LUCSS: Language-based User-customized Colorization of Scene Sketches

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Fig. 1. We present LUCSS, a language-based interactive colorization system for scene sketches. It takes advantage of both instance level segmentation and language models in a unified generative adversarial network, allowing users to accomplish different colorization goals in a form of language instructions. Left: input scene sketch and its content description automatically generated by LUCSS. Three right columns show the colorization results generated by LUCSS following three different instructions at the bottom. Texts underlined are user-specified, with the target colors highlighted in bold.

Abstract. We introduce LUCSS, a language-based system for interactive colorization of scene sketches, based on their semantic understanding. LUCSS is built upon deep neural networks trained via a large-scale repository of scene sketches and cartoon-style color images with text descriptions. It consists of three sequential modules. First, given a scene sketch, the segmentation module automatically partitions an input sketch into individual object instances. Next, the captioning module generates the text description with spatial relationships based on the instance-level segmentation results. Finally, the interactive colorization module allows users to edit the caption and produce colored images based on the altered caption. Our experiments show the effectiveness of our approach and the desirability of its components to alternative choices.

ACM Reference Format:
Changqing Zou, Haoran Mo, Ruofei Du, Xing Wu, Chengying Gao, and Hongbo Fu. 2018. LUCSS: Language-based User-customized Colorization of Scene Sketches. 1, 1 (September 2018), 14 pages. https://doi.org/10.1145/nnnnnnn.nnnnnn

1 INTRODUCTION

Sketching is one of the most efficient and compelling ways to communicate complex ideas among humans. While abstract sketches can be easily understood by us, teaching machines to understand the underlying semantics of sketches remains a challenging task. Recent research has achieved semantic understanding for individually-sketched objects and fostered applications such as sketch-based shape retrieval [Wang et al. 2015] and sketch classification [Eitz et al. 2012a].

Nevertheless, instance-level understanding, as often used in scene sketches, has not received much attention. Scene sketches usually contain multiple sketched objects, depict scenes of real or imaginary worlds, and widely appear in various scenarios, such as story books, sketch movies, and Computer-Aided Design (CAD) software. In this paper, we investigate the instance-level segmentation and interpretation of scene sketches. Our work can benefit a number of applications such as sketch-based co-retrieval [Xu et al. 2013] and context-based sketch classification [Zhang et al. 2018], which
currently take as input manual segmentation of individual scene objects.

With recent advances of deep neural networks and the availability of large-scale datasets such as MS COCO [Lin et al. 2014] and ImageNet [Deng et al. 2009], machines have outperformed humans in various image understanding tasks for natural images, such as image classification, face recognition, and image generation. Nevertheless, the power of deep networks for scene sketches is still unexplored, and the applications based on scene sketch understanding have rarely been investigated.

To address these problems, in [Zou et al. 2018], we have built a large-scale scene sketch dataset, called SketchyScene, and conducted initial studies on category-level semantic segmentation of scene sketches. In this paper, we investigate two research goals: 1) the capability of deep neural networks for scene sketch understanding, and 2) the potential applications based upon *instance-level* understanding.

To achieve these two goals in a unified framework, we present LUCSS, a language-based interactive colorization system, which consists of three interrelated modules: instance segmentation, captioning, and colorization. The instance segmentation module addresses how to employ deep networks for segmenting an input scene sketch into object instances. The colorization module can be considered as an application which produces a colorized image conforming to user-specified color requirements for segmented objects. Serving as a link between the segmentation and colorization modules, the captioning module takes the output of the segmentation module as input, and automatically generates a caption describing the input scene sketch. Motivated by the recent success of intelligent personal assistants such as Apple Siri and Amazon Alexa, which are enabled by speech recognition and natural language processing, we present a language-based approach that enables users to embed customized colors into the text description, instead of drawing color strokes on the sketch to specify the colors. Our approach is more compatible with voice commands for future multimodal colorization systems that can further enhance the user experience.

In this paper, we mainly address two challenging research problems. First, how shall we achieve precise instance-level segmentation? High-quality segmentation results are crucial to the subsequent colorization process, since users might specify different colors for individual objects. Unlike natural images, an input scene sketch consists of merely black lines and white background. Inferring instance segmentation of a sketched scene is thus challenging due to the sparsity of the visual features (for example, the foreground pixels only occupy 13% of all the pixels in SketchyScene [Zou et al. 2018]). Employing the state-of-the-art segmentation methods designed for natural images (e.g., [He et al. 2017]) directly on sketches does not provide promising results, as shown in Section 6. To address this problem, we enhance powerful segmentation models designed for natural image segmentation with the unique characteristics of scene sketches.

Second, how shall we colorize a high-resolution scene sketch with respect to language-based color inputs? Although the colorization of a single sketched object has been extensively investigated, the colorization of scene sketches with customized color labels remains an open problem. This challenge requires our system to build accurate correspondences between the object instances (parts of object instances) and text-based color specifications. Additionally, it requires the system to infer both object-level and object-part-level segmentation. For example, a user may assign different colorization goals to the window of the car as in shown in Figure 1. To tackle this problem, we present a novel architecture which embeds LSTM (Long Short-Term Memory) to a sophisticated Generative Adversarial Network (GAN).

Furthermore, generating high-quality and high-resolution colorization results (768 × 768) is not a trivial task. We address this issue by using a two-stage pipeline consisting of object colorization and background colorization. Our experimental results (Section 7 and the supplementary materials) show that the LUCSS colorization framework achieves visually pleasing results.

We highlight the major contributions of LUCSS as follows:

1. The first language-based, user-customizable colorization framework for scene sketches.
2. The first solution for instance-level segmentation of scene sketches.
3. A colorization dataset of scene sketches with text description and instance-level segmentation.

2 RELATED WORK

Our work is inspired by and build upon previous work in image segmentation, colorization, captioning, and generation with convolutional neural networks (CNNs) and conditional generative adversarial networks (cGANs).

2.1 Image Segmentation

In recent years, CNNs have been proven to yield the state-of-the-art accuracy in semantic object segmentation [Chen et al. 2017a, 2016; Shelhamer et al. 2016; Zhao et al. 2016]. The success of these methods is driven by large-scale, manually-annotated datasets, such as ImageNet [Deng et al. 2009] and MS COCO [Lin et al. 2014], which consist of millions of photographs with segmented objects. These methods often jointly predict a segmentation mask and an objectness score based on some appearance features that are specific to an individual class. Instance segmentation has become more common after the introduction of the R-CNN pipeline using category-independent region proposals [Hariharan et al. 2014]. Recently, a few methods have shown promise in the task of end-to-end trained instance segmentation [Girshick 2015; He et al. 2017; Ren et al. 2015a]. These approaches perform local and spatially-varying “objectness” estimates, with a simple global aggregation step in the end.

In our prior work [Zou et al. 2018], we conducted a pilot study on category-level semantic segmentation of scene sketches. In this paper, we investigate the problem of instance-level segmentation in scene sketches. Existing solutions for instance segmentation of natural images (e.g., [He et al. 2017]) cannot produce satisfactory results for scene sketches because they do not consider the unique characteristics of scene sketches. Please refer to Section 4 for further discussion.

2.2 Sketch Understanding

Sketch recognition is perhaps the most popular problem in sketch understanding. Since the debut of TU-Berlin dataset [Eitz et al.
many approaches have been proposed and the state-of-the-art approaches have even outperformed human beings in terms of the recognition accuracy [Yu et al. 2017]. Prior algorithms can be roughly classified into two categories: 1) those using hand-crafted features [Eitz et al. 2012b; Schneider and Tuytelaars 2014], and 2) those learning deep feature representations [Ha and Eck 2017; Yu et al. 2017]. The latter generally outperform the former by a clear margin.

Another stream of work has delved into parsing sketched objects into their semantic parts. Sun et al. [2012a] proposed an entropy descent stroke merging algorithm for both part-level and object-level sketch segmentation. Huang et al. [2014] leveraged a repository of 3D template models composed of semantically segmented and labeled components to derive part-level structures. Schneider and Tuytelaars [2016] performed sketch segmentation by looking at salient geometrical features (such as T-junctions and X-junctions) via a Conditional Random Field (CRF) framework. Instead of studying single object recognition or part-level sketch segmentation, we conduct an exploratory study for scene-level parsing of sketches, by using the large-scale scene sketch dataset SketchyScene [Zou et al. 2018].

2.3 Image Captioning
With the recent advances in deep neural networks and language learning models, a number of impressive algorithms for image captioning have been developed [Chen and Zitnick 2014; Donahue et al. 2014; Mao et al. 2015; Vinyals et al. 2016; Xu et al. 2015; Zhou et al. 2016]. We direct readers to a recent survey [Bernardi et al. 2016], which summarizes related datasets and an evaluation of various models. More recently, attention mechanisms have been applied to the network for narrowing down subjects and thus improving captioning results [Anderson et al. 2018; Das et al. 2017; Xu et al. 2015]. These modern image captioning models generally consist of two parts: an image encoder and a language model. The image encoder encodes a raw image into a feature map using a CNN, while the language model generates text sequentially with the extracted feature map and the inherited probabilistic dependency. In contrast to prior works which aim to generate human-like extractive captions, our captioning module directly produces a lower-level detailed description, which covers the entire scene sketch based on the results of instance segmentation. We use this instance-segmentation-based captioning module for user input assistance.

2.4 Scene Sketch Based Applications
While there is little work on semantic segmentation of scene sketches, some interesting applications have been proposed to utilize scenes with pre-tagged or pre-segmented sketched objects as input. For example, Sketch2Photo [Chen et al. 2009] combines sketching and photo montage for realistic image synthesis. Sketch2Cartoon [Wang et al. 2011] is a similar system which focuses on cartoon images. Similarly, Xu et al. [2013] propose Sketch2Scene, an automatic system which generates 3D scenes by co-retrieving and co-locating 3D shapes with respect to a scene of pre-segmented sketched objects. Sketch2Tag [Sun et al. 2012b] is a sketch-based image retrieval (SBIR) system, where scene items are automatically recognized and used as a text query to improve the retrieval performance. Our work provides automatic instance segmentation algorithms for scene sketches, and can immediately benefit the above applications.

2.5 Image Colorization
Image colorization assigns a three-dimensional label (RGB) to each pixel from an input gray-scale or sketch image. Early studies of colorization methods are mainly based on user interaction [Huang et al. 2005; Qu et al. 2006a; Yatziv and Sapiro 2006] or similar examples [Charpiat et al. 2008; Welsh et al. 2002] from gray-scale photographs. To achieve user-customized colorization, interactive strokes [Huang et al. 2005; Levin et al. 2004] are widely used to provide local guidance based on local intensity differences and spatial offsets [Luan et al. 2007; Qu et al. 2006b]. Further approaches using local guidance devise better similarity metrics by employing long range connections [An and Pellacini 2010; Xu et al. 2009] and local linear embeddings [Chen et al. 2005] to minimize user efforts. In addition to local guidance, non-local mean-based patch weight [Yao et al. 2010] and color palette [Chang et al. 2015] have also been proposed to provide global guidance.

Recent colorization systems [Cheng et al. 2015; Deshpande et al. 2015; Iizuka et al. 2016; Larsson et al. 2016; Yan et al. 2016], take advantage of deep CNNs and large-scale datasets to automatically produce plausible color images from gray-scale inputs. Adapting these models to scene sketches is a challenge since scene sketches are sparser than gray-scale images. Another line of research focuses on sketch colorization which generates color images from black-and-white sketches [Günlük et al. 2016; Liu et al. 2017b; Sangkloy et al. 2017a; Xian et al. 2017]. However, most of the prior sketch colorization approaches target object-level sketches, while our work is a scene-level sketch colorization method.

Sangkloy et al. [2017b] has developed a system to translate sketches to real images, with colorization goals assigned by user color strokes. This system can well convey the user’s colorization goals to image regions but its extensibility may be limited. PaintsChainer [Yonetosuji 2017] and Frans et al. [2017] have developed open-source interactive online applications for line-drawing colorization. Concurrently, Chen et al. [2017b] proposed a language-based colorization method for object-level sketches or gray-scale images. Our system is close to [Chen et al. 2017b] but we focus on scene-level sketch colorization.

2.6 Image Generation with GANs
Several recent studies, such as DCGAN [Radford et al. 2015], Pix2Pix [Isola et al. 2017], WGAN [Arjovsky et al. 2017], and SketchyGAN [Chen and Hays 2018], have demonstrated the value of variant GANs for image generation. The variations of conditional GANs have been further applied to text-to-image synthesis [Hong et al. 2018; Reed et al. 2016; Zhang et al. 2017], image inpainting [Pathak et al. 2016; van den Oord et al. 2016; Yeh et al. 2016], and image super-resolution [Ledig et al. 2017; Sønderby et al. 2016]. Nonetheless, all the aforementioned generators are conditioned solely on text or images. In contrast, LUCSS takes both image and text as input, presenting an additional challenge of fusing the features of a scene-level image and the corresponding text description.

Vol. 1, No. 1, Article Publication date: September 2018.
3 SYSTEM OVERVIEW

As illustrated in Figure 2, our system processes an input sketch through multiple stages. It first performs instance segmentation to recognize and locate individual objects in the scene sketch, and then automatically produces the caption describing lower-level detailed information of the sketch (e.g., object category, object position, quantity) with a template-based algorithm. Next, the user can specify colorization goals by changing the automatically-generated caption. Finally, the system colorizes the whole sketch into a color image, where each segmented instance meets the user’s requirements via a novel cGAN based model.

The system contains three sequential modules. The first one is an instance segmentation deep network. It takes as input a scene sketch image, and outputs the class labels and the instance identity label for each pixel belonging to the objects in the scene. In this module, we adapt the state-of-the-art segmentation models (including Deeplab V2 and Mask-RCNN) to the sketch data via analyzing the characteristics of the sketch data. The segmentation accuracy is significantly improved compared to the original models.

The second module is a language template-based caption generator. Taking the segmentation results as input, it analyzes the geometric relationships between object instances (e.g., position and occlusion relationships) and generates object-level scene descriptions. Figure 1 shows a typical result of this module. Besides captioning, this module provides a friendly interface for the user to assign different editing goals for individual object instances. This module can facilitate the system to build the exact correspondence between object instances in the scene and their corresponding sentences (since the caption is generated by the system from the segment instances, correspondences can be easily obtained by comparing the user-modified caption with the original one). In contrast to recent research [Chen et al. 2017b], which implicitly infers the correspondence between object parts and sentences using an attention mechanism, we leverage the captioning module to achieve more accurate correspondence, especially for complex scenes. As shown in the experiment of Section 7.1, implicit inference usually fails on a long caption with more than six sentences, but our approach has no such constraint. Hence it provides a better assurance that results will achieve user specifications.

The last module is a typical application based on the instance segmentation results. In this work we focus on the colorization task. Unlike recent research which aims to colorize single objects or relatively simple scenes [Chen et al. 2017b; Liu et al. 2017c; Varga et al. 2017], our work aims to solve a complex scene sketch colorization problem with the help of language-based user instruction. Our experiment in Section 5 found that even the most best model to date [Chen et al. 2017b] is unable to successfully colorize each individual object instance to exactly meet the user’s needs. The main reason is that a user’s language instructions usually have ambiguity, especially when the target scene is complex (e.g., there are multiple object instances belonging to the same category in a scene). Our solution is to decompose the colorization of the whole scene sketch into two sequential steps: instance colorization and background colorization. In instance colorization, each object instance is colorized. While in background colorization, the remaining regions which do not belong to any object instance are colored. This divide-and-conquer strategy leverages the natural advantages of the segmentation approach, making the colorization of a complex scene sketch resolvable.

Dataset. We use SketchyScene as the basic dataset to study the segmentation and colorization problem. SketchyScene contains 7,264 scene templates, each scene template corresponding to a color reference image. Moreover, SketchyScene provides the ground-truth for both semantic segmentation and instance segmentation of 7,264 scene sketches. Figure 3 shows a typical example of a scene sketch in SketchyScene. See the supplementary material for more details of SketchyScene.

4 SEGMENTATION AND CAPTIONING

4.1 Instance Segmentation

Formulation. Instance segmentation segments individual object instances, possibly of the same object class in a scene sketch. This is challenging, especially when the instances of the same class have occlusions, e.g., two trees growing together, as shown in Figure 3. Apart from using pixel-level class labels as supervision, spatial information like object bounding box is necessary. Generally, in an instance-level segmentation task, each unknown instance \( i \) in the input image can be denoted as a tuple \( [B, L, M] \). Here, \( M \) is a binary mask covering the instance, \( L \) is a class label, and \( B \) is the 4-D vector encoding the position and size of the bounding box in the format of \( [x, y, H, W] \), where \( [x, y] \) indicates the top-left corner and \( H \) and \( W \)
represent the height and width, respectively. Our goal of instance segmentation is to assign pixels of a scene sketch image to a specific instance mask $M$ located in an inferred $B$.

Unlike natural images, a sketch only consists of black lines and a white background. Given that only black pixels convey semantic information, our problem for instance segmentation of a scene sketch is defined as predicting $[B, L, M]$ for each black pixel. Taking the rightmost image of Figure 3 as an example, when segmenting trees, duck, house and cloud, every black pixel should be assigned to a specific instance mask $M$ with a class label $L$, located in $B$, while the remaining white pixels are treated as background.

**Challenges.** Segmenting a sketchy scene is challenging mainly due to the sparsity of visual features. First, a scene sketch image is dominated by white pixels. For the 7,264 examples of SketchyScene, the average background ratio is 87.83%. The remaining pixels belong to foreground classes. The classes, as measured by their sketch pixels, are thus quite unbalanced. Second, segmenting occluded objects in sketches is much harder than in natural images, where an object instance often contains uniform colors or texture so that context information can help in segmentation. Unfortunately, such cues do not exist in a scene sketch.

The sparsity of visual features causes the instance segmentation models, designed for natural images, perform poorly on scene sketches. In an initial experiment, we found that the segmentation results are unsatisfactory even with the state-of-the-art model Mask-RCNN [He et al. 2017] (see a representative result in Fig. 4 (3)). Although Mask-RCNN can successfully detect the bounding boxes of object instances in a scene sketch, the binary masks often fall out of the black lines.

**Methodology.** Our initial study in [Zou et al. 2018] has reported a significant finding on a semantic segmentation task. That is, the challenge for sketch scene segmentation is mainly caused by the large area of background. In a model tailored to this property the background pixels should not contribute to the loss during training. During the inference, background pixels are assigned to an arbitrary class label, and are filtered out by the drawing mask of the input sketch for the final output. Using this strategy, the adapted DeepLab-v2 model [Zou et al. 2018] can improve the semantic segmentation MIoU (Mean Intersection over Union) by more than 10%. On the test examples, this model achieved the best performance (63.1% on MIoU) over DeepLab-V3 models [Chen et al. 2017a], SegNet [Badrinarayanan et al. 2017], and FCN-based [Long et al. 2015] model.
Afterwards, we sequentially describe the objects from \([W, E, O]\). For objects from \(W\), the algorithm generates a general weather description according to object labels, e.g., “it is a sunny day”. For objects from \(E\), it produces the sentences which describe the information of class labels and absolute locations. A typical description is “There is a house in the center of the image”. For objects from \(O\), it produces the description of the formation of class labels and relative locations. A typical description is “A person is in front of the house”.

Algorithm 1: Sketch Captioning

| Input: pred_boxes \(B\), pred_class_labels \(L\), pred_class_masks \(M\),             |
| Output: caption \(T\) |
| 1 items ← Node \((B, L, M)\) |
| 2 for item ∈ items do |
| 3 \[ \text{if} \ item \in W \text{then} \]
| 4 \( T_{\text{Weather}} \leftarrow \text{Weather}(\text{item}) \) |
| 5 \[ \text{if} \ item \in E \text{then} \]
| 6 \( T_{\text{Environment}} \leftarrow \text{Environment}(\text{item}) \) |
| 7 \[ \text{if} \ item \in O \text{then} \]
| 8 \( T_{\text{Object}} \leftarrow \text{Object}(\text{item}) \) |
| 9 \( T \leftarrow T_{\text{Weather}} \cdot T_{\text{Environment}} \cdot T_{\text{Object}} \) |
| 10 return \( T \) |

The captioning module is applied to a human-machine interface as shown in the supplementary video. It is used to visualize the correspondence between an object in the input sketch and the corresponding sentence in the caption. Apart from captioning itself, there are two additional functions: 1) visualize if the sketch parsing results are accurate or not, and 2) visualize if the colorization goal is assigned to a desired object.

5 COLORIZATION

The colorization process contains two sequential steps: object instance colorization and background colorization. The object instance colorization step assigns target colors to the pixels belonging to segmented object instances, including their blanket inner regions. Background colorization assigns colors to the remaining pixels.

5.1 Object Instance Colorization

Overview. The proposed framework for object instance colorization as shown in Figure 6 is a conditional GAN model consisting of a generator \(G\) and a discriminator \(D\). \(G\) takes as input an object sketch image \(I\) and its corresponding language description \(S = \{w_1, w_2, \ldots, w_t\}\), where \(w_i\) are individual words in the sentence, and generates a color image. Compared with the generators in existing literature [Chen and Hays 2018; Isola et al. 2017], which learn mappings from an input sketch or image to an output image, our generator \(G\) models the interaction among the text description, visual information, and spatial relationships, and finally fuses the multi-modal features together. The generation of the color images is controlled by the text information. The discriminator, which is the opponent of the generator, is fed with both the generated images and the real color images at the same time, and serves the function of judging whether an image looks real or not.

Generator. The basic architecture of the generator is an encoder-decoder structure built on MRU blocks [Chen and Hays 2018]. It
consists of three modules: an image encoder which encodes the features of the $H \times W$ input sketch (segmented object sketch), a fusion module which fuses the text information into the image feature map generated by image encoder, and finally an image decoder which takes the fusion map produced by the fusion module and produces an $H \times W \times C$ map, where $C$ is the number of color channels. The MRU block is first proposed in [Chen and Hays 2018], which uses a learned mask to selectively extract features from the input images. Its cascaded structure of MRU blocks allows the ConvNet to repeatedly and progressively retrieve the information from the input image on the computation path. In this work, we use MRU blocks in both the encoder and decoder. In our implementation, we use five cascaded MRUs to encode the $H \times W$ input sketch image into an $H' \times W'$ feature map ($H' = \frac{H}{4}, W' = \frac{W}{4}$) for the encoder. For the decoder, five symmetric MRUs are cascaded as a multi-layer de-convolutional network. Skip-connections are applied between the encoder and the decoder, concatenating the output feature maps from the encoder blocks to the output of the corresponding decoder blocks.

The fusion module fuses the text information in $S$ into the $H' \times W'$ image feature map, and outputs an $H' \times W'$ fusion feature map. It is a core module of the generator and inserted into the bottleneck phase of the generator. The basic architecture of our fusion module is a convolutional multimodal LSTM, called recurrent multimodal interaction (RMI) model which was used to fuse the information of image referring expressions to segment out a referred region of the image [Liu et al. 2017a]. The typical characteristic of an RMI model is that the language model can access the image from the beginning of the language expression, allowing the modeling of the multimodal interaction. Our work uses RMI to mimic the human image colorization process. For each region in the input sketch, the fusion module reads the language feature map repeatedly until sufficient information is collected to colorize the target region image.

A concurrent system [Chen et al. 2017b] called LBIIE (Language-Based Image Editing) has used a similar model to segment and colorize object parts of interest in an image conditioned by language descriptions. We have implemented the fusion module for our generator with both RMI and LBIIE. We present the comparison results in the experimental section.

**Discriminator.** The discriminator $D$ takes in a generated image and outputs the probability of the image being realistic. The structure of the discriminator follows SketchyGAN [Chen and Hays 2018] which uses four cascaded MRUs. It takes four types of scales of the real and generated images.

**Loss and training.** We use a hybrid loss following SketchyGAN [Chen and Hays 2018] which includes a GAN loss and an auxiliary classification loss in the Discriminator, a GAN loss, an auxiliary classification loss, an L1 loss, a perceptual loss, and a diversity loss in the Generator. The auxiliary classification loss can improve the ability of both the Discriminator and the Generator, and further enhances the quality of the synthesized images. The L1 distance loss is for comparison between the synthesized image and the ground-truth cartoon image. The perceptual loss and diversity loss are for generating diverse results.

5.2 Background Colorization

The background colorization network takes as input the result of object instance colorization, and infers the colors of the background regions to produce the final colorful image. The network architecture still employs a cGAN structure similar to that used for object instance colorization, with some modification as detailed below.

**Generator.** The architecture of the generator is similar to that shown in Figure 6. We replace MRU blocks with residual blocks [He et al. 2016]. Both the encoder and decoder use five cascaded residual blocks. The residual unit numbers of the five residual blocks for the encoder are {1, 3, 4, 6, 3} (1, 3, 4, 3, 1) for the decoder). We make this change because an MRU block, which uses a binary mask to selectively extract features from a sketch, is more suitable for sketch images than color images. Our initial experiments confirm this speculation. The colorized backgrounds produced by the generator shown in Figure 6 (i.e., the generator used for object instance) usually have sharp region boundaries, leading to relatively poor visual effects (also see the results shown in the second column from right of Figure 15). Apart from the use of residual blocks, we have also conducted some experiments with the network replacing MRU blocks with the encoder blocks in [Isola et al. 2017].

**Discriminator.** For the discriminator, we use the architecture shown in Figure 7. It is a combination of the RMI model and five cascaded encode blocks used in pix2pix [Isola et al. 2017]. Unlike the generator, each of the five cascaded encoder blocks contains a single layer, which decreases the complexity of the entire cGAN. In addition, the input text information is also fused into the image feature by the RMI model. The joint modeling of the text and image helps the discriminator make a judgment monitored by the text information. Our experimental results (shown in supplementary materials) show that the joint modeling improves the capability of the whole network. Note that we do not use the RMI model to fuse the text information for the discriminator of object instance colorization. We simplify the discriminator because the discriminator with the fusion module does not improve the colorization significantly on single object sketches with lower resolution (192 × 192) in our initial experiments.

**Loss and training.** As for the loss and training, we follow the scheme of Pixel2Pix [Isola et al. 2017]. We only use a conditional GAN loss as well as a L1 distance loss. The diversity loss is not used here as we do object colorization, because we expect to suppress the diversity of the generated background.

6 SEGMENTATION EVALUATION

We conducted our experiments for segmentation on SketchyScene. The entire dataset, including 7,264 unique scene sketch templates, was randomly split into training (5,616), validation (355), and test (1,113) datasets.

**Segmentation models.** We compared four types of frameworks: Mask-RCNN (Model-1), Mask-RCNN + w/o BG (Model-2), Mask-RCNN + edgeList (Model-3), and Mask-RCNN + adapted DeepLabv2 + edgeList (Model-4). These four frameworks are abbreviated as Model-1 to Model-4 below. Model-1 is extended from Faster-RCNN [Ren et al. 2015b] by adding a parallel object mask prediction branch and is one of the most advanced methods proposed for instance segmentation on natural images. Model-2 is an adapted
We compared LUCSS to LBIE [Chen et al. 2017b] for scene sketch colorization, since to the best of our knowledge, LBIE is the only existing colorization work with the same goals as ours, i.e., taking a commented sketch as input, and outputting a color image. In general, the architecture of LBIE is similar to the RMI based architecture used for object colorization of LUCSS. Both of these two architectures are able to colorize an entire input sketch in a single step by implicitly inferring the correspondence between language descriptions and objects (or object parts). We therefore also include the RMI based architecture shown in Figure 6, which takes as input a scene sketch and a description of scene-level colorization requirement, and generates a color image in a single step instead of two steps used by LUCSS, as another baseline method. In the following paragraphs of this section, these three comparison approaches are called LUCSS, LBIE, and sRMI for short.

### 7.1 Data Collection

**Data collection for LUCSS: object colorization.** We collected three modalities of data to train the models of object colorization: color object instance, edge map, and text description (caption). We extracted color object instances and their edge maps from the 5,800 reference cartoon style images of SketchyScene. Figure 9 illustrates how the training data was prepared. We first leveraged Mask-RCNN trained on MS COCO to detect color object instances and then cut them out of the reference images. For each instance, we fused the extracted color object instances and their edge maps from the reference cartoon style images and the corresponding object sketch. In total we collected...
3,739 sets of object examples, each set consisting of a caption authored by crowd workers, a 192 × 192 color image, and a 192 × 192 edge map. The captions covered object instances from 20 categories, namely, moon, sun, cloud, house, bench, road, bus, car, bird, people, butterfly, cat, chicken, cow, dog, duck, sheep, tree, rabbit, and pig, which describes object instances in 15 different colors. The number of colors varies from one to three for each individual object instance (e.g., there are two colors for a red bus with gray windows). We further split the 3,739 sets of examples into two parts: 2,814 sets of examples used for training data, 357 sets for validation, and 568 sets for test.

![Image](image.png)

**Fig. 9.** Illustration of training data collection for object instance colorization. Top row: a reference image from SketchyScene (left); filter response of Hed [Xie and Tu 2015] and X-DoG [Winnemöller 2011] (middle); cut-out color object instances (right). Bottom row: user-written descriptions of the representative color object instances.

**Data collection for LUCSS: background colorization.** For background colorization, we used the following three modalities of training data: cartoon style color images, their captions, and color foreground object instances with blank background (See the left-most image of Figure 14 for an illustration). We used two types of strategies to extract the training data from the reference images of SketchyScene. The first one cut out objects from the reference images with mask-RCNN, and changed the color of all the pixels outside of the objects white. This strategy did not work well on some reference images where some object instances could not be detected. For these reference images, we used the other strategy: using the boundary of an object instance in the scene sketch as the boundary of the corresponding color object in the corresponding reference image (the object correspondence can be obtained from SketchyScene). We employed 5 workers to generate the captions. For each set of examples, the color details of two / three components, "sky", "land", and/or "background", were described. In total, we collected 1,328 sets of training examples. We used 1,200 sets of examples for training, the remaining 128 sets were equally split for validation and test. All the images were resized to 768 × 768 pixels.

**Data collection for sRMI and LBIE.** Similar to the data collection for LUCSS, we collected three types of data for sRMI and LBIE: (1) color images selected from the reference images of SketchyScene (we selected the reference images which were in the training set of SketchyScene and had the majority pixels belonging to the above-mentioned 20 categories), (2) corresponding edge maps, and (3) corresponding captions. To collect the captions in scales, we developed an on-line system to assist the crowd workers in generating captions for cartoon scenes. To ensure the description style is close to that generated by the captioning algorithm, we used a template-based approach for caption generation. More specifically, each sentence of a caption comes from a repository of caption templates, which describes the instances and their corresponding quantities, colors, and spatial relationship as Algorithm 1. In this way, We employed 24 workers and collected 1,328 sets of examples, 1,200 of which were used for the training and the rest for validation.

**Test data.** We selected 100 scene sketches from the test set of SketchyScene as the test data (the other scene sketches do not depict reasonable scenes if the objects outside the selected 20 categories are removed from the scene sketch). Each scene sketch we produced had up to three captions (varying on different evaluation tasks). Apart from being used to evaluate the colorization performance of LUCSS, LBIE, and sRMI, this test data has also been used for the experiments on the analysis of the components of LUCSS.

7.1.2 **Experimental Settings.** For object instance colorization, we used a batch size of 2 and trained with 100K iterations. In the initial phrase of the training, we used the ADAM optimizer [Kingma and Ba 2014] and set the learning rate of generator at 0.0002 and that of discriminator at 0.0001. After 50K iterations, we adjusted the learning rate of discriminator to 0.0002. For background colorization, we used batch size of 1 and trained with 100K iterations. We set the initial learning rate for both the generator and discriminator at 0.0002 and reduced it by 75% after each 20K iterations. We set the iteration number of LSTM at 15, the cell size of mLSTM at 512 for both object instance and background colorization modules.

7.1.3 **Comparison Results.** We conducted two sets of experiments to evaluate the performances of LUCSS, sRMI, and LBIE. **Single caption.** In the first set of experiments, we compared LUCSS, LBIE, and sRMI on the 100 scene sketches of the whole test data. For each test scene sketch, we produced one caption (by re-editing the results of captioning). Figure 10 shows the visual results of these three competitors on some representative test examples. Generally, LUCSS outperformed both LBIE and sRMI overwhelmingly. LUCSS colorized both objects (e.g., the roads, houses, clouds, moons, trees in the results), and backgrounds (the green land and sky) with smooth colors, while LBIE and sRMI generated a lot of color regions which covered more than one objects. sRMI relatively performed better than LBIE in some cases. We take the results in the third row of Figure 10 for example. sRMI colorized the sky and grass with smooth blue and green respectively, while the color generated by LBIE was mixed with multiple colors (e.g. white, yellow and pink).

With respect to faithfulness, which measures whether the colorization follows the language instructions, LUCSS achieved significantly better performance than LBIE and sRMI as well. We take the example in the fourth row of Figure 10 to explain our observation. LUCSS
It's a sunny day. There is a sun in the sky. Many clouds are floating in the air. A house is in the middle. A person is on the left of the house. A light brown dog is in front of the right trees. The sky is blue and all things are on green grass.

We can see the evidence from the sun (LBIE: blue sun; sRMI: white).

The results of LBIE on three different captions almost stayed the same. Although sRMI can respond to the changed captions in some cases, it colored most objects in wrong colors. It indicate that both LBIE and sRMI failed to obtain the correspondence between the captions and objects. In [Chen et al. 2017b], LBIE showed the ability to learn the correspondence between words and objects, which is possibly because the captions in [Chen et al. 2017b] contain much shorter sentences than these in this study (captions in our study typically contain more than 6 sentences, much longer than two or three sentences in [Chen et al. 2017b]).

7.2 Ablation Experiments

In this section, we design various experiments to analyze the two major components of LUCSS.

7.2.1 Object Colorization.

**LBIE versus MRU-RMI.** In this set of experiment, we evaluated the performance of two types of models, LBIE and MRU-RMI, for object colorization. The test data contained 568 sets of examples as discussed in the data collection section above. Each set of test examples contained an object sketch and a corresponding caption. LBIE is the same network as that used in the previous experiments. MRU-RMI is also the same network as sRMI, which was used to colorize a whole scene sketch in the previous experiments.

Figure 12 shows some representative results. It can be seen that both LBIE and MRU-RMI can learn an implicit part-level segmentation and colorize the object parts with the colors instructed by the captions (e.g., both LBIE and MRU-RMI assigned blue to the windows of the bus). Relatively, MRU-RMI achieved better performance on inferring the correspondence between words in the caption and object parts. This can be told from the colorization results for the roof of the house and the windows of the bus. Combining the results in both Figure 12 and 11, we can see that MRU-RMI is powerful for object-level sketch images and its performance would be significantly degraded when the sketch image size goes up to a large-size complex scene sketch. Moreover, for the face region of the person in Figure 12, we can see that MRU-based network also outperformed the atrous-convolution-based LBIE on the encoding of object-level sketch image features (performance of MRU based network is significantly degraded when the complexity and the size of sketch image increase).

**MRU versus ResNet blocks versus Pix2Pix.** In this set of experiments, we evaluated three different types of backbones for the encoder and decoder of the architecture used for object colorization. The first type of backbone is MRU, which is used by SkechyGAN[Chen and Hays 2018] as well as the encoder and decoder for object colorization of LUCSS. ResNet denotes the residual block.
In Figure 13, we show the results of two representative examples. MRU achieved better performance than both Pix2Pix and ResNet. Specifically, MRU generated clearer texture and object part boundaries compared to ResNet and Pix2Pix (e.g., see the window and the body of the colorized bus). In the aspect of following language instruction, the results of MRU are also superior to those of ResNet and Pix2Pix. This also indicates that the whole network based on MRU can infer more accurate correspondence between the caption and image content using the image features extracted by MRU.

### 7.2.2 Background Colorization
In this section, we first investigate the architecture of the GAN for the background colorization task, and then study what kind of backbone is more appropriate for this task.

**LIE versus ResNet-RMI.** In this set of experiments, we compared two types of architectures, which can be used for background colorization. The first architecture is LIE. The other is the architecture discussed in Section 5.2. We call this architecture ResNet-RMI in this section since the backbone of the generator uses ResNet blocks. Both LIE and ResNet-RMI were trained with 1,200 sketches in the training dataset, and tested on the test dataset.

In Figure 14, we illustrate the results of LIE and ResNet-RMI on two sets of representative examples. Both LIE and ResNet-RMI successfully colorized the regions of sky and grass with the colors specified in the captions. This indicates that the encoding modules of image, text and feature fusion modules of LIE and ResNet-RMI work well. However, the results by ResNet-RMI were visually more pleasing than LIE. It may be caused by the fact that LIE uses an asymmetrical encoder-decoder architecture (the encoder of LIE uses atrous convolution while the decoder uses regular convolution).

**MRU versus ResNet versus Pix2Pix.** In this set of experiments, we study which backbone network is more suitable for large-scale image background colorization. We still used the three types of backbone network: MRU, ResNet, and Pix2Pix. Results on representative
examples are shown in Figure 15. We can see ResNet outperforms Pix2Pix in terms of visual effects, which can be explained by the fact that ResNet is much deeper than Pix2Pix (a ResNet block has three convolution layers while a Pix2Pix block only has a single convolution layer). ResNet also has visually better results than MRU (e.g., MRU generated some artifacts surrounding foreground objects, while ResNet doesn’t), mainly because MRU is specialized for object-level sketches. When the MRU based network is used for a large size of color image, its performance is degraded (we can get the evidence by comparing the results in Figure 11 and Figure 12, additional evidence can be seen in SketchyGAN[Chen and Hays 2018]).

In the object colorization task, we randomly select 60 sketches from 20 classes as the input (3 sketches per class) and compare the results using two models: LBIE and MRU-RMI (our model). In the background colorization task, we random select 20 scene sketches as the input and compare the results via two models: LBIE and ResNet-RMI (our model). In both tasks, we further the performance of three backbones: MRU, ResNet blocks, and Pix2Pix.

In the faithfulness study, our goal is to evaluate whether the colorization results are consistent with the text description. Each participant was given the input caption with the corresponding colorization results from one of the two models, or one of the three backbones. We asked the participant to pick out the colorization result which best fits the text description.

In the effectiveness study, we compared the overall visual quality of the colorization results. Each participant was given the original sketch with the corresponding colorization results from one of the two models, or one of the three backbones. We asked the participants to pick out the most visually pleasing color image for the sketch.

Overall, in each study, we have collected $11 \times 20 \times 3 = 660$ trials for the object colorization task and $11 \times 20 = 220$ trials for the background colorization task. For both studies, we compare the selection rate of different models and backbones in Fig. 16 and 17. For both tasks, our MRU-RMI model and ResNet-RMI model greatly outperform the LBIE model in user evaluation. Based on our user evaluation, LUCSS is more faithful and produces more visually pleasing results to users. For object colorization, the MRU backbone stands out; while for background colorization, the ResNet backbone outperforms the rest.

8 CONCLUSION, DISCUSSION, AND FUTURE WORK
Understanding low-level scene sketches containing multiple sketched objects is a rarely studied problem. This problem is very challenging, especially when objects occlude each other in the depicted scene. The sparse nature of scene sketches leads to inferior performance of current models, even advanced ones, that are designed for natural images. In this work, we proposed a system called LUCSS to study how we can make machines understand complex scene sketches by adapting the existing powerful deep models for natural images to
sketches, as well as how this understanding can benefit related applications. We have focused language-based interactive colorization of scene sketches.

The current performance of LUCSS is limited by the segmentation performance since the highest mask AP is near 60%. It is necessary to propose more powerful algorithms by incorporating the characteristics of scene sketches with advanced models. Another limitation is that our current human-computer interaction needs improvement, though it is currently a practical solution considering the challenges of instance segmentation and inferring accurate correspondence between language descriptions and objects in the scene. As these challenging problems are solved by new datasets and more powerful models, LUCSS has the potential to become a far more mature system that could potentially generate fine-grained sketch colorization like generating a boy with ruddy cheek, or animating objects in a scene sketch by human speech commands.

Image synthesis frequently occurs when data is left out. Since LUCSS is limited by training data, LUCSS generates cartoon images rather than natural images. Complex sentences are input to LUCSS which then processes them, filling in any missing detail such as omitted colors, and outputs an image.

This raises a question: is it possible to synthesize user-customized scene-level natural images by using add-in user sketches to the images of MS COCO’s dataset to corroborate the existing language descriptions?

LUCSS has great application prospects in the field of child education, accessibility, and media production. For instance, by translating auto-generated caption text to human voice, LUCSS has the potential to read scene sketches to children and the blind. Via the interactive colorization system, both children and adults could create their own cartoon story books. In addition, the involved techniques in LUCSS may be useful in CAD and Virtual Reality (VR) industries. With text (voice) commands, LUCSS unlocks the potential to easily change the color schemes of a sketch scene and virtual environments.

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