Language-Based Image Editing with Recurrent attentive Models

Jianbo Chen*, Yelong Shen‡, Jianfeng Gao‡, Jingjing Liu‡, Xiaodong Liu‡
University of California, Berkeley* and Microsoft Research‡
jianbochen@berkeley.edu
yeshen, jfgao, jingjl, xiaodl@microsoft.com

Abstract

We investigate the problem of Language-Based Image Editing (LBIE) in this work. Given a source image and a natural language description, we want to generate a target image by editing the source image based on the description. We propose a generic modeling framework for two sub-tasks of LBIE: language-based image segmentation and image colorization. The framework uses recurrent attentive models to fuse image and language features. Instead of using a fixed step size, we introduce for each region of the image a termination gate to dynamically determine in each inference step whether to continue extrapolating additional information from the textual description. The effectiveness of the framework has been validated on three datasets. First, we introduce a synthetic dataset, called CoSaL, to evaluate the end-to-end performance of our LBIE system. Second, we show that the framework leads to state-of-the-art performance on image segmentation on the ReferIt dataset. Third, we present the first language-based colorization result on the Oxford-102 Flowers dataset, laying the foundation for future research.

1 Introduction

In this work, we aim to develop an automatic Language-Based Image Editing (LBIE) system. Given a source image, which can be a sketch, a grayscale image or a natural image, the system will automatically generate a target image by editing the source image following natural language instructions provided by users. Such a system has a wide range of applications from Computer-Aided Design (CAD) to Virtual Reality (VR). As illustrated in Figure 1, we can envision that a fashion designer presents a sketch of a pair of new shoes (i.e., the source image) to a customer, who can provide modifications on the style and color in verbal description, which can then be taken by the LBIE system to change the original design. The final output (i.e., the target image) is the revised and enriched design that would meet the customers requirement. Figure 2 showcases the use of LBIE for VR. While most VR systems are still using button-controlled or touchscreen interface, LBIE provides a natural user interface for future VR systems, where users can easily modify the base environment via natural language instructions.

LBIE can cover a broad range of tasks in image generation: shape, color, size, texture, position, etc. This paper focuses on the two basic sub-tasks of LBIE: language-based segmentation and colorization for shapes and colors. For example, in Figure 3, given the grayscale image and the expression “The flower has red petals with yellow stigmas in the middle”, the segmentation model will identify each region of the image as “petals”, “stigmas”, and the colorization model will paint each pixel with the suggested color. In this intertwined task of segmentation and colorization, the distribution of target images can be multi-modal in the sense that each pixel will have a definitive ground truth on segmentation, but not necessarily on color. For example, the pixels on petals in Figure 3 should be red based on the textual description, but the specific numeric values of the red color in RGB space is not uniquely specified. The system is required to colorize the petals based on real-world knowledge. Another uncertainty lies in the fact that the input description
Figure 1: In an interactive design interface, a sketch of shoes is presented to a customer, who then gives a verbal instruction on how to modify the design: “The insole of the shoes should be brown. The vamp and the heel should be purple and shining”. The system will colorize the sketch following the customer’s instruction. (images from [11]).

Figure 2: The image on the left is an initial virtual environment. The user provides a textual description: “The afternoon light flooded the little room from the window, shining the ground in front of a brown bookshelf made of wood. Besides the bookshelf lies a sofa with light-colored cushions. There is a blue carpet in front of the sofa, and a clock with dark contours above it...”. The system then modifies the virtual environment into the right image.

might not cover every detail of the image. Undescribed regions such as the leaves in the given example, should be rendered based on past memory. In summary, the ultimate goal is to generate images guided by the constraint of natural language expressions, but should also align with common sense of the real world.

Language-based image segmentation has been studied previously in [9]. However, our task is far more challenging because the textual description in our task often contains multiple sentences (as in Figure 2), while in [9] most of the expressions are simple phrases. To the best of our knowledge, language-based colorization has not been studied systematically before. In most previous work, images are generated either solely with natural language expressions [20],[30] or based on another image [11],[3],[31]. Instead, we want to generate a target image based on both natural language expressions and source image. Related tasks will be discussed in detail in Section 2.

A unique challenge in language-based image editing is the complexity of natural language expressions and their correlation with the source images. Like the example shown in Figure 2, the description usually consists of multiple sentences. Each sentence might refer to multiple objects in the source image. Many details also need to be inferred from multiple sentences. When human edits the source image based on a textual description, we often keep in mind which sentences are related to which region/object in the image, and go back to the sentences multiple times while editing that region. This behavior of “going back” often varies from region to region, depending on the complexity of the description for that region. An investigation of this problem is carried out on CoSaL, a dataset introduced for the purpose, detailed in Section 4.
Figure 3: Left: sketch image. Middle: grayscale image. Right: color image (from [17]). A language-based image editing system will take either of the first two images as the input, and generate the third color image following a natural language expression: “The flower has red petals with yellow stigmas in the middle”.

Our goal is to design a generic framework for the two sub-tasks in language-based image editing. A diagram of the model is shown in Figure 4. Inspired by the observation aforementioned, we introduce a recurrent attentive fusion module in our framework. The fusion module takes in image features encoding the source image via a convolutional neural network, and textual features encoding the natural language expression via an LSTM, and outputs the fused features to be upsampled by a deconvolutional network into target images. In the fusion module, recurrent attentive models are employed to extract distinct textual features based on the spatial features from different parts of an image. And a termination gate is introduced for each region to control the number of steps it interacts with the textual features. A Gumbel-Softmax reparametrization trick [12] is used for end-to-end training of the entire network. Details of the models and the training process are described in Section 3.

Our contributions are summarized as follows:

- We define a new task of language-based image editing (LBIE).
- We present a generic modeling framework based on recurrent attentive models for two sub-tasks of LBIE: language-based image segmentation and colorization.
- We introduce a synthetic dataset CoSaL to evaluate the end-to-end performance of the LBIE system.
- We achieve new state-of-the-art performance on language-based image segmentation on the ReferIt dataset.
- We present the first language-based colorization result on the Oxford-102 Flowers dataset, laying the foundation for future research.

2 Related Work

While the task of language-based image editing has not been studied, the community has taken significant steps in several related areas, including Language Based object detection and Segmentation (LBS) [9],[10], Image-to-Image Translation (IIT) [11], Generating Images from Text (GIT) [19], [30], Image Captioning (IC) [13], [24], [28], Visual Question Answering (VQA) [2], [29], Machine Reading Comprehension (MRC) [8], etc. We summarize the types of inputs and outputs for these related tasks in Table 1.
The flower has red petals with yellow stigmas in the middle.

**Figure 4:** A high-level diagram of our model, composed of a convolutional image encoder, an LSTM text encoder, a fusion module, a deconvolutional upsampling layer, with an optional convolutional discriminator.

| Inputs | Outputs |
|--------|---------|
| Text   | Image  | Text | Image |
| MRC    | YES    | NO   | YES  | NO   |
| VQA    | YES    | YES  | YES  | NO   |
| IIT    | NO     | YES  | NO   | YES  |
| IC     | NO     | YES  | YES  | NO   |
| GIT    | NO     | YES  | NO   | YES  |
| LBS    | YES    | YES  | NO   | YES  |
| LBIE   | YES    | YES  | NO   | YES  |

**Table 1:** The types of inputs and outputs for related tasks

**Recurrent attentive models**

Recurrent attentive models have been applied to visual question answering (VQA) to fuse language and image features [29]. The stacked attention network proposed in [29] identifies the image regions that are relevant to the question via multiple attention layers, which can progressively filter out noises and pinpoint the regions relevant to the answer. In image generation, a sequential variational auto-encoder framework, such as DRAW[7], has shown substantial improvement over standard variational auto-encoders (VAE) [15]. Similar ideas have also been explored for machine reading comprehension, where models can take multiple iterations to infer an answer based on the given query and document [4], [26], [25], [27]. In [22] and [21], a novel neural network architecture called ReasoNet is proposed for reading comprehension. ReasoNet...
performs multi-step inference where the number of steps is determined by a termination gate according to the difficulty of the problem. ReasoNet is trained using policy gradient methods.

Segmentation from language expressions

The task of language-based image segmentation is first proposed in [9]. Given an image and a natural language description, the system will identify the regions of the image that correspond to the visual entities described in the text. The authors in [9] proposed an end-to-end approach which is composed of three main components: a convolutional network to encode source images, an LSTM network to encode natural language descriptions, and a fully convolutional classification and upsampling network for pixel-wise segmentation.

One of the key differences between their approach and ours is the way of integrating image and text features. In [9], for each region in the image, the extracted spatial features are concatenated with the same textual features. Inspired by the alignment model of [13], in our approach, each spatial feature is aligned with different textual features based on attention models. Our approach yields superior segmentation results than that of [9] on a benchmark dataset.

Conditional GANs in image generation

Generative adversarial networks (GANs) [6] have been widely used as a powerful tool for image generation. Conditional GANs [16] are often employed when there are constraints that a generated image needs to satisfy. For example, deep convolutional conditional GANs [18] have been used to synthesize images based on textual descriptions [20] [30]. [11] proposed the use of conditional GANs for image-to-image translation. Different from these tasks, LBIE takes both image and text as input, presenting an additional challenge of fusing the features of the source image and the textual description.

3 The Framework

Overview The proposed modeling framework, as shown in 4, is based on neural networks, and is generic to both the language-based image segmentation and colorization tasks. The framework is composed of a convolutional image encoder, an LSTM text encoder, a fusion network that generates a fusion feature map by integrating image and text features, a deconvolutional network that generates pixel-wise outputs (the target image) by upsampling the fusion feature map, and an optional convolutional discriminator used for training colorization models.

Image encoder The image encoder is a multi-layer convolutional neural network (CNN). Given a source image of size $H \times W$, the CNN encoder produces a $M \times N$ spatial feature map, with each position on the feature map containing a $D$-dimensional feature vector ($D$ channels), $V = \{v_i : i = 1, \ldots, M \times N\}, v_i \in \mathbb{R}^D$.

Language encoder The language encoder is a recurrent Long Short-Term Memory (LSTM) network. Given a natural language expression of length $L$, we first embed each word into a vector through a word embedding matrix, then use LSTM to produce for each word a contextual vector that encodes its contextual information such as word order and word-word dependencies. The resulting language feature map is $U = \{u_i : i = 1, \ldots, L\}, u_i \in \mathbb{R}^K$. 
**Recurrent attentive fusion module** The fusion network fuses text information in $U$ into the $M \times N$ image feature map $V$, and outputs an $M \times N$ fusion feature map, with each position (image region) containing an editing feature vector, $O = \{o_i : i = 1, \ldots, M \times N\}, o_i \in \mathbb{R}^D$.

The fusion network is devised to mimic the human image editing process. For each region in the source image $v_i$, the fusion network reads the language feature map $U$ repeatedly with attention on different parts each time until enough editing information is collected to generate the target image region. The number of steps varies from region to region.

**Internal state** The internal state at time step $t$ is denoted as $S^t = \{s^t_i, i = 1, \ldots, M \times N\}$, which is a spatial feature map, with each position (image region) containing a vector representation of the editing information state. The initial state is the spatial feature map from the source image, $S^0 = V$. The sequence of internal states is modeled by Convolutional Gated Recurrent Units (C-GRUs) which will be described below.

**Attention** The attention at time step $t$ is denoted as $\hat{U}^t = \{\hat{u}^t_i, i = 1, \ldots, M \times N\}$, which is a spatial feature map generated based on the current internal state $S^t$ and the language feature map $U$:

$$\hat{U}^t = \text{Attention}(U, S^t; \theta_a)$$

where $\text{Attention}(.)$ is implemented as follows

$$
\begin{align*}
\beta_{ij} &\propto \exp\{s^t_i U^t_j\} \\
\hat{u}^t_i &\equiv \sum_{j=1}^L \beta_{ij} u_j.
\end{align*}
$$

**C-GRUs** C-GRUs update the current internal state $S^t$ by infusing the attention feature map $\hat{U}^t$:

$$S^{t+1} = \text{C-GRUs}(S^t, \hat{U}^t; \theta_c).$$

where $\text{C-GRUs}(.)$ is implemented as follows

$$
\begin{align*}
z &= \sigma(W_1 \otimes S^t + W_2 \otimes \hat{U}^t + b_1), \\
r &= \sigma(W_3 \otimes S^t + W_4 \otimes \hat{U}^t + b_2), \\
c &= \text{ReLU}(W_5 \otimes (r \odot S^t) + W_6 \otimes \hat{U}^t + b), \\
\hat{O}^t &= h = (1 - z) \odot S^t + z \odot c, \\
S^{t+1} &= W_7 \odot h,
\end{align*}
$$

where $\odot$ is the elementwise-product, and $\otimes$ is the convolutional operator. Note that $\hat{O}^t$ is the intermediate output of the fusion feature map at time step $t$. 

6
Termination gates There are $M \times N$ termination gates, each for one image region $v_i$ in $V$. Each termination gate generates a binary random variable according to the current internal state of its image region: $\tau_t^i \sim p(\cdot|f_{tg}(s_{it}; \theta_{tg}))$. If $\tau_t^i = 1$, the fusion process for the image region $v_i$ stops at $t$, and the editing feature vector for this image region is set as $o_i = \hat{o}_{t+1}^i$. When all terminate gates are true, the fusion process for the entire image is completed, and the fusion network outputs the fusion feature map $O$.

We define $\zeta = (\zeta_1, \zeta_2, \ldots, \zeta_{M \times N})$, where $\zeta_i = (\tau_{1}^i, \tau_{2}^i, \ldots, \tau_{T}^i)$, a categorical distribution with $p(\zeta_i = e_{t}) = \beta_t^i$, where

$$\beta_t^i = f_{tg}(s_{1}^i; \theta_{tg}) \prod_{k<t}(1 - f_{tg}(s_{k}^i; \theta_{tg})).$$

the probability of $i$th feature map stopping at time $t$.

Inference Algorithm 1 describes the stochastic inference process of the fusion network. The state sequence $S^{(1:T)}$ is hidden and dynamic, chained through attention and C-GRU in a recurrent fashion. The fusion network outputs for each image region $v_i$ an editing feature vector $o_i$ at the $t_i$-th step, where $t_i$ is controlled by the $i$th termination gate, which varies from region to region.

**Algorithm 1 Stochastic Inference of the Fusion Network**

**Require:** $V \in \mathbb{R}^{D \times (M \times N)}$: Spatial feature map of image.

**Require:** $U \in \mathbb{R}^{K \times L}$: Language feature map of expression.

**Ensure:** Fusion feature map $O \in \mathbb{R}^{D \times (M \times N)}$.

**function** FUSION($V, U$)

Initialize $S^{0} = V$.

for all $t = 0$ to $t_{max} - 1$ do

$\hat{U}^t = \text{Attention}(U, S^t; \theta_a)$

$S^{t+1}, \hat{O}^t = \text{C-GRUs}(S^t, \hat{U}^t; \theta_c)$

Sample $\tau_t^{t+1} \sim p(\cdot|f_{tg}(S^{t+1}; \theta_{tg}))$

if $\tau_t^{t+1} = 1$ and $\tau_s^t = 0$ for $s \leq t$ then

Set $O_i = \hat{O}_{t+1}^i$.

end if

end for

for all $i = 1$ to $M \times N$ do

if $\tau_i = 0$ then

Set $o_i = \hat{o}_{t_{max}-1}^i$

end if

end for

**end function**

Image decoder The image decoder is a multi-layer deconvolutional network. It takes as input the $M \times N$ fusion feature map $O$ produced by the fusion module, and unsamples from $O$ to produce a $H \times W \times D_e$ editing map $E$ of the same size as the target image, where $D_e$ is the number of classes in segmentation and 2 ($ab$ channels) in colorization.

Discriminator The discriminator $D_\phi(E)$ takes in a generated image and outputs the probability of the image being realistic. The structure of the discriminator follows that in [20], which uses a convolutional
neural network to extract features from the image. In our model, the discriminator serves the function of judging whether an image looks natural, but not whether it is compatible with language descriptions. The latter constraint is left to an $L1$ loss to be described later.

**Loss and training** Denote the loss as $L(\theta) = \mathbb{E}_\zeta[l(E(\zeta, \theta), Y)]$, where the expectation is taken over the categorical variables $\zeta$ generated by termination gates, and $l_\theta(\zeta) = l(E(\zeta, \theta), Y)$ is the loss of output at $\zeta$. Because the sample space is of exponential size $T^M \times N^T$, it is intractable to sum over the entire sample space. We denote the density of $\zeta$ by $p_\theta(\zeta)$. A naive approach to approximation is to subsample the loss and update parameters via the gradient of Monte Carlo estimate of loss:

$$\nabla_\theta L(\theta) = \nabla_\theta \mathbb{E}_\zeta[l_\theta(\zeta)] = \frac{1}{|S|} \sum_{\zeta \in S} p_\theta(\zeta) l_\theta(\zeta) + \nabla_\theta l_\theta(\zeta),$$

where $S$ is a subset of $\zeta$ sampled from the distribution $p_\theta(\zeta)$. In experiments, we found the above Monte Carlo estimate suffers from high variance. To resolve this issue, we employ the Gumbel-Softmax reparameterization trick [12], which replaces every $\zeta_i \in \{0, 1\}^T$ sampled from Cat$(\beta_1, \beta_2, \ldots, \beta_T)$ by another random variable $z_i$ generated from Gumbel-softmax distribution:

$$z_i^t = \frac{\exp((\log \beta_i^t + \epsilon_i^t) / \lambda)}{\sum_{k=1}^T \exp((\log \beta_i^t + \epsilon_i^t) / \lambda)},$$

where $\lambda$ is a temperature annealed via a fixed schedule and the auxiliary random variables $\epsilon_1^t, \ldots, \epsilon_T^t$ are i.i.d. samples drawn from Gumbel$(0, 1)$ independent of the parameters $\beta_i$:

$$\epsilon_i^t = -\log(-\log u_i^t), \quad u_i^t \sim \text{Unif}(0, 1).$$

Define $z(\epsilon, \theta) = (z_1, z_2, \ldots, z_{MN})$. The loss can be rewritten as $L(\theta) = \mathbb{E}_\epsilon[l_\theta(z(\epsilon, \theta))]$, and the update is approximated by taking the gradient of Monte Carlo estimates of the loss obtained from sampling $\epsilon$.

We use two different losses for segmentation and colorization respectively.

**Segmentation** In segmentation, we assume there is a unique answer for each pixel on whether or not it is being referred in the stage of segmentation. The response map $E$ is of size $H \times W \times D_e$, which produces a log probability for each class for each pixel. We use a pixel-wise softmax cross-entropy loss during training:

$$l(E, Y) = \text{Cross-Entropy}(\text{Softmax}(E), Y).$$

**Colorization** In colorization, the high-level goal is to generate realistic images under the constraint of natural language expressions and input scene representations, we introduce a mixture of GAN loss and $L1$ loss for optimization as in [11]. A discriminator $D_\phi$ parametrized by $\phi$ is introduced for constructing the GAN loss.
The response map $E$ is the predicted $ab$ color channels. It is combined with the grayscale source image to produce a generated color image $E'$. The generator loss is a GAN loss taking $E'$ as input, and $L_1$ loss between the $ab$ channels of the target image $Y$ and the response map $E$:

$$l(E, Y) = \log(1 - D_\phi(E)) + \gamma\|E - Y\|_1 \quad (\gamma = 0.01).$$

The discriminator $D_\phi$ is trained by first generating a sample $E$ via Algorithm 1, combined with the grayscale source image to produce $E'$, and optimize the following loss over $\phi$:

$$\log(D_\phi(E')) + \log(1 - D_\phi(Y)).$$

The generator loss and the discriminator loss are optimized alternatively in the training stage.

4 Experiments

We conducted three experiments to validate the performance of the proposed framework. A new dataset “CoSaL” was introduced to test the capability of understanding multi-sentence descriptions and associating the inferred textual features with visual features. Our framework also yielded state-of-the-art performance on the benchmark dataset ReferIt [14] for image segmentation. A third experiment was carried out on the Oxford-102 Flowers dataset [17], for the language-based colorization task.

4.1 Experiments on CoSaL

**Dataset** A synthetic dataset CoSaL - Colorizing Shapes with Artificial Language is introduced for studying the correlation between images and multi-sentence descriptions. Each image in the dataset consists of nine shapes, paired with a textual description of the image. The goal of the task is defined as: given a black-white image and its corresponding description, train a model that can automatically colorize the nine shapes following the textual description. Figure 5 shows an example of this task, which requires sophisticated coreference resolution, multi-step inference and logical reasoning.

The dataset was created as follows: first, we divide a white-background image into $3 \times 3$ regions. Each region contains a shape randomly sampled from a set of $S$ shapes (e.g., squares, fat rectangles, tall rectangles, circles, fat ellipses, tall ellipses, diamonds, etc.) Each shape is then filled with one of $C$ color choices, chosen at random. The position and the size of each shape are generated by uniform random variables. As illustrated in Figure 5, the difficulty of this task increases with the number of color choices. In our experiments, we specify $C = 3$ as a start point.

The descriptive sentences for each image can be divided into two categories: direct descriptions and relational descriptions. The former prescribes the color of a certain shape (e.g., *Diamond is red*), and the latter depicts one shape conditional of another (e.g., *The shape left to Diamond is blue*). To understand direct descriptions, the model needs to associate a specified shape with its textual features. Relational description adds another degree of difficulty, which calls for advanced inference capability of relational/multi-step reasoning. The ratio of direct descriptions to relational descriptions varies among different images, and all the colors and shapes in each image are uniquely determined by the description. In our experiment, we randomly generated 50,000 images with corresponding descriptions for training purpose, and 10,000 images with descriptions for testing.
**Metric**  For this task, we use *average IOU over nine shapes and the background* as the evaluation metric. Specifically, for each region, we compute the intersection-over-union (IOU), which is the ratio of the total intersection area to the total union area of predicted colors and ground truth colors. We also compute the IOU for the background (white) of each image. The IOU for 10 classes (9 shapes + 1 background) are computed over the entire test set and then averaged.

**Model Implementation**  A six-layer convolutional network is implemented as the image feature extractor. Each layer has a $3 \times 3$ kernel with stride 1 and output dimension 4, 4, 8, 8, 16, 16. ReLU is used for nonlinearity after each layer, and a max-pooling layer with a kernel of size 2 is inserted after every two layers. Each sentence in the textual description is encoded with bidirectional LSTMs that share parameters. The LSTMs have 16 units. In the fusion network, the attention model has 16 units, the GRU cells use 16 units, and the termination gate uses a linear map on top of the hidden state of each GRU cell. Two convolutional layers of kernel size $1 \times 1$ with the output dimension of 16, 7 are put on top of the fused features as a classifier. Then an upsampling layer is implemented on top of it, with a single-layer deconvolutional network of kernel size 16, stride 8 to upsample the classifier to the original resolution. The upsampling layer is initialized with bilinear transforms. The maximum of $T$ of termination steps vary from 1 to 4. When $T = 1$, the model is reduced to simply concatenating features extracted from the convolutional network with the last vector from LSTM.

**Results**  Table 2 shows the average IoU of two models, with $T = 1$ and $T = 4$, respectively. Results show that the model with attention and $T = 4$ achieves a better performance when there are more relational descriptions in the dataset. When there are more direct descriptions, the two models achieve similar performance. This demonstrates the framework’s capability of interpreting multiple sentences and associating them with the source image.

| Number of direct descriptions | Attention | 4   | 6   | 8   |
|-------------------------------|-----------|-----|-----|-----|
| T 1 No                        | 0.2107    | 0.2499 | 0.3186 |
| T 1 Yes                       | 0.4030    | 0.5220 | **0.7097** |
| T 4 Yes                       | **0.5033** | **0.5313** | 0.7017 |

Table 2: The average IoU of two models, without attention at $T = 1$ and with attention at $T = 1, 4$. Performance varies among datasets with different ratios of direct to relational descriptions.

Figure 5 illustrates how the model with $T = 3$ interprets the nine sentences during each inference step. Sentences in red are attended to in the first step. Those in yellow and green are attended in the next two consecutive steps. One observation from the experiment was that the model first extracted information from direct descriptions, and then focused on relational descriptions for additional reasoning.

### 4.2 Experiments on ReferIt

**Dataset**  The ReferIt dataset is composed of 19,894 photographs of real world scenes, along with 130,525 natural language descriptions on 96,654 distinct objects in those photographs [14]. The dataset contains 238 different object categories, including animals, people, buildings, objects and background elements (e.g., grass, sky). Both training and development datasets include 10,000 images.
The inverse-triangle is blue.
The color of the shape above the ellipse is blue.
The rectangle is yellow.
The triangle is gray.
The ellipse is blue.
The fat ellipse is light-green.
The circle is gray.
The color of the shape left to the diamond is gray.
The fat half-ellipse is black.

Figure 5: Right: ground truth image. Left: illustration of which sentences are attended to at each time step. Red, yellow and green represent the first, second and third time step, respectively.

| Model        | Precision@0.5 | Precision@0.6 | Precision@0.7 | Precision@0.8 | Precision@0.9 | IoU  |
|--------------|---------------|---------------|---------------|---------------|---------------|------|
| SCRC bbox [10] | 9.73%         | 4.43%         | 1.51%         | 0.27%         | 0.03%         | 21.72%|
| GroundR bbox [5] | 11.08%       | 6.20%         | 2.74%         | 0.78%         | 0.20%         | 20.50%|
| Hu, etc.[9] | **34.02%** | 26.71% | **19.32%** | 11.63% | 3.92% | 48.03% |
| Our model   | 32.53%        | **27.9%**     | 18.76%        | **12.37%**    | **4.37%**     | **50.09%**|

Table 3: The results of previous models and our model on the ReferIt dataset.

**Metric** Following [9], we use two metrics for evaluation: 1) **overall intersection-over-union (overall IoU)** of the predicted and ground truth of each region, averaged over the entire test set; 2) **precision@threshold**, the percentage of test data whose (per image) IoU between prediction and ground truth is above the threshold. Thresholds are set to 0.5, 0.6, 0.7, 0.8, 0.9.

**Model Implementation** A VGG-16 architecture [23] is used as the image encoder for images of size 512 × 512. Textual descriptions are encoded with an LSTM of 1,024 units. In the fusion network, the attention model uses 512 units and the GRU cells 1,024 units, on top of which is a classifier and an upsampling layer similar to the implementation in Section 4.1. The maximum number of inference steps is 3. ReLU is used on top of each convolutional layer. $L_2$-normalization is applied to the parameters of the network.

**Results** Table 3 shows the experimental results of our model and the baseline methods on the ReferIt dataset. We see that our framework yields a better IoU and precision than [9]. Our hypothesis is that the outperformance resulted from the unique attention mechanism used by our fusion network, which can efficiently associate individual descriptive sentences with different regions of the source image. There is not much discrepancy between the two models with $T = 1$ and $T = 3$, probably due to the fact that most textual descriptions in this dataset are simple. Examples of semantic labels are provided in supplementary materials.
Figure 6: First row: original images. Second row: results from the image-to-image translation model in [11], without text input. Third row: results from our model, taking textual descriptions into account.

Figure 7: First row: original images. Second, third and fourth rows: results generated from our framework with arbitrary text input: “The petals of the flower are red/blue/yellow”.

4.3 Experiments on Oxford-102 Flower Dataset

Dataset  In this experiment, we use the Oxford-102 Flowers dataset [17], which contains 8,189 images from 102 flower categories. Each image has five textual descriptions [20]. Following [20], [19] and [1], we split the dataset into 82 classes for training and 20 classes for testing. Given a grayscale image of a flower and a description of the shapes and colors of the flower, the goal is to colorize the image following the description.

Model Implementation  A fifteen-layer convolutional network similar to [31] is used for encoding $64 \times 64$ images. Textual descriptions are encoded with an LSTM of 512 units. In the fusion network, the attention model uses 128 units and the GRU cells 128 units. The image encoder is composed of 2 deconvolutional layers, each followed by 2 convolutional layers, to upsample the fusion feature map to the target image space of $64 \times 64 \times 2$. The maximum length of the spatial RNN is 1. The discriminator is composed of five layers of convolutional networks of stride 2, with the output dimension 256, 128, 64, 32, 31. The discriminator score is the average of the final output. ReLU is used for nonlinearity following each convolutional layer, except for the last one which uses the sigmoid function.
**Results**  Due to the lack of available models for the task, we compare our framework with a previous model developed for image-to-image translation as baseline, which colorizes images without the injection of texts. The colorization results on 10 randomly-sampled images from the test set are shown in Figure 6. As we can see, without text input, the baseline approach often colorizes images with the same color (in this dataset, most images are painted with blue and white), while our framework can generate flowers similar to their original colors which are specified in texts. Figure 7 also provides some examples of images generated with arbitrary text input using the trained model.

5 Conclusion and Future Work

In this paper we introduce the problem of Language-Based Image Editing (LBIE), and propose a generic modeling framework for two sub-tasks of LBIE: language-based image segmentation and colorization. At the heart of the proposed framework is a fusion module that uses recurrent attentive models to dynamically decide, for each region of an image, whether to continue the text-to-image fusion process. Our models have demonstrated superior empirical results on three datasets, including the ReferIt dataset for image segmentation, the Oxford-102 Flower dataset for colorization, and a proposed CoSaL dataset for evaluating the end-to-end performance of the LBIE system. In future, we will extend the framework to other image editing subtasks. Another interesting area is to build a dialogue-based image editing system that allows users to edit images in a more interactive and natural way.

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