Text2Scene: Generating Abstract Scenes from Textual Descriptions

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Abstract

In this paper, we propose an end-to-end model that learns to interpret natural language describing a scene to generate an abstract pictorial representation. The pictorial representations generated by our model comprise the spatial distribution and attributes of the objects in the described scene. Our model uses a sequence-to-sequence network with a double attentive mechanism and introduces a regularization strategy. These scene representations can be sampled from our model similarly as in language-generation models. We show that the proposed model, initially designed to handle the generation of cartoon-like pictorial representations in the Abstract Scenes Dataset, can also handle, under minimal modifications, the generation of semantic layouts corresponding to real images in the COCO dataset. Human evaluations using a visual entailment task show that pictorial representations generated with our full model can entail at least one out of three input visual descriptions 94\% of the times, and at least two out of three 62\% of the times for each image.

1. Introduction

Language comprehension is a long standing goal in Artificial Intelligence. Understanding natural language can enable systems that seamlessly communicate with humans, perform actions through complex natural language commands, or answer complex questions from knowledge contained in large amounts of text. A special case is the language describing visual information such as scenes. Understanding language referring to objects in a scene might require building an intermediate representation that is also visual in nature. Moreover, visual grounding of language can directly impact tasks in robotics, computer-aided design, and image search and retrieval.

Our paper focuses on the textual description of a scene and proposes a task of abstract scene generation to demonstrate this type of language understanding. We introduce a data-driven end-to-end model to interpret important semantics in visually descriptive language in order to generate pictorial representations. We specifically focus on generating a scene representation consisting of a list of objects, along with their attributes and locations, provided a set of natural language utterances describing what is true or known about the scene. Generating such a representation is challenging because input textual descriptions might only indirectly hint at the presence of attributes (e.g. Mike is surprised should change facial attributes on the generated object “Mike”), they also frequently contain complex information about relative spatial configurations (e.g Jenny is running towards Mike and the duck makes the orientation of “Jenny” dependent on the positions of “Mike”, and “duck”), and they could also hint at the presence of objects only indirectly through the mention of an activity that implies the object or group of objects (e.g. some people hints at the presence of several objects of type “person”). These examples are illustrated in Figure 1.

We model this text-to-scene task with a sequence-to-sequence approach where objects are placed sequentially on an initially empty canvas. More specifically, our proposed model, named TEXT2SCENE, consists of a text encoder which maps input sentences to a set of embedding representations, an object decoder which predicts the next object conditioned on the current scene state and input representations.
representations, and an attribute decoder which determines the attributes of the predicted object. Our model was trained and originally designed to handle the generation of abstract scenes as introduced in the dataset of [41]. Then we further show that our model can also be trained to generate semantic object layouts corresponding to real images in the COCO dataset [16] while only requiring minimal modifications. COCO scenes do not contain as rich a set of attribute annotations for each object but generally exhibit a larger variation in spatial configurations for objects.

Another challenge in our setup is evaluating the generated output from this task. For instance, image descriptions in the Abstract Scenes dataset might not explicitly refer to all the visual elements in the corresponding “ground truth” scene (e.g. in Figure 1 “table” is in the scene but is not mentioned in the text). In this case, the generated output is still valid as it does not negate any of the input statements, so the corresponding scenes in the datasets can only be considered as a reference output. Therefore, we introduce a set of metrics inspired in metrics used for machine translation to quantify the alignment between semantic frames in language and corresponding visual features. Additionally, we perform human evaluations in the form of a visual entailment task where humans need to judge whether a generated scene negates any of the input language descriptions when considering them as propositional statements.

We conduct extensive quantitative and qualitative analysis on two distinct datasets (Abstract Scenes and COCO) and the results show the ability of our models for generating scenes with multiple objects and complex semantic relations. Our TEXT2SCENE model compares favorably against the parsing + conditional random field (CRF) model introduced in [32] and thus is the state-of-the-art on this benchmark. Finally, to the best of our knowledge, TEXT2SCENE is the first model proposed for this type of task that shows positive results on both abstract images and semantic layouts corresponding to real images, thus opening the task that shows positive results on both abstract images and semantic layouts corresponding to real images.

Our main contributions can be summarized as follows:

- We propose an end-to-end trainable approach based on a sequence-to-sequence model to generate a pictorial representation of input language describing a scene.

- We show that the same model devised for the task of generating abstract scenes, can also be reasonably used to generate semantic object layouts of real images.

- We provide quantitative baselines on the task of text-to-scene generation for the Abstract Scenes Dataset [41] and the COCO Dataset [16].

2. Related Work

Most research on visually descriptive language has focused on the task of image captioning or mapping images to text [5, 18, 13, 10, 27, 28, 19, 2]. However, there has been less work in the opposite direction of mapping text to images, this is, using text as an input to synthesize size images [9, 22, 30, 24]. Most of these recent approaches have leveraged conditional Generative Adversarial Networks (cGANs) to produce controllable image synthesis conditioned on text. While these works have managed to generate results of increasing quality, there are major challenges when attempting to synthesize images for complex scenes with multiple interacting objects. In our work, we do not attempt to produce pixel-level output but rather abstract representations containing the semantic elements that compose the scene but devoid of specific texture-level image information. Our method can be considered as an intermediate step for generation of more complex scenes.

Our work is also related to prior research on using abstract scenes to mirror and analyze complex situations in the real world [31, 32, 6, 26]. The most related is [32] where a graphical model was introduced to generate an abstract scene from the input textual description of the scene. Unlike this previous work, our method does not use a semantic parser to obtain a set of tuples but is trained directly from input sentences in an end-to-end fashion. Moreover, we show our method compares favorably to this previous work. Our work is also related to [29] where a sequence-to-sequence model is proposed to transform an abstract scene layout to text. Our work poses the problem in the opposite direction and demonstrates good results on both cartoon-like scenes and semantic layouts corresponding to real images.

Most closely related to our approach are the recent works of [8] and [11], as these works also exploit some form of abstract scene generation. [8] targets image synthesis using conditional GANs (pixel-level output) but unlike prior works, it generates semantic object layouts as an intermediate step. In our work, we specifically focus on layout generation as an isolated task, and our method works for both cartoon-like scenes, and scenes corresponding to real images. The work of [11] performs pictorial generation from a chat log which makes the task less ambiguous as chat logs provide more detailed and specific descriptions of the scene compared to image captions. In our work, the descriptions used are considerably more underspecified so our proposed model has to infer its output by also leveraging commonly occurring patterns across other images. Additionally, our model is the only one targeting both the type of abstract scenes used in [11], and semantic object layouts corresponding to real images as in [8, 23] under an unified framework.
3. Model

Our TEXT2SCENE model generates a scene in an initially empty two dimensional canvas sequentially in three steps: (1) given the current two dimensional canvas, the model attends to its input text to decide what is the next object to add to the canvas, or decides the generation should end; (2) if the decision is to add a new object, the agent zooms in the local context of the object in the input text to determine its attributes (e.g. pose, size) and relations with its surroundings (e.g. location, interactions with other objects); (3) given the attributes extracted in the previous step, the agent refers back to the canvas and grounds the extracted textual attributes into their corresponding visual representations.

In order to model this process, we adopt an encoder-decoder sequence-to-sequence approach \[24\]. Specifically, TEXT2SCENE consists of a text encoder which takes as input a sequence of \( M \) words \( w_i \) (section 3.1), an object decoder which predicts sequentially \( T \) objects \( o_t \), and an attribute decoder that predicts for each object \( o_t \) their locations \( l_t \) and set of \( k \) attributes \( \{R^h_{t}\} \) (section 3.2). Additionally we incorporate a regularization that encourages attending to most words in the input text so that no referred objects are missing in the output scene (section 3.3). Figure 2 shows an example of a step-by-step generation of our model.

3.1. Text Encoder

Our text encoder consists of a bidirectional recurrent neural network with Gated Recurrent Units (GRUs). For a given input text with \( M \) words, we compute for each word \( i \):

\[
h_t^E = \text{BiGRU}(x_t, h_{t-1}^E, h_{t+1}^E),
\]

where BiGRU is a bidirectional GRU cell, \( x_t \) is a word embedding corresponding to the \( i \)-th word, and \( h_t^E \) is a vector encoding the current word and its context. We use \( \{h_t^E, x_t\} \) as our encoded input text representation that will be input to our object and attribute decoders.

3.2. Object and Attribute Decoders

We formulate scene generation as a sequential process where at each step \( t \), our model predicts the next object \( o_t \) and its \( k \) attributes \( \{R^h_{t}\} \) from input text encoding \( \{h_t^E, x_t\} \) and current scene state \( S_t \). For this part, we use a convolutional GRU (ConvGRU) which is similar to a regular GRU but uses convolutional operators to compute its hidden state. Our ConvGRU has two cascaded branches: one for decoding object \( o_t \) and the other for decoding attributes \( \{R^h_{t}\} \).

Scene State Representation We compute the current scene state representation \( h_t^S \) by feeding current scene canvas \( S_t \) to a convolutional neural network (CNN) \( \Omega \). The output of \( \Omega \) is an \( H \times W \times C \) feature map, where \( N = H \times W \) is the spatial dimension and \( C \) is the feature dimension. This representation provides a good idea about the current location of all objects in the scene but it might fail to capture small objects. In order to compensate for this, a one-hot indicator vector of the object predicted in the previous step \( o_{t-1} \) is also used. We set the initial object using a special start-of-sentence token.

The temporal states of the generated scene are modeled using a convolutional GRU (ConvGRU) as follows:

\[
h_t^D = \text{ConvGRU}(\Omega(S_t), h_{t-1}^D),
\]

where the initial hidden state is created by spatially replicating the last hidden state in the text encoder GRU.

Attention-based Object Decoder Our object decoder uses an attention-based model that outputs scores for all possible objects in a vocabulary of objects \( V \). It takes as input at each time step \( t \) the encoded scene state \( h_t^D \), input text representation \( \{h_t^E, x_t\} \) and the previously predicted object \( o_{t-1} \). Following \[28\], we adopt a soft-attention mechanism on visual input \( h_t^D \), and following \[17\], we adopt a soft-attention mechanism on textual input \( \{h_t^E, x_t\} \) as follows:

\[
u_t^o = \text{AvgPooling}(\Psi^o(h_t^D)),
\]

\[
e_t^i = \Phi^i([u_t^o; o_{t-1}]; \{h_t^E, x_t\}),
\]

\[
p(o_t) \propto \Theta^o([u_t^o; o_{t-1}; e_t^i]),
\]

where \( \Psi^o \) is a CNN with spatial attention on input canvas state \( h_t^D \). The attended features are then spatially collapsed into a vector \( u_t^o \) using average pooling. \( \Phi^i \) is the text-based attention module which uses \( [u_t^o; o_{t-1}] \) to attend the input text represented by \( \{h_t^E, x_t\} \). \( \Theta^o \) is a two-layer perceptron producing the likelihood of the next object \( p(o_t) \) using a softmax function.

Attention-based Attribute Decoder The attribute set \( \{R^h_{t}\} \) corresponding to object \( o_t \) can be predicted from the visual context in \( S_t \) and the semantic context in input text \( \{h_t^E, x_t\} \). We use another attention module \( \Phi^R \) to "zoom in" the context of \( o_t \) in the input text, extracting a new context vector \( e_t^R \). For each spatial location in \( h_t^D \), we train a set of classifiers, predicting both the location likelihood \( \{l_t\}_{t=1..N} \) as a special case of attribute, and all other attribute likelihoods \( \{R^h_{t}\} \). For the purpose of locations, the possible locations are discretized into positions in a grid to turn it into a classification problem. We use a fixed resolution \((28 \times 28)\) in our experiments, as will be explained in the implementation section. In general our attributes are
3.3. Regularization

The purpose of our regularization mechanism is to encourage attention weights for the decoders to not miss any referred objects in the input text. Let \( \{ \alpha_{ti} \} \) and \( \{ \alpha_{wi} \} \) be the attention weights from \( \Phi^o \) and \( \Phi^a \) respectively. For each step \( t \), \( \sum_i \alpha_{ti} = 1 \), \( \sum_i \alpha_{wi} = 1 \) since these are computed using a softmax function. Then we define the following regularization loss which encourages the model to distribute the attention across all the words in the input sentence:

\[
L^{O}_{\text{attn}} = \sum_i (1 - \sum_t \alpha_{ti})^2,
\]

and similarly we define a regularization \( L^{A}_{\text{attn}} \) for attribute attention weights.

3.4. Objective

The final loss function for a given example in our model with reference values \( (o_t, l_t, \{ R^k_t \}) \) for object, location, and attributes is:

\[
L = -w_o \sum_t \log p(o_t) - w_l \sum_t \log p(l_t) \\
- \sum_k w^k_T \sum_t \log p(R^k_t) + w^O_L^{O}_{\text{attn}} + w^A_L^{A}_{\text{attn}}
\]

where the first three terms are negative log-likelihood losses corresponding to the object, location, and attribute softmax classifiers, and \( w_o, w_l, \{ w^k_T \}, w^O_L, \) and \( w^A_L \) are hyperparameters.

Implementation Details

Our model shares several design choices for our experiments on the Abstract Scenes and COCO datasets: We use GloVe \[21\] as our word embeddings, which are fixed throughout our experiments. The text encoder uses a one layer bidirectional GRU with a hidden dimension of 256. We discretize the possible values for spatial locations into the indices of a grid of size \( 28 \times 28 \). \( \Phi^o \) and \( \Phi^a \) are two-layer ConvNets with 256 and 1 output channels respectively. \( \Theta^o \) consists of two fully connected layers outputting a likelihood scores for all object categories. \( \Theta^a \) consists of four convolutional layers with output channels \( (512, 256, 256, 1 + \sum_k |R^k|) \), where \( |R^k| \) denotes the discretized range of the \( k \)-th attribute. In the last layer (with a channel size of \( 1 + \sum_k |R^k| \)), the first depth channel encodes the location likelihood of the predicted object. A 2D softmax function is applied to this channel to normalize the likelihoods over spatial domain. The rest channels encode the attribute likelihoods for each spatial location. A 1D softmax function is applied to the channels of each attribute along the depth dimension. Every convolutional and fully connected layers, except the last layer, are followed by a ReLU activation function.

For the Abstract Scenes dataset, \( S_t \) is represented directly as an RGB image, and the CNN encoder \( \Omega \) is a
Table 1. Specific architecture choices of the different modules involved in our model. Here $|V|$ is the size of object vocabulary for each dataset.

| Module | Input Shape | Operation | Output Shape |
|--------|-------------|-----------|--------------|
| $\Omega$ (for COCO) | (83, 64, 64) | Conv: (83, 128, 7, 7), stride 2 | (128, 32, 32) |
| & (128, 32, 32) | Residual block, 128 filters | (128, 32, 32) |
| & (128, 32, 32) | Residual block, 256 filters, stride 2 | (256, 16, 16) |
| & (256, 16, 16) | Bilateral upsampling | (256, 28, 28) |
| $\Psi^\theta$ | (512, 28, 28) | Conv: (512, 256, 3, 3) | (256, 28, 28) |
| & (256, 28, 28) | Conv: (256, 1, 3, 3) | (1, 28, 28) |
| $\Psi^A$ | (1324, 28, 28) | Conv: (1324, 256, 3, 3) | (256, 28, 28) |
| & (256, 28, 28) | Conv: (256, 1, 3, 3) | (1, 28, 28) |
| $\Theta^\theta$ | (1324 + $|V|$,) Linear: (1324 + $|V|$)→512 | (512,) |
| & (512,) | Linear: 512→$|V|$ | ($|V|$,) |
| $\Theta^A$ | (1324 + $|V|$, 28, 28) | Conv: (1324 + $|V|$, 512, 3, 3) | (512, 28, 28) |
| & (512, 28, 28) | Conv: (512, 256, 3, 3) | (256, 28, 28) |
| & (256, 28, 28) | Conv: (256, 256, 3, 3) | (256, 28, 28) |
| & (256, 28, 28) | Conv: (256, $1 + \sum k |R_k|$, 3, 3) | (1 + $\sum_k |R_k|$, 28, 28) |

pre-trained ResNet-34 [7], with the last residual group (conv5 x) removed, followed by a bilateral upsampling operation to resize the spatial resolution to $28 \times 28$. We do not finetune $\Omega$ for the Abstract Scenes dataset. We include a BatchNorm layer between each pair of the convolutional and ReLU layers.

For the COCO dataset, $S_t$ is a three dimensional tensor $V \times H \times W$, where at each location in $(H, W)$ there is an indicator vector of size $V$, which is the number of object categories. The encoder CNN $\Omega$ consists of 2 residual blocks. The first residual block has two 3x3 convolutional layers as the skip connection. The second residual block consists of one 1x1 convolutional layer with stride 2, and two 3x3 convolutional layers as the skip connection. Table 1 provides detailed information of all the network modules in our model.

For optimization we use Adam [12] with an initial learning rate of $5e^{-5}$. The learning rate is decayed by 0.8 every 3 epochs. Models are trained until validation errors stop decreasing. The model with the minimum validation error is used for evaluation.

4. Experiments

We conduct experiments on two text-to-scene tasks: (I) generating abstract scenes of clip arts in the Abstract Scenes dataset; and (II) constructing semantic object layouts of real images in the COCO dataset.

4.1. Clip-art Generation on Abstract Scenes

We use the dataset introduced by [31], which contains over 1,000 sets of 10 semantically similar scenes of children playing outside. The scenes are composed with 58 clip art objects. The attributes we consider for each clip art object are their locations, sizes ($|R_{size}| = 3$), and the directions the object is facing ($|R_{direction}| = 2$). For the person objects, we also explicitly model the pose ($|R_{pose}| = 7$) and expression ($|R_{expression}| = 5$). There are three sentences describing different aspects of a scene. The three sentences are fed separately into the text encoder. The output features are concatenated in temporal order. We convert all sentences to lowercase and discard punctuation and stop-words, which results in a vocabulary size of 2538. We restrict the maximum length of each sequence to 5. The last sentence is padded with a special end-of-sentence token. After filtering empty scenes, we obtain 9997 samples. Following [31], we reserve 1000 samples as the test set. We also reserve 497 samples for validation. The final
train/val/test splits are 8500/497/1000. We set the hyperparameters \((w_o, w_l, w_{pos}, w_{expression}, w_{size}, w_{direction}, w_{att}\_o, w_{att}\_a)\) in Section 3.4 to \((8,2,2,2,1,1,1)\) to make the losses of the object prediction branch and attributes prediction branch comparable. Exploration of the best hyperparameters is left for future work.

**Baselines and Competing Approach** We compare our full model with [32]. We reproduce the results of [32] from the released source codes. We also consider variants of our full model: (1) TEXT2SCENE (w/o attention): a model without any attention module. In particular, we replace \(c^r_t\) with a pure average pooling operation, discard \(c^g_t\) in Eq. 5, and replace \(u^t\) with \(h^D\). (2) TEXT2SCENE (w object attention): a model with attention modules for object prediction but no dedicated attentions for attribute prediction. Specifically, we replace \((w^o, c^o_t)\) with \((h^O_t, c^g_t)\) in Eq. 8. In this case, the semantic-visual alignment would be learned directly from \(h^O\) and the context vector \(c^g_t\) from the object decoder. (3) TEXT2SCENE (w both attentions): a model with attention modules for both object prediction and attribute prediction but no regularization.

| Methods                      | U-obj Prec | U-obj Recall | B-obj Prec | B-obj Recall | Pose Prec | Expr Prec | U-obj Coord | B-obj Coord |
|------------------------------|------------|--------------|------------|--------------|-----------|-----------|-------------|-------------|
| Zitnick et al. 2013          | 0.722      | 0.655        | 0.280      | 0.265        | 0.407     | 0.370     | **0.449**   | **0.416**   |
| TEXT2SCENE (w/o attention)   | 0.665      | 0.605        | 0.228      | 0.186        | 0.305     | 0.323     | 0.395       | 0.338       |
| TEXT2SCENE (w object attention) | 0.731    | 0.671        | 0.312      | 0.261        | 0.365     | 0.368     | 0.406       | 0.427       |
| TEXT2SCENE (w both attentions) | 0.749   | 0.685        | 0.327      | 0.272        | 0.408     | 0.374     | 0.402       | 0.467       |
| TEXT2SCENE (full)            | **0.760**  | **0.698**    | **0.348**  | **0.301**    | **0.418** | **0.375** | **0.409**   | **0.483**   |

Table 2. Quantitative evaluation on the Abstract Scenes Dataset

| Methods                      | Scores | \(\geq 1\) | \(\geq 2\) | Obj-Single | Obj-Pair | Location | Expression |
|------------------------------|--------|------------|------------|------------|----------|----------|------------|
| Reference                    | 0.919  | 1.0        | 0.97       | 0.905      | 0.88     | 0.933    | 0.875      |
| Zitnick et al. 2013          | 0.555  | 0.92       | 0.49       | 0.53       | 0.44     | 0.667    | 0.625      |
| TEXT2SCENE (w/o attention)   | 0.455  | 0.75       | 0.42       | 0.431      | 0.36     | 0.6      | 0.583      |
| TEXT2SCENE (full)            | **0.644** | **0.94** | **0.62**   | **0.628**  | **0.48** | **0.667** | **0.708**  |

Table 3. Human Evaluation on Abstract Scenes Dataset

4.2. Semantic Layout Generation on COCO

We also test our approach by generating semantic object layouts corresponding to real images in the COCO dataset given an input textual caption. The semantic layouts contain bounding boxes of the objects annotated in the images. COCO [16] has 80 categories of objects in 123,287 images. Each image has 5 textual descriptions. We use the official val2017 split as our test set and use 5000 samples from the train2017 split for validation. The sentences are preprocessed as in our previous experiment. We use a vocabulary of size of 9908 by taking into account the most frequent words (appear at least 5 times) in the training split. We normalize the bounding boxes and discard objects with areas smaller than 0.01 the size of the image. We order the objects from bottom to top as the y-coordinate typically indicate the distances between the objects and the camera. We further order the objects with the same y-coordinate based on their x-coordinates (from left to right) and categorical indices. After filtering out empty scenes, we obtain a train/val/test split of size 107299/4752/4732. The attributes we consider for COCO are locations, sizes (\(|R^{size}| = 17\)), and aspect ratios (\(|R^{ratio}| = 17\)). For the size attribute, we estimate the size range of the bounding boxes in the training split, and discretize it evenly into 17 scales. We also use 17 aspect ratio scales, which are \(\{\frac{1}{n}, \frac{1}{n+1}\}_{n=1}^{8}\) and \(\{1, 1\}_{n=0}^{8}\). We restrict the maximum length of the output object sequence to 9 and pad the sequence with a special ending token. For sequences shorter than 9, we also fill them with a special padding token. We set the hyperparameters \((w_o, w_l, w_r^{size}, w_r^{ratio}, w_{att}\_o, w_{att}\_a)\) in Section 3.4 to \((5,2,2,1,0)\) to make the losses of the object prediction branch and attributes prediction branch comparable, and leave the exploration of the best hyperparameters for future work.

**Baselines** For the task of generating semantic layouts, we compare the performance of equivalent TEXT2SCENE (w/o attention), TEXT2SCENE (w object attention) and TEXT2SCENE (w both attentions) models as defined in section 4.1.

4.3. Evaluation

**Automatic Metrics** Our tasks pose new challenges on evaluating the semantic matches between the textual descriptions and the visual features of the generated scenes/layouts since there is no absolute one-to-one correspondence between text and scenes. We draw inspiration...
from the evaluation metrics applied in machine translation [14] but we aim at aligning multimodal visual-linguistic data instead. To this end, we propose to compute the following metrics: precision/recall on single objects (U-obj), “bigram” object pairs (B-obj); classification accuracies for poses, expressions; Euclidean distances (defined as a Gaussian function with a kernel size of 0.2) for bounding box size, aspect ratio, coordinates of U-obj and B-obj. A “bigram” object pair is defined as a pair of objects with overlapping bounding boxes as illustrated in Figure 3.

Human Evaluation We collect human evaluations on 100 groups of images for the Abstract Scenes dataset via Amazon Mechanical Turk (AMT). The human annotators are asked to judge whether a sentence is entailed given a corresponding clip-art scene. Each scene in this dataset is associated with 3 sentences that are used as the statements. Each sentence-scene pair is reviewed by three turkers to determine if the entailment is true, false or uncertain. To further analyze if the approach could capture finer-grained semantic alignments between the textual description and the generated abstract scenes, we apply the predicate-argument semantic frame analysis of [4] on the corresponding triplets obtained from input sentences using a semantic parsing method as computed by [31]. We subdivide each sentence by the structure in the triplet as: sub-pred corresponding to sentences referring to only one object, sub-pred-obj corresponding to sentences referring to object pairs with semantic relations, pred:loc corresponding to sentences referring to locations, and pred:pa corresponding to sentences mentioning facial expressions.

Extrinsic Evaluation through Captioning For the generation of scenes in the COCO dataset, we also employ caption generation as an extrinsic evaluation, similarly as in

| Methods | U-obj Prec | U-obj Recall | B-obj Prec | B-obj Recall | Size | ARatio | U-obj Coord | B-obj Coord |
|---------|------------|--------------|------------|--------------|------|--------|-------------|-------------|
| TEXT2SCENE (w/o attention) | 0.733 | 0.648 | 0.378 | 0.318 | 0.577 | 0.249 | 0.221 | 0.221 |
| TEXT2SCENE (w object attention) | **0.738** | 0.661 | 0.402 | 0.335 | 0.598 | **0.259** | 0.234 | 0.242 |
| TEXT2SCENE (w both attentions) | 0.716 | 0.654 | 0.391 | 0.346 | 0.585 | 0.258 | 0.362 | 0.232 |
| TEXT2SCENE (full) | 0.720 | **0.688** | **0.406** | **0.368** | **0.601** | 0.243 | **0.390** | **0.248** |

Table 4. Quantitative evaluation on COCO.

| Methods | B-1 | B-2 | B-3 | B-4 | METEOR | ROUGE_L | CIDEr | SPICE |
|---------|-----|-----|-----|-----|--------|---------|-------|-------|
| Reference | 0.678 | 0.492 | 0.348 | 0.248 | 0.227 | 0.495 | 0.838 | 0.160 |
| TEXT2SCENE (w/o attention) | 0.591 | 0.391 | 0.254 | 0.169 | 0.179 | 0.430 | 0.531 | 0.110 |
| TEXT2SCENE (w object attention) | 0.591 | 0.391 | 0.256 | 0.171 | 0.179 | 0.430 | 0.524 | 0.110 |
| TEXT2SCENE (w both attentions) | 0.600 | 0.401 | 0.263 | 0.175 | 0.182 | 0.436 | 0.555 | 0.114 |
| TEXT2SCENE (full) | **0.615** | **0.415** | **0.275** | **0.185** | **0.189** | **0.446** | **0.601** | **0.123** |

Table 5. Extrinsic captioning evaluation results on COCO.

Figure 4. Examples of generated abstract scenes from textual descriptions.

We generate captions from the semantic layouts and compare them back to the original captions used to generate the scene. We also use as reference an approach similar to [29] where the caption is generated from the reference layout. We use commonly used metrics for captioning such as BLEU [20], METEOR [3], ROUGE_L [15], CIDEr [25] and SPICE [1].

4.4. Results

Abstract Scenes Table 2 presents quantitative results. TEXT2SCENE (full) shows significant improvement over the previous work of [32] and our variant that does not use attention on all the metrics except U-obj Coord. This metric tests for exact matching of corresponding object locations, which penalizes our method because it generates more diverse than the reference scenes yet remarkably maintains the semantics of the input text. Human evaluation results on Table 3 confirm this, where Scores are the percentage of scene-textual pairs with a true en-
Figure 5. Examples of generated layouts of COCO images from captions and generated captions from layouts. Our model learns the presence (first row, text in purple) and count (second row, text in blue) of the objects, and their spatial relations (third and fourth rows, text in red) reasonably well. The last row shows the cases when the layouts are underspecified in the input captions.

tailment; \((\geq 1) (\geq 2)\) denotes at least one (two) out of three sentence-scene annotated as true by majority votes. TEXT2SCENE (full) outperforms the no-attention variant and the previous work under these experiments, including on statements with specific semantic information such as Obj-single, Obj-pair, and expression, and are actually comparable on location statements. We also perform human evaluation on the reference scenes provided in the Abstract Scenes dataset as an upper bound on this task. Results also show that it is more challenging to generate the semantically related object pairs. Overall, the results also suggest that our proposed metrics correlate with human judgment on the task.

Figure 4 shows qualitative results of our models on Abstract Scene, in comparison with baseline approaches and reference scenes. These examples illustrate that the models are able to capture the semantic nuances such as the spatial relation between two objects (e.g., the bucket and shovel are correctly placed in Jenny’s hands in the last row) and object locations (e.g., Mike is on the ground near the swing set in the last row).

**COCO Layouts** Compared to our previous experiments, quantitative results on COCO in Table 4 seem to suggest that the attribute attention might be less impactful on this dataset. We conjecture it is because the objects in the COCO images while realistic, exhibit weaker compositionality compared to the abstract scenes dataset which was built explicitly to depict complex relationships between objects. Also the layout representation has fewer attributes (e.g., location, size and aspect ratio). These attributes have larger variances on the realistic COCO data and are usually underspecified in the input captions. While the spatial relations between objects can be learned from the object attention, the size and aspect may be predicted mainly from the prior distribution of the COCO data. But overall we found that semantically plausible layouts were generated. As shown in our qualitative examples Figure 5, our model learns the presence (first row, text in purple) and count (second row, text in blue) of the objects, and their spatial relations (third and fourth rows, text in red) reasonably well. Additionally, in our extrinsic evaluation on a captioning task, shown in Table 5, we also find that our model produces reasonable results leading to a CIDEr score of 0.601, which, for reference, is considerably larger than CIDEr scores obtained from synthetically generated pixel-level images in [8].

We include more qualitative results on Abstract Scene and COCO in Fig. 6 and Fig. 7.
5. Conclusions

This work presents an end-to-end approach for generating pictorial representations of the visually descriptive language. We provide extensive quantitative and qualitative analysis of our method on two distinctive datasets. The results demonstrate the ability of our models for capturing finer semantic matching from descriptive text to generate scenes. We establish quantitative baselines for text-to-scene generation on the Abstract Scenes and the COCO Datasets.

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| Caption                                                                 | TEXT2SCENE | Reference |
|------------------------------------------------------------------------|------------|-----------|
| Mike talks to the dog. Jenny kicks the soccer ball. The duck wants to play. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| The snake wants the cherry pie. The owl wants to eat the snake. The snake likes to play football. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Mike is wearing a gold crown. The dog is wearing sunglasses. Rain is coming out of the gray cloud. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Jenny offers to share her pie with the bear. Mike found a bunch of balloons. The bear cannot scare Mike and Jenny. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Jenny is kicking her foot. Mike is happy that it is raining. The pie is cooking. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Mike is kicking the soccer ball. The sandbox is empty. Nobody is playing on the swings. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Mike is holding a bottle of mustard. Jenny is holding a bottle of ketchup. Jenny is crying because she hates rain. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| It is getting stormy in the park. The lightning started a fire in the park. Jenny and Mike are worried about the stormy weather. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Jenny is wearing a hat. Jenny is walking a dog. There is an owl in the tree. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| The balloon landed in the park. Jenny wants to go see the balloon. Mike is wearing a viking hat. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Jenny is wearing the catcher’s mitt. Mike is going to throw the tennis ball. There is a plane in the sky. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Jenny is on the swing. Jenny is wearing glasses. Mike is sitting alone in the grass. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Jenny is kicking a football. A cat is sitting on a table. Mike is about to eat a hotdog. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Mike and Jenny are on the swings. Jenny is mad the Frisbee almost hit the cat. The cat is watching Mike and Jenny swing. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Mike let the balloons fly away. Jenny wants the cold drink. Red apples grow on the tree. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Mike is wearing a silly hat. Jenny is wearing a viking hat. Jenny and Mike are happy to see the bear. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Jenny is throwing a Frisbee. Mike is wearing a catcher’s mitt. Jenny is standing at the tree. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Mike and Jenny are mad. The hotdog and drink are on the table. The basketball is in the grass. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Mike and Jenny are scared of the snake. Mike and Jenny are holding hands. The cat is sitting next to Jenny. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |
| Mike has a pirate hat on. Some fruit is in the tree. Jenny has some balloons. | ![Image](https://via.placeholder.com/150) | ![Image](https://via.placeholder.com/150) |

Figure 6. More qualitative examples on the Abstract Scene dataset
| Input Caption | Predicted Layout | Reference Image | Input Caption | Predicted Layout | Reference Image |
|---------------|-----------------|-----------------|---------------|-----------------|-----------------|
| **An attractive young woman leads a grey horse through a paddock.** | ![Prediction](image1) | ![Reference](image2) | **A couple of women ride horses through some water.** | ![Prediction](image3) | ![Reference](image4) |
| **A person holding a surf board in a body of water.** | ![Prediction](image5) | ![Reference](image6) | **This is a man riding a board in the water.** | ![Prediction](image7) | ![Reference](image8) |
| **A laptop computer a keyboard and two monitors.** | ![Prediction](image9) | ![Reference](image10) | **A plate with an orange cake dessert and a fork.** | ![Prediction](image11) | ![Reference](image12) |
| **A man and a woman stand under an umbrella at a street crossing on a rainy day.** | ![Prediction](image13) | ![Reference](image14) | **Two women walk outside, both holding up umbrellas.** | ![Prediction](image15) | ![Reference](image16) |
| **A woman is riding her bike down the street in front of traffic.** | ![Prediction](image17) | ![Reference](image18) | **A horse and several cows feed on hay.** | ![Prediction](image19) | ![Reference](image20) |
| **A bowl full of fresh green apples are kept.** | ![Prediction](image21) | ![Reference](image22) | **Cat sleeping in front of a powered on laptop.** | ![Prediction](image23) | ![Reference](image24) |
| **A woman holds a phone next to the laptop a child is working on.** | ![Prediction](image25) | ![Reference](image26) | **The woman sits at the table with the two children doing crafts.** | ![Prediction](image27) | ![Reference](image28) |
| **A man helping a boy on a paddle board in the water.** | ![Prediction](image29) | ![Reference](image30) | **A man holding a horse, so a little boy can take a ride.** | ![Prediction](image31) | ![Reference](image32) |
| **A small boat in the water beside a sea airplane.** | ![Prediction](image33) | ![Reference](image34) | **Children are sitting on the side of the boat in the water.** | ![Prediction](image35) | ![Reference](image36) |

Figure 7. More qualitative examples on the COCO dataset. The presence (purple), count (blue), and spatial relation (red) of the objects are highlighted in the captions.