TAC-GAN – Text Conditioned Auxiliary Classifier Generative Adversarial Network

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Abstract

In this work, we present the Text Conditioned Auxiliary Classifier Generative Adversarial Network, (TAC-GAN) a text to image Generative Adversarial Network (GAN) for synthesizing images from their text descriptions. Former approaches have tried to condition the generative process on the textual data; but allying it to the usage of class information, known to diversify the generated samples and improve their structural coherence, has not been explored. We trained the presented TAC-GAN model on the Oxford-102 dataset of flowers, and evaluated the discriminability of the generated images with Inception-Score, as well as their diversity using the Multi-Scale Structural Similarity Index (MS-SSIM). Our approach outperforms the state-of-the-art models, i.e., its inception score is $3.45$, corresponding to a relative increase of $7.8\%$ compared to the recently introduced StackGAN. A comparison of the mean MS-SSIM scores of the training and generated samples per class shows that our approach is able to generate highly diverse images with an average MS-SSIM of $0.14$ over all generated classes.

1. Introduction

Synthesizing diverse and discriminable images from text is a difficult task and has been approached from different perspectives. Making the images realistic, while still capturing the semantics of the text are some of the challenges that remain to be solved.

Generative Adversarial Networks (GAN) have shown promising results for image synthesis [5]. GANs use an adversarial training mechanism, based on the minimax algorithm in which a generative model $G$ and a discriminative model $D$ are trained simultaneously with conflicting objectives. $G$ is trained to model the data distribution while $D$ is trained to classify whether the data is real or generated. The model is then sampled by passing an input noise vector $z$ through $G$. The framework has received a lot of attention since its inception (e.g., [15, 17, 19, 21, 27]).

Extending these ideas, Odena et al. [17] proposed the Auxiliary Classifier Generative Adversarial Network (AC-GAN). In that model, the Generator synthesizes images conditioned on a class label and the Discriminator not only classifies between real and generated input images, but also assigns them a class label.

In this paper, we present the Text Conditioned Auxiliary Classifier Generative Adversarial Network (TAC-GAN), which builds upon the AC-GAN by conditioning the generated images on a text description instead of on a class label. In the presented TAC-GAN model, the input vector of the Generative network is built based on a noise vector $z$ and an-
other vector containing an embedded representation of the textual description. While the Discriminator is similar to that of the AC-GAN, it is also augmented to receive the text information as input before performing its classification.

To evaluate our model, we use the Oxford-102 dataset of flowers. Additionally, we use Skip-Thought vectors to generate text embeddings from the image captions. Images generated using TAC-GAN are not only highly discriminable, but are also diverse. Similarly to [19], we also show that our model learns to disentangle the content of the generated images from their style. By interpolating between different text descriptions, it is possible to synthesize images that differ in content while maintaining the same style. Evaluation results show that our approach outperforms the state of the art models by 7.8% on inception score. Figure 1 shows some results generated by our approach.

The rest of the paper is structured as follows. Section 2 provides an overview of the existing methods for text and image generation. The basics of the GAN framework are explained in Section 3.1, and the architecture of the AC-GAN is presented in Section 3.2. Our presented model, TAC-GAN, is described in Section 4. Section 5 provides an evaluation and comparison of the presented TAC-GAN with state of the art methods for text to image generation. Section 6 provides an analysis of the images generated using TAC-GAN, and Section 7 concludes the paper and provide an overview of the future work.

2. Related Work

A considerable amount of work on image modelling focused on other tasks such as image inpainting (e.g., [8]) or texture generation (e.g., [4]). These tasks produced new images based on an existing image. However, image synthesis not relying on such existing information has not had much success until recently [18].

In the last few years, approaches based on Deep Learning have arisen, which are able to synthesize images with varied success. Variational Autoencoders (VAE) [3, 11], once trained, can be interpreted as generative models that produce samples from a distribution that approximates that of the training set. The DRAW model [7] extends the VAE architecture by using recurrent networks and an attention mechanism, transforming it into a sequence encoding/decoding process such that “the network decides at each time-step ‘where to read’ and ‘where to write’ as well as ‘what to write’”, and being able to produce highly realistic handwritten digits. Mansimov et al. [14], extended the DRAW model by using a Bidirection RNN and conditioning the generating process on text captions, producing results that were slightly better than those of other state of the art models.

Alternatively, Generative Adversarial Networks (GAN) [5] have gained a considerable amount of interest since its inception, having been used in tasks such as single-image super resolution [12], Simulated+Unsupervised learning [22], image-to-image translation [9] and semantic image

![Figure 2. The architecture of the TAC-GAN. Here, $t$ is a text description of an image, $z$ is a noise vector of size $N_z$, $I_{\text{real}}$ and $I_{\text{wrong}}$ are the real and wrong images respectively, $I_{\text{fake}}$ is the image synthesized by the generator network $G$, $\Psi(t)$ is the text embedding for the text $t$ of size $N_t$, and $C_r$ and $C_w$ are one-hot encoded class labels of the $I_{\text{real}}$ and $I_{\text{wrong}}$, respectively. $L_G$ and $L_D$ are two neural networks that generate latent representations of size $N_l$, each, for the text embedding $\Psi(t)$. $D_S$ and $D_C$ are the probability distribution that the Discriminator outputs over the sources (real/fake) and the classes respectively.](image-url)
This flower has yellow petals along with green and yellow stamen.

This flower is red and yellow in color, with petals that are ruffled and curled.

This flower has petals that are yellow with red lines.

This flower is white and pink in color, with petals that are oval shaped.

A yellow flower with large petal with a large long pollen tubes.

The petals on this flower are white with yellow stamen.

This flower is pink and black in color, with petals that are black near the ovary.

The petals on this flower are white with yellow stamen.

Figure 3. Images synthesized from text descriptions using different noise vectors. In each block, the images at the bottom are generated from the text embeddings of the image description and a noise vector. The image on the top of each block are real images corresponding to the text description.

3. Background

This section describes some of the existing work our approach is built upon. Section 3.1 describes the basic GAN framework, and Section 3.2 describes the AC-GAN.

3.1. Generative Adversarial Networks

The basic framework of Generative Adversarial Networks (GAN) was first introduced by Goodfellow et al. [5]. GANs are generative models that introduce a new paradigm of adversarial training [6] in which a generative model $G$ and a discriminative model $D$ are trained simultaneously. $G$ is trained to model the data distribution, while $D$ is trained to classify if the data is real or generated. In this case both $G$ and $D$ are both neural networks. Let $\mathcal{X}$ be a dataset used for training the GAN, and $I_{\text{real}}$ denote a sample from $\mathcal{X}$. The two networks are then trained to minimize conflicting

Where Networks [20], were able to make the synthesized images correspond to a textural description used as input, with a resolution of $64 \times 64$. With a similar approach, the StackGAN model [27] leverages the benefits of using multiple stages and is capable of generating highly realistic $256 \times 256$ images.
objectives. Given an input noise vector \( z \), \( G \) is trained to generate samples \( I_{\text{fake}} \) that are similar to those of the training set \( \mathcal{X} \), i.e., to generate fake samples. \( D \), on the other hand, receives a sample \( I \) as input and is trained to return a probability distribution \( P(S|I) \), interpreted as the probability that \( I \) pertains to the dataset \( \mathcal{X} \), (i.e., is a real sample).

Specifically, \( D \) is trained to maximize, and \( G \) is trained to minimize, the following value:

\[
\mathbb{E}\left[ \log P(S = \text{real}|I_{\text{real}}) \right] + \mathbb{E}[\log P(S = \text{fake}|I_{\text{fake}})]
\]

(1)

In the context of this model, \( \mathcal{X} \) is composed of images, and each \( I \) is an image.

3.2. Auxiliary Classifier Generative Adversarial Networks (AC-GAN)

The AC-GAN [17] is a variant of the GAN architecture in which \( G \) conditions the generated data on its class label, and the Discriminator performs an auxiliary task of classifying the synthesized and the real data into their respective class labels. In this setting every produced image is associated with a class label \( c \) and a noise vector \( z \), which are used by \( G \) to generate images \( I_{\text{fake}} = G(c, z) \). The Discriminator of an AC-GAN outputs a probability distribution over sources (fake or real), as well as a probability distribution over the class labels: \( D_S(I) = P(S | I) \) and \( D_C(I) = P(C | I) \). The objective function consists of two parts: (1) the log-likelihood of the correct source \( L_s \); and (2) the log-likelihood of the correct class \( L_c \):

\[
L_s = \mathbb{E}[\log P(S = \text{real} | X_{\text{real}})] + \mathbb{E}[\log P(S = \text{fake} | X_{\text{fake}})]
\]

(2)

\[
L_c = \mathbb{E}[\log P(C = c | X_{\text{real}})] + \mathbb{E}[\log P(C = c | X_{\text{fake}})]
\]

(3)

During training, \( D \) maximizes \( L_c + L_s \), while \( G \) minimizes \( L_c - L_s \).

4. Text Conditioned Auxiliary Classifier Generative Adversarial Network (TAC-GAN)

Our proposed model, the TAC-GAN, generates images of size \( 128 \times 128 \) that comply to the content of the input text.

To train our model, we use the Oxford-102 flowers dataset, which has, for every image, a class label and at least five text descriptions. For implementing TAC-GAN we use the Tensorflow [11] implementation of a Deep Convolutional Generative Adversarial Network (DCGAN) [13], in which \( G \) is modeled as a Deconvolutional (fractionally-strided convolutions) Neural Network, and \( D \) is modeled as a Convolutional Neural Network (CNN). For our text embedding function \( \Psi \), we use Skip-Thought vectors to generate an embedding vector of size \( N_t \).

We start by describing the model architecture, and proceed with the training procedure.

4.1. Model Architecture

In our approach we introduce a variant of AC-GAN, called Text Conditioned Auxiliary Classifier Generative Adversarial Networks (TAC-GAN), to synthesize images from text. As opposed to AC-GANs, we condition the generated images from TAC-GANs on text embeddings and not on class labels.

Figure 2 shows the architecture of a TAC-GAN.

4.1.1 Preliminaries

Let \( \mathcal{X} = \{ X_i | i = 1, \ldots, n \} \) be a dataset, where \( \mathcal{X}_i \) are the data instances and \( n \) is the number of instances in the dataset (\(|\mathcal{X}| = n \)). Every data instance is a tuple \( X_i = (I_i, C_i) \), where \( I_i \) is an image, \( T_i = (t_{i1}, t_{i2}, \ldots, t_{ik}) \) is a set of \( k \) text descriptions of the image, and \( C_i \) is the class label to which the image corresponds. For training the TAC-GAN we randomly pick a text description \( t_{ij} \) from \( T_i \) and generate a text embedding \( \Psi(t_{ij}) \in \mathbb{R}^{N_t} \). We then generate a latent representation \( I_{\text{fake}}^j = L_G(\Psi(t_{ij})) \) of the text embedding, where \( L_G \) is a fully connected neural network with \( N_t \) neurons. Therefore \( I_{\text{fake}}^j \in \mathbb{R}^{N_t} \), where \( N_t \) is a hyperparameter of the model. This representation is then concatenated to a noise vector \( z \in [-1, 1]^N_z \), creating a vector \( z_{\text{fake}} \in \mathbb{R}^{N_z + N_t} \). Here, \( N_z \) is also a hyperparameter of the model. \( z_{\text{fake}} \) is then passed through a fully connected layer \( FC_G \) with \( 8 \times 8 \times (8 \times N_z) \) neurons, where \( N_z \) is another hyperparameter of the model. The output of \( FC_G \) is finally reshaped into a convolutional representation \( I_{\text{fake}} \) of shape \( 8 \times 8 \times (8 \times N_z) \).

4.1.2 Generator Network

The Generator Network is very similar to that of the AC-GAN. However, instead of feeding the class label to which the synthesized image is supposed to pertain, we input the noise vector \( z_{\text{fake}} \), containing information related to the textual description of the image.

In our model, \( G \) is a neural network consisting of a sequence of transposed convolutional layers. It outputs an up-scaled image \( I_f \) (fake image) of shape \( 128 \times 128 \times 3 \).

4.1.3 Discriminator Network

Let \( I_r \) denote the real image from the dataset corresponding to the text description \( t_{ij} \), and \( I_w \) denote another image that does not correspond to \( t_{ij} \). Additionally, let \( C_r \) and \( C_w \) correspond to the class labels of \( I_r \) and \( I_w \), respectively. We
use \( l_w \) to teach the Discriminator to consider fake any image that does not belong to the desired class. In the context of the Discriminator, let \( t_r = t_f^l \) be the text description of the real and fake images (notice that the fake image was generated based on the text description of \( t_r \)). A new latent representation \( l_r = \mathcal{L}_D(\Psi(t_r)) \) for the text embeddings is generated, where \( \mathcal{L}_D \) is another fully connected neural network with \( N_l \) neurons, and hence \( l_r \in \mathbb{R}^{N_l} \).

A set \( \mathcal{A} = \{(I_f, C_f, l_f), (I_r, C_r, l_r), (I_w, C_w, l_w)\} \) is created, to be used by the discriminator. The set is composed of three tuples containing an image, a corresponding class label, and a corresponding text embedding. Notice that \( I_f \) was created conditioned on the same class as \( C_f \) and on the same text description as \( l_f \). Therefore, \( C_f = C_r \) and \( l_f = l_r \). Similarly, \( I_w \) is wrong because it does not correspond to its \( l_w \), since \( l_w = l_r \). Therefore, it is possible to convert the previous definition of \( \mathcal{A} \) into \( \mathcal{A} = \{(I_f, C_f, l_f), (I_r, C_r, l_r), (I_w, C_w, l_w)\} \). The values of these images are used by the discriminator in the following way.

The Discriminator network is composed of a series of convolutional layers and receives an image \( I \) (any of the images from \( \mathcal{A} \)). By passing through the convolutional layers, the image is downsampled into an image \( \mathbf{M}_D \) of size \( M \times M \times F \), where \( M \) and \( F \) are hyperparameters of the model. \( l_r \) is replicated spatially to form a vector of shape \( M \times M \times N_l \), and is concatenated with \( \mathbf{M}_D \) in the \( F \) (channels) dimension, similarly to what is done in \cite{19}. This concatenated vector is then fed to another convolutional layer with spatial dimension \( M \times M \). Finally, two fully connected layers \( FC_1 \) and \( FC_2 \) are used with 1 and \( N_c \) neurons, respectively, along with the sigmoid activation function. \( FC_1 \) produces a probability distribution \( D_S \) over the sources (real/fake), while \( FC_2 \) produces a probability distribution \( D_C \) over the class labels. Details of the architecture are described in Figure 2.

This discriminator design was inspired by the GAN-CLS model proposed by Reed et al. \cite{19}. The parameters of \( \mathcal{L}_G \) and \( \mathcal{L}_D \) are trained along with the TAC-GAN. The training process is described in detail in Section 4.3.

### 4.2. Implementation Details

Our Generator network is composed by three transposed convolutional layers with 256, 128 and 64 filter maps, respectively. The output of each layer has a size twice as big as that of the images fed to them as input. The output of the last layer is the produced \( I_f \) used as input to the Discriminator. \( D \) is composed of three convolutional layers with 128, 256, and 384 filter maps, respectively. The output of the last layer is \( \mathbf{M}_D \). The kernel size of all the convolutional layers until the generation of \( \mathbf{M}_D \) is 5 × 5.

Table 1. Global parameters used in the model

| Parameter | Value | Parameter | Value |
|-----------|-------|-----------|-------|
| Learning Rate | 0.0002 | \( N_r \) | 4800 |
| \( \beta_1 \) | 0.5 | \( N_I \) | 100 |
| \( \beta_2 \) | 0.999 | \( N_c \) | 100 |
| \( \epsilon \) | \( 10^{-8} \) | \( N_r \) | 64 |
| \( M \) | 8 | \( N_f \) | 64 |
| \( F \) | 384 | | |
The flower has 5 large petals that are yellow and visible filament and unique anthers

This flower has large red petals and a yellow stigma in the middle of it

This flower has large red petals and a yellow stigma in the middle of it

This flower is purple and yellow in color, with petals that are oval shaped

Figure 5. All images generated in the first and second row use the same noise vector $z_1$. Similarly, all images generated in the third and fourth rows use the same noise vector $z_2$. The first image of the first row and the last image of the second row use a text embedding that was constructed from the captions 1 and 2, respectively. An interpolation between these two embeddings was used for synthesizing all images in between them. The first image of the third row and the last image of the fourth row use a text embedding constructed from the captions 3 and 4. An interpolation between these two embeddings was used for synthesizing all images in between them. Notice that captions 2 and 3 are the same, but we use a different noise vector to generate the two different outputs.

After the concatenation between $M_D$ and the spatially replicated $l_r$, the last convolutional layer is composed of 512 filter maps of size $1 \times 1$ and stride 1.

We always use same convolutions, and training is performed using the Adam optimizer [10]. Table 1 shows the hyperparameters used by our model.

4.3. Training

In this section, we explain how training is performed in the TAC-GAN model. We then explain how the loss function could be easily extended so that any other potentially useful type of information can be leveraged by the model.

4.3.1 Training Objectives

Let $L_{D_S}$ denote the training loss related to the source of the input (real, fake or wrong). Then $L_{D_S}$ is calculated as a sum of the binary cross entropy, denoted by $H$ below, between the output of the discriminator and the desired value for each of the images:

$$L_{D_S} = H(D_s(I_r, l_r), 1) + H(D_s(I_f, l_r), 0) + H(D_s(I_w, l_r), 0)$$

Similarly, let $L_{D_G}$ denote the training loss related to the class to which the input image is supposed to pertain:

$$L_{D_G} = H(D_c(I_f, l_r), C_r) + H(D_c(I_w, l_r), C_w)(5)$$

The Discriminator then minimizes the training objective $L_{D_C} + L_{D_S}$.

In the case of the Generator network, there are no real or wrong images to be fed as input. The training loss, given by $L_{G_C} + L_{G_S}$, can therefore be defined in terms of only the Discriminator’s output for the generated image ($L_{G_S}$), and the expected class to which the synthesized image is expected to pertain ($L_{G_C}$):

$$L_{G_S} = H(D_s(I_f, l_r), 1)$$

$$L_{G_C} = H(D_s(I_f, l_r), C_r)$$

Notice that, while $L_{D_S}$ penalizes the cross-entropy between $D_S(I_f, l_r)$ and 0 (making $D$ better at deeming generated images fake), $L_{G_S}$ penalizes the cross-entropy between $D_S(I_f, l_r)$ and 1 (approximating the distribution of the generated images to that of the training data).

4.3.2 Extending the current model

The training losses for both the $G$ and $D$ is a sum of the losses corresponding to different types of information. In the presence of other types of information, one can easily extend such a loss by adding a new factor to the sum.

Specifically, assume a new dataset $Y$ is present, containing, for each real image $I_r$ in $X$, a corresponding vector $Q_r$, containing details, such as the presence of certain objects in the $l_r$, the location where such details appear, etc. The Discriminator could be extended to output the probability distribution $D_Y(I)$ from any input image. Let $L_{D_Y}$ denote the related Discriminator loss:
This flower has overlapping pink pointed petals surrounding a ring of short yellow filaments

This flower has long thin yellow petals and a lot of yellow anthers in the center

Figure 6. A comparison between the results of our model (TAC-GAN) and those of the StackGAN [27] in Phase-I and Phase-II. The images were synthesized based on the caption on the top of each block.

Table 2. Inception Score of the generated samples on the Oxford-102 dataset.

| Model              | Inception Score |
|--------------------|-----------------|
| TAC-GAN            | 3.45 ± 0.05     |
| StackGAN           | 3.20 ± 0.01     |
| GAN-INT-CLS        | 2.66 ± 0.03     |

Evaluating generative models, like GANs, have always been a challenge [14]. While no standard evaluation metric exists, recent works have introduced a lot of new metrics [5, 17, 18]. However, not all of these metrics are useful for evaluating GANs [23]. Salimans et al. [21] proposed that inception score can be considered as a good evaluation metric for GANs to show the discriminability of the generated images. Odena et al. [17] have shown that Multi-Scale Structural Similarity (MS-SSIM) can be used to measure the diversity of the generated images.

We use inception score to evaluate our approach. Table 2 shows the inception score of the images generated by our model compared to those of similar models for image generation from text. It can be seen that our approach produces
Figure 7. Comparison of the mean MS-SSIM scores of the images of the training data in the Oxford-102 flowers dataset and the sample data generated by the TAC-GAN. Each point represents a class and denotes how similar to each other the images of that class are in the two data sets. The maximum score for samples of a class in the training set is 0.28 and the mean of the average MS-SSIM over all the classes is 0.14±0.019. The maximum MS-SSIM score for samples of a class generated by the TAC-GAN is 0.23 and the mean of the average MS-SSIM over all classes for the generated images is 0.13 ± 0.016.

better scores than those of other state of the art approaches. This shows that our approach generates images with higher discriminability.

To show that our model produces very diverse sample, we used the MS-SSIM [13,25]. Figure 7 shows the mean MS-SSIM values of each class of the training dataset, compared to that of each class of the sampled images. It can be seen that our model produces more diverse images than those of the training data, which corroborates with the results from [17].

6. Analysis and Discussion

Additionally, we show that our model confirms findings in other approaches (e.g., [19, 27]), i.e., it learns separate representations for the style and the content of the generated images. The images in Figure 4 are produced by interpolating between two different noise vectors, while maintaining the same input text. While the content of the image remains roughly unchanged, its style transitions smoothly from one of the vectors to the other.

Similarly, because we use vector embeddings for the textual descriptions, it is possible to interpolate between the two embeddings. In Figure 5 we fix the same z for all generated images and interpolate between the vector embeddings resulting from applying Ψ to two text descriptions. It can be seen that the resulting images maintain a similar style while smoothly transitioning from one content to another.

7. Conclusion and Future Work

We described the TAC-GAN, a model capable of generating images based on textual descriptions. The results produced by our approach are slightly better to those of other state of the art approaches.

The model is easily extensible: it is possible to condition the networks not only on text, but in any other type of potentially useful information. It remains to be examined what influence the usage of other types of information might have in the stability of training, and how much they help, as opposed to hinder, the capacity of the model in producing better quality, higher resolution images.

Many approaches have used a multi-staged architecture, where images produced in the first phase are iteratively refined in subsequent phases. We believe that the results of our model can benefit from such a pipeline, and be able to further improve the results reported in this work.

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