Text-to-Image Generation Grounded by Fine-Grained User Attention

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Abstract

Localized Narratives [29] is a dataset with detailed natural language descriptions of images paired with mouse traces that provide a sparse, fine-grained visual grounding for phrases. We propose TRECS, a sequential model that exploits this grounding to generate images. TRECS uses descriptions to retrieve segmentation masks and predict object labels aligned with mouse traces. These alignments are used to select and position masks to generate a fully covered segmentation canvas; the final image is produced by a segmentation-to-image generator using this canvas. This multi-step, retrieval-based approach outperforms existing direct text-to-image generation models on both automatic metrics and human evaluations: overall, its generated images are more photo-realistic and better match descriptions.

1. Introduction

Text-to-image synthesis goes back at least to 1983 [2]. WordsEye [7] marked a significant evolution: it was a retrieval-based system that extracted relevant 3D models from a database to depict scenes described in text. More recently, deep neural networks based on Generative Adversarial Networks (GANs) [13] have enabled end-to-end trainable photo-realistic text-to-image generation [31, 43, 40]. In contrast with these end-to-end models, others proposed hierarchical models [16, 36, 22]: in these, object bounding boxes and segmentation masks are used as intermediate representations for realistic image generation. Several other approaches also use intermediate scene graph representations [19, 42] for improving image synthesis. Others have explored dialogue-based interactions in which users incrementally provide instructions to refine and adjust generated scenes [34, 9]. This provides users with greater control by allowing them to designate the relative positions of objects in the scene. However, the language used is restricted, and the images are synthetic 3D visualizations or cartoons.

The Localized Narratives dataset [29] provides an alternative paradigm. Instead of writing short captions, annotators scan a mouse pointer over images while describing them. They transcribe their speech, allowing the text and traces to be time-aligned (Figure 1 top). These grounded narratives support the task of user attention grounded text-to-image generation [29]: generate an image given a free-form narrative and aligned traces (Figure 1 bottom).

Pont-Tuset et al. (2020) [29] present a proof of concept method which naively generates images using exact matches between words and labels; we build on this core approach. Our system, TRECS (Tag-Retrieve-Compose-Synthesize, Fig. 2), significantly enhances the image generation process by improving how language evokes image elements and how traces inform their placement.

- A tagger predicts object labels for every word. We train a BERT [8] model on the output of a constrained Hidden Markov Model (HMM). The HMM is generated from noisy narrative-to-image alignments. Several other approaches also use intermediate scene graph representations [19, 42] for improving image synthesis. Others have explored dialogue-based interactions in which users incrementally provide instructions to refine and adjust generated scenes [34, 9]. This provides users with greater control by allowing them to designate the relative positions of objects in the scene. However, the language used is restricted, and the images are synthetic 3D visualizations or cartoons.

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Figure 1. [Top]: Localized narratives comparing against standard captions. [Bottom]: Image synthesis from descriptions and traces.

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Figure 2. Multi-stage TReCS system for image synthesis using both descriptions and mouse traces.

- Selected masks are **composed** corresponding to trace order, with separate canvases for background and foreground objects (closely related to **stuff** and **thing** masks from [5]). The foreground mask is placed over the background one to create a full scene segmentation.

- Finally, a realistic image is **synthesized** by inputting the complete segmentation to mask-to-image translation models such as SPADE [28] or CC-FPSE [24].

TReCS exploits both text and mouse traces. Compared to other strategies, especially those requiring scene graphs, pointing with a mouse while talking is a more natural way for users to indicate their intent during image synthesis.

Localized Narratives are longer and more detailed than standard captions; they average 41.8 words in length, four times that of MS-COCO captions (averaging 10.5 words). This presents a major challenge for existing direct text-to-image models like AttnGAN [40]. Our multi-stage strategy better copes with the detail and captures the spatial configurations of the described objects and backgrounds. On the COCO portion of Localized Narratives (LN-COCO), TReCS beats AttnGAN on automatic metrics of image quality as well as side-by-side human evaluations of both realism and image-text alignment: TReCS is preferred 77% of the time for realism (compared to AttnGAN’s 23%), and 52.4% of the time for alignment (compared to AttnGAN’s 32.0%, with the remainder being ties or failures for both models). On the Open Images portion of Localized Narratives (LN-OpenImages), AttnGAN obtains better scores on automatic metrics, but TReCS’s output is still judged better in human evaluations, with 77.2% of TReCS images preferred for realism (compared to AttnGAN’s 22.8%), and 45.8% preferred for language alignment (compared to AttnGAN’s 40.5%). We show that high quality images can be generated for many narratives, but there is nevertheless much room for improvement on this challenging task.

Our key contributions are:

- We show, for the first time (to the best of our knowledge), viability for the very difficult task of grounded text-to-image synthesis for narratives (as compared to prior work on shorter captions).

- We propose TReCS, a sequential generation model that uses state-of-the-art language and vision techniques to generate high quality images that are aligned with both language and spatial mouse traces.

- We conduct both automatic and human evaluations that demonstrate the improved quality of TReCS generated images over prior state-of-the-art. Through extensive ablative studies, we identify key components of the TReCS pipeline that are essential for the user attention grounded text-to-image generation task.

2. The TReCS System

We observed that outputs from leading end-to-end text-to-image models [43, 40, 22] leave much to be desired; in particular, their generated images captured a visual gist of the descriptions but lacked well-defined objects and coherent composition. Motivated by the fact that models like SPADE [28] can produce realistic images when given gold-standard segmentation masks, [29] briefly sketch out an alternative based on mask retrieval and composition, followed by segmentation-to-image generation. We found this approach produces recognizable objects in some cases, but also often produces blank images—due largely to the limited use of the language in the narratives. Our TReCS system (Figure 2) significantly enhances this strategy by better
modeling the relation between language and the selection and placement of visual elements.

2.1. Sequence Labeling with Pixel Semantics

Traces in Localized Narratives cover a small portion of an image’s pixels, but their fine-grained alignment to the narrative makes them valuable indicators of the placement and scale of described items. Given both sources of information, a skilled artist could render a scene that visually captures a narrative. Datasets often used for text-to-image generation, e.g. COCO [23], Caltech-UCSD Birds [39], and Oxford Flowers-102 [26], do not contain such fine-grained descriptions. The latter two furthermore lack diversity in both descriptions and images.

TRECS exploits word-trace alignments and transition information to assign image labels to each word in training set narratives (Fig. 3). These are used to train a BERT [8] model to predict tags for new narratives. To address noise in the traces and alignments, we combine three long-standing methods to automatically refine word-object assignments: tf-idf weighting [25], IBM Model 1 [4], and Hidden Markov Models [30]. We use two key observations: (1) narratives mention items that are found in the images and (2) traces pass through coherent image regions and thus provide useful category transition information (e.g., cloud labels frequently occur next to sky labels). To extract semantic labels of the image, we rely on the COCO-Stuff dataset [5], which provides pixel-level semantic segmentation masks for the COCO portion of Localized Narratives.

As a starting point, we directly use word-trace alignments and gold-standard segmentation masks of each image in the training set to tag its narrative with image labels. For a given phrase and its corresponding trace, we obtain the convex hull for the trace and determine the image label that is assigned most frequently within it. This label is assigned to all words in the phrase. Using the hull rather than just the trace reduces noise, especially when annotators refer to an item by circling it with the mouse pointer (a common approach when describing objects). This produces assignments such as:

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this/snow picture/other shows/snow a/snow person/person skiing/snow on/snow the/snow snow/snow he/snow wore/person a/person helmet/person on/person
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![Figure 3. Overview of mouse trace sequence tagging.](image)

![Figure 4. Semantic label refinement process.](image)

Words do not always match their assigned labels, but the overall phrase extents correspond with traces that visited image regions with those labels. However, strong word-label associations are missed, producing evidently inappropriate tags such as he/snow and ski/other.

Constrained Label Refinement We combine these assignments with several further steps to obtain cleaner assignments (Fig. 4). First, we compute term frequency-inverse document frequency (tf-idf) scores $\alpha_w$ for each word $w$ in the vocabulary, treating each narrative as a document. We use these to reduce the influence of common, uninformative phrases (e.g. “in the image”). tf-idf scores $\alpha_c$ for image labels $c$ are computed similarly. Next, we learn word-label alignments by pairing each narrative and the corresponding bag of image labels and training IBM Model 1 on this corpus. From this, we obtain translation probabilities $P(w|c)$.

We construct an HMM with these building blocks. The emission distributions are obtained by scaling the translation probabilities with the $\alpha_w$ scores:

$$e(w|c) \propto \alpha_w \cdot P(w|c).$$

Similarly, the transition probabilities are defined as:

$$t(c'|c) \propto \alpha_{c'} \cdot \text{Count}(c \rightarrow c')$$

where the counts are obtained from the noisy word-trace assignments discussed above. Add-1 smoothing is used for both distributions. Finally, we scale the contribution of the transitions: for a given step we use $e(w|c')t(c'|c)^{10}$, which
we found necessary to allow tags to flip due to peaky emissions. To assign tags to a training sentence (used to auto-supervise BERT as described in the next section), we constrain Viterbi decoding to only those image labels annotated on the image itself. The HMM produces more appropriate and semantically aligned tags; for example, the above narrative is tagged as:

Auto-Supervised Training When human-annotated data is scarce, a weak generative model with strong initialization can label examples for a more powerful model that generalizes better. Garrette and Baldridge (2012)ym show that such auto-supervised training is effective for low-resource part-of-speech tagging. Here, we fine-tune a pretrained BERT model on the constrained HMM labels. We visually inspected the sequence tags and found that this improved both tagging quality (recall that there are no gold-standard per-word image category annotations) and final image generation quality (see detailed results in Sec. 4.2).

2.2. Semantically Aligned Mask Retrieval

For a narrative we wish to generate an image for, the BERT tagger detects image classes that TR:ES must include in the final generated image. We prepare a full semantic scene segmentation by: (1) identifying masks which match those detected classes, (2) are relevant to the narrative, and (3) are spatially aligned to the traces.

We train a cross-modal dual encoder to retrieve $k$ training set images that best match the narrative, and then select COCO-Stuff masks of the detected classes from those images. For each detected class instance $c_i$, we extract the masks that match that class in the top $k$ images; to satisfy spatial alignment, we select the mask $m_i$ with the highest mean intersection over union (mIOU) with the convex hull $S_i$ corresponding to the traces for instance $i$:

$$m_i = \arg\max_{M_{c_i,j}, \forall j \in \{1,...,k\}} \text{mIOU}(M_{c_i,j}, S_i)$$

where $M_{c_i,j}$ denotes mask instances of class $c_i$ for the $j$th retrieved image.

We train an image-text dual encoder (Figure 5) for cross-modal retrieval using the model and code of Parekh et al. (2020) for Text, we extract pre-trained BERT embeddings, which are passed into a 1-layer transformer with 8 attention heads and a hidden dimension of 128 units. The outputs are passed to a fully-connected layer which maps them to $\mathbb{R}^{2048}$. For images, we use a pretrained Inception v3 model fine-tuned during training.

Following prior work, we pre-train on Conceptual Captions and then train on LN-COCO (the Localized Narratives portion for MS-COCO images). The model is trained by minimizing the softmax margin loss with negatives samples from the same batch, which simulates image-caption and caption-image retrieval in each batch.

2.3. Mask Composition

The masks selected in the second stage must be composed to represent the scene as a complete semantic segmentation (Fig. 2, bottom right) that is consistent with language and spatial descriptions. Object (thing) classes (e.g. person, cat, airplane), have specific sizes, shapes, and identifiable features, while background (stuff) classes (e.g. grass, sky, water) are amorphous. stuff masks are also generally larger, so they often occlude thing masks if care is not taken. Here, we use a straightforward but effective strategy that separately proposes composed layers for thing (foreground) and stuff (background) masks and then superimposes the former over the latter.

The thing layer is created by centering each mask on its corresponding set of traces. They are placed in the reverse order they appear in the narrative—a good default strategy as annotators tend to describe salient objects before less notable details. This strategy works poorly for the stuff layer because the masks are larger and clash with each other—as such, many background scenes composed this way would contain only one or two stuff classes. To address this, we instead use a full semantic segmentation map from a single image—the one which has the stuff objects with the highest mIOU with the stuff hulls identified from the narrative and the corresponding traces. Because they are derived from a real image, these background stuff masks are semantically coherent with respect to both the narrative and each other. Finally, pixels not associated with an explicit semantic mask are assigned the class label of the closest stuff pixel. In addition to providing more coherent backgrounds, this also reduced the number of generated images with large blank regions.
2.4. Mask-to-Image Translation

The first three stages of TReCS construct a novel scene segmentation respecting the descriptions and traces. The last stage aims to produce a photo-realistic image given the full scene segmentation. Compared to free-form text-to-image generation, generating from a segmentation mask is much more constrained. Mask-to-image translation is an area which has seen remarkable recent progress [18, 38, 28, 24]. When given a full segmentation mask for an image, existing networks are able to generate high fidelity images.

For the final stage of TReCS, we experiment with two state-of-the-art mask-to-image generation models: SPADE [28] and CC-FPSE [24], and find that CC-FPSE works better for our use case (see Section 4.2). SPADE and CC-FPSE consist of a generator and a discriminator that are trained adversarially with the GAN framework [13]. The CC-FPSE generator learns a mask-to-image mapping using conditional convolution kernels; the weights of each kernel are predicted based on the mask layout. This gives the model explicit control over the generation process depending on the labels at each spatial location. The CC-FPSE discriminator incorporates multi-scale feature pyramids, which promote higher fidelity details and textures.

Scene segmentation masks created by TReCS are composed from multiple masks retrieved from different images and placed according to the narrative’s traces, creating a mismatch with the gold standard segmentation masks that SPADE and CC-FPSE are trained on. Nevertheless, we find that this strategy works well compared to direct text-to-image generation, as we show in Section 4.1.

3. Evaluation Metrics

Image Quality We rely foremost on side-by-side human evaluations. In each case, a human evaluator is presented with output from two competing models for the same narrative and is forced to pick which image is more photo-realistic. (Presentation order is randomized for each judgment.) Each image is rated by 5 independent annotators to allow for a majority vote (reducing variation) and provide nuanced breakdowns. See the Appendix for details.

Inception Score (IS) [32] is a widely-used automated metric. To compute IS, the predictions of a model (usually Inception v3 [35] pretrained on ImageNet) are obtained for a set of images, and the distribution of its predictions is measured. Higher IS is achieved both when generated images denote clear objects and when predictions are diverse.

Fréchet Inception Distance (FID) [15] improves on IS by comparing real and generated examples. Two multivariate Gaussians are fit to the Inception outputs of the real and generated samples; the FID score is then the Fréchet distance between the two Gaussians. Lower FID indicates greater similarity between the real and generated distributions.

Image-Language Alignment Generated images should also match the description. [16] assessed this fit by running a generated image through an image captioning model and computing BLEU, METEOR and CIDER scores of the generated caption given the original description. They showed that this approach correlated with human judgments. Nevertheless, this is a very indirect measure as it involves two generative models and automated text similarity measures. More importantly, as shown in [29], generating long narratives from the image alone (not including mouse traces) rather than short captions is a much harder problem, which makes caption-based measures less reliable. Hence, in this paper, we focus our evaluation for image-language alignment on human evaluations.

Similar to the human evaluation for image quality, we present generated images from two models, but also including the narrative they were conditioned on. The evaluators are asked to select the image that is more closely aligned to the narrative. Because at times neither image is a good match, evaluators can also select Neither.

4. Experimental Results

Using automatic evaluations and human judgments, we compare TReCS’s performance with existing text-to-image generation models. We evaluate all models on the COCO validation set of Localized Narratives (LN-COCO) and on a held out test set of Open Images data [21] that is covered by Localized Narratives (LN-OpenImages). The latter provides a stronger test of model generalization. We also perform several ablations and variations to better understand the impact of choices for each of TReCS’s stages.

4.1. Main Results

Many models have been proposed for text-to-image synthesis [16, 40, 22, 37]. We compare closely to AttnGAN [40], as we observed that the pretrained version produced better images for LN-COCO compared to others (e.g. ObjGAN [22], see Table 1). For fair comparison with TReCS, we fine-tuned AttnGAN on LN-COCO’s training set. Note, however, that AttnGAN uses only the narratives and not the traces—giving TReCS an advantage with respect to available inputs. Incorporating traces into end-to-end models like AttnGAN is non-trivial and worth exploring in future.

Image Quality Qualitatively, TReCS’s images are crisper and more realistic, as seen in cherry-picked (Fig. 8) and random (Fig. 9) examples. AttnGAN tends to produce textures and blobs that are semantically relevant (e.g. giraffe patterns) but do not represent clear objects. This is confirmed in side-by-side human evaluation of image quality (Fig. 6): for 77.0% of 1000 LN-COCO narratives, the TReCS image was preferred to the AttnGAN image. The same preference was found for the LN-OpenImages test set. We attribute the improvement in image quality to our staged
AttnGAN swap leadership on these measures: e.g., TReCS was selected 88.3% of the time on LN-COCO, compared to 11.7% for AttnGAN. On LN-OpenImages, TReCS was selected unanimously 84.1%, compared to 15.9% for AttnGAN.

Figure 7. Human evaluation of image-text alignment on LN-COCO validation and LN-OpenImages test sets. Models were fine-tuned on the LN-COCO training set. Of the decisions with 5/5 votes (indicating unanimous preference), TReCS was selected 71.0% of the time on LN-COCO, compared to 27.8% for AttnGAN. On LN-OpenImages, TReCS was selected unanimously 61.4%, compared to 37.9% for AttnGAN.

Table 1 shows IS and FID scores for both models on both datasets. Clearly, fine-tuning AttnGAN on LN-COCO makes a large improvement (59.4 FID → 51.8 FID), so all other AttnGAN results in this paper are for the fine-tuned version. On LN-OpenImages, TReCS and fine-tuned AttnGAN swap leadership on these measures: e.g., TReCS is 3.1 FID points better on LN-COCO and 5.3 FID points worse on LN-OpenImages. We find that these metrics provide valuable feedback while developing models, but stress that human evaluation provides the better measure of generated image quality. Note that it is possible to optimize for IS directly and create incomprehensible or adversarial images that nonetheless achieve IS as high as 900 [3].

**Image-Text Alignment** TReCS also outperforms AttnGAN on human evaluations of image-text alignment (see Fig. [7]). Of 1000 LN-COCO held out images, 52.4% were chosen by human raters as being better aligned to the given narrative, compared to 32.0% of AttnGAN images. We observe a similar trend on LN-OpenImages, with TReCS winning 45.8% of contests to AttnGAN’s 40.5%.

TReCS also has distinctly better performance when considering cases for which there is full agreement (i.e. decisions where 5/5 voters selected either model, or neither). For these images, TReCS is selected 71.0% of the time, as compared to 27.8% for AttnGAN (the remaining being Neither). Similarly, on LN-OpenImages, TReCS is selected unanimously 61.4% of the time, as compared to 37.9% for AttnGAN, indicating a clear preference for TReCS images when evaluating for text-alignment.

TReCS’s superior performance may be due to its ability to handle longer free form descriptions. Narratives are much longer (average of 41.8 words) than MS-COCO captions (average of 10.5 words). Also, the narratives are transcriptions of free-form speech and incorporate filler words used in everyday speech. This data presents a challenge for existing text-to-image synthesis models, which were originally created to handle concise and clean captions. By explicitly assigning image labels to words, performing cross-modal matching during mask retrieval, and composing foreground and background’s separately, TReCS captures the full range of described objects more effectively.

### 4.2. Ablations

**Sequence Labeling** Using HMM tags (Section 2.1), we fine-tuned an uncased BERT-Large model [8]. Weights are optimized using Adam [20] with a learning rate of 1e-5.
In this image a lady wearing green cap, blue jacket is skiing. She is holding two sticks. The ground is full of snow. In the background there are trees ... In this picture we can see a zebra on grass and eating grass and in the background we can see trees. This is a collage of two photos. Here we can see a woman playing in the ground and she is holding a racket with her hands. And there is a mesh. In this picture we can see a bus and a person in it. ... Some grass is seen on the ground. There are some cars and tree in the background. Here I can see sky. In this image I can see a dog is sitting in a vehicle. I can also see a tree and few plants in the background. Here I can see sky. Here we can see a giraffe in the middle and we can see grass present in baskets on the fencing, we can see plants and trees present there is it teddy bear with spectacles with sitting on a sofa with keyboard microphone and video game.

Figure 8. Original and generated images for cherry picked examples from LN-COCO.

| Sequence Labels | Generator | IS ↑ | FID ↓ |
|-----------------|-----------|------|------|
| BERT (raw labels) | CC-FPSE | 20.0 | 49.9 |
| HMM             | SPADE    | 20.2 | 50.6 |
| HMM             | CC-FPSE | 20.7 | 49.0 |
| BERT (HMM)      | SPADE    | 20.2 | 49.5 |
| BERT (HMM)      | CC-FPSE | 21.3 | 48.7 |

Table 2. Ablation experiments on the validation set of LN-COCO. ↑ (↓) indicates that a higher (lower) number equates better performance. BERT (raw labels) indicate a BERT model that was trained on raw segmentation labels, as compared to the HMM processed labels. A dual-encoder with $k=5$ is used for mask retrieval.

During training and inference, we set the class probabilities of the COCO-Stuff other and background tags to 0. This assists in downstream image generation, as we found that these classes were not meaningful when presented to the mask-to-image translation models.

Table 2 shows that training BERT on the output of the HMM (auto-supervision) improves image quality over training it on noisy labels (20.0/49.9 → 21.3/48.7) or using the output of the HMM itself (20.7/49.0 → 21.3/48.7). Note that the HMM tags exploit ground-truth image-level labels (and hence are not valid for testing). We observed from manually inspecting image outputs that auto-supervision improved both image quality and image-text alignment.

Mask Retrieval The retrieval model is strong (Table 3): given a query narrative, the groundtruth image is retrieved 53.8% of the time in the top 5 and 95.4% in the top 100, over 8573 images in LN-COCO’s validation set. Inspecting retrieved results (e.g. Fig. 10) indicates that this underestimates performance: many retrieved images are good matches, but these narrative-image connections are not in the paired data. Ilharco et al. (2020) [17] provide human evaluations that show retrieval performance is underestimated by the available data, and Parekh et al. (2020) [27] provide new annotations that partly address this gap.

Increasing $k$ (number of retrieved images) improves im-
A person wearing jacket, helmet is on a ski board holding ski sticks. There is snow. On the back there is a banner, stand, ropeway ...

Group of people standing and we can see kites in the air and sky with clouds. A far we can see trees. This is grass.

In this picture we can see one boy is holding a bat and playing a game, he is keeping a cap. soundings there is ...

In the picture there is a road on the road there are many vehicles there are many poles on the road there are many trees ...

The image is outside of the city. In the image in middle there are few bags, on right side we can see a person standing ...

In this image we can see three fire engines on the road. In the background there are trees, houses and sky.

In this image I can see few benches and the ground covered with the snow. In the background i can see few ...

In this image I can see the road ... In the back there are signal lights and the vehicles. I can see many trees, building ...

In this image I can see a cat on a vehicle.

This picture shows a man standing and skiing and we see blue cloudy sky and a tree and he wore a cap on his head

This woman wore yellow t-shirt, headband, holding bottle and standing beside this yellow hydrant. On this grass ...

This is the picture of a floor where we have some laptops, bags and an other back pack in which some things ...

Figure 9. Original and generated images for random examples from LN-COCO.
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Appendix

We provide additional implementation details, further results for randomly sampled LN-COCO and LN-OpenImages examples, and greater detail on our human evaluation procedure.

A. Implementation Details

A.1. BERT Sequence Tagger

The sequence tagger is implemented in TensorFlow \cite{1}. We fine-tuned the public pretrained uncased BERT-Large model \cite{35} to perform sequence tagging on our HMM tags. Weights were optimized using Adam \cite{20} with a learning rate of 1e-5. The model was trained with a batch size of 128 over 10 epochs, on a 2x2 TPU. During training, we set the class probabilities of the COCO-Stuff other and background tags to 0. This assists in downstream image generation, as we found that these classes were not meaningful when presented to the mask-to-image translation models, i.e. SPADE \cite{28} and CC-FPSE \cite{24}.

A.2. Mask Retrieval

For the text modality, we use the pretrained public uncased BERT-Base model \cite{35} to perform sequence tagging on our HMM tags. Weights were optimized using Adam \cite{20} with a learning rate of 1e-5. The model was trained with a batch size of 128 over 10 epochs, on a 2x2 TPU. During training, we set the class probabilities of the COCO-Stuff other and background tags to 0. This assists in downstream image generation, as we found that these classes were not meaningful when presented to the mask-to-image translation models, i.e. SPADE \cite{28} and CC-FPSE \cite{24}.

A.3. Mask-to-Image Translation

For SPADE \cite{28} and CC-FPSE \cite{24}, we used the official models released by the authors. All models are pretrained on COCO-Stuff \cite{5}.

A.4. Evaluation Metrics

We use a standard codebase \cite{4} to compute IS. Similarly, we compute FID scores using a popular PyTorch repository \cite{7}.

A.5. Dataset Details

We conduct all experiments on Localized Narratives \cite{29}. The LN-COCO training set contains 130,810 examples, and the validation set contains 8573 examples. In addition, we run evaluations on a held out test set of the Open Images subset of Localized Narratives (LN-OpenImages). For this, we sampled 10,000 random images for computing IS and FID.

B. Human Evaluation

We collected two human evaluation metrics for comparing image generation models: (1) realism of generated images, and (2) language alignment of generated images. We mostly compare our results with AttnGAN \cite{40}, and hence utilize a side-by-side comparison format to minimize bias and variance in collected ratings. Figure \cite{1} displays the user interface that is shown to the human evaluators. Each annotator is asked to answer the two questions displayed, selecting the image that is more realistic, and a better match to the caption. The presentation order of images are random to avoid bias (i.e. TRECS images appear as Image 1 50% of the time).

In addition, we observed in our experiments that a small proportion of images generated by both models are not well aligned with the provided captions. For example, a blank image might be generated by both TRECS and AttnGAN in certain cases. For these scenarios, evaluators may select a 3rd option that indicates that neither image is matched.

We collected five independent ratings for a randomly selected subset of 1000 LN-COCO validation examples and 1000 LN-OpenImages examples (sampled from the 10,000 LN-OpenImages test examples). We use majority voting over the five ratings as the final quality rating, but also display the full range of votes for each model in our results figures. The 1000 synthesized images (for both LN-COCO and LN-OpenImages) will be publicly released to facilitate reproducibility and comparison with other models.

Annotators were employed as contractors and were paid hourly wages that are competitive for their locale. They have standard rights as contractors. They are fluent non-native English speakers.
C. Qualitative Results

C.1. Randomly Sampled Images

Figure 12 and 13 show several randomly sampled images from LN-COCO and LN-OpenImages respectively. The outputs are consistent on these two subsets, indicating TReCS is able to generate plausible looking images for most provided narratives. While there is room for improvement, we observe that in most outputs, TReCS is able to generate relevant objects, despite occasional glitches.

We observe that some images are blank or with very few objects (e.g. the image in the first column and third row from the bottom in Figure 13). We believe it is due to the limitation of the candidates pool used in the mask retrieval module. If there are no relevant masks returned from the retrieval module, the system is unable to draw anything meaningful. This would likely be improved significantly by expanding the corpus of retrievable masks.

C.2. Effect of Captions on Generated Images

It is possible that one image in the Localized Narratives dataset can be annotated by multiple independent annotators, providing different captions for the same image. TReCS is able to read the differences from different captions and generate corresponding images, which emphasis the importance of language grounding and user attention in this text-to-image synthesis problem. For example, the image in the left column of Figure 14 depicts two black dogs playing with a frisbee. However, the first annotator doesn’t describe dog explicitly, and the resulting image is unable to depict the dogs. For the other images, the dogs are captured and well generated.

Similarly, we observe variations in the second column of Figure 14 with background scenes differing based on the provided description. In the first image, the annotator describes a mountain and a lake, which is depicted in the generated image. Additionally, we observe that the third annotator mistakenly described the giraffe as a zebra, resulting in the generated image depicting a zebra. This emphasizes the integrality of language grounding within the TReCS system.
| Caption | Original | AttnGAN | TRēCS | Caption | Original | AttnGAN | TRēCS |
|---------|----------|---------|-------|---------|----------|---------|-------|
| In this picture we can see a train in blue colour on a railway track. We can see two persons inside a train. This is a signal. These are boards ... | ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) | In this image i can see a few persons standing. On the table there is a system, bottle, speaker, mouse, cup and a tissue. At the back side the woman ... | ![Image](image4.png) | ![Image](image5.png) | ![Image](image6.png) |
| He is standing. He is wearing a cap, he is holding a bat. There is a toy on the left side. We can see in the background green color banner. | ![Image](image7.png) | ![Image](image8.png) | ![Image](image9.png) | This is picture of a place where we have some people sitting on the chairs in front of the table on which there are some things like laptop, bottles and ... | ![Image](image10.png) | ![Image](image11.png) | ![Image](image12.png) |
| In this picture there are trees in the right side. Towards the left there is a wooden tray, on the tray there are banana peels and some bird are on the tree. In the ... | ![Image](image13.png) | ![Image](image14.png) | ![Image](image15.png) | In this image, there are two persons standing and they are smiling, in the background there is a white color wall. | ![Image](image16.png) | ![Image](image17.png) | ![Image](image18.png) |
| In this image in the center there is one television and under the television there is a table on the table there is one remote, books and some objects and some wires ... | ![Image](image19.png) | ![Image](image20.png) | ![Image](image21.png) | This is a picture of a place where we have some people sitting on the chairs in front of the table on which there are some things like laptop, bottles and ... | ![Image](image22.png) | ![Image](image23.png) | ![Image](image24.png) |
| In this image in the center there is one person who is holding a racket and he is playing tennis, and on the background there is a board and on the left side there ... | ![Image](image25.png) | ![Image](image26.png) | ![Image](image27.png) | This is the picture outside of the building. At the right side of the image there is a clock on the pole. At the back there are ... | ![Image](image28.png) | ![Image](image29.png) | ![Image](image30.png) |
| In this picture we can see a glass with drink in it, and the glass is on the table. | ![Image](image31.png) | ![Image](image32.png) | ![Image](image33.png) | A picture inside of a hall. This is window with curtain. On floor there is a couch. Pictures on green wall. This is lamp ... | ![Image](image34.png) | ![Image](image35.png) | ![Image](image36.png) |
| In this image, in the middle there is a table, on that table there are some plates which are in white color, there are some glasses, there are ... | ![Image](image37.png) | ![Image](image38.png) | ![Image](image39.png) | In this image there is a bench on stone slab. Bottom of image is a grassy land. Background of image there are few plants. | ![Image](image40.png) | ![Image](image41.png) | ![Image](image42.png) |
| Here in the front we can see boats travelling in the river and beside that we can see a train travelling on a track and we can see plants and trees present ... | ![Image](image43.png) | ![Image](image44.png) | ![Image](image45.png) | In this image there is a person standing with the snow skating sticks in a snow mountain and at the back ground there are plants ... | ![Image](image46.png) | ![Image](image47.png) | ![Image](image48.png) |
| This image is clicked in a open lad. To the left there is a recliner chair. On it there is a teddy bear, clothes and beside it there are many toys. To the teddy ... | ![Image](image49.png) | ![Image](image50.png) | ![Image](image51.png) | This is the picture might be taken on sea shore. In the image in middle there is a person and we can also see another person ... | ![Image](image52.png) | ![Image](image53.png) | ![Image](image54.png) |
| This picture shows a stop sign board on the road and we say few paper stucked on it and we see a brick wall on the side | ![Image](image55.png) | ![Image](image56.png) | ![Image](image57.png) | This is a picture taken in the outdoors. There are two persons skating in snow. In front of the people there are trees and ... | ![Image](image58.png) | ![Image](image59.png) | ![Image](image60.png) |

Figure 12. Randomly sampled TRēCS images from LN-COCO.
| Caption | Original | AttnGAN | TRECS | Caption | Original | AttnGAN | TRECS |
|---------|---------|---------|-------|---------|---------|---------|-------|
| In this image we can see a house, a fence, there are plants, trees, there is a vehicle, a board with text on it, also we can see the cloudy sky. | ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) | This is an inner view of a building containing a roof, fence and windows. We can also see some painting on the walls and pillars, decors and ... | ![Image](image4.png) | ![Image](image5.png) | ![Image](image6.png) |
| In this picture there is a dog in the center of the image and there is a door in the background area of the image. As we can see in the image there is a white color wall, rack, lights, baskets, table, sofa, pillows and on table there are photo frames ... | ![Image](image7.png) | ![Image](image8.png) | ![Image](image9.png) | The picture is taken in a court. In the foreground of the picture there is a girl and a woman playing with ball ... | ![Image](image10.png) | ![Image](image11.png) | ![Image](image12.png) |
| In this image I can see the depiction picture of a man. I can also see he is sitting. I can see he is wearing a blazer, a shirt ... | ![Image](image13.png) | ![Image](image14.png) | ![Image](image15.png) | In this image there is the sky towards the top of the image, there are trees, there is a building, there is text on the building ... | ![Image](image16.png) | ![Image](image17.png) | ![Image](image18.png) |
| In this image I can see a dog is eating food. This is wooden floor. Background it is blur. | ![Image](image19.png) | ![Image](image20.png) | ![Image](image21.png) | In this image there is the lake beside that there are so many trees. | ![Image](image22.png) | ![Image](image23.png) | ![Image](image24.png) |
| The person wearing black dress is standing on a bicycle and holding a water bottle in his hand and there are few people ... | ![Image](image25.png) | ![Image](image26.png) | ![Image](image27.png) | In this image I can see the person and the person is wearing black color dress and I can see the gray color background. | ![Image](image28.png) | ![Image](image29.png) | ![Image](image30.png) |
| In this image, there are group of people standing, walking and sitting on the bench in front of the table. And on the table ... | ![Image](image31.png) | ![Image](image32.png) | ![Image](image33.png) | In this image there are two women’s are doing ramp walk on the stage. The right side women is holding a handbag and ... | ![Image](image34.png) | ![Image](image35.png) | ![Image](image36.png) |
| In this image there is an art of two broken coins and there is a text. | ![Image](image37.png) | ![Image](image38.png) | ![Image](image39.png) | This is a inside view of a building, where there are lights, CC camera, iron grills, door, staircase, name board hanging ... | ![Image](image40.png) | ![Image](image41.png) | ![Image](image42.png) |
| In this image I can see a person standing with open hands at a hill station. I can see buildings and at the top of the image ... | ![Image](image43.png) | ![Image](image44.png) | ![Image](image45.png) | This seems like panorama shot of a building, where we can see grill on the both the sides and a green wall with text on it. | ![Image](image46.png) | ![Image](image47.png) | ![Image](image48.png) |
| In the center of the image there is a woman standing and holding object. In the background we can see decors, cupboards, table. | ![Image](image49.png) | ![Image](image50.png) | ![Image](image51.png) | In this image we can see a few houses, there are some trees, plants, windows and a pole, also we can see some vehicles on the ... | ![Image](image52.png) | ![Image](image53.png) | ![Image](image54.png) |

Figure 13. Randomly sampled TRECS images from LN-OpenImages.
These are the two black are playing with a red color plate and It’s a grass at here this is the green color iron fencing and at the top there are green trees.

In the picture we can see two dogs which are black in color, they are walking on the grass, in the background we can see a railing with green color and trees behind it.

Here there are two dogs playing with the toy and here there is grass present in the ground, in the back there are green color trees and here there is iron fencing.

On the ground there is a green grass and two dogs are running. And in the front there is a dog with blue band. Behind the dog there is another dog holding a red color plate in his hand ...

In this image there are 2 dogs running by holding a flying disk in a garden, and in back ground there are iron grills, trees, grass.

In this picture we can see a giraffe standing and in the background we can see a mountain with grass, trees and there is a lake

In this picture we can see a giraffe standing on a ground with small plants, stones on it and aside to this we have a water, hills with trees.

In this picture we have a zebra standing on the grass there are some trees.

There is a giraffe in the middle of the image, on the grass of the land. In front of it, there are plants and grass. In the background, there is water pond, trees, plants and grass on the hill, and ...

There is a giraffe standing and there are trees and water behind it.

Figure 14. TReCS images based off different descriptions of the same image from LN-COCO. Descriptions are shown verbatim.