Learning to Generate Grounded Image Captions without Localization Supervision

Chih-Yao Ma†, Yannis Kalantidis‡, Ghassan AlRegib†, Peter Vajda†, Marcus Rohrbach‡, Zsolt Kira†
†Georgia Tech, ‡Facebook
{cyma,alregib,zkira}@gatech.edu, {yannisk,vajdap,mrf}@fb.com

Abstract

When generating a sentence description for an image, it frequently remains unclear how well the generated caption is grounded in the image or if the model hallucinates based on priors in the dataset and/or the language model. The most common way of relating image regions with words in caption models is through an attention mechanism over the regions that is used as input to predict the next word. The model must therefore learn to predict the attention without knowing the word it should localize. In this work, we propose a novel cyclical training regimen that forces the model to localize each word in the image after the sentence decoder generates it and then reconstruct the sentence from the localized image region(s) to match the ground-truth. The initial decoder and the proposed reconstructor share parameters during training and are learned jointly with the localizer, allowing the model to regularize the attention mechanism. Our proposed framework only requires learning one extra fully-connected layer (the localizer), a layer that can be removed at test time. We show that our model significantly improves grounding accuracy without relying on grounding supervision or introducing extra computation during inference.

1 Introduction

Vision and language tasks, such as image captioning, combine linguistic descriptions with data from real-world scenes. Deep learning models for such tasks have achieved great success, driven in part by the development of attentional mechanisms that focus on various objects in the scene while generating captions. The resulting models, however, are known to have poor grounding performance [21], leading to undesirable behaviors such as object hallucinations [31], despite having high captioning accuracy. That is, they often do not correctly associate generated words with the appropriate image regions (e.g., objects) in the scene, resulting in models that lack interpretability.

Several existing approaches have tried to improve the grounding of captioning models. One class of methods generate sentence templates with slot locations explicitly tied to specific image regions. These slots are then filled in by visual concepts identified by off-the-shelf object detectors [22]. Other methods have developed specific grounding or attention modules that aim to attend to the correct region(s) for generating each visually groundable word. Such methods, however, rely on explicit supervision for optimizing the grounding or attention modules [21, 50], and require bounding box annotations for each visually groundable word. Generating such annotations is cumbersome, involving not just bounding box annotation but also their association with words.

In this work, we propose a novel cyclical training regimen that is able to significantly improve grounding performance without any grounding annotations. The key insight of our work is that current models use attention mechanisms conditioned on the hidden features of recurrent modules such as LSTMs, which leads to effective models with high accuracy but entangle grounding and

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decoding. Since LSTMs are effective at propagating information across the decoding process, the network does not necessarily need to associate particular decoded words with their corresponding image region(s).

Based on this insight, we develop a cyclical training regimen to force the network to ground individual decoded words: decoding → localization → reconstruction. Specifically, the model of the decoding stage can be any state-of-the-art captioning model; in this work, we extend the widely used Up-Down model [2]. At the localization stage, each word generated by the first decoding stage is localized through a localizer, and the resulting grounded image region(s) are then used to reconstruct the ground-truth caption in the final stage. Both decoding and reconstruction stages are trained using a standard cross-entropy loss. Key to our method, both stages share the same decoder, thereby causing the localization stage to guide the decoder to improve its attention mechanism.

Our method is simple and only adds a fully-connected layer to perform localization. During inference, we only use the (shared) decoder, thus we do not add any computational cost. Despite this, we are able to significantly surpass prior unsupervised models quantitatively and qualitatively. We measure performance on the challenging Flickr30k Entities dataset [26] and achieve 39% and 21% relative improvements in terms of grounding accuracy compared to the upper bound of a fully-supervised method on the val and test sets, respectively. We further find that our method can even outperform supervised method on infrequent words, owing to its self-supervised nature.

Contributions summary. We propose object re-localization as a form of self-supervision for grounded image captioning and present a cyclical training regimen that re-generates sentences after re-localizing the objects, implicitly imposing grounding consistency. In our evaluation, we also show that the proposed training regime can boost grounding accuracy over a state-of-the-art baseline, enabling grounded models to be trained without bounding box annotations, while retaining high captioning quality. We also analyse the design choices of our model by experimentally ablating alternatives. Our code will be released and is provided in supplementary to show our commitment to open-source research.

2 Related work

Visual captioning. Neural models for visual captioning have lately been receiving significant attention [2, 23, 22, 9, 37, 30, 38, 29, 34, 25]. Most current state-of-the-art models contain attention mechanisms, allowing the process to focus on subsets of the image when generating the next word. These attention mechanisms can be defined over spatial locations [39], over semantic metadata [20, 44, 45, 48] or over a predefined set of regions extracted via a region proposal network [23, 46, 2, 22, 7, 19]. In the latter case, off-the-shelf object detectors are first used to extract object proposals [27, 13] and the captioning model then learns to dynamically attend over them when generating the caption.

Visual grounding. Although attention mechanisms are generally shown to improve captioning quality and metrics, it has also been shown that they don’t really focus on the same regions as a human.
would [6]. This make models less trustworthy and interpretable, and therefore creating *grounded* image captioning models, *i.e.* models that further link generated words or phrases to specific regions of the image, has recently been an active research area. A number of approaches have been proposed, *e.g.* for grounding phrases or objects from image descriptions [28, 15, 42, 8, 50, 47], grounding visual explanations [3], visual co-reference resolution for actors in video [29], or improving grounding via human supervision [32]. Recently, Zhou et al. [50] presented a model with self-attention based context encoding and direct grounding supervision that achieves state-of-the-art results in both the image and video tasks. They exploit ground-truth bounding box annotations to significantly improve the visual grounding accuracy over an unsupervised model that doesn’t explicitly use ground supervision. In contrast, we focus on reinforcing the visual grounding capability of the existing captioning model via a novel cyclical training regimen without using human supervisions or bounding box annotations, and present a method that can increase grounding accuracy while maintaining comparable captioning performance with state of the arts.

**Cyclical training.** Cycle consistency [41, 51, 11, 5] has been used recently in a wide range of domains, including machine translation [11], unpaired image-to-image translation [51], Visual Question Answering [33], question answering [35], image captioning [5], video captioning [40, 10], captioning and drawing [16] as well as domain adaptation [14]. While the cyclical training regime has been explored vastly in both vision and language domains, it has not yet been used for enforcing the *visual grounding* capability of a captioning model.

### 3 Method

**Notation.** For a visual captioning task, we denote the input image as $I$ and the target sentence as $S$. Each image is represented by a spatial feature map extracted by a ResNet-101 model and a bag of regions obtained from Faster-RCNN as $R = \{r_1, r_2, ..., r_N\} \in \mathbb{R}^{d \times N}$. The target sentence is represented as one-hot vectors $y_t^i \in \mathbb{R}^s$, where $T$ is the sentence length, $t \in 1, 2, ..., T$, and $s$ is the dictionary size.

#### 3.1 Baseline

We extend the state-of-the-art Up-Down [2] model as our baseline captioning model. Specifically, our baseline model uses two LSTM modules: Attention LSTM and Language LSTM. The Attention LSTM identifies which visual representation in the image is needed for the Language LSTM to generate the next word $w_t$. The Attention LSTM encodes the global image feature $v_g$, previous hidden state output of the Language LSTM $h_{t-1}^L$, and the previous word embedding $e_{t-1}$ into the hidden state $h_t^A$.

$$h_t^A = LSTM_{Attn}([v_g; h_{t-1}^L; e_{t-1}]), \quad e_{t-1} = W_e y_{t-1}.$$  

(1)

where $[;]$ denotes concatenation, and $W_e$, $W_h$, and $W_o$ are the learned parameters. We omit the Attention LSTM input hidden and cell states to avoid notational clutter in the exposition.

The Language LSTM uses the hidden state $h_t^A$ from the Attention LSTM to dynamically attend on the bag of regions $R$ for obtaining visual representations of the image $\hat{r}_t$ to generate a word $y_t$.

$$z_{t,n} = (W_a h_t^A)^\top r_n, \quad \alpha_t = \text{softmax}(z_t), \quad \hat{r}_t = \alpha_t^\top R.$$  

(2)

The conditional probability distribution over possible output words $y_t$ is computed as:

$$h_t^L = LSTM_{Lang}([\hat{r}_t, h_t^A]), \quad p(y_t | y_{1:t-1}) = \text{softmax}(W_o h_t^L),$$  

(3)

where $y_{1:t-1}$ is a sequence of outputs $(y_1, ..., y_{t-1})$.

#### 3.2 Overview

Our goal is to enforce the generated caption to be visually grounded without ground-truth grounding supervision. Towards this end, we propose a novel cyclical training regimen that is comprised of *decoding, localization*, and *reconstruction* stages, as illustrated in Figure 2.

The intuition of our method is that the baseline network is not forced to generate a correct correspondence between the attended objects and generated words, since the LSTM can learn priors in the
A person is sitting on a stone.

A man is sitting on a bench.

Decoding → localization → reconstruction

Decoding loss + Recon. loss

Figure 2: Proposed cyclical training regimen: decoding → localization → reconstruction. The decoder attends to the image regions and sequentially generate each of the output words. The localizer then uses the generated words as input to locate the image regions. Finally, the shared decoder during reconstruction stage use the localized image regions to regenerate a sentence that matches with the ground-truth sentence.

Specifically, let $y_t = D^i(\hat{r}_t; \theta_i)$ be the initial decoder with parameters $\theta_i$, trained to generate a sentence $y_t$ for an image, as in the baseline model presented in Section 3.1. Also let $L(y_t; \theta_l)$ define a localizer unit with parameters $\theta_l$, that learns to map each generated word to region(s) in the image, i.e., $\hat{r}_t = L(y_t, R; \theta_l)$. Finally, let $y'_t = D^r(\hat{r}_t; \theta_r)$ be a second decoder, that is required to reconstruct the ground-truth caption using the localized region(s), instead of the attention computed by the decoder itself. We can then define the cycle:

$$y'_t = D^r(\mathcal{L}(D^i(\hat{r}_t; \theta_i), R; \theta_l); \theta_r), \quad \theta_i = \theta_r,$$

where the initial and reconstruction decoders, $D^i$ and $D^r$ respectively, share parameters. Note that although the parameters are shared, the inputs for the two decoders differ, leading to unique LSTM hidden state values during a run. Through cyclical joint training, both the decoding and reconstruction stages are required to generate the same ground-truth sentence. They are both optimized to maximize the likelihood of the correct caption:

$$\theta^* = \arg\max_{\theta} \sum \log p(y_t; \theta) + \arg\max_{\theta} \sum \log p(y'_t; \theta),$$

During training, the localizer regularizes the region attention of the reconstructor and the effect is further propagated to the initial decoder, since the two share parameters. Note that the gradient from reconstruction loss will not backprop to the decoder in the decoding stage since the generated words used as input to the localizer are leafs in the computational graph. The decoder is specifically regularized to update its attention mechanism to match with the localized image regions $\hat{r}_t \mapsto \hat{r}_t'$. In Sec. 4.3, we demonstrate that the localized image regions $\hat{r}_t'$ indeed have higher attention accuracy than $\hat{r}_t$ when using ground-truth words as inputs for the localizer.

3.3 Cyclical Training

We now describe each stage of our cyclical model in detail, as illustrated in Figure 2.

Decoding. We first use the baseline decoder presented in Sec. 3.1 to generate a sequence of words $y = [y_1, y_2, \ldots, y_T]$, where $T$ is the ground-truth sentence length.

\[1\] With $D^i$, $D^r$ we represent the complete decoder architecture, including the two LSTMs and soft-attention module for the initial decoding and reconstruction stages.
Soft-attention
Switch
(decoding or recon.)

Localizer
Localizer

Logit
Language
LSTM

Decoding stage
Localization & Recon. stage

Localization. Following the decoding process, a localizer is then learned to localize the image regions from each generated word $y_t$.

$$e_t = W_e y_t, \quad z_{t:n} = (W_f e_t)^\top r_n \quad \text{and} \quad \beta_t = \text{softmax}(z_t^t), \quad (6)$$

where $e_t$ is the embedding for the word generated by the decoder at step $t$, $r_n$ is the image representation of a region proposal, and $W_e$ and $W_f$ are the learned parameters. Based on the localized weights on the image regions $\beta_t$, the localized region representation can be obtained by $\hat{r}_t^l = \beta_t^\top R$.

Reconstruction. Finally, the shared decoder relies on the localized region representation $\hat{r}_t^l$ to generate the next word $w_t^l$. The probability over possible output words is:

$$h_t^L = \text{LSTM}_{Lang}(\hat{r}_t^l, h_{t-1}^L), \quad p(y_t^l | y_{1:t-1}) = \text{softmax}(W_h h_t^L), \quad (7)$$

Given the target ground truth caption $y_{1:T}^t$ and our proposed captioning model parameterized with $\theta$, we minimize the following cross-entropy losses:

$$\mathcal{L}_{CE} (\theta) = -\lambda_1 \sum_{t=1}^T \log(p_0(y_t^s | y_{1:t-1}^s))\mathbbm{1}_{\langle y_t^s = y_t^t \rangle} - \lambda_2 \sum_{t=1}^T \log(p_0(y_t^s | y_{1:t-1}^s))\mathbbm{1}_{\langle y_t^s = y_t^c \rangle} \quad (8)$$

where $\lambda_1$ and $\lambda_2$ are weighting coefficients selected on the validation split.

4 Experiments

Datasets. We use the standard Flickr30k Entities dataset [26] for evaluating our proposed approach. The Flickr30k Entities image dataset contains 275k annotated bounding boxes from 31k images associated with natural language phrases. Each image is annotated with 5 crowdsourced captions. There are 290k images for training, 1k images for validation, and another 1k images for testing.

Captioning evaluation metrics. We measure captioning performance using four language metrics, including BLEU [24], METEOR [4], CIDEr [36], and SPICE [1].

Grounding evaluation metrics. Following the grounding evaluation from GVD [50] on the generated sentences, we define the number of object words in the generated sentences as A, the number of object words in the GT sentences as B, the number of correctly predicted object words in the generated sentences as C and the counterpart in the GT sentences as D, and the number of correctly

$\footnote{The Flickr30k Entities dataset can be downloaded at: \url{https://hockenmaier.cs.illinois.edu/DenotationGraph/} }$

$\footnote{The object words are words in the sentences that are annotated with corresponding image regions.}$

Figure 3: Proposed model architecture (left) and how the model operates during decoding, localization, and reconstruction stages (right). During the decoding stage, the soft-attention module uses the hidden state of the Attention LSTM to compute attention weights on image regions. During the localization and reconstruction stage, the soft-attention module instead uses the generated word from decoding stage to compute attention weights on image regions.
### Table 1: Ablation study on the Flickr30k Entities val set. Sup.: fully-supervised method trained with ground-truth grounding annotations. Note that the since supervised methods are used as upper bound, their numbers are not bolded.

| #          | Captioning Evaluation | Grounding Evaluation |
|------------|-----------------------|----------------------|
|            | B@1 | B@4 | M  | C  | S   | F1all | F1loc |
| Baseline (Unsup.) | 70.1 | 27.7 | 22.3 | 62.1 | 16.0 | 4.18 (+0%) | 11.9 (+0%) |
| Baseline + Cls (Sup.) | 69.1 | 26.8 | 22.7 | 61.5 | 16.7 | 4.27 (+2%) | 12.7 (+9%) |
| Baseline + Attn. + Cls. (Sup.) | 70.1 | 28.2 | 22.2 | 63.2 | 16.3 | 7.91 (+100%) | 21.3 (+100%) |
| Cyclical | 69.4 | 26.9 | 22.3 | 62.2 | 16.2 | 5.63 (+39%) | 14.6 (+29%) |

predicted and localized words as E. A region prediction is considered correct if the object word is correctly predicted and also correctly localized (i.e., IoU with GT box > 0.5). We then compute two versions of the precision and recall as 

\[ \text{Precision} = \frac{|E \cap A|}{|A|}, \quad \text{Recall} = \frac{|E \cap B|}{|B|} \]

The precision and recall for the two metrics are computed for each object class, and it is set to zero if an object class has never been predicted. The scores are computed for each object class and averaged by the total number of object classes [50].

#### 4.1 Implementation Details

**Region proposal and spatial features.** We use a Faster-RCNN model [27] with a ResNeXt-101 backbone [43] for region proposal and feature extraction (fc6 layer output). The Faster-RCNN model is pre-trained on the Visual Genome dataset [18]. We extracted 100 region proposals from each image. In practice, we also use the Conv features besides the region proposal features. The Conv feature map is the output of the conv4 layer from ResNet-101 [12] pre-trained on the ImageNet. The region proposals are represented using the grounding-aware region encoding (see Appendix).

**Training.** We train the model with ADAM optimizer [17]. The initial learning rate is set to $1e^{-4}$. Learning rates automatically drop by 10x when the CIDEr score is saturated. The batch size is 32. We learn the word embedding layer from scratch for fair comparisons with existing work. The hyper-parameters $\lambda_1$ and $\lambda_2$ are set to 0.5 after hyper-parameter search between 0 and 1.

#### 4.2 Captioning and Grounding Comparison

We first compare the proposed method with our baseline with or without grounding supervision on the validation set, as shown in Table 2. Similar to GVD [50], we train the attention mechanism (Attn.) of the baseline method as well as adding the region classification task (Cls.) using the ground-truth grounding annotation. Using the resultant supervised baseline model as the upper bound, our proposed method with cyclical training achieves relative 39% and 29% grounding accuracy improvements for $F1_{all}$ and $F1_{loc}$ respectively, while maintaining the captioning evaluations performances.

When compared with the existing approaches on the test set (see Table 2), our proposed baseline achieves comparable captioning evaluation performances with higher grounding accuracy. When compared to the supervised baseline model, the proposed cyclical training regimen achieves 21% and 11% relative grounding accuracy improvements without utilizing any of the grounding annotations or additional computation during inference.

#### 4.3 Analysis

**Are localized image regions better than attended image regions during training?** Given our intuition described in Sec. 3, we expect the decoder to be regularized to update its attention mechanism to match with the localized image regions $r \mapsto \hat{r}$. This indicates that the localized image regions should be more accurate than the attended image regions by the decoder during training. To verify this, we compute the attention accuracy for both decoder and localizer over ground-truth sentences following [28, 49]. The attention accuracy for localizer is 20.4% and is higher than the 19.3% from the decoder.

**Should we explicitly make attended image regions to be similar to localized image regions?** One possible way to regularize the attention mechanism of the decoder is to explicitly optimize
Table 2: Performance comparison with the state of arts on the Flickr30k Entities test set. Sup.: fully-supervised method trained with ground-truth grounding annotations.

| Method                | B@1 | B@4 | M   | C   | S   | F1all | F1loc |
|-----------------------|-----|-----|-----|-----|-----|-------|-------|
| ATT-FCN [45]          | 64.7| 19.9| 18.5| -   | -   | -     | -     |
| NBT [22]              | 69.0| 27.1| 21.7| 57.5| 15.6| -     | -     |
| Up-Down [2]           | 69.4| 27.3| 21.7| 56.6| 16.0| 4.14  | 12.3  |
| GVD (Unsup.) [50]     | 69.2| 26.9| 22.1| 60.1| 16.1| 3.97  | 11.6  |
| GVD (Sup.) [50]       | 69.9| 27.3| 22.5| 62.3| 16.5| 7.77  | 22.2  |
| Baseline (ours, Unsup.)| 70.0| 27.6| 22.4| 61.3| 16.3| 4.85  | 12.3  |
| Baseline (ours, Sup.) | 69.4| 26.9| 22.4| 61.4| 16.6| 8.03  | 22.2  |

Cyclical 68.9 26.6 22.3 60.9 16.3 4.85 (21%) 13.4 (11%)

Table 3: Model ablation study on the Flickr30k Entities val set. See Sec. 4.3 for details on the analysis.

| θ          | Captioning Eval. | Grounding Eval. |
|------------|------------------|------------------|
|            | M    | C    | S    | F1all | F1loc |
| Baseline (Unsup.) | 22.3 | 62.1 | 16.0 | 4.18  | 11.9  |
| Cyclical    | 22.2 | 62.2 | 16.2 | 5.63  | 14.6  |
| - Attention consistency | 22.3 | 61.8 | 16.2 | 4.19  | 11.3  |
| - Localizer using $h^A$ | 22.2 | 61.8 | 16.1 | 4.58  | 11.3  |

Figure 4: Average F1all-score per class, as a function of class frequency.

Is using only the generated word for localization necessarily? Our proposed localizer (Eq. 6 and Figure 3) relies on purely the word embedding representation to locate the image regions. This forces the localizer to rely only on the word embedding without biasing it with the memorized information from the Attention LSTM. As shown in the Table 3 (localizer using $h^A$), although this achieves comparable captioning performance, it has lower grounding accuracy improvement compared to our proposed method.

How does the number of annotations affect grounding performance? In Figure 4, we present the average F1-score on the Flickr30k Entities val set when grouping classes according to their frequency of appearance in the training set. We see that, unsurprisingly, the largest difference in grounding accuracy between the supervised and our proposed cyclical training is for the 50 most frequently appearing object classes, where enough training data exists. As the number of annotated boxes decreases, however, the difference in performance diminishes, and cyclical training appears to be more robust. Overall, we see that the supervised method is biased towards frequently appearing objects, while grounding performance for the proposed approach is more balanced among classes.

4.4 Qualitative Analysis

We additionally conduct qualitative analysis for comparing the baseline (Unsup.) and the proposed method in Figure 5. Each highlighted word has a corresponding image region annotated on the original image. The image regions are selected based on the region with the maximum attention weight in $\alpha_t$. We can see that our proposed method significantly outperformed the baseline (Unsup.)

4We group the 460 object classes in 10 groups, sorted by the number of annotated bounding boxes.
Figure 5: Generated captions and corresponding visual grounding regions with comparison between baseline (left) and proposed approach (right). Our proposed cyclical training regimen is able to generate more descriptive sentences while selecting the correct regions for generating the corresponding words.

Figure 6: Correct (top) examples and examples with errors (bottom) from the proposed method.

in terms of both the quality of the generated sentence and grounding accuracy. In addition, we also show a number of correct and incorrect examples of our proposed method in Figure 6. We observe that while the model is able to generate grounded captions for the images, it may sometimes overlook the semantic meaning of the generated sentences, for example, "A young girl [... walking down a brick wall". Similarly, the model can overlook the spatial relationship between the objects, for instance, "A man [...] is holding up a flag". Please refer to the Appendix for the complete sequence of attended image regions and further discussions on the qualitative results.

5 Conclusion

Working from the intuition that typical attentional mechanisms in the visual captioning task are not forced to ground generated words since recurrent models can propagate past information, we devise a novel cyclical training regime to explicitly force the model to ground each word without grounding annotations. Our method only adds a small fully-connected layer during training, which can be removed during inference, and we show thorough quantitative and qualitative results demonstrating a 30% and 20% relative improvement over existing methods.
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Appendix

Qualitative Results. In Figure 7, 8, 9, 10, 11, 12, 13, and 14, we illustrated the sequence of attended image region when generating each word for a complete image description. At each step, only the top-1 attended image region is shown. This is the same as how the grounding accuracy is measured. Please see the description for Figure 7 - 14 for further discussions on the qualitative results.

Region proposal features. Following GVD [50], the region proposals are represented using the grounding-aware region encoding, which is the concatenation of i) region feature, ii) region-class similarity matrix, and iii) location embedding.

For region-class similarity matrix, we define a set of object classifiers as $W_c$, and the region-class similarity matrix can be computed as $M_s = \text{softmax}(W_c^T R)$, which captures the similarity between regions and object classes. We omit the ReLU and Dropout layer after the linear embedding layer for clarity. We initialize $W_c$ using the weight from the last linear layer of an object classifiers pre-trained on the Visual Genome dataset [18].

For location embedding, we use 4 values for the normalized spatial location. The 4-D feature is then projected to a $d_s = 300$-D location embedding for all the regions.

Network architecture. The vocabulary size is 8639. The embedding dimension for encoding the sentences is 512. We use a dropout layer with ratio 0.5 after the embedding layer. The hidden state size of the Attention and Language LSTM are 1024. The dimension of other learnable matrices are: $W_e \in \mathbb{R}^{8639 \times 512}$, $W_a \in \mathbb{R}^{1024 \times 512}$, $W_o \in \mathbb{R}^{1024 \times 8639}$, $W_l \in \mathbb{R}^{512 \times 512}$.

Training details. Images are randomly cropped to $512 \times 512$ during training, and resized to $512 \times 512$ during inference. Before entering the proposed cyclical training regimen, the decoder was pre-trained for about 35 epochs. The total training epoch with the cyclical training regimen is around 80 epochs. The total training time takes about 1 day.

Software and hardware configuration. Our code is implemented in PyTorch. All experiments were ran on the 1080Ti, 2080Ti, and Titan Xp GPUs.
Figure 7: A group of men in white uniforms are standing in a field with a crowd watching. We can see that our proposed method attends to the sensible image regions for generating visually-groundable words, e.g., man, uniforms, field, and crowd. Interestingly, when generating standing, the model pays its attention on the image region with a foot on the ground.

Figure 8: A young girl wearing a winter hat and a purple coat is smiling at the camera. The proposed method is able to select the corresponding image regions to generate girl, hat, and coat correctly. We have also observed that the model tends to localize the person’s face when generating camera.
Figure 9: A white horse with a rider in a blue helmet and white shirt jumping over a hurdle. While the model is able to correctly locate objects such as horse, rider, helmet, shirt, and hurdle, it mistakenly describes the rider as wearing a blue helmet, while it’s actually black, and with white shirt while it’s blue.

Figure 10: A man in a red shirt is standing on a wooden platform. Our method correctly attends on the correct regions for generating man, shirt, and platform.
Figure 11: A man in a yellow jacket and blue helmet riding a bike. The proposed method correctly generates a descriptive sentence while precisely attending to the image regions for each visually-groundable words: man, jacket, helmet, and bike.

Figure 12: A man in an orange shirt and a hat is standing next to a blue wall. While our method is able to ground the generated sentence on the objects like: man, shirt, hat, and wall, it completely ignores the person standing next to the man in the orange cloth.
Figure 13: A girl in a white shirt and black pants is jumping on a red couch. Our method is able to ground the generated descriptive sentence with the correct grounding on: girl, shirt, pants, and couch.

Figure 14: A man in a blue robe walks down a cobblestone street. Our method grounds the visually-relevant words like: man, robe, and street. We can also see that it is able to locate the foot on ground for walks.
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