Abstract—Generative adversarial networks conditioned on simple textual image descriptions are capable of generating realistic-looking images. However, current methods still struggle to generate images based on complex image captions from a heterogeneous domain. Furthermore, quantitatively evaluating these text-to-image synthesis models is still challenging, as most evaluation metrics only judge image quality but not the conformity between the image and its caption. To address the aforementioned challenges we introduce both a new model that explicitly models individual objects within an image and a new evaluation metric called Semantic Object Accuracy (SOA) that specifically evaluates images given an image caption. Our model adds an object pathway to both the generator and the discriminator to explicitly learn features of individual objects. The SOA uses a pre-trained object detector to evaluate if a generated image contains objects that are specifically mentioned in the image caption, e.g. whether an image generated from “a car driving down the street” contains a car. Our evaluation shows that models which explicitly model individual objects outperform models which only model global image characteristics. However, the SOA also shows that despite this increased performance current models still struggle to generate images that contain realistic objects of multiple different domains.

1 INTRODUCTION

Generative adversarial networks (GANs) are capable of generating realistic-looking images that adhere to characteristics described in a textual manner, e.g. an image caption. For this, most networks are conditioned on an embedding of the textual description (either on sentence level, word level, or both). Often, the textual description is used on multiple levels of resolution, e.g. first to obtain a course layout of the image at lower levels (e.g. $64 \times 64$ pixels) and then to iteratively improve the details of the image on higher resolutions (e.g. $128 \times 128$ and $256 \times 256$ pixels). This approach has led to good results on reasonably simple, well-structured data sets containing a specific class of objects (e.g. faces, birds, or flowers) at the center of the image. In this work we extend this approach by additionally focusing specifically on salient objects within the generated image. Furthermore, we introduce a new evaluation metric called Semantic Object Accuracy (SOA) that is able to evaluate generated images on a more fine-grained level than existing evaluation metrics.

Once the images and textual descriptions become more complex, e.g. by containing more than one object and having a large variety in backgrounds and scenery settings, however, the image quality drops drastically. This is likely because until recently almost all approaches were only conditioned on an embedding of the complete textual description, without paying attention to individual objects or relations between objects. Recent approaches have started to tackle this challenge by either relying on specific scene layouts or by explicitly focusing on individual objects within the image. However, generating complex scenes containing multiple objects from a big variety of classes is still a challenging problem.

Furthermore, the most commonly used evaluation metrics for GANs, the Inception Score (IS) and the Fréchet Inception Distance (FID), are not designed to evaluate images that contain multiple objects and depict complex scenes. In fact, both of these metrics depend on an image classifier (the Inception-Net), which is pre-trained on ImageNet, a data set whose images almost always contain only a single object centered in the image. They also do not evaluate the consistency between image description and generated image and, therefore, can not evaluate whether a model generates images that actually depict what is described in the caption. Even evaluation metrics specifically designed for text-to-image synthesis evaluation such as the R-precision often fail to evaluate more detailed aspects of an image, such as the quality of individual objects.

As such, our contributions are twofold: we introduce a novel GAN architecture called OP-GAN that focuses specifically on individual objects and generates them at meaningful locations in the image, while simultaneously generating a background that fits with the overall image description. Our approach relies on an object pathway similar to, which iteratively attends to all objects that need to be generated given the current image description and which is conditioned on the image description and a one-hot label describing the object’s class (e.g. “person”). In parallel, a global pathway generates the background features which later on get merged with the object features.

Second, we introduce an evaluation metric specifically for text-to-image synthesis tasks which we call Semantic Object Accuracy (SOA). In contrast to most current evaluation metrics, our metric focuses on individual objects and parts of an image and also takes the caption into consideration.

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when evaluating an image. Image descriptions often explicitly or implicitly mention what kind of objects are seen in an image, e.g. an image described by the caption “a person holding a cell phone” should depict both a person and a cell phone. To evaluate this, we sample all image captions from the COCO validation set that explicitly mention one of the 80 main object categories (e.g. “person”, “dog”, “car”, etc.) and use them to generate images. We then use a pre-trained object detector \(^7\) and check whether it detects the explicitly mentioned objects within the generated images.

We evaluate several variations of our proposed model as well as several state-of-the-art approaches that provide pre-trained models. Our results show that current architectures are not able to generate images that contain objects of the same quality as the original images. While some models already achieve results close to or better than real images on scores such as the IS and R-precision, none of the models comes close to generating images that achieve SOA scores close to the real images. However, our results also show that models that attend to individual objects in one way or another tend to perform better than models, which only focus on global image semantics.

2 Related Work

Modern architectures are able to synthesize realistic, high-resolution images of many domains, such as faces, birds, and flowers. In order to generate images of relatively high resolution many GAN \(^1\) architectures use multiple discriminators at various resolutions \(^9\). Additionally, most GAN architectures now use some form of attention for improved image synthesis \(^7\) as well as matching aware discriminators \(^10\) which need to identify whether real images correspond to a given textual description.

Originally, most GAN approaches for text-to-image synthesis encoded the textual description into a single vector which was then used as a condition in a conditional GAN (cGAN) architecture \(^9\), \(^10\). However, this faces limitations when the image content becomes more complex and consists of multiple objects as e.g. in the COCO data set \(^11\). As a result, many approaches now use attention mechanisms to attend to specific words of the sentence \(^7\), use intermediate representations such as scene layouts \(^2\) condition on additional information such as object bounding boxes \(^3\) or perform interactive image refinement \(^12\). Many approaches also generate images directly from semantic layouts without any additional textual input \(^22\), \(^24\). Some approaches perform a multimodal translation from text to images and back. \(^15\) introduce a bidirectional architecture that does both text-to-image and image captioning. Similarly, \(^16\) learn text-to-image by redescription, i.e. they train a text-to-image model and an image captioning model. They then compare the generated image caption for the generated image with the original image caption to train their text-to-image model.

**Direct Text-to-Image Synthesis** Approaches that do not rely on additional conditional information and do not use any intermediate representations such as scene layouts use only the image caption as conditional input. \(^10\) use a GAN to generate images from captions directly and without any attention mechanism. Captions are embedded and used as conditioning vector and they introduce the widely adopted matching aware discriminator. The matching aware discriminator is trained to distinguish between real and matching caption-image pairs (“real”) and real but mismatching caption-image pairs (“fake”) as well as matching caption with generated images (“fake”). \(^17\) modify the sampling procedure during training to obtain a curriculum of mismatching caption-image pairs and introduce an auxiliary classifier that specifically predicts the semantic consistency of a given caption-image pair. \(^9\), \(^18\) use multiple generators and discriminators for text-to-image synthesis and are one of the first ones that achieve good image quality at resolutions of \(256 \times 256\) on complex data sets such as the COCO data set. \(^19\) have a similar architecture as \(^18\) with multiple discriminators but only use one generator. \(^20\) manage to generate realistic high-resolution images from text with a single discriminator and generator.

\(^7\) extend \(^9\) and are the first ones to introduce an attention mechanism to the text-to-image synthesis task with GANs. The attention mechanism attends to specific words in the caption and conditions different image regions on different words to improve the overall image quality. \(^21\) extend on this and also consider semantics from the text description during the generation process. \(^22\) introduce a dynamic memory part that selects “bad” parts of the initial image and tries to refine them based on the most relevant word for the given part of the image. \(^23\) refine the attention module by having spatial and channel-wise word-level attention and introduce a word-level discriminator to provide fine-grained feedback based on individual words and image regions associated with that word.

**Text-to-Image Synthesis with Layouts** When using more complex data sets that contain multiple objects per image, generating an image directly becomes more difficult. Therefore, many current approaches use additional information such as bounding boxes for objects or intermediate representations such as scene graphs or scene layouts. There are some approaches that can be seen as models that generate these image layouts for models that need it \(^24\), \(^25\), \(^26\), \(^27\) and \(^28\) build on \(^10\) by additionally conditioning the generator on bounding boxes or keypoints of relevant objects. \(^29\) decompose textual description into basic visual primitives to generate images in a compositional manner. \(^2\) introduced the concept of a scene graph. They take the caption as input and first generate a scene graph from it which is then used to generate an image layout and finally the image. Similar to \(^2\) \(^30\) use the caption to infer a scene layout which is then used to generate images.

Given a coarse image layout (bounding boxes and object labels) \(^31\) generate images by disentangling each object into a specified part (e.g. object label) and unspecified part (appearance). \(^3\) generate images conditioned on bounding boxes for the individual foreground objects by introducing an object pathway that is dedicated to generating individual objects. \(^4\) update the grid-based attention mechanism \(^7\) by combining attention with scene layouts and using attention to attend to individual objects of the scene layout. Additionally, an object discriminator is introduced which focuses on individual objects and provides feedback whether the object is at the right location and matches the description. \(^32\) refine the attention grid-based attention mechanism...
between word phrases and specific image regions of various sizes based on an initial set of bounding boxes.

Introduce a new feature normalization method and fine-grained mask maps to generate visually different images from a given layout. [34] generate images from scene graphs and allow the model to crop objects from other images to paste them into the generated image at the correct location. [35] generate a visual relation scene layout based on the caption. For this, they introduce a dedicated module, the visual relation layout module, which generates bounding boxes for entities in a given caption. This visual relation layout is then used to condition the GAN network during the image generation process.

Semantic Image Manipulation Finally, there is a growing body of work that allows humans to directly describe the image in an iterative process or that allows for direct semantic manipulation of the image. [32] add dialogues to improve the generation process which is not only conditioned on an image caption but also on a dialogue describing the image. [36] facilitate semantic image manipulation by using an image layout as an intermediate representation at which the user can perform manipulation, e.g. adding or removing objects. [37] allow users to input object instance masks into an existing image represented by a semantic layout. Once the user chose an object mask one network decides where within the image layout it should be positioned and another network decides on the concrete object mask. The output is the updated image layout which could, in theory, be used by other approaches to synthesize real images. [38] generate images iteratively from consecutive textual commands, [39] provide interactive image editing, based on a current image and instructions on how to update the image, and [40] generate individual images for a sequence of sentences. [41] do interactive image generation but do not use text as direct input but instead update the scene graph from the text over the course of the interaction. [42], [43] and [44] modify visual attributes of individual objects in an image while keeping text irrelevant parts of the image the same as before.

3 APPROACH

A traditional generative adversarial network (GAN) [1] consists of two networks: a generator \( G \) which generates new data points from randomly sampled inputs, and a discriminator \( D \) which tries to distinguish between generated and real data samples. In conditional GANs (cGANs) [45] both the discriminator and the generator are conditioned on additional information, e.g. a class label or textual information. This has been shown to improve performance and leads to more control over the data generating process. For a traditional cGAN with generator \( G \), discriminator \( D \), condition \( c \) (e.g. a class label), data point \( x \), and a randomly sampled noise vector \( z \) the training objective \( V \) is:

\[
\min_G \max_D V(D,G) = \mathbb{E}_{x,c \sim p_{data}}[\log D(x,c)] + \mathbb{E}_{z \sim \mathcal{N}(0,1), c \sim \mathcal{N}(0,1)}[\log(1 - D(G(z,c),c))].
\]  

We use the AttnGAN [7] as our baseline architecture and add our object-centric modifications to it. The AttnGAN is a conditional GAN for text-to-image synthesis that uses attention and a novel additional loss to improve the quality of the generated images and their conformity to the image caption. Similarly to previous approaches, it consists of a generator and three discriminators, see the top row of Figure 1 for an overview. The discriminators provide feedback at various stages of the image generation process to stabilize training. Attention is used such that different words of the caption have more or less influence on different regions of the generated image. This means that, for example, the word “sky” has more influence on the generation of the top half of the image than the word “grass” even if both words are present in the image caption.

Additionally, [7] introduce the Deep Attentional Multimodal Similarity Model (DAMSM). The DAMSM computes the similarity between images and captions and is pre-trained on real images and associated captions. The resulting DAMSM is then used during training the GAN to provide additional, fine-grained feedback to the generator about how well the generated image matches the caption for which it was generated.

We adapt the AttnGAN architecture with multiple object pathways which are learned end-to-end in both the discriminator and the generator, see B and C in Figure 1. These object pathways are conditioned on individual object labels (e.g. “person”, “car”, etc.) and the same object pathway is applied multiple times at a given image resolution at different locations and for different objects. This is similar to the approach introduced by [3]. However, [3] only use one object pathway in the generator at a small resolution of \( 16 \times 16 \) and only the discriminator working on \( 64 \times 64 \) pixel images was equipped with an object pathway. In our approach, the generator contains three object pathways at various resolutions (\( 16 \times 16 \), \( 64 \times 64 \), and \( 128 \times 128 \)) to further refine object features at higher resolutions. Additionally, each of our three discriminators working on image resolutions of \( 64 \times 64 \), \( 128 \times 128 \), and \( 256 \times 256 \) respectively is equipped with its individual object pathway, see D in Figure 1. For a more detailed overview of our architecture see the supplementary material.

For a given image caption \( \varphi \) we have several objects which are associated with this caption and which we represent with one-hot vectors \( \sigma_i, i = 1 \ldots n \) (e.g. \( \sigma_2 = \text{person} \), \( \sigma_1 = \text{car} \), etc.). Each object pathway at a given resolution is applied iteratively for each of the objects \( \sigma_i \) at a given location. The location is determined by a bounding box describing the object’s location and size in the image. Each object pathway starts with an “empty” zero-tensor \( \rho \) at the location of the specific object’s bounding box. After the object pathway has processed each object, \( \rho \) contains features at each of the objects’ locations and is zero everywhere else.

In the generator, we first concatenate the image caption’s embedding \( \varphi \), the one-hot label \( \sigma_i \), and some randomly sampled noise vector \( z \). This concatenated vector is then used to obtain the final conditioning label \( \iota_i \) for the current object \( \sigma_i \) by applying a fully connected layer with a non-linearity to it (\( A \) in Figure 1). The generator’s first object pathway takes this conditioning label \( \iota_i \), replicates it spatially to a resolution of \( 4 \times 4 \), and then uses multiple convolutional layers and nearest neighbor upsampling to generate features for the given object at a spatial resolution of \( 16 \times 16 \). The
features are then transformed onto $\rho$ into the location of the respective bounding box with a spatial transformer network (STN) [46]. This procedure is repeated for each object $\sigma_i$ associated with the given caption $\varphi$ (B.2 in Figure 1).

The global pathway in the first generator also gets the locations and labels for the individual objects. It spatially replicates these labels at the locations of the respective bounding boxes and then applies some convolutional layers to the resulting layout to obtain a layout encoding (B.1 in Figure 1). This layout encoding, the image caption, and the randomly sampled noise are used to generate coarse features for the full image at low resolution.

At higher levels in the generator the object pathways are conditioned on the object features of the current object and the one-hot label $\sigma_i$ for that object (C.2 in Figure 1). For this, we again use an STN to extract the features at the bounding box location of the object $\sigma_i$ and resize the features to a spatial resolution of $16 \times 16$ (second object pathway) or $32 \times 32$ (third object pathway). We obtain a conditioning label in the same manner as for the first object pathway, replicate it spatially to the same dimension as the extracted object features, and concatenate it with the object features along the channel axis. Following this, we again apply multiple convolutional layers and nearest neighbor upsampling to update the features of the given object and transform them to a higher resolution ($64 \times 64$ and $128 \times 128$ respectively). Finally, in the first object pathway, we use an STN to transform the features into the bounding box location and add them onto $\rho$. The global pathway in the higher layers (C.1 in Figure 1) stays unchanged from the baseline architecture, i.e. it is the same as in the original AttnGAN.

Our final loss function for the generator is the same as in the original AttnGAN and consists of an unconditional, a conditional, and a caption-image matching part. The unconditional loss is

$$L_{G}^{\text{uncon}} = -E_{x \sim p_{G}}[\log D(x)],$$

the conditional loss is

$$L_{G}^{\text{con}} = -E_{(\hat{x},c) \sim p_{G},(c) \sim p_{\text{data}}}[\log D(\hat{x}, c)],$$

and the caption-image matching loss is

$$L_{G}^{\text{DAMSM}} = -E_{(\hat{x},c) \sim p_{G},(c) \sim p_{\text{data}}}[\log D(\hat{x}, c)],$$

which measures text-image similarity at the word level and is calculated with the pre-trained models provided by [7]. The complete loss for the generator then is:

$$L_{G} = L_{G}^{\text{uncon}} + L_{G}^{\text{con}} + \lambda L_{G}^{\text{DAMSM}},$$

where we set $\lambda = 50$ as in the original implementation.

As in our baseline architecture, we employ three discriminators at three spatial resolutions: $64 \times 64$, $128 \times 128$, and $256 \times 256$. Similarly to the generator, each discriminator possesses a global and an object pathway which extracts
features in parallel (D in Figure 1). Each discriminator’s global pathway takes the whole image as input and extracts features (D.1). Each discriminator possesses its own object pathway (D.2) which is used to extract features of individual objects at different locations. We first use an STN to extract the features of the object $\sigma_i$ at the location specified by its bounding box. The extracted object features are transformed with the STN to the respective spatial resolution for the three discriminators and are then concatenated along the channel axis with the one-hot vector $\sigma_i$ describing the object which should be at this location. The respective object pathway then applies multiple convolutional layers before adding the extracted features onto $\rho$ at the location of the bounding box with the help of an STN.

The global pathway in each of the discriminators works on the full input image and applies convolutional layers with stride two to decrease the spatial resolution. Once the spatial resolution reaches that of the tensor $\rho$ we concatenate the two tensors (full image features and object features $\rho$) along the channel axis. We follow the implementation of the AttnGAN and use convolutional layers with stride two to further reduce the spatial dimension until we reach a resolution of $4 \times 4$.

As in the original AttnGAN, we calculate both a conditional (image and image caption) and an unconditional (only image) loss for each of the three discriminators. The conditional input $c$ during training consists of the image caption embedding $\varphi$ and the information about objects $\sigma$ (bounding boxes and object labels) associated with the image $x$, i.e. $c = \{\varphi, \sigma\}$. In the unconditional case the discriminators are trained to classify images as real or generated without any influence of the image caption by minimizing the following loss:

$$L^\text{uncon}_{D_i} = -E_{(x)\sim p_{\text{data}}}[\log D(x)] - E_{(\hat{x})\sim p_{\rho}}[\log(1 - D(\hat{x}))].$$

(6)

In order to optimize the conditional loss we concatenate the extracted features with the image caption embedding $\varphi$ along the channel axis and minimize

$$L^\text{cond}_{D_i} = -E_{(x,c)\sim p_{\text{data}}}[\log D(x,c)] - E_{(\hat{x},c)\sim p_{\rho}\times p_{\text{cond}}}[\log(1 - D(\hat{x},c))].$$

(7)

for each discriminator. Finally, to specifically train the discriminators to check for caption-image consistency we use the matching aware discriminator loss [10] with mismatching-caption-image pairs and minimize

$$L^\text{ls}_{D_i} = -E_{(x,\sigma)\sim p_{\text{data}},(\varphi)\sim p_{\text{cond}}}[\log(1 - D(x,c))],$$

(8)

where image $x$ and caption $\varphi$ are sampled individually and randomly from the data distribution and are, therefore, unlikely to align.

We introduce an additional loss term similar to the matching aware discriminator loss $V_{\sigma}(D)$ which works on individual objects. Instead of using mismatching image-caption pairs, we use correct image-caption pairs, but with incorrect bounding boxes and minimize:

$$L^\text{obj}_{D_i} = -E_{(x,\varphi)\sim p_{\text{data}},(\sigma)\sim p_{\text{conf}}}[\log(1 - D(x,c))].$$

(9)

Thus, the complete objective we minimize for each individual discriminator is:

$$L_{D_i} = L^\text{uncon}_{D_i} + L^\text{cond}_{D_i} + L^\text{ls}_{D_i} + L^\text{obj}_{D_i}.$$  

(10)

We leave all other training parameters as in the original implementation and the training procedure itself also stays the same.

## 4 Evaluation of Text-to-Image Models

Quantitatively evaluating generative models is difficult [47]. While there are several evaluation metrics that are commonly used to evaluate GAN models, many of them have known weaknesses and are not designed specifically for text-to-image synthesis tasks. In the following, we first discuss some of the common evaluation metrics for GANs, their weaknesses and why they might be inadequate for evaluating text-to-image synthesis models. Following this, we introduce our novel evaluation metric, Semantic Object Accuracy (SOA), and describe how it can be used to evaluate text-to-image models in more detail.

### Current Evaluation Metrics

#### Inception Score and Fréchet Inception Distance

Most GAN approaches are trained on relatively simple images which only contain one object at the center (e.g., ImageNet, CelebA, etc.). These methods are evaluated with metrics such as the Inception Score (IS) [5] and Fréchet Inception Distance (FID) [6], which use an Inception-Net usually pre-trained on ImageNet. The IS evaluates roughly how distinctive an object in each image is (i.e. ideally the classification layer of the Inception-Net has small entropy) and how many different objects the GAN generates overall (i.e. high entropy in the output of different images). The FID measures how similar generated images are to a control set of images, usually the validation set. For this, it compares the activations of the final convolutional layer of the Inception-Net for generated and real images and calculates the Wasserstein-2 distance between the two. Consequently, the IS should be as high as possible, while the FID should be as small as possible.

Both evaluation metrics have known weaknesses [48], [49]. For example, the IS does not measure the similarity between objects of the same class, so a network that only generates one “perfect” sample for each class can achieve a very good IS despite showing an intra-class mode dropping behavior. Li et al. [4] also note that the IS overfits within the context of text-to-image synthesis and can be “gamed” by increasing the batch size at the end of the training. Furthermore, the IS uses the output of the classification layer of an Inception-Net pre-trained on the ImageNet data set. This might not be the best thing to do on a more complex data set in which each image contains multiple objects at distinct locations throughout the image, as opposed to the ImageNet data set which consists of images usually depicting one object in the image center. Figure 2 shows some exemplary failure cases of the IS on images sampled from the COCO data set. The FID relies on representative ground truth data to compare the generated data against and also assumes that features are of Gaussian distribution, which is often not the case. For more complex data sets the FID also still suffers from the problem that the image statistics are obtained with a network pre-trained on ImageNet which might not be a representative data set.

**R-precision** [7] use the R-precision metric to evaluate how well an image matches a given description or caption.
For this, first, an image is generated conditioned on a given caption. Then, another 99 captions are chosen randomly from the dataset. Both the generated images and the 100 captions are then encoded with the respective image and text encoder. Finally, the cosine distance between the image embedding and each caption embedding is calculated to obtain a similarity score between the given image and caption. The 100 captions are then ordered in descending similarity and the top \( k \) (usually \( k=1 \)) most similar captions are used to calculate the R-precision.

Intuitively, R-precision calculates if the real caption is more similar to the generated image (in feature space) than \( k \) randomly sampled captions. However, the drawback is that this metric does not necessarily evaluate the quality of individual (foreground) objects. For example, the real caption could state that “there is a person standing on a snowy hill” while the 99 random captions do not mention “snow” (which usually covers most of the background in the generated image) or “person” (but e.g. giraffe, car, bedroom, etc). In this case, an image with only white background (snow) would already make the real caption rank very highly in the metric and if there is a shape roughly resembling a person somewhere in the image the real caption would most likely be ranked at the top. See Figure 3 for a visualization of this. As such, this metric does not focus on the quality of individual objects but rather concentrates on global background and salient features.

Classification Accuracy Score \([50]\) introduce the Classification Accuracy Score (CAS) to evaluate conditional image generation models. For this, a classifier is trained on images generated by the conditional generative model. The classifier’s performance is then evaluated on the original test set of the data set that was used to train the generative model. If the classifier achieves high accuracy on the test set this indicates that the data it was trained on is representative of the real distribution. The authors find that neither the IS, the FID, nor combinations thereof are predictive of the CAS, further indicating that the IS and FID are only of limited use for evaluating image quality.

In contrast to the IS, which measures the diversity of a whole set of images, the diversity score \([51]\) measures the perceptual difference between a pair of images in feature space. This metric can be useful when images are generated from conditional inputs (e.g. labels or scene layouts) to examine whether a model can generate diverse outputs for a given condition (e.g. generate visually different cats). However, the metric does not say anything directly about the quality of the generated images or their congruence with any conditional information. \([14]\), \([51]\), \([52]\) run a semantic segmentation network on generated images and compare the predicted segmentation mask to the ground truth segmentation mask used as input for the model. However, this metric needs a ground truth semantic segmentation mask and does not provide information about specific objects within the image.

Semantic Object Accuracy (SOA)

So far, most evaluation metrics are designed to evaluate the holistic image quality but do not evaluate individual areas or objects within the image. Furthermore, except for R-precision, none of the scores takes the image caption into account when evaluating the generated image. To address the challenges and issues mentioned above we introduce a novel evaluation metric based on a pre-trained object detection network. The pre-trained object detector is used to evaluate images by checking if it recognizes specific objects that the image should contain based on the caption or image description. For example, if the image caption is “there is a person eating a pizza” we can infer that the image should contain both a person and a pizza and the object detector should ideally be able to recognize both objects within the image. Since this evaluation measures directly whether objects specifically mentioned in the caption are recognizable in an image we call this metric Semantic Object Accuracy (SOA).

Some previous works have used similar approaches to evaluate the quality of the generated images. \([3]\) evaluate how often expected objects (based on the caption) are detected by an object detector. However, only a subset of the captions is evaluated (only for the 30 most common objects) and the evaluated captions contain false positives (e.g. captions containing the phrase “hot dog” are evaluated based on the assumption that the image should contain a dog). \([15]\) introduce a detection score that calculates (roughly) whether a pre-trained object detector detects an object in a generated
image with high certainty. No information from the caption is taken into account in this evaluation though, meaning any detection with high confidence is “good” even if the detected object does not make sense in the context of the caption. \[53\] use a pre-trained object detector to calculate the mean average precision and report precision-recall curves. However, the evaluation is done on synthetic data sets and without textual information as conditional input. \[31\] use classification accuracy as an evaluation metric in which they report the object classification accuracy in generated images. For this, they use a ResNet-101 model which is trained on real objects cropped and resized from the original data. However, in order to calculate the score, the size and location of each object in the generated image must be known, so this evaluation is not directly applicable to approaches that do not use scene layouts or similar representations. \[35\] use recall and intersection-over-union (IoU) to evaluate the bounding boxes in their generated scene layout but do not apply these evaluations to generated images directly.

**SOA** Since we work with the COCO data set we filter all captions in the validation set for specific keywords that are related to the available labels for objects (e.g. person, car, zebra, etc). For each of the 80 available labels in the COCO data set we find all captions that imply the existence of the respective object and use the model that is to be evaluated to generate three images for each of the captions. See the supplementary material for a detailed overview of how exactly the captions were chosen for each label. We then run the YOLOv3 network \[8\] pre-trained on the COCO data set on each of the generated images and check whether it recognizes the given object. We report the recall as a class average recall/IoU (SOA-C), i.e. on average in how many images per class, the YOLOv3 network detected an object of class \(c\).

\[\text{SOA-C} = \frac{1}{|C|}\sum_{c\in C}\frac{1}{|I_c|}\sum_{i\in I_c} \text{YOLOv3}(i_c),\]

\(11\)

for object classes \(c\in C\) and images \(i\in I\) that are supposed to contain an object of class \(c\). The SOA-I is calculated as

\[\text{SOA-I} = \frac{1}{\sum_{c\in C}|I_c|}\sum_{c\in C}\sum_{i\in I_c} \text{YOLOv3}(i_c),\]

\(12\)

and

\[\text{YOLOv3}(i_c) = \begin{cases} 1 & \text{if YOLOv3 detected an object of class } c \\ 0 & \text{otherwise} \end{cases}\]

\(13\)

Since many images can also reasonably contain objects that are not specifically mentioned (for example an image described by “lots of cars are on the street” could still contain persons, dogs, etc) in the caption we do not calculate a false negative rate but instead only focus on the recall, i.e. the true positives. See the supplementary material for a more detailed overview of which keywords we use for each of the object labels to filter relevant captions and which keywords are excluded to increase the number of relevant captions.

**SOA-Intersection over Union** Several approaches (e.g. \[3\], \[4\], \[30\], \[31\], \[35\]) use additional conditioning information such as scene layouts or bounding boxes. For these approaches, our evaluation metric can also calculate the intersection over union (IoU) between the location at which different objects should be and locations at which they are detected, which we call SOA-IoU. To calculate the IoU we use every image in which the YOLOv3 network detected the respective object. Since many images contain multiple instances of a given object we calculate the IoU between each predicted bounding box for the given object and each ground truth bounding box. The final IoU for a given image and object is then the maximum of the values, i.e. the reported IoU is an upper bound on the actual IoU.

Overall this approach allows a more fine-grained evaluation of the image content since we can now also focus on individual objects and their features within the images. To get an easier idea of the overall performance of a given model we calculate both the class average recall/IoU (SOA-C/SOA-IoU-C) and image average recall/IoU (SOA-I/SOA-IoU-I). Additionally, we report the SOA-C for the forty most and least common labels (SOA-C-Top40 and SOA-C-Bot40) to see how well the model can generate objects of common and less common classes.

## 5 Experiments

We perform multiple experiments and ablation studies on our approach. In a first step, we add the object pathway (OP) on multiple layers of the generator and to each discriminator and call this model OPv2. We also train this model with the additional bounding box loss we introduced in section 3. When the model is trained with the additional bounding box loss we refer to it as BBL.

Different approaches differ in how many objects per image they use during training. If an image layout is used typically all objects (foreground and background) are used as conditioning information. Other approaches limit the number of objects per image they use per training \([2\), \[3\]. To examine the effect of training with different numbers of objects per image we train our approach with either a maximum of three objects per image (standard) or with up to ten objects per image, which we refer to as many objects (MO). When training with a maximum of three objects per image we sample randomly from the training set at train time, i.e. each batch contains images which contain zero to three objects. If an image contains more than three objects we choose the three largest ones in terms of area of the bounding box.

When training with up to ten objects per image we slightly change our sampling strategy so that each batch consists of images that contain the same amount of objects. This means that, e.g., each image in a batch contains exactly four objects, while in the next batch each image might contain exactly seven objects. This increases the training efficiency as most of the images contain less than five objects.

As a result of the different settings we perform the following experiments:

1. **OPv2**: apply the object pathway (OP) on multiple layers of the generator and on all discriminators,
training without the bounding box loss and with a maximum of three objects per image.

2) $Opl2 + BBL$: same as $Opl2$ but with the bounding box loss added to the discriminator loss term.

3) $Opl2 + MO$: same as $Opl2$ but with a maximum of ten objects per image.

4) $Opl2 + BBL + MO$ (OP-GAN): combination of all three approaches.

We train each model two times on the 2014 split of the COCO data set and except for the changes outlined here the training procedure and all hyperparameters stay the same as in the original AttnGAN [7]. Crucially, no hyperparameter tuning was performed and the entire preprocessing chain stays the same. At test time we use bounding boxes generated by a network [4] as the conditioning information. Therefore, except for the image caption no other ground truth information is used at test time.

6 Evaluation and Analysis

Table 1 and Table 2 give an overview of our results and results from the recent literature for the COCO data set. The first half of the table shows the results on the original images from the data set and results from related literature while the second half shows our results. To make a direct comparison we calculated the IS, FID, and R-precision scores ourselves for all models which are provided by the authors. When no pre-trained model is available we report the results directly from the papers. As such, the values from AttnGAN [7], AttnGAN+OP [3], Obj-GAN [4], and DM-GAN [22] are the ones most directly comparable to our reported values since they were calculated in the same way.

Note that there is some inconsistency in how the FID is calculated in different prior works. Some approaches, e.g. [4], compare the statistics of the generated images only with the statistics of the respective “original” images (i.e. the images corresponding to the captions that were used to generate a given image). We, on the other hand, generate 30,000 images from 30,000 randomly sampled captions and compare their statistics with the statistics of the full validation set. Many of the recent publications also do not report the FID or R-precision. This makes a direct comparison difficult as the IS is likely the least meaningful score of the three since it easily overfits [4] and due to the reasons mentioned in Section 4. We calculate each of the reported values of our models (IS, FID, R-precision) three times for each trained model (i.e. six times in total) and report the average and standard deviation. To calculate the SOA scores we generate three images for each caption in the given class, except for the “person” class, for which we randomly sample 30,000 captions (from over 60,000) and generate one image for each of the 30,000 captions.

Quantitative Results

Overall Results As Table 1 shows, all our models outperform the baseline AttnGAN in all metrics. The IS is increased by 16 − 21%, the R-precision by 6 − 8%, the SOA-C by 19 − 27%, the SOA-I by 18 − 22%, and the FID by 13 − 17%. This was achieved by simply adding our object pathways to the baseline model without any further tuning of the architecture, hyperparameters, or the training procedure. Our approach also outperforms most other approaches based on FID, R-precision, SOA-C, and SOA-I. We also report the results for our models when using the ground truth bounding boxes at test time in the supplementary material. While there are two approaches that report a IS higher than our models, it has previously been observed that this score is most likely the least meaningful for this task and can be gauged to achieve higher numbers [4]. The DM-GAN is the only model that performs on par or better than our model based on the scores, however, the differences in the scores might be reduced if we fine-tuned our models’ hyperparameters.

We also calculated the various scores for the original images of the COCO data set. For the IS we sampled three times 30,000 images from the validation set and resized them to 256 × 256 pixels. To calculate the FID we randomly sampled three times 30,000 images from the training set and compared them to the statistics of the validation set. The R-precision was calculated on three times 30,000 randomly sampled images and the corresponding caption from the validation set and the SOA-C and SOA-I were calculated on the real images corresponding to the originally chosen captions.

As we can see, the IS is close to the current state of the art models with a value of 34.88. It is possible to achieve a much higher IS on other, simpler data sets, e.g. IS > 100 on the ImageNet data set [54]. This indicates that the IS is indeed not a good evaluation metric, especially for complex images consisting of multiple objects and various locations. The difference between the R-precision on real and generated images is even larger. On the original images, the R-precision score is only 68.58, which is much worse than what current models can achieve (> 88).

One reason for this might be that the R-precision calculates the cosine similarity between an image embedding and a caption embedding and measures how often the caption that was used to generate an image is more similar than 99 other, randomly sampled captions. However, the same encoders that are used to calculate the R-precision are also used during training to minimize the cosine similarity between an image and the caption it was generated from. As a result, the model might already overfit to this metric through the training procedure. Our observation is that the models tend to heavily focus on the background to make it match a specific word in the caption (e.g. images tend to be very white when the caption mentions “snow” or “ski”, very blue when the caption mentions “surf” or “beach”, very green when the caption mentions “grass” or “savanna”, etc.) This matching might lead to a high R-precision score since it leads, on average, to a large cosine similarity. Real images do not always reflect this, since a large part of the image might be occupied by a person or an animal, essentially “blocking out” the background information. Regardless of what the actual reason is, the question remains whether evaluation metrics like the IS and R-precision are meaningful and helpful when models that can not (as of now) generate images that would be confused as “real” achieve scores comparable to or better than real images.

The FID and the SOA values are the only two evaluation
metrics (that we used) for which none of the current state of the art models can come close to the values obtained with the original images. The FID is still much smaller on the real data (6.09) compared to what current models can achieve (> 26 for the best models). While the FID still uses a network pre-trained on ImageNet it compares activations of convolutional layers for different images and is, therefore, likely still more meaningful and less dependent on specific object settings than the IS. Similarly, the SOA-C (SOA-I) on real data is 74.97 (80.84), while current models achieve values of around 30 – 35 (40 – 48). Since the network used to calculate the SOA values is not part of the training loop the models can not easily overfit to this evaluation metric like they can for the R-precision. Furthermore, the results of the SOA evaluation confirm the impression that none of the models is able to generate images with multiple distinct objects of a quality similar to real images.

Impact of the Object Pathway. To get a clearer understanding of how the evaluation metrics might be impacted by the object pathway we calculate our scores for a different number of generated objects. More specifically, we only apply the object pathway for a maximum given number of objects (0, 1, 3, or 10) per image. Intuitively, we would assume that without the application of the object pathway the IS and FID should be decreased, since the object pathway is not used to generate any object features and the images should, therefore, consist mostly of background. Additionally, we can get an intuition of how important the object pathway is for the overall performance of the network by looking at how it affects the R-precision and SOA-C.

As Table 1 shows, all models perform markedly worse when the object pathway is not used (0 obj). Interestingly, we find that the models trained with up to ten objects per image seem to rely more heavily on the object pathway than models trained with only three objects per image. For models trained with only three objects per image (OPv2 and OPv2 + BBL) the IS decreases by around 0 – 1, the R-precision decreases by around 2 – 3, the SOA-C (SOA-I) decreases by around 5 (7 – 9) and the FID increases by around 3 – 5. On the other hand, models trained with up to 10 objects suffer much more when the object pathway is removed, with the IS decreasing by around 4 – 6, the R-precision decreasing by around 9 – 14, the SOA-C (SOA-I) decreasing by around 12 – 14 (20 – 22) and the FID increasing by around 10 – 20. These results indicate that the object pathway is indeed an important part of the model and is responsible for at least some of the improvements compared to the baseline architecture.

Impact of Bounding Box Loss. Adding the bounding box loss to the object pathways slightly improves the IS, FID, and SOA-C, but has a small negative effect on the R-precision. Note that the weighting of the bounding box loss in the overall loss term was not optimized but simply weighted with the same strength as the matching aware discriminator loss $L_{cls}^D$. It is possible that the positive effect of the bounding box loss could be increased by weighting it differently. When we look at the results of the SOA evaluation we see that the bounding box loss has a negative effect on the SOA-IoU values (i.e. objects are not perfectly located where the bounding box is defined), but slightly
Table 1
Inception Score (IS), Fréchet Inception Distance (FID), R-precision, and Semantic Object Accuracy on Class (SOA-C) and Image Average (SOA-I) on the MS-COCO data set. Results of our models are obtained with generated bounding boxes (results with ground truth bounding boxes in the supplementary material). Scores for models marked with ✤ were calculated with a pre-trained model provided by the respective authors.

| Model                        | IS ↑                  | FID ↓             | R-precision (k=1) ↑ | SOA-C ↑ | SOA-I ✤ |
|------------------------------|----------------------|------------------|---------------------|---------|---------|
| Original Images              | 34.88 ± 0.01         | 6.09 ± 0.05      | 68.58 ± 0.08        | 74.97   | 80.84   |
| AttnGAN [7]                  | 23.61 ± 0.21         | 33.10 ± 0.11     | 83.80               | 25.88   | 39.01   |
| [8]                         | 23.74 ± 0.36         | 86.44 ± 3.38     | 82.44               | 25.46   | 40.48   |
| AttnGAN + OP [5]            | 24.76 ± 0.43         | 33.35 ± 1.15     | 82.44               | 25.46   | 40.48   |
| MirrorGAN [16]              | 26.47 ± 0.41         | 74.52            |                     |         |         |
| Obj-GAN [4]                 | 24.09 ± 0.28         | 36.52 ± 0.13     | 87.84 ± 0.08        | 27.14   | 41.24   |
| HiGAN [27]                  | 27.43 ± 0.25         | 32.32 ± 0.23     |                     |         |         |
| DM-GAN [27]                 | 28.74 ± 0.30         | 27.34 ± 0.11     | 91.87 ± 0.28        | 33.44   | 48.03   |
| SD-GAN [21]                 | 35.69 ± 0.50         | 26.65 ± 0.09     | 87.90 ± 0.26        | 33.11   | 47.95   |

OPv2, 0 obj 27.83 ± 0.34 30.61 ± 1.55 85.20 ± 0.83 27.25 ± 1.87 39.47 ± 2.69
OPv2, 1 obj 27.97 ± 0.85 27.48 ± 0.65 87.55 ± 0.81 27.27 ± 0.95
OPv2, 3 obj 27.51 ± 1.06 28.24 ± 1.01 87.27 ± 0.95
OPv2, 10 obj 27.43 ± 1.03 28.45 ± 1.08 87.07 ± 1.09 32.22 ± 0.50 46.82 ± 0.56
OPv2 + BBL, 0 obj 27.44 ± 0.40 32.97 ± 0.85 85.61 ± 0.45 25.22 ± 2.02 35.08 ± 2.27
OPv2 + BBL, 1 obj 28.52 ± 0.61 27.45 ± 0.76 86.49 ± 0.82
OPv2 + BBL, 3 obj 28.03 ± 0.27 28.20 ± 0.47 86.10 ± 0.37
OPv2 + BBL, 10 obj 27.94 ± 0.81 28.40 ± 0.66 85.57 ± 0.77 32.59 ± 1.82 46.12 ± 1.74
OPv2 + MO, 0 obj 23.78 ± 0.68 38.16 ± 0.74 79.18 ± 0.50 19.36 ± 1.53 27.42 ± 0.78
OPv2 + MO, 1 obj 27.55 ± 0.94 27.43 ± 1.02 88.53 ± 0.37
OPv2 + MO, 3 obj 27.83 ± 0.91 27.44 ± 0.91 88.99 ± 0.21
OPv2 + MO, 10 obj 27.76 ± 0.81 27.51 ± 0.82 88.93 ± 0.21 31.85 ± 1.41 46.14 ± 1.30
OPv2 + BBL + MO, 0 obj 22.17 ± 1.43 46.14 ± 1.56 72.64 ± 1.35 18.56 ± 2.45 25.10 ± 3.47
OPv2 + BBL + MO, 1 obj 28.12 ± 0.27 27.63 ± 0.66 86.78 ± 0.23
OPv2 + BBL + MO, 3 obj 28.41 ± 0.25 27.46 ± 0.83 87.71 ± 0.09
OPv2 + BBL + MO, 10 obj 28.33 ± 0.35 27.43 ± 0.85 87.81 ± 0.21 32.94 ± 0.23 47.58 ± 0.52

Impact of Training on Many Objects  Training the model with up to ten objects per image has only minor effects on the IS and SOA-C, but improves both the FID and R-precision. However, we observe that the models trained with only three objects per image slightly decrease in their performance once the object pathway is applied multiple times. Usually, the models trained on only three objects achieve their best performance when applying the object pathway only once, i.e. only generating one object. Once the model is trained on up to ten objects though, we do not observe this behavior anymore and instead achieve comparable or even better results when applying the object pathway more than once per image.

SOA Scores Table 2 shows the results for the SOA and SOA-IoU. The SOA-I values are consistently higher than the SOA-C values. Since the SOA-I is calculated on image average (instead of class average like the SOA-C) it is skewed by objects that often occur in captions and images (e.g. persons, cats, dogs, etc.). The SOA values for the most and least common 40 objects show that the models perform much better on the more common objects. Actually, most models perform about two to three times better on the common objects showing their problem in generating objects that are not often observed during training. For a detailed overview of how each model performed on the individual labels please refer to the supplementary material.

When we look at the IoU scores we see that the Obj-GAN [4] achieves by far the best IoU scores (around 0.5), albeit at the cost of lower SOA scores. Our models usually achieve an IoU of around 0.2 – 0.3 on average. Training with up to ten objects per image and using the bounding box loss slightly increases the IoU. However, similar to previous work [3,4] we find that the AttnGAN architecture tends to place salient object features at many locations of the image which affects the IoU scores negatively.

When looking at the SOA for individual objects (see Figure 5) we find that there are objects for which we can achieve very high SOA values (e.g. person, cat, dog, zebra, pizza, etc.). Interestingly, we find that all tested methods perform “good” or “bad” at the same objects. For example, all models perform reasonably well on objects such as person and pizza (many examples in the training set) as well as e.g. plane and traffic light (few examples in the training set). Conversely, all models fail on objects such as table and skateboard (many examples in the training set) as well as e.g. hair dryer and toaster (few examples in the training set).

We found that objects need to have three characteristics to achieve a high SOA and the highest SOA scores are achieved when objects possess all three characteristics. The first important characteristic is easily predictable: the higher the occurrence of an object in the training data, the better (on average) the final performance on this object. Secondly, large objects, i.e. objects that usually cover a large part of the image (e.g. bus or elephant), are usually modeled better than objects that are usually small (spoon or baseball glove). The final and more subtle characteristic is the surface texture of an object. Objects with highly distinct surface textures (e.g. zebra, giraffe, pizza, etc.) achieve high SOA scores because the object detection network relies on these textures to detect objects. However, while the models are able to correctly match the surface texture (e.g. black and white stripes for
A model was able to generate features (e.g. textual features) as the SOA scores are calculated with a pre-trained object detector which might focus more on the general texture and less on actual shapes of objects \[55\]. Consequently, the detector might give the wrong impression that an 80% object detection rate for an object means in 80% of the cases the object is recognizable and of real-world quality. This is not the case, as the SOA scores are more aptly interpreted as cases where objects possess the “correct” surface texture but their shape is more a general “blob” consisting of the texture and not a distinct form (e.g. a snout and for legs for a zebra). See Fig. 6 for a visualization of this.

This is still one of the weaknesses of the SOA score as it might give the wrong impression that an 80% object detection rate for an object means in 80% of the cases the object is recognizable and of real-world quality. This is not the case, as the SOA scores are calculated with a pre-trained object detector which might focus more on the general texture and less on actual shapes of objects \[55\]. Consequently, the results of the SOA are more aptly interpreted as cases where a model was able to generate features (e.g. textual features) that an independently pre-trained object detector would classify as a given object. The overall quality of the metric is, therefore, strongly dependent on the object detector and future improvements in this area might also lead to more meaningful interpretations of the SOA scores.

Figure 4 shows images generated by our different models. All images shown in this paper were generated without ground truth bounding boxes but instead use generated bounding boxes \[4\] as conditioning information. The first column shows the respective image from the data set, while the next four columns show the generated images. We can see that all models are capable of generating recognizable foreground objects. It is often difficult to find qualitative differences in the images generated by the different models. However, we find that the models using the bounding box loss usually improve the generation of rare objects. Training with ten objects per image usually leads to a slightly better image quality overall, especially for “crowded” images that contain many objects.

As we saw in the quantitative evaluation the object pathway can have a large impact on the image quality. Figure 7 shows what happens when (some of) the object pathways are not used in the full model (OPv2 + BBL + MO). Again, the first column shows the original image from the data set and the second column shows images generated without the use any of the object pathways. The next three columns show generated images when we consecutively use the object pathways, starting with the lowest object pathway.

**TABLE 2**

Comparison of the recall values for the different models. We used generated bounding boxes to calculate the values. Numbers in brackets show scores when the object pathway was not used at test time.

| Model           | SOA-C / IoU | SOA-I / IoU | SOA-C-Top40 / IoU | SOA-C-Bot40 / IoU |
|-----------------|-------------|-------------|-------------------|-------------------|
| Original Images | 74.97 / 0.550 | 80.84 / 0.570 | 78.77 / 0.546 | 71.18 / 0.554 |
| AttnGAN         | 25.88 / -- | 39.01 / -- | 37.47 / -- | 14.29 / -- |
| AttnGAN + OP    | 25.46 / 0.236 | 40.48 / 0.311 | 39.77 / 0.308 | 11.15 / 0.164 |
| Obj-GAN         | 27.14 / 0.513 | 41.24 / 0.598 | 39.88 / 0.587 | 14.40 / 0.438 |
| DM-GAN          | 33.44 / -- | 48.03 / -- | 47.73 / -- | 19.15 / -- |
| OPv2            | 32.22 (27.25) / 0.201 | 46.82 (39.47) / 0.264 | 46.70 (39.38) / 0.251 | 17.74 (15.12) / 0.152 |
| OPv2 + BBL      | 32.59 (25.22) / 0.201 | 46.12 (35.08) / 0.207 | 46.76 (34.81) / 0.190 | 18.42 (15.63) / 0.118 |
| OPv2 + MO       | 31.85 (19.36) / 0.206 | 46.14 (27.42) / 0.270 | 45.80 (26.10) / 0.257 | 17.90 (12.62) / 0.154 |
| OPv2 + BBL + MO | 32.94 (18.56) / 0.212 | 47.58 (25.10) / 0.276 | 47.37 (24.83) / 0.264 | 18.40 (10.60) / 0.160 |
Fig. 7. Comparison of images generated by our model (OP-GAN) with OPs switched on and off.

and iteratively adding the next object pathway until we reach the full model. When no object pathway is used (first column) we clearly see that only background information is generated. Once the first object pathway is added we also get foreground objects and their quality gets slightly better by adding the higher-level object pathways.

Qualitative Results

Figure 8 shows examples of images generated by our model (OPv2 + BBL + MO) and those generated by several recent state of the art models [3], [4], [7], [22]. We observe that our model often generates images with foreground objects that are more recognizable than the ones generated by the other models. For more common objects (e.g. person, bus or plane) all models manage to generate features that resemble the object but in most cases do not generate a coherent representation from these features and instead distribute them throughout the image. As a result, we notice features that are associated with an object but not necessarily form one distinct and coherent appearance of that object. Our model, on the other hand, is often able to generate one (or multiple) coherent object(s) from the features, see e.g. the generated images containing a bus, cattle, or the plane.

When generating rare objects (e.g. cake or hot dog) we can see that our model generated a much more distinct object than the other models. Indeed, most models fail completely to generate rare objects and instead only distribute colors associated with these objects throughout the image. Finally, when we inspect more complex scenes (last two rows on the right) we see that our model is also capable of generating multiple diverse objects within an image. As opposed to the other images for “room showing a sink and some drawers” we can recognize a sink-like shape and drawers in the image generated by our model. Similarly, our model can also generate an image containing a reasonable shape of a banana and a cup of coffee, whereas the other models only seem to generate the texture of a banana without the given shape and completely ignore the cup of coffee.

7 Conclusion

In this paper, we introduced a novel GAN architecture (OP-GAN) that specifically models individual objects based on some textual image description. This is achieved by adding object pathways to both the generator and discriminator which learn features for individual objects at different resolutions and scales. Our experiments show that this consistently improves the baseline architecture without object pathways based on quantitative and qualitative evaluations. Furthermore, our model achieves state-of-the art results in common quantitative evaluation metrics and adds an additional level of control over the image generation process.

We also introduce a novel evaluation metric named Semantic Object Accuracy (SOA) which evaluates how well a model can generate individual objects within complex scenes. This new SOA evaluation allows to evaluate text-to-image synthesis models in more detail and to detect failure and success modes for individual objects and object classes. Evaluation of several state-of-the art approaches using this SOA metric shows that no current approach is able to generate realistic foreground objects for most of the 80 classes.
in the COCO data set. While some models achieve high accuracy for several of the most common objects, all of them fail when it comes to modeling rare objects or objects that do not have an easily recognizable surface structure. However, using the SOA as an evaluation metric on text-to-image synthesis models provides more detailed information about how well they perform for different object classes or image captions. This is valuable for developing good generative models and can help to guide future improvements on a more meaningful level.

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Acknowledgments

The authors gratefully acknowledge partial support from the German Research Foundation DFG under project CML (TRR 169) and the European Union under project SOCRATES (No. 721619). We also thank the NVIDIA Corporation for their support through the GPU Grant Program.

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INFORMATION ABOUT CAPTIONS FOR SOA

Table 3 gives a detailed overview of how we chose the captions for each label to calculate the Semantic Object Accuracy (SOA) scores. The second column shows how many captions we found in total for the given label. The third column shows which words we filtered the captions for to obtain captions for the given label. This means that we chose all captions that contained at least one of those words as a valid caption for the given label. In the fourth column we show (were applicable) which words were explicitly excluded when looking for captions for the given label. Finally, the last column shows some examples of “false positives”, i.e. captions that are included in the set of captions for the given label even though they do not necessarily explicitly ask for the presence of the given label as understood by humans. Code to use the SOA can be found here: https://github.com/tohinz/semantic-object-accuracy-for-generative-text-to-image-synthesis.

MODEL ARCHITECTURE

Table 4 shows our model’s architecture. More details and the code can be found here: https://github.com/tohinz/semantic-object-accuracy-for-generative-text-to-image-synthesis. We train our model on four NVIDIA GeForce GTX 1080Ti GPUs. Training one model takes between two and four weeks, depending on the exact setting.

FURTHER RESULTS

Table 5 and Table 6 show the detailed results of the YOLOv3 detection network on the individual labels for all models. Table 7 shows the various scores for our models when they are evaluated with ground truth bounding boxes (instead of generated bounding boxes) at test time.
| Label      | # Sent. | Words in Captions                                              | Excluded Strings                                      | False Positives                                                                 |
|------------|---------|----------------------------------------------------------------|--------------------------------------------------------|-------------------------------------------------------------------------------|
| Person     | 61586   | person, people, human, man, men, woman, women, child, children  | A sign advertising an eatery in which people can eat burgers. |                                                                               |
| Dining Table | 7678    | table, desk                                                      | A sweet dish is kept in a bowl on a table mat.         |                                                                               |
| Cat        | 6609    | cat, kitten                                                     | A double parking meter decorated with cat art.         |                                                                               |
| Dog        | 5614    | dog, pup                                                        | Two stuffed dogs under a blanket looking at a picture book. |                                                                               |
| Train      | 5397    | train                                                          | A red train engine sits on the tracks.                 |                                                                               |
| Bus        | 4027    | bus                                                            | The sign is pointing the direction of the bus route.   |                                                                               |
| Clock      | 3870    | clock                                                          |                                                        |                                                                               |
| Giraffe    | 3866    | giraffe                                                        |                                                        |                                                                               |
| Pizza      | 3655    | pizza                                                          |                                                        |                                                                               |
| Horse      | 3615    | horse                                                          |                                                        |                                                                               |
| Elephant   | 3133    | elephant                                                       |                                                        |                                                                               |
| Zebra      | 3070    | zebra                                                          |                                                        |                                                                               |
| Bed        | 2923    | bed                                                            |                                                        |                                                                               |
| Boat       | 2819    | boat, ship                                                     |                                                        |                                                                               |
| Toilet     | 2796    | toilet                                                         |                                                        |                                                                               |
| Bird       | 2691    | bird                                                           |                                                        |                                                                               |
| Skateboard | 2665    | skateboard                                                     |                                                        |                                                                               |
| Car        | 2650    | car, auto                                                      |                                                        |                                                                               |
| Bench      | 2633    | bench                                                          |                                                        |                                                                               |
| Laptop     | 2376    | laptop                                                         |                                                        |                                                                               |
| Surfboard  | 2270    | surfboard                                                      |                                                        |                                                                               |
| Truck      | 2213    | truck                                                          |                                                        |                                                                               |
| Umbrella   | 2107    | umbrella                                                       |                                                        |                                                                               |
| Kite       | 2025    | kite                                                           |                                                        |                                                                               |
| Sports Ball| 2001    | ball                                                           |                                                        |                                                                               |
| Cake       | 2012    | cake                                                           |                                                        |                                                                               |
| Cow        | 1981    | cow                                                            |                                                        |                                                                               |
| Bicycle    | 1920    | bike, bicycle                                                  |                                                        |                                                                               |
| Chair      | 1884    | chair                                                          |                                                        |                                                                               |
| Frisbee    | 1775    | frisbee                                                        |                                                        |                                                                               |
| Bear       | 1740    | bear                                                           |                                                        |                                                                               |
| Sandwich   | 1649    | sandwich                                                       |                                                        |                                                                               |
| Sheep      | 1626    | sheep                                                          |                                                        |                                                                               |
| Vase       | 1597    | vase                                                           |                                                        |                                                                               |
| Bowl       | 1570    | bowl                                                           |                                                        |                                                                               |
| Sink       | 1529    | sink                                                           |                                                        |                                                                               |
| Stop Sign  | 1491    | stop sign                                                      |                                                        |                                                                               |

A museum sign showing the main entrance and car park. A man playing with a white ball on a red umbrella. Female tennis player looks on as she waits for the ball serve. A young boy sitting on top of a cow statue. A man drives his bike taxi with luggage in the back. A very old panda bear doll with a handkerchief. Furniture shaped like sheep on an open field. That sign almost looks like a stop sign with no words on it.
| Item            | ID  | Description                        | Example                                                                 |
|-----------------|-----|------------------------------------|-------------------------------------------------------------------------|
| Banana          | 1466| banana                             | Four cell phones on a wooden table with their screens on.               |
| Monitor         | 1437| monitor, tv, screen                | Mountaineous view as seen from a jet airliner                          |
| Skis            | 1419| skis                               | A table with measuring cups and bowls on it                             |
| Hot Dog         | 1717| hot dog, chili dog, cheese dog, corn dog | A toy hot dog and ketchup bottle on a table                          |
| Fire Hydrant    | 1408| hydrant                            | A large open room has an overhead bookshelf                           |
| Sofa            | 1404| sofa, couch                         | A group of dirt bike racers in a row                                  |
| Teddybear       | 1284| teddybear                           | A large fork sculpture stands in the water as a large boat passes      |
| Aeroplane       | 1195| plane, jet, aircraft               | Items from a handbag laid out neatly on a carpet                      |
| Tie             | 1062| tie                                 |                                                                        |
| Tennis Racket   | 993 | racket                              |                                                                        |
| Cell Phone      | 956 | cell phone, mobile phone            |                                                                        |
| Refrigerator    | 949 | refrigerator, fridge               |                                                                        |
| Cup             | 902 | cup                                 |                                                                        |
| Broccoli        | 840 | broccoli                            |                                                                        |
| Donut           | 805 | donut                               |                                                                        |
| Bottle          | 766 | bottle                              |                                                                        |
| Suitcase        | 736 | suitcase                            |                                                                        |
| Snowboard       | 732 | snowboard                           |                                                                        |
| Book            | 731 | book                                |                                                                        |
| Remote          | 670 | remote                              |                                                                        |
| Traffic Light   | 645 | traffic light                       |                                                                        |
| Keyboard        | 603 | keyboard                            |                                                                        |
| Apple           | 510 | apple, pineapple                    |                                                                        |
| Oven            | 506 | oven, microwave oven                |                                                                        |
| Motorcycle      | 495 | motorcycle, dirt bike, motobike, scooter |                                                                        |
| Carrot          | 463 | carrot                              |                                                                        |
| Scissor         | 450 | scissors                            |                                                                        |
| Parking Meter   | 430 | parking meter                       |                                                                        |
| Microwave       | 416 | microwave                           |                                                                        |
| Orange          | 378 | oranges                             |                                                                        |
| Knife           | 376 | knife                               |                                                                        |
| Fork            | 363 | fork                                |                                                                        |
| Baseball Bat    | 322 | baseball bat                        |                                                                        |
| Toothbrush      | 267 | toothbrush                          |                                                                        |
| Wine Glass      | 264 | wine glass                          |                                                                        |
| Backpack        | 220 | backpack, rucksack                  |                                                                        |
| Spoon           | 206 | spoon                               |                                                                        |
| Handbag         | 107 | handbag, purse                       |                                                                        |
| Toaster         | 89  | toaster                             |                                                                        |
| Potted Plant    | 81  | potted plant                        |                                                                        |
| Mouse           | 72  | computer mouse                      |                                                                        |
| Baseball Glove  | 39  | baseball glove                      |                                                                        |
| Hair Drier      | 35  | hair drier                          |                                                                        |
### Table 4
Overview of the individual layers used in our networks to generate images of resolution $256 \times 256$ pixels. Values in brackets ($C, H, W$) represent the tensor’s shape. Numbers in the columns after convolutional, residual, or dense layers describe the number of filters / units in that layer. ($fs=x, s=y, pw=z$, BN=B) describes the filter size, stride, padding, and batch norm for that convolutional / residual layer. Everything not specifically mentioned or explained (e.g. RNN-Encoder, DAMSM) is the same as in the AttnGAN [7].

| Optimizer: Adam | Learning Rate | 0.0002 |
| Activation Functions | Training Epochs | 120 |
| Attention Mask | Batch Size | 24 |
| Upsample Block | Z-Dim / Img-Caption-Dim | 100 / 256 |
| Upsampling | Layout Encoder | |
| Conv (fs=3, s=1, p=1, BN=1) | Input Shape | |
| Residual Block | Conv (fs=3, s=2, p=1, BN=0) | 50, LR |
| Conv x 2 (fs=3, s=2, p=1, BN=1) | Conv x 2 (fs=3, s=2, p=1, BN=1) | 25, LR, 12, LR |
| Add original input to output of previous conv | Output Shape | (12, 2, 2) |
| Prepare Label | Discriminator $64 \times 64$ | |
| Input Shape (Label $\sigma_i$) | Global Pathway Input | |
| Dense (BN=1) | Input Shape | |
| Reshape | Conv (fs=4, s=2, p=1, BN=0) | 96, LR |
| Replicate | Conv (fs=4, s=2, p=1, BN=1) | 192, LR |
| Initial Generator | Output Shape | (192, 16, 16) |
| Global Pathway Input | Object Pathway Input | |
| Input Shape | Input Shape | (3, 64, 64) |
| Dense (BN=1) | Conv (fs=4, s=1, p=1) | |
| Reshape | Transform ObjectFeat w/ STN | |
| Upsample x 2 (fs=3, s=1, p=1) | Concatenate with labels $\sigma_i$ | |
| Object Pathway Input | Conv (fs=4, s=1, p=1) | 192, LR |
| Prepare Label | Transform ObjectFeat w/ STN | |
| Upsample x 2 (fs=3, s=1, p=1) | Output Shape | (192, 16, 16) |
| Transform with STN | ConcatPathways | (384, 16, 16) |
| ConcatPathways | Conv x 2 (fs=1, s=2, p=1, BN=1) | 384, LR, 768, LR |
| Upsample x 2 (fs=3, s=1, p=1) | Concat w/ Sentence Embedding | (1024, 4, 4) |
| Output Shape | Conv (fs=3, s=1, p=1, BN=1) | 768, LR |
| Generator $128 \times 128$ | Conv (fs=4, s=4, p=1, BN=1) | 1, Sigmoid |
| Global Pathway Input | Discriminator $128 \times 128$ | |
| Input Shape | Global Pathway Input | |
| Dense (BN=1) | Input Shape | (3, 128, 128) |
| Reshape | Conv (fs=4, s=2, p=1, BN=0) | 96, LR |
| Upsample x 2 (fs=3, s=1, p=1) | Conv (fs=4, s=2, p=1, BN=1) | 192, LR |
| Object Pathway Input | Output Shape | (192, 32, 32) |
| Input Shape (Label $\sigma_i$) | Object Pathway Input | |
| Prepare Label | Input Shape | (3, 128, 128) |
| Extr ObjFeat w/ STN | Extract ObjectFeat w/ STN | |
| Concatenate | Concatenate with labels $\sigma_i$ | |
| Upsample x 2 (fs=3, s=1, p=1) | Conv (fs=4, s=1, p=1) | 192, LR |
| TransformObjFeat w/ STN | Transform ObjectFeat w/ STN | |
| ConcatPathways | Output Shape | (192, 32, 32) |
| Upsample (fs=3, s=1, p=1) | ConcatPathways | (384, 32, 32) |
| Output Shape | Conv x 4 (fs=4, s=2, p=1, BN=1) | 384, LR, 768, LR |
| Generator $256 \times 256$ | Concat w/ Sentence Embedding | (1536, LR, 768, LR) |
| Global Pathway Input | Conv (fs=3, s=1, p=1, BN=1) | 768, LR |
| Input Shape | Conv (fs=4, s=4, p=1, BN=1) | 1, Sigmoid |
| Attention Mask | Discriminator $256 \times 256$ | |
| Concatenate | Discriminator $256 \times 256$ | |
| Residual x 3 | Global Pathway Input | |
| Object Pathway Input | Input Shape | (3, 256, 256) |
| Input Shape (Label $\sigma_i$) | Conv (fs=4, s=2, p=1, BN=0) | 96, LR |
| Prepare Label | Conv (fs=4, s=2, p=1, BN=1) | 192, LR |
| Extr ObjFeat w/ STN | Output Shape | (192, 64, 64) |
| Concatenate | Object Pathway Input | |
| Upsample x 2 (fs=3, s=1, p=1) | Input Shape | (3, 256, 256) |
| TransformObjFeat w/ STN | Extract ObjectFeat w/ STN | |
| ConcatPathways | Concatenate with labels $\sigma_i$ | |
| Upsample (fs=3, s=1, p=1) | Conv (fs=4, s=1, p=1) | 192, LR |
| Output Shape | Transform ObjectFeat w/ STN | |
| Generator $256 \times 256$ | Output Shape | (192, 64, 64) |
| Global Pathway Input | Input Shape | (3, 256, 256) |
| Input Shape | Extract ObjectFeat w/ STN | |
| Attention Mask | Concatenate with labels $\sigma_i$ | |
| Concatenate | Transform ObjectFeat w/ STN | |
| Residual x 3 | Transform ObjectFeat w/ STN | |
| Object Pathway Input | Output Shape | (192, 64, 64) |
| Input Shape (Label $\sigma_i$) | ConcatPathways | (384, 64, 64) |
| Prepare Label | Conv x 6 (fs=4, s=2, p=1, BN=1) | 384, LR, 768, LR |
| Extr ObjFeat w/ STN | ConcatPathways | (384, LR, 768, LR) |
| Concatenate | Conv x 6 (fs=4, s=2, p=1, BN=1) | 1536, LR, 3072, LR |
| Upsample x 2 (fs=3, s=1, p=1) | Concat w/ Sentence Embedding | (1536, LR 768, LR) |
| TransformObjFeat w/ STN | Conv (fs=3, s=1, p=1, BN=1) | 768, LR |
| ConcatPathways | Conv (fs=4, s=4, p=1, BN=1) | 1, Sigmoid |
| Label          | Orig. Img. Recall | Img. + DM-GAN | DM-GAN + OP | Obj-GAN | Ours |
|----------------|-------------------|---------------|-------------|---------|------|
| Person         | 0.953             | 0.624         | 0.698       | 0.840   | 0.827|
| Dining Table   | 0.379             | 0.566         | 0.104       | 0.061   | 0.453|
| Cat            | 0.868             | 0.644         | 0.734       | 0.697   | 0.264|
| Dog            | 0.813             | 0.610         | 0.651       | 0.778   | 0.323|
| Train          | 0.826             | 0.627         | 0.491       | 0.654   | 0.370|
| Bus            | 0.848             | 0.651         | 0.615       | 0.665   | 0.511|
| Clock          | 0.900             | 0.502         | 0.469       | 0.184   | 0.359|
| Giraffe        | 0.949             | 0.662         | 0.581       | 0.725   | 0.486|
| Pizza          | 0.876             | 0.630         | 0.793       | 0.847   | 0.363|
| Horse          | 0.891             | 0.611         | 0.650       | 0.723   | 0.528|
| Elephant       | 0.937             | 0.647         | 0.373       | 0.653   | 0.522|
| Zebra          | 0.915             | 0.650         | 0.902       | 0.882   | 0.420|
| Bed            | 0.732             | 0.601         | 0.704       | 0.661   | 0.472|
| Boat           | 0.736             | 0.502         | 0.211       | 0.284   | 0.208|
| Toilet         | 0.912             | 0.591         | 0.281       | 0.325   | 0.315|
| Bird           | 0.797             | 0.551         | 0.358       | 0.430   | 0.284|
| Skateboard     | 0.822             | 0.427         | 0.040       | 0.119   | 0.126|
| Car            | 0.752             | 0.488         | 0.143       | 0.202   | 0.124|
| Bench          | 0.760             | 0.547         | 0.107       | 0.079   | 0.311|
| Laptop         | 0.876             | 0.617         | 0.071       | 0.252   | 0.337|
| Surfboard      | 0.794             | 0.414         | 0.140       | 0.091   | 0.218|
| Truck          | 0.835             | 0.631         | 0.472       | 0.524   | 0.442|
| Umbrella       | 0.884             | 0.548         | 0.074       | 0.150   | 0.177|
| Kite           | 0.822             | 0.410         | 0.291       | 0.163   | 0.310|
| Sports Ball    | 0.507             | 0.161         | 0.112       | 0.064   | 0.027|
| Cake           | 0.726             | 0.570         | 0.471       | 0.365   | 0.206|
| Cow            | 0.886             | 0.598         | 0.425       | 0.566   | 0.472|
| Bicycle        | 0.686             | 0.546         | 0.281       | 0.251   | 0.284|
| Chair          | 0.717             | 0.566         | 0.175       | 0.142   | 0.157|
| Frisbee        | 0.803             | 0.350         | 0.025       | 0.018   | 0.050|
| Bear           | 0.638             | 0.637         | 0.812       | 0.794   | 0.431|
| Sandwich       | 0.674             | 0.630         | 0.505       | 0.634   | 0.310|
| Sheep          | 0.910             | 0.593         | 0.303       | 0.403   | 0.239|
| Vase           | 0.858             | 0.600         | 0.114       | 0.152   | 0.468|
| Bowl           | 0.675             | 0.633         | 0.315       | 0.113   | 0.170|
| Sink           | 0.712             | 0.431         | 0.075       | 0.128   | 0.127|
| Stop Sign      | 0.874             | 0.608         | 0.183       | 0.225   | 0.207|
| Banana         | 0.788             | 0.578         | 0.552       | 0.593   | 0.208|
| Monitor        | 0.754             | 0.594         | 0.278       | 0.225   | 0.477|
| Skis           | 0.576             | 0.315         | 0.010       | 0.023   | 0.057|
| Hot Dog        | 0.711             | 0.621         | 0.404       | 0.355   | 0.227|
| Fire Hydrant   | 0.927             | 0.613         | 0.414       | 0.256   | 0.388|
| Sofa           | 0.834             | 0.584         | 0.253       | 0.179   | 0.259|
| Teddy Bear     | 0.806             | 0.643         | 0.637       | 0.688   | 0.336|
| Aeroplane      | 0.916             | 0.575         | 0.612       | 0.382   | 0.211|
| TV             | 0.800             | 0.574         | 0.138       | 0.074   | 0.157|
| Tennis Racket  | 0.830             | 0.432         | 0.019       | 0.044   | 0.071|
| Cell Phone     | 0.590             | 0.513         | 0.036       | 0.054   | 0.067|
| Refrigerator   | 0.881             | 0.631         | 0.593       | 0.252   | 0.408|
| Cup            | 0.706             | 0.586         | 0.061       | 0.054   | 0.022|
| Broccoli       | 0.756             | 0.575         | 0.130       | 0.137   | 0.240|
| Donut          | 0.854             | 0.655         | 0.076       | 0.089   | 0.213|
| Bottle         | 0.782             | 0.590         | 0.072       | 0.047   | 0.020|
| Suitcase       | 0.851             | 0.612         | 0.049       | 0.043   | 0.407|
| Snowboard      | 0.746             | 0.411         | 0.055       | 0.030   | 0.085|
| Book           | 0.628             | 0.500         | 0.006       | 0.032   | 0.340|
| Remote         | 0.619             | 0.440         | 0.014       | 0.015   | 0.120|
| Traffic Light  | 0.942             | 0.450         | 0.607       | 0.565   | 0.409|
| Keyboard       | 0.783             | 0.495         | 0.397       | 0.083   | 0.064|
| Apple          | 0.588             | 0.593         | 0.054       | 0.021   | 0.162|
| Oven           | 0.699             | 0.606         | 0.067       | 0.074   | 0.520|
| Motorcycle     | 0.910             | 0.597         | 0.422       | 0.409   | 0.396|
| Carrot         | 0.590             | 0.537         | 0.081       | 0.045   | 0.097|

*TABLE 5: Results of YOLOv3 detections on generated and original images. Recall provides the fraction of images in which YOLOv3 detected the given object. IoU (Intersection over Union) measures the maximum IoU per image in which the given object was detected. No ground truth information besides the caption was used for all measurements.*
| Label             | Op2 recall | Op2 + BL recall | Op2 + MO recall | Op2 + BL + MO recall |
|-------------------|------------|-----------------|-----------------|----------------------|
| Person            | 0.751      | 0.674           | 0.727           | 0.758                |
| Dining Table      | 0.103      | 0.112           | 0.467           | 0.106                |
| Cat               | 0.676      | 0.621           | 0.315           | 0.766                |
| Dog               | 0.545      | 0.719           | 0.770           | 0.555                |
| Train             | 0.601      | 0.714           | 0.412           | 0.591                |
| Bus               | 0.732      | 0.775           | 0.364           | 0.763                |
| Clock             | 0.433      | 0.330           | 0.089           | 0.582                |
| Giraffe           | 0.860      | 0.842           | 0.356           | 0.754                |
| Pizza             | 0.849      | 0.882           | 0.445           | 0.809                |
| Horse             | 0.778      | 0.796           | 0.322           | 0.757                |
| Elephant          | 0.639      | 0.654           | 0.361           | 0.625                |
| Zebra             | 0.961      | 0.949           | 0.388           | 0.930                |
| Bed               | 0.792      | 0.771           | 0.463           | 0.783                |
| Boat              | 0.257      | 0.280           | 0.225           | 0.265                |
| Toilet            | 0.466      | 0.592           | 0.248           | 0.278                |
| Bird              | 0.653      | 0.632           | 0.258           | 0.659                |
| Skateboard        | 0.109      | 0.108           | 0.077           | 0.075                |
| Car               | 0.278      | 0.192           | 0.130           | 0.188                |
| Bench             | 0.226      | 0.185           | 0.249           | 0.277                |
| Laptop            | 0.267      | 0.211           | 0.324           | 0.351                |
| Surfboard         | 0.249      | 0.202           | 0.148           | 0.180                |
| Truck             | 0.577      | 0.717           | 0.342           | 0.530                |
| Umbrella          | 0.127      | 0.123           | 0.160           | 0.193                |
| Kite              | 0.402      | 0.490           | 0.077           | 0.370                |
| Sports Ball       | 0.119      | 0.148           | 0.004           | 0.085                |
| Cake              | 0.394      | 0.386           | 0.287           | 0.528                |
| Cow               | 0.588      | 0.641           | 0.331           | 0.525                |
| Bicycle           | 0.401      | 0.404           | 0.276           | 0.361                |
| Chair             | 0.265      | 0.214           | 0.143           | 0.279                |
| Frisbee           | 0.041      | 0.036           | 0.016           | 0.030                |
| Bear              | 0.695      | 0.770           | 0.347           | 0.682                |
| Sandwich          | 0.701      | 0.654           | 0.391           | 0.693                |
| Sheep             | 0.513      | 0.557           | 0.240           | 0.511                |
| Vase              | 0.165      | 0.147           | 0.184           | 0.220                |
| Bowl              | 0.199      | 0.140           | 0.253           | 0.211                |
| Sink              | 0.219      | 0.126           | 0.129           | 0.167                |
| Stop Sign         | 0.366      | 0.437           | 0.261           | 0.347                |
| Banana            | 0.457      | 0.331           | 0.256           | 0.356                |
| Monitor           | 0.502      | 0.461           | 0.207           | 0.354                |
| Skis              | 0.039      | 0.020           | 0.017           | 0.027                |
| Hot Dog           | 0.465      | 0.553           | 0.296           | 0.470                |
| Fire Hydrant      | 0.413      | 0.411           | 0.254           | 0.335                |
| Sofa              | 0.390      | 0.258           | 0.317           | 0.327                |

TABLE 6: Results of YOLOv3 detections on ablations of our model. Recall provides the fraction of images in which YOLOv3 detected the given object. IoU (Intersection over Union) measures the maximum IoU per image in which the given object was detected. No ground truth besides the caption was used for all measurements.
TABLE 7
IS, FID, R-precision, SOA-C, and SOA-I values of our models evaluated with ground truth bounding boxes at test time.

| Model                          | IS ↑       | FID ↓      | R-precision (k=1) ↑ | SOA-C ↑  | SOA-I ↑  |
|-------------------------------|------------|------------|---------------------|----------|----------|
| OPx2, gen 0 obj               | 27.93 ± 0.34 | 30.55 ± 1.09 | 85.32 ± 0.82        | 27.25 ± 1.87 | 39.47 ± 2.69 |
| OPx2, gen 1 obj               | 26.25 ± 0.54 | 26.90 ± 0.82 | 88.31 ± 0.95        |          |          |
| OPx2, gen 3 obj               | 27.96 ± 0.91 | 27.82 ± 1.11 | 87.86 ± 1.77        |          |          |
| OPx2, gen 10 obj              | 27.54 ± 0.98 | 28.81 ± 1.37 | 87.20 ± 1.53        | 32.72 ± 0.50 | 47.40 ± 0.64 |
| OPx2 + BBL, gen 0 obj         | 27.36 ± 0.85 | 32.88 ± 1.02 | 83.61 ± 1.22        | 25.22 ± 2.02 | 35.08 ± 2.27 |
| OPx2 + BBL, gen 1 obj         | 28.06 ± 0.71 | 27.03 ± 0.98 | 86.62 ± 1.74        |          |          |
| OPx2 + BBL, gen 3 obj         | 27.85 ± 0.75 | 28.10 ± 1.17 | 85.91 ± 1.36        |          |          |
| OPx2 + BBL, gen 10 obj        | 27.54 ± 0.68 | 29.04 ± 1.02 | 85.51 ± 1.83        | 32.71 ± 1.02 | 46.62 ± 1.64 |
| OPx2 + MO, gen 0 obj          | 23.72 ± 0.67 | 23.84 ± 0.81 | 79.11 ± 0.45        | 19.36 ± 1.53 | 27.42 ± 0.78 |
| OPx2 + MO, gen 1 obj          | 27.48 ± 0.93 | 27.29 ± 1.09 | 88.64 ± 0.52        |          |          |
| OPx2 + MO, gen 3 obj          | 28.17 ± 0.82 | 27.22 ± 1.10 | 89.59 ± 0.25        |          |          |
| OPx2 + MO, gen 10 obj         | 27.85 ± 0.93 | 27.50 ± 1.05 | 89.43 ± 0.21        | 32.73 ± 1.37 | 47.17 ± 1.58 |
| OPx2 + BBL + MO, gen 0 obj    | 22.14 ± 1.48 | 45.96 ± 2.22 | 72.85 ± 3.93        | 18.56 ± 2.45 | 25.10 ± 3.47 |
| OPx2 + BBL + MO, gen 1 obj    | 27.67 ± 0.17 | 27.62 ± 0.96 | 87.03 ± 0.27        |          |          |
| OPx2 + BBL + MO, gen 3 obj    | 28.72 ± 0.53 | 26.96 ± 0.99 | 88.57 ± 0.09        |          |          |
| OPx2 + BBL + MO, gen 10 obj   | 28.60 ± 0.63 | 27.23 ± 1.11 | 88.60 ± 0.18        | 33.76 ± 0.57 | 48.42 ± 0.28 |