Connecting Vision and Language with Localized Narratives

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Abstract

We propose Localized Narratives, an efficient way to collect image captions with dense visual grounding. We ask annotators to describe an image with their voice while simultaneously hovering their mouse over the region they are describing. Since the voice and the mouse pointer are synchronized, we can localize every single word in the description. This dense visual grounding takes the form of a mouse trace segment per word and is unique to our data. We annotate 500k images with Localized Narratives: the whole COCO dataset and 380k images of the Open Images dataset. We provide an extensive analysis of these annotations, which we will release early 2020. Moreover, we demonstrate the utility of our data on two applications which benefit from our mouse trace: controlled image captioning and image generation.

1. Introduction

Much of our language is rooted in the visual world around us. A popular way to study this connection is through Image Captioning, which uses datasets where images are paired with human-authored textual captions [9, 61, 49]. Yet, many researchers want deeper visual grounding which links specific words in the caption to specific regions in the image [34, 35, 47, 48]. Hence Flickr30K Entities [43] enhanced Flickr30K [61] by connecting the nouns from the captions to bounding boxes in the images. But these connections are still sparse and important aspects remain ungrounded, such as words capturing relations between nouns (as “holding” in “a woman holding a balloon”). Visual Genome [29] provides short descriptions of regions rather than of the whole image, thus words are not individually grounded. Finally, both datasets [29, 43] were acquired with expensive crowdsourcing campaigns, which involve manually drawing a large number of bounding boxes. Moreover, these campaigns are complicated as they feature multiple stages where different annotators provide different pieces of information for the same image.

In this paper we propose Localized Narratives, an efficient way to collect image captions with dense visual grounding. We ask annotators to describe an image with their voice while simultaneously hovering their mouse over the region they are describing. The process is illustrated in Figure 1: the annotator says “woman” while using their mouse to indicate her spatial extent. Later they move the mouse from the woman to the balloon following its string, while saying “holding”. This provides direct visual grounding of this relation. They also describe attributes such as “clear blue sky” and “light blue jeans”. Since the voice and the mouse pointer are synchronized, we can determine the image location of every single word in the description. This provides dense visual grounding in the form of a mouse trace segment for each word, which is unique to our data.

In order to obtain written-word grounding, we additionally need to transcribe the voice stream. We observe that automatic speech recognition [16, 1, 44] typically results in imperfect transcriptions. To get data of the highest quality, we ask annotators to transcribe their own speech, im-
mediately after describing the image. This delivers an accurate transcription, but without temporal synchronization between the mouse trace and the written words. To address this issue, we perform a sequence-to-sequence alignment between automatic and manual transcriptions, which leads to accurate and temporally synchronized captions. Overall, our annotation process tightly connects four modalities: the image, its spoken description, its textual description, and the mouse trace. Together, they provide dense grounding between language and vision.

Localized Narratives is an efficient annotation protocol. Speaking and pointing to describe things comes natural to humans [24, 40]. Hence this step takes little time (39.6 sec. on average). While the manual transcription step takes longer (108.3 sec.), we estimate it takes about as long as regular image captioning [9, 61], since typing appears to be the main bottleneck in terms of speed. Hence, the visual grounding of captions comes at little additional cost in Localized Narratives, as opposed to the annotation process of Flickr30K Entities and Visual Genome [29, 43] which is more complicated and requires manually drawing bounding boxes. Moreover, if automatic speech recognition improves in the future, since speaking is faster than typing, our approach will eventually become even more efficient than regular captioning while also providing more information.

The low cost of Localized Narratives enables us to collect data at scale: we annotate the complete training and validation sets of COCO [33] as well as 377,591 images of the Open Images [31] dataset. We will publicly release Localized Narratives for these 500,878 images early 2020. We provide extensive analysis of our data and show that: (i) Our data is rich: we ground all type of words (nouns, verbs, prepositions, etc.), and our captions are significantly longer than in previous datasets [9, 61, 29, 49]. (ii) Our annotations are diverse both in the language modality (e.g., caption length varies widely with the content of the image) and in the visual domain (different pointing styles and ways of grounding relationships). (iii) Our annotation protocol is very efficient: visual grounding comes at a little extra cost with respect to classical captioning. (iv) Our mouse traces match well the location of the objects being mentioned.

Since Localized Narratives provides four synchronized modalities, it enables many applications (Tab. 1). We envision that having each word in the captions grounded, beyond the sparse set of boxes of previous datasets [43, 26, 37, 29], will enable richer results in many of these tasks and open new doors for tasks and research directions that would not be possible on the previously existing data annotations.

As a first example along these lines, we show how we can use the mouse trace as a fine-grained control signal for a user to request a caption on a particular image (Sec. 5.1). Mouse traces are a more natural way for humans to provide a sequence of grounding locations, compared to drawing a list of bounding boxes [11]. We therefore envision its use as assistive technology for visually impaired people. In future work, the mouse trace in our Localized Narratives could be used as additional attention supervision at training time, replacing or complementing the self-supervised attention mechanisms typical of modern systems [3, 49, 7, 62, 58]. This might train better systems and improve test-time captioning performance when only the image is given as input.

Another example we demonstrate is image generation given Localized Narratives as input (Sec. 5.2). This task has the user describing the desired contents of an image while moving the mouse over an initially-empty canvas, while an image generation model based on Localized Narratives data enables the generation of a realistic image that matches the provided description.

Besides the two tasks we present here, Localized Narratives are a natural fit for: (i) image retrieval: the user naturally describes the content of an image they are looking for, in terms of both what and where; (ii) grounded speech recognition: taking the content of an image into account would allow a better speech transcription, e.g. plant and planet are easier to distinguish in the visual domain than in the voice domain; (iii) voice-driven environment navigation: the user describes where they want to navigate to, using relative spatial language.

To summarize, our paper makes the following contributions: (i) We introduce Localized Narratives, an efficient way to collect image captions where every word is localized in the image with a mouse trace segment; (ii) We use Localized Narratives to annotate 500,878 images and provide a thorough analysis of the data. We will publicly release the data early 2020. (iii) We demonstrate the utility of our data through controlled image captioning and image generation.

| Image | Text | Speech | Grounding | Task |
|-------|------|--------|-----------|------|
| In    | Out  | -      | -         | -    |
| Out   | In   | -      | -         | -    |
| In    | Out  | -      | -         | -    |
| In    | Out  | -      | -         | -    |
| -     | In   | Out    | -         | -    |
| In    | Out  | In     | -         | -    |
| In    | In   | Out    | -         | -    |
| In    | Out  | In     | Out       | -    |
| Out   | In   | In     | Out       | -    |
| In    | Out  | In     | In        | -    |

Table 1. Tasks enabled by Localized Narratives. Each row represents different uses of the four elements connected in a Localized Narrative: image, textual caption, speech, and grounding (mouse trace); labeled as being input (In) or output (Out) for each task.
The man at bat readies to swing at the pitch while the umpire looks on.

Figure 2. Sample annotations from (a) COCO Captions [9], (b) Visual Genome [29], (c) Flickr30K Entities [43], and (d) Localized Narratives (Ours). For the sake of clarity, (b) shows a subset of region descriptions and (d) shows a shorter-than-average Loc. Narrative.

2. Related Work

Captioning Datasets. Here we review related annotation efforts which connect vision and language via captioning (Tab. 2). We focus on how their captions are grounded, as this is the key differentiating factor of Localized Narratives from these works. As a starting point, classical image captioning [9, 61, 49] simply provides a whole caption for the whole image (Fig. 2(a)). This lack of proper grounding was shown to be problematic [34, 35, 47, 48].

Flickr30K Entities [43] annotated the nouns mentioned in the captions of Flickr30K [61] and drew their bounding box in the image (Fig. 2(b)): the grounding is therefore from nouns to regions (including their attached adjectives, Tab. 2). Visual Genome [29] and related previous efforts [26, 37] provide short phrases describing regions in the images (Fig. 2(c)): grounding is therefore at the phrase level (Tab. 2). Despite that Visual Genome uses these regions as a seed to generate a scene graph, where each node is grounded in the image, the connection between the region descriptions and the scene graph is not explicit.

In Localized Narratives, in contrast, every word is grounded to a specific region in the image represented by its trace segment (Fig. 2(d)). This includes all types of words (nouns, verbs, adjectives, prepositions, etc.), in particular valuable spatial‐relation markers (“above”, “behind”, “riding”, “holding”, etc.). Another disadvantage of Flickr30K Entities and Visual Genome is that their annotation process consists of multiple stages performed by different annotators within the same image. Our annotations instead are obtained in a single stage, by a single annotator for any image. This simplifies the infrastructure setup, facilitates scalability, and benefits consistency. Finally, Flickr30K Entities and Visual Genome processes require manually drawing a large number of bounding boxes, an unnatural and time-consuming requirement compared to our simpler and more natural protocol.

SNAG [51] is a proof of concept where annotators describe images using their voice while their gaze is tracked using specialized hardware. This enables inferring the image location they are looking at. As a consequence of the expensive and complicated setup, only 100 images were annotated. In our proposed Localized Narratives, instead, we collect the data using just a mouse and a microphone as input devices, which are commonly available. This allows us to annotate a much larger set of images (500,878 to date).

In the video domain, ActivityNet-Entities [65] adds visual grounding to the ActivityNet Captions dataset, also in a two-stage process where boxes where drawn a posteriori.

Visual Question Answering Datasets. Another popular way to study the connection between vision and language is Visual Question Answering (VQA). The importance of visual grounding was also recognised in this domain. Several recent efforts therefore provide visually grounded VQA datasets [13, 21, 63, 66].

Image Annotation using Voice. Recently a few papers appeared that propose to use voice as an input modality for computer vision tasks [12, 52, 51, 19, 18, 17]. The closest work to ours [17] uses voice to simultaneously annotate the class name and the bounding box of an object instance in an image. With Localized Narratives we bring it to the next level by producing richer annotations both in the language and vision domains with long free-form captions associated to synchronized mouse traces.

| Dataset                  | Grounding          | Num. of images | Num. of captions | Words/caption |
|--------------------------|--------------------|----------------|------------------|---------------|
| COCO Captions [9]        | Whole capt. → Whole im. | 123,287        | 616,767          | 10.5          |
| Conceptual Capt. [39]   | Whole capt. → Whole im. | 3,334,173      | 3,334,173        | 10.3          |
| ReferIt [26]            | Short phrase → Region | 19,894         | 130,525          | 3.6           |
| Google Refexp [37]      | Short phrase → Region | 26,711         | 104,560          | 8.4           |
| Visual Genome [29]      | Short phrase → Region | 108,077        | 5,408,689†      | 5.1           |
| Flickr30K Ent. [43]     | Nouns → Region     | 31,783         | 154,915          | 12.4          |
| Loc. Narr. (Ours)       | Each word → Region | 500,878        | 520,878          | 41.3          |
3. Annotation Process

The core idea behind the Localized Narratives annotation protocol is to ask the annotators to describe the contents of the image using their voice while hovering their mouse over the region being described. Both voice and mouse location signals are timestamped, so we know where the annotators are pointing while they are speaking every word.

Figure 3 shows voice and mouse trace data, where the color gradient represents temporal synchronization. We summarize here how to process this data to produce a Localized Narrative example. First, we apply an Automatic Speech Recognition (ASR) algorithm and get a synchronized, but typically imperfect, transcription (Fig. 3(c)). After finishing a narration, the annotators transcribe their own recording, which gives us an accurate caption, but without synchronization with the mouse trace (Fig. 3(d)). Finally, we obtain a correct transcription with timestamps by performing sequence-to-sequence alignment between the manual and automatic transcriptions (Fig. 3(e)). This time-stamped transcription directly reveals which trace segment corresponds to each word in the caption, and completes the creation of a Localized Narrative instance. Below we describe each step in detail.

Annotation Instructions. One of the advantages of Localized Narratives is that it is a natural task for humans to do: speaking and pointing at what we are describing is a common daily-life experience [24, 40]. This makes it easy for annotators to understand the task and perform as expected, while increasing the pool of qualified annotators.

We trained the annotators simply by asking them to read these instructions and to watch a video of the expected annotation process.

Automatic and Manual Transcriptions. We apply an ASR algorithm [15] to obtain an automatic transcription of the spoken caption, which is timestamped but typically contains transcription errors. To fix these errors, we ask the annotators to manually transcribe their own recorded narration. Right after they described an image, the annotation tool plays their own voice recording accompanied by the following instructions:

- Use the mouse to point at the objects in the scene.
- Simultaneously, use your voice to describe what you are pointing at.
  - Focus on concrete objects (e.g., cow, grass, person, kite, road, sky).
  - Do not comment on things you cannot directly see in the image (e.g., feelings that the image evokes, or what might happen in the future).
  - Indicate an object by moving your mouse over the whole object, roughly specifying its location and size.
  - Say the relationship between two objects while you move the mouse between them, e.g., "a man is flying a kite", "a bottle is on the table".
  - If relevant, also mention attributes of the objects (e.g., old car).

We trained the annotators simply by asking them to read these instructions and to watch a video of the expected annotation process.

The manual transcription is accurate but not timestamped, so we cannot associate it with the mouse trace to recover the location of each word in the image.

Transcription Alignment. We obtain a correct transcription with timestamps by performing a sequence-to-sequence alignment between the manual and automatic transcriptions (Fig. 4).

Formally, let \( \mathbf{a} = \{a_1, \ldots, a_n\} \) and \( \mathbf{m} = \{m_1, \ldots, m_m\} \) be the automatic and manual transcriptions of the spoken caption, where \( a_i \) and \( m_j \) are individual words. \( a_i \) is timestamped: let \([t^1_i, t^2_i]\) be the time segment during which \( a_i \) was spoken. Our goal is to align \( \mathbf{a} \) and \( \mathbf{m} \) to transfer the timestamps from the automatically transcribed words \( a_i \) to the manually provided \( m_j \).

To do so, we apply Dynamic Time Warping [30] between \( \mathbf{a} \) and \( \mathbf{m} \). Intuitively, we look for the best matching between the two sequences of words that preserves their order. For-
nally, let $\mu$ be a matching function that assigns each word $a_i$ to a word $m_{\mu(i)}$ such that if $i_2 > i_1$ then $\mu(i_2) \geq \mu(i_1)$. We then look for the optimal matching $\mu^*$ such that:

$$\mu^* = \arg \min_\mu \sum_{i=1}^{[a]} d(a_i, m_{\mu(i)})$$  \hspace{1cm} (1)

where $d$ is the edit distance between two words, i.e., the number of character inserts, deletes, and replacements required to get from one word to the other.

Note that $\mu^*$ assigns each $a_i$ to exactly one $m_j$, but $m_j$ can match to zero or multiple words in $a$. Let the set of matches for $m_j$ be defined as $A_j = \{i | \mu^*(i) = j\}$. The timestamp $[t_0^j, t_1^j]$ of $m_j$ is the interval spanned by the matching words (if any) or to the time between neighboring matching words (if none). Formally:

$$t_0^j = \begin{cases} \min \{t_i^j | i \in A_j\} & \text{if } A_j \neq \emptyset, \\ \max \{t_i^j | i \in A_k | k < j\} & \text{if } \exists k < j \text{ s.t. } A_k \neq \emptyset \\ T^0 & \text{otherwise}, \end{cases}$$

$$t_1^j = \begin{cases} \max \{t_i^j | i \in A_j\} & \text{if } A_j \neq \emptyset, \\ \min \{t_i^j | i \in A_k | k > j\} & \text{if } \exists k > j \text{ s.t. } A_k \neq \emptyset \\ T^1 & \text{otherwise}, \end{cases}$$

where $T^0$ is the first time the mouse pointer enters the image and $T^1$ is the last time it leaves it. Finally, we define the trace segment associated with a word $m_j$ as the segment of the mouse trace spanned by the time interval $[t_0^j, t_1^j]$ (Fig. 4).

4. Dataset and Analysis

Image Sources and Scale. We annotated images from COCO [33, 9] and Open Images [31, 28]. In order to facilitate future comparison to previous work, we re-annotated the full set of 123,287 images of COCO (train and validation). For Open Images, we annotated 377,591 images, selected from the train split. To enable cross-modal applications, we selected images for which object segmentations [5], object bounding boxes or visual relationship annotations [31] are already available. All the analyses in the remainder of this section are done on the full COCO dataset.

Overall, we annotated 500,878 images (Tab. 2), which is approximately 4 times more than the entire COCO dataset. For analysis purposes, we annotated 5,000 COCO images with replication 5 (5 different annotators annotated each image). Beyond this, we prioritized having a larger set covered, so the rest of images were annotated with replication 1. We used 80 different annotators in total.

Richness. The mean length of the captions we produced is 41.3 words (Tab. 2), substantially longer than previous captioning datasets (e.g. 4 times longer than COCO captions). We also compare in terms of the average number of nouns, pronouns, adjectives, verbs, and adpositions (prepositions and postpositions, Tab. 3). We determined this using the spaCy [20] part-of-speech tagger. Localized Narratives has a higher occurrence for each of these parts-of-speech categories compared to previous datasets, which indicates that our annotations provide richer use of natural language in connection to the images they describe.

Diversity. To illustrate the diversity of our captions, we plot in Figure 5 the distribution of the number of nouns per caption, and compare it to similar distributions obtained over previous datasets. We observe that the variance in the number of nouns is significantly higher in Localized Narratives (up to 45 nouns in some images). This indicates that the Localized Narratives captions tend to cover a lot more in terms of capturing image content. At the same time, we note that this poses an additional challenge for captioning methods: automatically adapting the length of the descriptions to each image, as a function of the richness of its content. Beyond nouns, Localized Narratives provide visual grounding for every word (verbs, prepositions, etc.). This is especially interesting for relationship words, e.g. “woman holding balloon” (Fig. 1) or “with a hand under his chin” (Fig. 2(d)). This opens the door to a new venue of research: understanding how humans naturally ground visual relationships.

Diversity in Localized Narratives is present not only in the language modality, but also in the visual modality, such as the different ways to indicate the spatial location of objects in an image. In contrast to previous works, where the grounding is in the form of a bounding box, our instructions lets the annotator hover the mouse over the object in any way they feel natural. This leads to diverse styles of creating trace segments (Fig. 6): circling around an object (sometimes without even intersecting it), scribbling over it, underlining in case of text, etc. This diversity also presents another challenge opened by Localized Narratives: detect and adapt to different trace styles in order to make full use of them.

| Dataset          | Words | Nouns | Pron. | Adj. | Adp. | Verbs |
|------------------|-------|-------|-------|------|------|-------|
| COCO Captions    | 10.5  | 3.6   | 0.2   | 0.8  | 1.7  | 0.9   |
| Flickr30K        | 12.4  | 3.9   | 0.3   | 1.1  | 1.8  | 1.4   |
| Loc. Narratives  | 41.3  | 11.8  | 4.0   | 2.0  | 5.1  | 3.0   |

Table 3. Richness of the captions of Localized Narratives compared to previous works.
Annotation Cost. Annotating one image with Localized Narratives takes 148 seconds on average. We consider this a relatively low cost given the amount of information harvested, and it allows us to scale up the annotation efforts (500,878 images so far). Figure 7 breaks down this time into the different steps of our annotation process. While manual transcription takes up the majority of the time (108.3 sec., 73%), we estimate it takes about as long as normal image captioning [9, 61], since typing seems to be the main bottleneck. The annotation step of Localized Narratives only takes 39.0 seconds (27%), a little additional cost in exchange for visually grounding all words in the caption. In the future, when ASR systems improve further, manual transcription could be skipped and Localized Narratives could become even faster than classical captioning, thanks to our core idea of using speech. Finally, we observe that annotators take 6.8 seconds to start narrating, presumably parsing and analyzing the image. The talking itself takes 29.1 seconds, during which they continuously move their mouse.

Localization Accuracy. To analyze how well the mouse traces match the location of actual objects in the image, we extract all instances of any of the 80 COCO object classes in our captions (exact string matching). We recover 146,723 instances. We then associate a mouse trace segment to the closest ground-truth box of its corresponding class. Figure 8 displays the 2D histogram of the positions of all trace segment points (left) and their distance to the box center (right), normalized by the box size (peak in Fig. 8 right). We observe that the majority of the trace points are within the correct bounding box. Furthermore, the mode of the distance to the box center is 0.58, which is nicely halfway to the box boundaries (peak in Fig. 8 right). There is, however, a non-negligible percentage of trace points that fall outside the box, which we attribute to two different effects. First, circling around the objects is commonly used by annotators (Fig. 1 and Fig. 6). This causes the mouse traces to be close to the box, but not inside it. Second, some annotators sometimes start moving the mouse before they describe the object, or vice versa. We see both cases as a research opportunity to better understand the connection between vision and language.

Inter-Annotator Agreement. As said at the beginning of this section, we annotated 5,000 COCO images with replication 5. We take advantage of this data to measure inter-annotator agreement, with a focus on the defining feature of our data: its grounding on the image. We represent the full mouse trace with their histogram over a $8 \times 8$ grid on the image, which we call mouse trace map. We then compare pairs of mouse traces by the squared distance between the two respective mouse trace maps. Figure 9 displays the his-
There is a kid standing and holding a doll in his hand and there is another kid in the right corner holding a mobile in his hand.

In the image in the center we can see two kids were holding teddy bears. In the background there is a wall.

In this picture we can see a person skiing on ski boards, in the bottom there is snow, we can see some people standing and sitting here, at the bottom there is snow, we can see a flag here.

In this image I can see ground full of snow and on it I can see few people are standing. Here I can see a flag and on it I can see something is written. I can also see something is written over here.

In this image there are doughnuts kept on the grill. In the front there is a white color paper attached to the machine. On the right side there is a machine which is kept on the floor. In the background there are group of people standing near the table. On the left side there is a person standing on the floor. In the background there is a wall on which there are different types of doughnuts. At the top there are lights.

As we can see in the image there is a white color wall, few people here and there and there are food items.

Figure 10. Qualitative results for controlled image captioning. Captioning controlled by mouse traces (top) and without traces (bottom). The latter misses important objects (e.g. skiers in the sky, mobile phone – all in bold), and it does not highlight object positions and order.

togram of the distances between pairs of mouse trace maps made on the same image by different annotators (---). For comparison, we also display the histogram of distances between pairs of mouse trace maps made on different images (---). While overlapping, the two distributions can be distinguished, which indicates a good level of inter-annotator agreement when annotating Localized Narratives.

5. Applications

5.1. Controlled Image Captioning

An interface using a mouse trace provides a mechanism that humans can efficiently use to communicate their spatial and temporal preferences about image regions. In this section, we show that incorporating a mouse trace allows to control the captioning process, taking into account the user preferences. In practice, one especially useful application is assistive technology for the visually impaired [57, 64], who can utilize the mouse to express their preferences in terms of how the image description should be presented.

Method. We start from a state-of-the-art, transformer-based encoder-decoder image captioning model [49, 7, 62]. This model consumes Faster-RCNN features [46] of the top 16 highest scored object proposals in the image. The Faster-RCNN module is pre-trained on Visual Genome [29]. The model uses these features to predict an image caption based on an attention model, inspired by the Bottom-Up Top-Down approach of [3].

We modify this model by adding new input signals such that it can consume the mouse trace at both training and test time. The result is a model that consumes four types of features: (i) Faster R-CNN features of the automatically-detected top object proposals, representing their semantic information; (ii) the coordinate and size features of these proposals, representing the location of the detected objects. (iii) the total time duration of the mouse trace, capturing information about the expected length of the full description. (iv) the position of the mouse trace as it moves over the image, representing the visual grounding. To create this representation, we first divide the mouse trace evenly into pseudo-segments based on the prior median word duration (0.4 sec over the whole training set). We then represent each pseudo-segment by its encapsulating bounding box, resulting in a set of features which take the same form as (ii).

Setup. Our goal is to show that a mouse trace enables controlled caption generation and leads to improved captioning quality. To that end, we consider four settings in which one or more of the feature types are given to the model. Our first baseline only uses visual features (i). This corresponds to a standard captioning model [3, 7]. Our second baseline uses features (i + ii), now adding the position of the object proposal on top of its visual features. Our full model uses all features, now incorporating the mouse trace information in (iii + iv). Notice that this model automatically puts the position of the mouse trace in correspondence with the position of the object proposals (ii), which enables it to reason over localized visual features (i). Additionally, we also train a model that uses the overall trace length but not the position of its points; this setup enables us to disentangle the effects of providing information on the expected caption length (which is only a byproduct of the trace) from using the actual location information of the mouse trace (as the full model does).

We perform experiments on the Localized Narratives collected on COCO images, using the standard 2017 training and validation splits. We report the results using the standard captioning metrics: CIDEr-D [53], ROUGE-L [32], SPICE [2], BLEU-1 and BLEU-4 [41].

Results. Figure 10 shows three qualitative examples of controlled image captioning from mouse traces. Quantitatively, Table 4 shows our main results on the validation set. If we compare the baselines to our controlled image captioning model, we see massive improvements: CIDEr-D and BLEU-4 both improve by more than a factor 3× (the other scores also improve substantially). These improvements are much higher than what is typically seen in image captioning, and can be directly attributed to the impact of
Table 4. Controlled image captioning results on the COCO validation set. Our method (last row) greatly outperforms the baselines on all metrics. The ablation (iii) vs (iv) shows that this is mainly caused by the visual grounding through the mouse traces, not a side effect of trace length.

| Features (progressive) | CIDEr-D | ROUGE-L | SPICE | BLEU-1 | BLEU-4 |
|------------------------|--------|---------|-------|-------|-------|
| (i) RCNN features      | 0.293  | 0.317   | 0.257 | 0.322 | 0.081 |
| + (ii) their positions  | 0.295  | 0.318   | 0.257 | 0.323 | 0.082 |
| + (iii) trace length    | 0.373  | 0.334   | 0.265 | 0.372 | 0.097 |
| + (iv) trace positions  | 1.065  | 0.483   | 0.365 | 0.522 | 0.246 |

5.2. Image Generation

Generating an image conditioned on a semantic segmentation map is a well-studied application [8, 22, 42, 56]. However, while such segmentation maps give control over the image to be synthesized, they do not provide a natural interface for the user. In this section, we show how we can use labelled mouse traces to generate images. This opens up a new and intuitive way for the user to provide guidance to the image generation process.

We start from the state-of-the-art conditional image generation method SPADE [42] and use their publicly available model that is pre-trained on COCO-stuff [6, 33], which features 182 semantic classes, including object and background classes (stuff). At test time, the model takes as input a segmentation map where pixels are labeled with these classes, and generates an image. In this section we exploit Localized Narratives as a natural interface for producing these segmentation maps efficiently, as the user can specify both the location and class label of the desired image elements at the same time, and can intuitively specify elements in their order of importance.

Localized Narrative to Semantic Segmentation Map. For this application we need to convert the labelled traces into an appropriate segmentation map. We found that scene elements should have a realistic shape for SPADE to produce a pleasing image. Furthermore, SPADE deals poorly with maps which consist mostly of unlabelled pixels. To overcome this, we first collect masks for 1000 instances of each class from the COCO-stuff training set (both object and background classes). Given a trace segment with a class label, we first create its convex hull. We then compare it to all training instances of the same class and select the mask with the highest spatial overlap. This mask has a natural shape since it comes from a real instance.

Equipped with these retrieved masks, we construct a semantic segmentation map. We start from an empty map where all pixels are unlabelled, and iteratively add masks in the same order as the trace segments. An object mask is pasted on top of the current map, overwriting any previously labelled pixels. A background mask only overwrites pixels labeled as another background class. This approach results in using masks that cover more surface compared to the input trace segments, which helps reducing the surface of unlabelled pixels.

Results. Figure 11 shows two examples created based on Localized Narratives. In both examples, the images get increasingly complex as the Localized Narrative continues, while also preserving previous details. In the first example, the closed boat becomes open once the user indicated that a person should be visible on the boat. Moreover, the addition of the mountain alters the appearance of the water. In the second example, adding the clouds effectively changes the weather conditions and therefore the illumination.

6. Conclusions

This paper introduces Localized Narratives, an efficient way to collect image captions in which every single word is visually grounded by a mouse trace. We annotated 500k images with Localized Narratives: the whole COCO dataset [33] and 380k images of Open Images [31, 28]. Our analysis shows that our data is rich and provides accurate grounding. We demonstrated the utility of our data through two applications which use the mouse traces: controlled image captioning and image generation.
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