Abstract

The ability to detect that something has changed in an environment is valuable, but often only if it can be accurately conveyed to a human operator. We introduce Viewpoint Invariant Change Captioning, and develop models which can both localize and describe via natural language complex changes in an environment. Moreover, we distinguish between a change in a viewpoint and an actual scene change (e.g. a change of objects’ attributes). To study this new problem, we collect a Viewpoint Invariant Change Captioning Dataset (VICC), building it off the CLEVR dataset and engine. We introduce 5 types of scene changes, including changes in attributes, positions, etc. To tackle this problem, we propose an approach that distinguishes a viewpoint change from an important scene change, localizes the change between “before” and “after” images, and dynamically attends to the relevant visual features when describing the change. We benchmark a number of baselines on our new dataset, and systematically study the different change types. We show the superiority of our proposed approach in terms of change captioning and localization. Finally, we also show that our approach is general and can be applied to real images and language on the recent Spot-the-diff dataset.

1. Introduction

Change detection in images is a long-standing research problem, with applications in a variety of domains including facility monitoring, medical imaging, and aerial photography, among others [17, 44, 48]; a key challenge in change detection is to distinguish the important changes from the irrelevant ones [47] since the former are those that should likely trigger a notification. Existing systems aim to sense or localize a change, but typically do not convey detailed semantic content. This is an important limitation for a realistic application, where analysts would benefit from such knowledge, helping them to better understand and judge the significance of the change. Alerting a user on every detected difference likely will lead to a frustrated operator; it is desirable to have a change detection system that does not output a binary indicator of change/no-change, but instead outputs a concise description of what has changed, and where.

Expressing image content in natural language is an active area of Artificial Intelligence research, with numerous approaches to image captioning having been recently proposed [3, 13, 35, 57]. These methods have the benefit of conveying visual content to human users in a concise and natural way. They can be especially useful, when tailored to a specific task or objective, such as e.g. explaining the model’s predictions [20, 42] or generating non-ambiguous referring expressions for specific image regions [37, 59].

In this work we propose a new task, Viewpoint Invariant Change Captioning, where an important scene change has to be identified and conveyed using natural language, in the presence of distractors, where only a viewpoint change occurs. We aim to generate detailed and informative descrip-
tions, that correctly refer to the changed objects in complex scenes (see Figure 1).

In order to study different types of changes, we rely on the image generation engine by [25], which allows us to produce complex compositional scenes. We build our Viewpoint Invariant Change Captioning Dataset (VICC) by creating pairs of “before” and “after” images with: (a) viewpoint change only, and (b) with viewpoint change combined with a scene change. Overall, VICC covers 5 scene change types (including attribute changes, object appearance, removal, and movement), and overall almost 80K image pairs. We augment these image pairs with automatically generated change descriptions (see Figure 2).

To distinguish a viewpoint-only change, from e.g. an object movement, one needs to “compare” the two images and find the relevant disagreements and true correspondences. To tackle this challenge, we propose a Viewpoint Invariant Dynamic Attention Model (VIDAM) that learns to localize the changes via an attention mechanism. Specifically, it consists of two components: a Change Localizer with a separate spatial attention for each image in the “before”/“after” pair, and a Dynamic Speaker that generates descriptions about the change by modulating focus among the visual information relayed from the Change Localizer. Both components are neural networks that are trained jointly with only caption-level supervision, i.e. no information about the change location is used during training.

We evaluate our VIDAM model on our new VICC dataset, and compare it to a number of baselines, including a naive pixel-difference captioning baseline. We show that our approach outperforms the baselines in terms of change caption correctness as well as change localization. The most challenging change types to describe are object movement and texture change, while movement is also the hardest to localize. Finally, we show that our approach generalizes to other settings, by applying it to the recent real-world Spot-the-Diff dataset [24] with pairs of static images (no viewpoint changes). Our model performs similarly to the approach of [24], who unlike us, rely on the assumption that the image pairs are aligned.

2. Related Work

Here we discuss prior work on change detection, task-specific image captioning, and attention mechanism.

2.1. Change detection

One popular domain for image-based change detection is aerial/satellite imagery [32, 51, 60], where changes can often be linked to disaster response scenarios (e.g. damage detection) [17] or monitoring of land cover dynamics [28, 52]. Prior approaches tend to rely on unsupervised methods for change detection, e.g. image differencing, due to high cost of obtaining ground-truth annotations [10]. Notably, [17] propose a semi-supervised approach with humans in the loop, relying on a hierarchical shape representation.

Another domain is street scenes [1, 27]. Notably, [48] propose a Panoramic Change Detection Dataset, built off Google Street View panoramic images. In their follow-up work, [49] propose an approach to change detection which relies on dense optical flow to address the difference in viewpoints between the images. In a recent work, [40] rely on 3D models to identify scene changes by re-projecting images on one another. Another line of work targets change detection in video, e.g. using a popular CDnet benchmark [16, 56], where background subtraction is a successful strategy [9]. Instead of relying on costly pixel-level video annotation, [29] propose a weakly supervised approach, which estimates pixel-level labels with a CRF.

Other works address a more subtle, fine-grained change detection, where an object may change its appearance over time, e.g. for the purpose of a valuable object monitoring [14, 23]. To tackle this problem, [50] estimate a dense flow field between images to address viewpoint differences.

We use the image generation engine by [25] to build complex compositional scenes. Our VIDAM model relies on an attention mechanism rather than pixel-level difference or flow. Finally, our task is not only to detect the changes, but also to describe them with natural language, going beyond the discussed prior works.

2.2. Task-specific caption generation

While most image captioning works focus on a generic task of obtaining image relevant descriptions [3, 13, 55], some recent works explore pragmatic or “task-specific” captions. Some focus on generating textual explanations for deep models’ predictions [19, 20, 42]. Others aim to generate a discriminative caption for an image or image region, which would allow to distinguish it from a distractor [4, 11, 37, 36, 53, 59]. This is relevant to our case, as part of the change caption serves as a referring expression to put an object in context of the other objects. However, our primary focus is to correctly describe the scene changes.

The most related to ours is the work of [24], who also address the task of change captioning for a pair of images. There are several key differences between our and their work. First, we consider a setting where we have to distinguish between viewpoint-only changes and viewpoint changes combined with the scene changes, unlike [24] who assume there is always a change between the two images. Second, their pixel-difference based approach relies on an assumption that the two images are aligned, while we tackle the viewpoint invariant change description. We show that our approach generalizes to their proposed dataset as we obtain similar performance to their method.
Table 1: VICC Dataset statistics: number of image pairs, captions, and bounding boxes for each change type (VIEWPOINT, COLOR, TEXTURE, ADD, DROP, MOVE).

| Type   | Templates                                                                 |
|--------|---------------------------------------------------------------------------|
| COLOR  | ... changed to ...                                                         |
|        | ... turned ...                                                             |
|        | ... became ...                                                             |
| TEXTURE| ... changed to ...                                                         |
|        | ... turned ...                                                             |
|        | ... became ...                                                             |
| ADD    | ... has appeared.                                                          |
|        | ... has been newly placed.                                                 |
|        | ... has been added.                                                        |
| DROP   | ... has disappeared.                                                       |
|        | ... is missing.                                                            |
|        | ... is gone.                                                               |
|        | ... is no longer there.                                                    |
| MOVE   | ... moved.                                                                 |
|        | ... is in a different location.                                            |
|        | ... changed its location.                                                 |
| VIEWPOINT| no change was made.                                                        |
|        | the scene is the same as before.                                           |
|        | the two scenes seem identical.                                            |

Table 2: For each change type we construct a few templates, based on which the change part of the caption is obtained.

2.3. Attention in image captioning

Soft attention mechanism [7] over the visual features was first used for image captioning by [57]. Multiple works have since adopted and extended this approach [15, 33, 45], including performing attention over object detections [3].

Our VIDAM model relies on two forms of attention: spatial attention, used by our Change Localizer to find changes between two images, and a “dynamic” attention, used by our Dynamic Speaker to adaptively focus on “before”, “after” or “difference” visual representations.

3. Viewpoint Invariant Change Captioning Dataset (VICC)

We build our Viewpoint Invariant Change Captioning Dataset (VICC) off the CLEVR dataset and engine [25].

We start by generating random scenes with multiple objects in them, which serve as “before” images. For each “before” image we then proceed to create two “after” images. In the first one, we introduce a viewpoint change, that is we vary the “camera” position to achieve a different angle, zoom, and/or lighting conditions. We have a specific allowed range for the transformation parameters: for each \((x, y, z)\) camera location, we randomly sample a number from the range between \(-2.0, 0\) and \(2.0\), and jitter the original coordinates by the sampled amount. In the second image, we introduce a viewpoint change and a scene change. We consider the following types of scene changes: (a) an object’s color is changed, (b) an object’s texture is changed, (c) a new object is added, (d) an existing object is dropped, (e) an existing object is moved. In the following we refer to these as: COLOR, TEXTURE, ADD, DROP, MOVE, and VIEWPOINT for no scene change. In total, we generate 39,803 “before” images with respectively 79,606 “after” images. We make sure that the number of data points for each scene change type are balanced. When generating an image, we apply similar constraints as in [25] (i.e. minimum/maximum number of objects per scene, amount of occlusion allowed). The dataset is split into 67,660, 3,976, and 7,970 train/val/test image pairs, respectively.

In addition to generating the “before” and “after” scenes, we also generate natural language change captions. Each caption is automatically constructed from two parts: the referring part (e.g. “A large blue sphere to the left of a red object”) and the change part (e.g. “has been moved”). Note that for all the change types except ADD, the referring expression is generated based on the “before” image, while for ADD, the “after” image is used. To get the change part, we construct a set of change type specific templates (see Table 2).

Finally, we also obtain spatial locations of where each scene change took place, so that we can evaluate the correctness of change localization. More specifically, we get bounding boxes for the objects that are affected by a change, either only in one image or both “before” and “after”, de-
pending on the change type. The overall dataset statistics are presented in Table 1, and some examples of viewpoint change vs. scene change with their corresponding descriptions and bounding boxes are shown in Figure 2.

4. Viewpoint Invariant Dynamic Attention Model (VIDAM)

We propose a Viewpoint Invariant Dynamic Attention Model (VIDAM) for change detection and captioning. Given a pair of “before” and “after” images (\(I_{\text{bef}}\) and \(I_{\text{aft}}\), respectively), our model first detects whether a scene change has happened, and if so, locates the change on both \(I_{\text{bef}}\) and \(I_{\text{aft}}\). The model then composes a sentence that not only correctly describes the change, but also that is spatially and temporally grounded to the image pair. Our model includes a multi-attention component, followed by a dynamic speaker module to generate descriptions. An overview of our model is shown in Figure 3.

We describe the implementation details of our Change Localizer in 4.1, and our Dynamic Speaker in 4.2. In 4.3, we detail our training procedure for jointly optimizing the Change Localizer and the Dynamic Speaker using change descriptions as the only supervision.

4.1. Change localizer

Our Change Localizer \(f_{\text{loc}}(X_{\text{bef}}, X_{\text{aft}}; \theta_{\text{loc}}) = (l_{\text{bef}}, l_{\text{aft}})\) is a function parameterized by \(\theta_{\text{loc}}\) that takes \(X_{\text{bef}}\) and \(X_{\text{aft}}\) as inputs, and outputs feature representations \(l_{\text{bef}}\) and \(l_{\text{aft}}\) that encode the change manifested in the input pairs. In our implementation, \(X_{\text{bef}}, X_{\text{aft}} \in \mathbb{R}^{C \times H \times W}\) are image features of \(I_{\text{bef}}, I_{\text{aft}}\), respectively, encoded by a pretrained ResNet [18].

The Change Localizer first subtracts \(X_{\text{bef}}\) from \(X_{\text{aft}}\) in order to capture semantic difference in the representation space. The resulting tensor \(X_{\text{diff}}\) is concatenated to both \(X_{\text{bef}}\) and \(X_{\text{aft}}\) which are then used to generate two separate spatial attention maps \(a_{\text{bef}}, a_{\text{aft}} \in \mathbb{R}^{1 \times H \times W}\). Following [38], we utilize elementwise sigmoid instead of softmax to compute our attention maps. Finally, \(a_{\text{bef}}\) and \(a_{\text{aft}}\) are applied to the input features to do a weighted-sum pooling over the spatial dimensions:

\[
X_{\text{diff}} = X_{\text{aft}} - X_{\text{bef}}
\]

\[
X_{\text{bef}}' = [X_{\text{bef}} ; X_{\text{diff}}], X_{\text{aft}}' = [X_{\text{aft}} ; X_{\text{diff}}]
\]

\[
a_{\text{bef}} = \sigma(\text{conv}_2(\text{conv}_1(X_{\text{bef}}'))) \tag{1}
\]

\[
a_{\text{aft}} = \sigma(\text{conv}_2(\text{conv}_1(X_{\text{aft}}'))) \tag{2}
\]

\[
l_{\text{bef}} = a_{\text{bef}} \odot X_{\text{bef}}, l_{\text{bef}} \in \mathbb{R}^{C} \tag{3}
\]

\[
l_{\text{aft}} = a_{\text{aft}} \odot X_{\text{aft}}, l_{\text{aft}} \in \mathbb{R}^{C} \tag{4}
\]

where \([;]\), \(\sigma\), and \(\odot\) indicate concatenation, convolutional layer, elementwise sigmoid, and weighted-sum pooling, respectively. It is important to note that the convolutional layers used to generate the attention maps are shared across inputs.

This particular architectural design allows the system to attend to images differently depending on the type of a change and the amount of a viewpoint shift, which is a capability crucial for the proposed task. For instance, to correctly describe MOVE the model has to localize and match the moved object in both images; having single attention that locates the object only in one of the images is likely to cause confusion between MOVE and ADD/DROP. Even if there is an attribute change (i.e. COLOR, TEXTURE) which does not involve object displacement, single attention might not be enough to correctly localize the changed object under significant viewpoint shift. Unlike [58, 39, 34, 30, 42], VIDAM utilizes dual attention to process multiple visual inputs separately and thereby addresses viewpoint invariance.

4.2. Dynamic speaker

Our Dynamic Speaker module is based on the following intuition: in order to successfully describe the change, the model should not only learn where to look in each image (enforced by the Change Localizer), but also when to look at each image. Ideally, we would like the model to show a dynamic reasoning process in which it learns whether to focus on “before” \((l_{\text{bef}})\), “after” \((l_{\text{aft}})\), and/or the difference \((l_{\text{diff}} = l_{\text{aft}} - l_{\text{bef}})\) as it generates a sequence of words.

To this end, our Dynamic Speaker predicts an attention \(\alpha_{i}^{(t)}\) over the visual features \(l_{i}'s\) at each time step \(t\), and obtains the dynamically attended feature \(l_{\text{dyn}}^{(t)}\):

\[
l_{\text{dyn}}^{(t)} = \sum_{i} \alpha_{i}^{(t)} l_{i}
\]

where \(i \in \{\text{bef}, \text{diff}, \text{aft}\}\). We use the attentional Recurrent Neural Network [6] to model this formulation.

Our Dynamic Speaker consists of two modules, namely the dynamic attention module and the caption module. Both are recurrent modules based on LSTMs [21]. At each time step \(t\), the LSTM decoder in the dynamic attention module takes as input the previous hidden state of the caption module \(h_{c}^{(t-1)}\) and some latent projection \(v\) of the visual features \(l_{\text{bef}}, l_{\text{diff}}, \text{and } l_{\text{aft}}\) to predict attention weights \(\alpha_{i}^{(t)}\):

\[
v = \text{ReLU}(W_{d_{1}} [l_{\text{bef}} ; l_{\text{diff}} ; l_{\text{aft}}] + b_{d_{1}}) \tag{5}
\]

\[
u^{(t)} = [v ; h_{c}^{(t-1)}] \tag{6}
\]

\[
h_{d}^{(t)} = \text{LSTM}_{d}(h_{d}^{(t-1)}, u^{(t)}, h_{d}^{(0:t-1)}) \tag{7}
\]

\[
\alpha_{i}^{(t)} \sim \text{Softmax}(W_{\alpha} h_{d}^{(t)} + b_{a}) \tag{8}
\]

where \(h_{d}^{(t)}\) and \(h_{c}^{(t)}\) are LSTM outputs at decoder time step \(t\) for dynamic attention module and caption module, respectively, and \(W_{d_{1}}, b_{d_{1}}, W_{d_{2}}, \text{and } b_{a}\) are learnable parameters. Using the attention weights predicted from equation
(11), the dynamically attended feature $f_{\text{dyn}}^{(t)}$ is obtained according to equation (7). Finally, $f_{\text{dyn}}^{(t)}$ and the embedding of the previous word $w_{t-1}$ (ground-truth word during training, predicted word during inference) are input to the LSTM decoder of the caption module to begin generating distributions over the next word:

$$x^{(t-1)} = E\mathbb{1}_{w_{t-1}}$$  \hspace{1cm} (12)$$

$$c^{(t)} = [x^{(t-1)}; l_{\text{dyn}}^{(t)}]$$  \hspace{1cm} (13)$$

$$h_{c}^{(t)} = \text{LSTM}_{c}(h_{c}^{(t-1)}|c^{(t)}; h_{c}^{(t-1)}_{\text{dyn}})$$  \hspace{1cm} (14)$$

$$w_{t} \sim \text{Softmax}(Wc h_{c}^{(t)} + b_{c})$$  \hspace{1cm} (15)$$

where $\mathbb{1}_{w_{t-1}}$ is a one-hot encoding of the word $w_{t-1}$, $E$ is the embedding layer, and $W_{c}$ and $b_{c}$ are learnable parameters.

4.3. Training

We jointly train the Change Localizer and the Dynamic Speaker end-to-end by maximizing the likelihood of the observed word sequence. Let $\theta$ denote all the parameters in VIDAM. Given a target ground-truth sequence $(w_{1}^{*}, \ldots, w_{T}^{*})$, the objective is to minimize the cross entropy loss:

$$L_{XE}(\theta) = -\sum_{t=1}^{T} \log(p_{\theta}(w_{t}^{*}|w_{1}^{*}, \ldots, w_{t-1}^{*}))$$  \hspace{1cm} (16)$$

where $p_{\theta}(w_{t}|w_{1}, \ldots, w_{t-1})$ is given by equation (15). Similar to [38], we apply $L_{1}$ regularization to the spatial attention masks generated by our Change Localizer in order to minimize unnecessary activations. We also use an entropy regularization over the attention weights generated by our Dynamic Speaker to encourage exploration in using visual features. The final loss function we optimize is as follows:

$$L(\theta) = L_{XE} + \lambda_{L_{1}}L_{1} - \lambda_{ent}L_{ent}$$  \hspace{1cm} (17)$$

where $L_{1}$ and $L_{ent}$ are $L_{1}$ regularization and entropy regularization, respectively, and $\lambda_{L_{1}}$ and $\lambda_{ent}$ are hyperparameters.

5. Experiments

In this section, we evaluate VIDAM on the Viewpoint Invariant Change Captioning task against a number of baselines we discuss below. We present quantitative results on the ablations done and discuss their implications. We also provide qualitative analysis on the generated sentences and the corresponding attention weights of VIDAM. In the end, we test the general applicability of our approach to a real-world dataset with human descriptions [24].

5.1. Experimental setup

Here, we detail our experimental setup in terms of implementation, baselines, and evaluation schemes.

Implementation Details. Similar to [22, 26, 46], we use ResNet-101 [18] pretrained on ImageNet [12] to extract visual features from the images. We use features from the convolutional layer right before the global average pooling, obtaining features with dimensionality of 1024 x 14 x 14. The LSTMs used in the dynamic speaker have a hidden state dimension of 512. The word embedding layer is trained from scratch and each word is represented by a 300-dim vector. We train our model for 40 epochs using the Adam Optimizer [31] with a learning rate of 0.001 and a batch size of 128. The hyperparameters for the regularization terms are $\lambda_{L_{1}} = 2.5e^{-03}$ and $\lambda_{ent} = 0.0001$. Our model is implemented using PyTorch [43], and our code and dataset are available at: https://github.com/Seth-Park/viewpoint-invariant-change-captioning.

Baselines. Capt-Pix-Diff is a model that directly utilizes pixel-wise difference in the RGB space between “before” and “after” images. Similar to [24], we use pyramid reduce downsampling on the RGB difference to match the spatial resolution of the ResNet features. The downsampled tensor is concatenated with the ResNet features on which we apply a series of convolutions and max-pooling. The resulting feature is input to an LSTM to generate sentences. Capt-Rep-Diff is similar to Capt-Pix-Diff, but it relies on representation difference (i.e. $X_{\text{diff}}$) instead of pixel differ-
Table 3: Language evaluation of Viewpoint Invariant Change Captioning. Our proposed model outperforms all baselines on BLEU-4 (B), CIDEr (C), METEOR (M), and SPICE (S) under each evaluation protocol (i.e. Total, Scene Change, Viewpoint Change). The numbers are in %.

| Approach        | Total       | Scene Change       | Viewpoint Change       |
|-----------------|-------------|--------------------|------------------------|
|                 | B C M S     | B C M S            | B C M S                |
| Capt-Pix-Diff   | 30.2 75.9 23.7 17.1 | 21.9 36.2 17.7 7.9 | 43.4 98.2 38.9 26.3 |
| Capt-Rep-Diff   | 33.5 87.9 26.7 19.0 | 26.0 51.8 21.1 10.1 | 49.4 105.3 41.7 27.8 |
| Capt-Att        | 42.7 106.4 32.1 23.2 | 38.3 87.2 27.9 18.0 | 53.5 106.6 43.2 28.4 |
| Capt-Dual-Att   | 43.5 108.5 32.7 23.4 | 38.5 89.8 28.5 18.2 | 56.3 108.9 44.0 28.7 |
| Ours            | **47.3** 112.3 **33.9** 24.5 | **42.9** 94.6 **29.7** 19.9 | **59.8** 110.8 **45.2** 29.1 |

Table 4: Breakdown of language metrics by change types: Color (C), Texture (T), Add (A), Drop (D), Move (M), and Viewpoint (V). The numbers are in %.

| Approach        | CIDEr | METEOR | SPICE |
|-----------------|-------|--------|-------|
|                 | C     | T      | A     | D     | M     | V     | C     | T      | A     | D     | M     | V     |
| Capt-Pix-Diff   | 4.2   | 16.1   | 30.1  | 27.1  | 18.0  | 98.2  | 7.4   | 16.0   | 24.4  | 20.9  | 18.2  | 38.9  |
| Capt-Rep-Diff   | 44.5  | 21.9   | 50.1  | 49.7  | 26.5  | 105.3 | 19.2  | 18.2   | 25.7  | 23.5  | 18.9  | 41.7  |
| Capt-Att        | 112.1 | 75.9   | 91.5  | 98.4  | 49.6  | 106.6 | 30.5  | 25.4   | 30.2  | 31.2  | 22.2  | 43.2  |
| Capt-Dual-Att   | 115.8 | 82.7   | 85.7  | 103.0 | 52.6  | 108.9 | 32.1  | 26.7   | 29.5  | 31.7  | 22.4  | 44.0  |
| Ours            | **120.4** | **86.7** | **108.2** | **103.4** | **56.4** | **110.8** | **32.8** | **27.3** | **33.4** | **31.4** | **23.5** | **45.2** |

5.3. Localization

To understand the importance of localization, we compare models with and without spatial attention mechanism. We observe that Capt-Att significantly outperforms Capt-Rep-Diff, indicating that the capacity to explicitly locate the change has a high impact on the caption quality in general. It is interesting to note from Table 4 that the improvements are more pronounced in scene change (i.e. C, T, A, D, M) than viewpoint change, which is intuitive since the localization ability should matter when there actually is a scene change.

5.4. Single attention vs. dual attention

Using multiple spatial attentions has been shown to be useful for many purposes including multi-step/hierarchical reasoning [58, 39, 34] and model interpretability [30, 42]. To this extent, we train a model that deploys dual attention and evaluates its application to Viewpoint Invariant Change Captioning. Compared to Capt-Att, Capt-Dual-Att achieves...
Table 5: Pointing game accuracy results. We report per change-type performance (Color (C), Texture (T), Add (A), Drop (D), Move (M)) as well as the total performance. The numbers are in %.

|       | C    | T    | A    | D    | M    | Total |
|-------|------|------|------|------|------|-------|
| Capt-Att | 46.68 | 57.90 | 22.84 | 47.80 | 17.57 | 39.37 |
| Capt-Dual-Att | 40.97 | 46.55 | 54.33 | 45.67 | 19.89 | 39.35 |
| Ours   | 54.52 | 65.75 | 48.68 | 50.06 | 22.77 | 48.10 |

Figure 4: Qualitative results comparing Capt-Att and VIDAM. The blue and red attention maps are applied to “before” and “after”, respectively. The blue and red attention maps are the same for Capt-Att whereas in VIDAM they are separately generated. The heat map on the lower-right is the visualization of the dynamic attention weights where the rows represent the amount of attention given to each visual feature (e.g. loc bef, diff, loc aft) per word.

We observe that our model outperforms all previously discussed baselines for both captioning and Pointing Game evaluations. In Figure 4, we compare localization and caption results predicted by Capt-Att and VIDAM. We observe that a single spatial attention mechanism used in Capt-Att cannot locate and associate the moved object in “before” and “after” images, thus confusing the properties of the target object (i.e. large cyan matte). On the other hand, our model is able to locate and match the target object in both scenes via dual attention, and discover that the object has moved. Moreover, it can be seen from the dynamic attention weights that the model demonstrates some reasoning capacity in which it first focuses on the “before” when addressing the changed object and gradually shifts attention to “diff” and “after” when mentioning the change. A similar reasoning process can be found in Figure 5 where the model attends to “before” when referring to the target object and its relation to another object, and then attends to “diff” and “after” when talking about how the color changed.

The experiments above demonstrate the general effectiveness of our model in tackling the proposed task. However, to further validate the viewpoint invariance of our model, we run evaluations on difficult test samples with severe viewpoint shifts. We use the following heuristics to measure the amount of viewpoint change: for each object in the scene, excluding the changed object, we compute the IoU of the object’s bounding boxes across the image pair. We assume the more the viewpoint changes, the less the bounding boxes will overlap. We compute the mean of these IoUs to represent the “difficulty” of the data point. We take the top 25% difficult test samples and re-evaluate our methods. The results are in Table 6. We observe that our model outperforms all baselines on both captioning metrics and Pointing Game even on these difficult samples.

5.6. Measuring viewpoint invariance

5.7. Applicability to real-world dataset

Finally, we evaluate our VIDAM model on the recent Spot-the-Diff dataset [24] with real images and human-provided descriptions (Figure 6). This dataset features mostly well aligned image pairs, with one or more changes
the tiny cyan rubber cube that is to the left of the tiny purple cube changed to brown
the cyan matte cube changed to brown
the big purple matte block that is in front of the yellow metal thing turned metallic
the large purple rubber block that is to the left of the matte cylinder became metallic
there is a person walking in the parking lot
there is one more person in the after photo

Table 6: Captioning and Pointing Game evaluations on difficult examples. Using the same captioning metrics as before, we evaluate methods under the Scene Change protocol for the captioning task. Our proposed model outperforms all baselines on both captioning and localization tasks even on the test data points with the most severe viewpoint shift.

| Approach    | Captioning | Pointing Game |
|-------------|------------|---------------|
|             | B          | C             | M            | S             | Acc. |
| Capt-Pix-Diff | 19.4       | 31.8          | 16.3         | 7.1           | –    |
| Capt-Rep-Diff | 23.7       | 43.8          | 19.3         | 8.7           | –    |
| Capt-Att     | 36.5       | 80.2          | 26.8         | 16.9          | 37.36|
| Capt-Dual-Att| 37.7       | 86.1          | 27.8         | 17.5          | 32.71|
| Ours         | 40.7       | 87.6          | 28.3         | 18.2          | 46.16|

Figure 6: An example output of our model on the Spot-the-Diff dataset [24]. The top sentence shows our model’s prediction, the bottom sentence shows the ground-truth.

6. Conclusion

We have presented a new task, Viewpoint Invariant Change Captioning, along with the new dataset and the novel Viewpoint Invariant Dynamic Attention Model to jointly localize and describe changes between images. Our dynamic attention scheme is superior to the baselines and its visualization provides an interpretable view on the change caption generation mechanism. Our model is robust to viewpoint in the sense that it can distinguish scene changes from purely viewpoint changes. Our new Viewpoint Invariant Change Captioning Dataset is a new challenging benchmark in the field of Vision and Language, where many challenges need to be addressed, e.g., establishing correspondences between the objects in the presence of viewpoint changes, resolving ambiguities and correctly generating the referring parts of the description.
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Supplementary Material

In this supplementary material, we provide an analysis on the performance of our model VIDAM in terms of what change types the model confuses the most and to what it is confused with. Additionally, we investigate how different levels of viewpoint difficulty affect the model performance, and show examples of difficult and easy data points with the corresponding predictions generated from VIDAM.

A. Confusion Matrix of Change Types

In order to analyze the behavior of our method on different change types, we parse the sentences generated by our model and categorize the type of change that is detected by our model based on the parsed results. We compare that to the ground-truth change type information, and plot the confusion matrix in Figure 7. As we have already shown (Table 4 in the main paper), the most challenging change types are TEXTURE and MOVE, which are most often confused with the VIEWPOINT only change. It is interesting to note that for all change types most of the confusion comes from misidentifying scene changes as VIEWPOINT, and that such confusion is the most severe for MOVE. This is intuitive in the sense that in order to correctly distinguish MOVE from VIEWPOINT, the model has to spatially relate every other object in the scene whereas for other scene change types the changes are relatively salient and do not necessarily require understanding the spatial relationships between the objects. Moreover, MOVE is also confused with ADD and DROP, as it may be difficult to correctly establish a correspondence between all the objects in “before” and “after” scenes.

B. Difficulty Based on Viewpoint Variations

In subsection 5.6 of the main paper, we discuss how VIDAM outperforms baselines on the most difficult subset of our dataset, where difficulty is defined in terms of viewpoint shift measured by an IoU-based heuristic. To validate this heuristic and provide further insights, we compare results of our model and the baselines on the top 25% (hard) and the bottom 25% (easy) samples sorted by difficulty, in Table 7. As we see, there is a significant performance drop from easy to hard examples for all methods, indicating that our IoU-based heuristic is a reasonable approximation of difficulty and that viewpoint variation is indeed an important factor to be addressed in the proposed task. In Figure 8, we present some hard and easy examples and the corresponding predictions by our model. We notice that depending on the viewpoint shift, the problem becomes significantly difficult even for a simple scene. For instance in the leftmost example of Figure 8 where there are only three objects, we see that it becomes hard to localize the changed object as it escapes the scene due to significant viewpoint variation. On the other hand, even for more complex scenes like the rightmost example in Figure 8, localizing is easier with small viewpoint change.

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Table 7: Captioning and Pointing Game evaluations on top 25% (hard) and bottom 25% (easy) examples sorted by viewpoint "shift" difficulty. Same metrics and evaluation protocols are used as in Table 6 of the main paper.

![Table illustration](image-url)

Figure 8: Difficult and easy examples chosen via IoU-based heuristics. The examples on the left are difficult ones where the viewpoint shift is noticeable. Examples on the right are easy ones where the viewpoint change is not significant. We also show the corresponding attentions and sentences generated by our model, where the top sentences are predicted and the bottom sentences are ground-truth.

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