dimension as 300. Max pooling is applied over the hidden states of all tokens, followed by two fully connected layers (1024->512) for the phrase representation. For visual representation, we attached two fully connected layers (1024->512) on top of the region features.

Training Details  We trained our model using Adam [21] with a learning rate of 0.0001. We used a mini-batch size of 32 image-sentence pairs (31 negative images per sentence for the contrastive loss). Unlike [10], we did not fine-tune our vision backbone during training for efficiency. Similarly, the GloVe embeddings [31] also stayed unchanged during training. We observed in our experiments that the model converges quickly within a few epochs on both Flickr30K Entities and ReferItGame datasets. Our implementation is in TensorFlow and will be made publicly available.

Object-Phrase Matching  We made use of the WordNet [27] to define a similarity score between object labels of image regions and sentence phrases. We empirically observe that using WordNet is more reliable than using word embedding for noun matching. Specifically, the headnoun for each phrase was first identified using the off-the-shelf POS tagger provided by NLTK [2], which uses the Penn Treebank tag set. If the headnoun matches one of the detector class names, the phrase was further mapped to the class. If not, the headnoun was looked up in WordNet [27] to find its corresponding synset, as well as the synset’s lemmas and hypernyms. If any of them exists in the object classes, the phrase was mapped to the corresponding class. If there are multiple synsets for a phrase, the most frequent one was considered. The WordNet synset was able to resolve phrases such as “spectators” to “person” and “sweater” to “clothing”. With the 545 classes in Open Images Dataset [22], our matching strategy expanded the mapping to 18k out of 70k unique phrases in Flickr30k Entities and 7k out of 27k in ReferItGame training set.

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https://github.com/endernewton/tf-faster-rcnn
https://github.com/tensorflow/models/blob/master/research/object_detection/g3doc/detection_model_zoo.md
| Method          | Flickr30K ACC (%) | ReferItGame ACC (%) |
|-----------------|-------------------|---------------------|
| Max Margin      | 42.11             | 22.94               |
| NCE             | 48.35             | 26.63               |
| Distill         | 45.05             | 17.25               |
| NCE+Distill     | **50.96**         | **27.59**           |

Table 1: Ablation results of our proposed methods on Flickr30K and ReferItGames. Region features are from the Faster R-CNN ResNet-101 model pre-trained on COCO. Classifier logits for distillation are from the Faster R-CNN Inception-ResNet-V2 model pre-trained on Open Images Dataset.

Figure 2: Visualization of region-phrase matching. We compare results of using only NCE loss (left), and using our full model NCE+Distill (right). For each pixel, we compute a matching score by averaging scores from all proposals covering the pixel. The red color corresponds to high matching scores. Our knowledge distillation for region-phrase matching helps to better identify the extent of objects.

4.2 Ablation Study

To fully understand our model, we conduct ablation studies on both Flickr30K Entities and ReferItGame datasets. Specifically, we consider four different variants of our model: (1) our model with only image-sentence score function (Eq. 2) supervised by a max margin loss following [19, 46], denoted as “Max Margin”; (2) our model with only image-sentence score function (Eq. 2) supervised by the NCE loss (Eq. 5), denoted as “NCE”; (3) our model with only region-phrase score function (Eq. 1) supervised by the distillation loss (Eq. 4), denoted as “Distill”; and (4) our full model with both region-phrase and image-sentence score functions supervised by our joint loss (Eq. 6), denoted as “NCE+Distill”.

Table 1 presents our ablation results. First, we observe that NCE loss substantially outperforms the standard max margin loss by +6.2%/+3.7% on Flickr30K Entities and ReferItGame, respectively. These results suggest the effectiveness of contrastive learning, as also demonstrated in the concurrent work [14]. Moreover, using only distillation loss for region-phrase matching (Distill) underperforms NCE. However, our full model that combines both region-phrase and image-sentence matching using the joint loss brings a large boost over NCE. We conjecture that NCE and Distill provide complementary information for phrase grounding. Finally, Figure 2 visualizes the grounding results of NCE and NCE+Distill. Our full model (NCE+Distill) can better locate objects corresponding to the current phrase.

4.3 Comparison to Latest Methods

We further compare our results to latest methods of weakly supervised phrase grounding on both Flickr30K Entities and ReferItGame.

**Baselines** We consider a number of baselines. Our main competitors are those methods using object detectors, including KAC [4], UTG [40], MTG [10] and WPT [37]. Among these methods, KAC and UTG used detectors during both training and inference. MTG made use of detectors during
## Table 2: Results on Flickr30K Entities. We report phrase localization accuracy and list the settings of different methods. “Backbone” denotes the visual backbone used to extract region features. Detector\textsubscript{K} denotes the detector that provides external knowledge. Dataset notations: PV=PASCAL VOC, CC=COCO, OI=Open Images, CL=Color Name, and PL=Place365.

| Method | Backbone | Require | Detector\textsubscript{K} | Detector\textsubscript{K} | ACC (%) |
|--------|----------|---------|------------------|------------------|--------|
| GroundeR \[34\] | VGG16 PV | N/A | N/A | N/A | 28.94 |
| MATN \[46\] | VGG16 PV | N/A | N/A | N/A | 33.10 |
| UTG \[40\] | N/A | Yes | Yes | VGG16 PV | 35.90 |
| KAC \[4\] | VGG16 PV | Yes | Yes | VGG16 PV | 36.14 |
| | VGG16 PV | Yes | Yes | VGG16 CC | 38.71 |
| MTG \[10\] | Res101 CC+Res50 CC+Res50 CL | N/A | N/A | N/A | 48.66 |
| WPT \[37\] (w2v-max union) | N/A | Yes | Yes | IRV2 CC | 37.57 |
| | N/A | Yes | Yes | IRV2 CC+IRV2 OI | 48.20 |
| | N/A | Yes | Yes | IRV2 CC+IRV2 OI+WRN18 PL | 50.49 |
| NCE+Distillation (Ours) | VGG16 PV | Yes | No | VGG16 CC | 40.38 |
| | Res101 CC | Yes | No | IRV2 OI | 50.96 |

## Table 3: Results on ReferItGame. We report phrase localization accuracy and settings of different methods. “Backbone” denotes the visual backbone used to extract region features. Detector\textsubscript{K} denotes the detector that provides external knowledge. Dataset notations: PV=PASCAL VOC, CC=COCO, OI=Open Images, CL=Color Name, and PL=Place365.

| Method | Backbone | Require | Detector\textsubscript{K} | Detector\textsubscript{K} | ACC (%) |
|--------|----------|---------|------------------|------------------|--------|
| GroundeR \[34\] | VGG16 PV | N/A | N/A | N/A | 10.70 |
| MATN \[46\] | VGG16 PV | N/A | N/A | N/A | 13.61 |
| UTG \[40\] | N/A | Yes | Yes | VGG16 CC+YOLOv2 CC | 20.91 |
| KAC \[4\] | VGG16 PV | Yes | Yes | VGG16 PV | 13.38 |
| | VGG16 PV | Yes | Yes | VGG16 CC | 15.83 |
| WPT \[37\] (w2v-max union) | N/A | Yes | Yes | IRV2 CC | 15.40 |
| | N/A | Yes | Yes | IRV2 CC+IRV2 OI+WRN18 PL | 26.48 |
| NCE+Distillation (Ours) | VGG16 PV | Yes | No | VGG16 CC | 24.52 |
| | Res101 CC | Yes | No | IRV2 OI | 27.59 |

**Results** Our results are summarized in Table 2 (Flickr30K Entities) and Table 3 (ReferItGame). Table 2 and 3 compares both the settings of different methods and their phrase localization accuracy. Not surprisingly, methods using object detectors perform better than those not using detectors. Among all methods, our NCE+Distillation achieves the best performance on both datasets. Specifically, in training and WPT applied detectors during inference. While these baselines have very different sets of detectors and backbones, we try to match their settings in our experiments. Moreover, to make a fair comparison with WPT, we handle plural head noun cases following their “union” strategy for multiple instances grounding. For example, given a plural head noun, such as “men”, we report the minimum bounding box of top 5 ranked proposals as predicted bounding box. We detect such phrases automatically using NLTK WordNet morphy library.4 Our baselines also include previous methods that do not use object detectors, such as MATN \[46\] and GroundR \[34\] for completeness.

[4] https://www.nltk.org/howto/wordnet.html
comparison to UTG and KAC, our method removes the need of object detector at inference time, and show large performance boost (+3.4%\/+3.6% on Flickr30K Entities and ReferItGame for UTG and +1.7%\/+8.7% on Flickr30K and ReferItGame for KAC), when using the same backbones and detectors, as well as similar pre-training schemes. Our inference setting is similar to MTG. However, our results are significantly better (+2.6% Flickr30K Entities), despite that our method only uses a single backbone network during inference (vs. three backbones in MTG).

When using a stronger backbone (Res101 CC) and a better detector pre-trained on a larger scale dataset (IRV OI), our results are further improved by 10.6% and 3.0% on Flickr30K Entities and ReferItGame, respectively. Our final results thus outperform the latest method of WPT under a similar training setting. In comparison to WPT, our method does not require object detectors during inference, thus is more applicable for real world deployment. Finally, our results also outperform the results of a concurrent work from [14] (50.96\% vs. 47.88\%) when trained on the Flickr30K Entities dataset. A better result (51.67\%) was reported in [14] by training on COCO Caption dataset [6] and using a strong language model (BERT [7]). We conjecture that the same practices can help to further improve the performance of our model.

5 Conclusion

In this paper, we presented a novel contrastive learning framework for weakly supervised visual phrase grounding. The key idea of our method is to learn a score function measuring the similarity between region-phrase pairs, distilled from object detection outputs and further supervised by image-sentence pairs. Once learned, this score function can be used for visual grounding without the need of object detectors at test time. While conceptually simple, our method demonstrated strong results on major benchmarks, surpassing state-of-the-art methods that use expensive object detectors. Our work thus offers a principled approach to leverage object information, as well as an efficient method for weakly supervised grounding. We believe that our work provides a step forward towards modeling the link between vision and language.

References

[1] Jimmy Ba and Rich Caruana. Do deep nets really need to be deep? In NeurIPS, pages 2654–2662, 2014.
[2] Steven Bird and Edward Loper. NLTK: The natural language toolkit. In ACL Interactive Poster and Demonstration Sessions, pages 214–217, 2004.
[3] Cristian Bucilă, Rich Caruana, and Alexandru Niculescu-Mizil. Model compression. In SIGKDD, 2006.
[4] Kan Chen, Jiyang Gao, and Ram Nevatia. Knowledge aided consistency for weakly supervised phrase grounding. In CVPR, 2018.
[5] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. arXiv preprint arXiv:2002.05709, 2020.
[6] Xinlei Chen, Hao Fang, Tsung-Yi Lin, Ramakrishna Vedantam, Saurabh Gupta, Piotr Dollár, and C Lawrence Zitnick. Microsoft COCO captions: Data collection and evaluation server. arXiv preprint arXiv:1504.00325, 2015.
[7] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In ACL, 2019.
[8] Tuong Do, Thanh-Toan Do, Huy Tran, Erman Tjiputra, and Quang D Tran. Compact trilinear interaction for visual question answering. In ICCV, pages 392–401, 2019.
[9] Mark Everingham, LV Gool, CKI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes VOC dataset and challenge. IJCV, 2010.
[10] Zhiyuan Fang, Shu Kong, Charless Fowlkes, and Yezhou Yang. Modularized textual grounding for counterfactual resilience. In CVPR, pages 6376–6388, 2019.
[11] Akira Fukui, Dong Huk Park, Daylen Yang, Anna Rohrbach, Trevor Darrell, and Marcus Rohrbach. Multimodal compact bilinear pooling for visual question answering and visual grounding. In EMNLP, 2016.
[12] Nuno Garcia, Pietro Morerio, and Vittorio Murino. Modality distillation with multiple stream networks for action recognition. In ECCV, 2018.
[13] Saurabh Gupta, Judy Hoffman, and Jitendra Malik. Cross modal distillation for supervision transfer. In CVPR, pages 2827–2836, 2016.
[14] Tanmay Gupta, Arash Vahdat, Gal Chechik, Xiaodong Yang, Jan Kautz, and Derek Hoiem. Contrastive learning for weakly supervised phrase grounding. arXiv preprint arXiv:2006.09920, 2020.
[15] Michael Gutmann and Aapo Hyvärinen. Noise-contrastive estimation: A new estimation principle for unnormalized statistical models. In AISTATS, pages 297–304, 2010.

[16] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531, 2015.

[17] R Devon Hjelm, Alex Fedorov, Samuel Lavoie-Marchildon, Karan Grewal, Phil Bachman, Adam Trischler, and Yoshua Bengio. Learning deep representations by mutual information estimation and maximization. arXiv preprint arXiv:1808.06670, 2018.

[18] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. Neural computation, 9(8):1735–1780, 1997.

[19] Andrej Karpathy, Armand Joulin, and Li F Fei-Fei. Deep fragment embeddings for bidirectional image sentence mapping. In NIPS, 2014.

[20] Sahar Kazemzadeh, Vicente Ordonez, Mark Matten, and Tamara Berg. ReferItGame: Referring to objects in photographs of natural scenes. In EMNLP, pages 787–798, 2014.

[21] R Devon Hjelm, Alex Fedorov, Samuel Lavoie-Marchildon, Karan Grewal, Phil Bachman, Adam Trischler, and Yoshua Bengio. Learning deep representations by mutual information estimation and maximization. arXiv preprint arXiv:1808.06670, 2018.

[22] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531, 2015.

[23] R Devon Hjelm, Alex Fedorov, Samuel Lavoie-Marchildon, Karan Grewal, Phil Bachman, Adam Trischler, and Yoshua Bengio. Learning deep representations by mutual information estimation and maximization. arXiv preprint arXiv:1808.06670, 2018.

[24] Jinyu Li, Michael L Seltzer, Xi Wang, Rui Zhao, and Yifan Gong. Large-scale domain adaptation via teacher-student learning. arXiv preprint arXiv:1708.05466, 2017.

[25] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft COCO: Common objects in context. In ECCV, pages 740–755, Springer, 2014.

[26] Zelun Luo, Jun-Ting Hsieh, Lu Jiang, Juan Carlos Niebles, and Li Fei-Fei. Graph distillation for action detection with privileged modalities. In ECCV, 2018.

[27] George A Miller. Wordnet: A lexical database for english. Communications of the ACM, 38(11):39–41, 1995.

[28] Jonghwan Mun, Kimin Lee, Jinwoo Shin, and Bohyung Han. Learning to specialize with knowledge distillation for visual question answering. In NeurIPS, pages 8081–8091, 2018.

[29] Bryan A Plummer, Liwei Wang, Chris M Cervantes, Juan C Caicedo, Julia Hockenmaier, and Svetlana Lazebnik. Flickr30K entities: Collecting region-to-phrase correspondences for richer image-to-sentence models. In ICCV, 2015.

[30] Anna Rohrbach, Marcus Rohrbach, Ronghang Hu, Trevor Darrell, and Bernt Schiele. Grounding of textual phrases in images by reconstruction. In ECCV, 2016.

[31] Ariadna Romero, Nicolas Ballas, Samira Ebrahimi Kahou, Antoine Chassang, Carlo Gatta, and Yoshua Bengio. FitNets: Hints for thin deep nets. arXiv preprint arXiv:1412.6550, 2014.

[32] Liwei Wang, Yin Li, Jing Huang, and Svetlana Lazebnik. Learning to specialize with knowledge distillation for visual question answering. In NeurIPS, pages 8081–8091, 2018.

[33] Raymond Yeh, Minh N Do, and Alexander Schwing. Unsupervised textual grounding: Linking words to image concepts. In CVPR, 2018.

[34] Raymond Yeh, Jinjun Xiong, Wen-Mei Hwu, Minh Do, and Alexander Schwing. Interpretable and globally optimal prediction for textual grounding using image concepts. In NIPS, 2017.

[35] Sergey Zagoruyko and Nikos Komodakis. Paying more attention to attention: Improving the performance of convolutional neural networks via attention transfer. In ICLR, 2017.
[43] Hanwang Zhang, Yulei Niu, and Shih-Fu Chang. Grounding referring expressions in images by variational context. In CVPR, 2018.

[44] Jianming Zhang, Sarah Adel Bargal, Zhe Lin, Jonathan Brandt, Xiaohui Shen, and Stan Sclaroff. Top-down neural attention by excitation backprop. IJCV, 2018.

[45] Ziqi Zhang, Yaya Shi, Chunfeng Yuan, Bing Li, Peijin Wang, Weiming Hu, and Zhengjun Zha. Object relational graph with teacher-recommended learning for video captioning. In CVPR, 2020.

[46] Fang Zhao, Jianshu Li, Jian Zhao, and Jiashi Feng. Weakly supervised phrase localization with multi-scale anchored transformer network. In CVPR, 2018.

[47] Luowei Zhou, Nathan Louis, and Jason J Corso. Weakly-supervised video object grounding from text by loss weighting and object interaction. In BMVC, 2018.

[48] Yuanen Zhou, Meng Wang, Daqing Liu, Zhenzhen Hu, and Hanwang Zhang. More grounded image captioning by distilling image-text matching model. In CVPR, 2020.