ATML Report

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Abstract

The field of image generation through generative modelling is abundantly discussed nowadays. It can be used for a highly varied range of applications such as up-scaling already existing images, creating non-existing objects, such as interior design scenes, products or even human faces, and achieving transfer-learning processes. In this context, Generative Adversarial Networks (GANs) are a class of widely studied machine learning frameworks first appearing in the paper "*Generative adversarial nets*" by Goodfellow et al. [1] that achieve the aforementioned goal. In our work, we reproduce and evaluate a novel variation of the original GAN network, the GANformer, proposed in "*Generative Adversarial Transformers*" by Hudson and Zitnick [2]. The goal of this project was to recreate the methods presented by this paper to reproduce the original results and comment on the authors' claims. Due to resources and time limitations, we had to constraint the networks training times and dataset types and sizes. Our research successfully recreated both variations of the proposed GANformer model and found extreme differences between the authors' and our results. Moreover, discrepancies between the publication methodology and the one implemented, made available in the code, allowed us to study two undisclosed variations of the presented procedures.

1 Introduction

This project aims at investigating the reliability and reproducibility of a paper accepted for publication in a top machine learning conference. The models have been implemented using code and information provided by the authors.

With this work, we are going to verify the empirical results and claims of the paper "*Generative Adversarial transformers*" by Hudson and Zitnick [2], by reproducing three of the computational experiments performed by the authors: (1) the **StyleGAN2** by Karras et al. [3, 4], a GAN network that uses one global latent style vector to modulate the features of each layer, hence controlling the style of all image features globally. (2) the **GANformer** with **Simplex Attention** by Hudson and Zitnick [2], which generalises the StyleGAN design with k latent vectors that cooperate through attention. Thus, allowing for a spatially finer control over the generation process since multiple style vectors impact different regions in the image concurrently, particularly permitting communication in one direction, in the generative context – from the latent vectors to the image features. (3) the **GANformer** with **Duplex Attention** by Hudson and Zitnick [2], which is based on the same principles as the previous but propagating information from global latent vectors to local image features, enabling both top-down and bottom-up reasoning to coincide.

Add the fact that we extend the two GANformer experiments, with the possibility to keep the attention optional on the discriminator

The first model is used as a baseline, while the remaining are the architectures introduced by the authors. They consider the GANformer as "a novel and efficient type of transformer" which demonstrates its strength and robustness over a range of tasks of visual generative modelling — simulated multi-object environments (real-world indoor and outdoor scenes) — achieving state-of-the-art results in terms of both image quality and diversity while benefiting from fast learning and better data-efficiency.

2 Background

2.1 Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) [1] are deep-learning-based generative models which learn to determine whether a sample is from the model or the data distribution. The classic architecture, illustrated in Appendix A.1 in Figure 4, is composed by two main neural networks: the *generator* $G(z)$, which generates new plausible examples

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in the problem domain — images in our case — , and the *discriminator* $D(x)$, which classify the examples as real (coming from the training dataset) or fake (generated by G). More details are provided in Appendix A.1.

2.2 StyleGAN2

StyleGAN are a re-design of the GANs generator architecture, which aim is to control the image synthesis process [4]. The typical architecture of a StyleGAN is shown in Appendix A.1 in Figure 5, together with the technical details.

In particular, we are interested in the second version of the StyleGAN, the StyleGAN2 [3], which are a revisiting of the architecture of the StyleGAN synthesis network. Figure 6 in Appendix A.1 exemplifies the various changes made to the original architecture up to the final StyleGAN2 network. Further informations are provided in Appendix A.1.

The StyleGAN2 architecture makes it possible to control the image synthesis via scale-specific modifications to the styles. In particular, this approach attains layer-wise decomposition of visual properties, allowing StyleGAN to control global aspects of the picture such as pose, lighting conditions or colour schemes, in a coherent manner over the entire image.

However, while this model successfully disentangles global properties, it is more limited in its ability to perform spatial decomposition, as it provides no direct means to control the style of a localised regions within the generated image.

2.3 Transformers

Transformers are deep-learning models based on an *attention mechanism*, which is designed to handle sequential input data and evaluate the relationship between each input-output item [5]. This models, unlike Recurrent Neural Networks (RNNs), avoid using convolutions or aligned sequence, and do not necessarily require ordered input data to be processed.

The architecture is composed by an *encoder-decoder* structure where, the encoder maps an input sequence of symbol representations $(x_1, \ldots, x_n)$ to a sequence of continuous representations $z = (z_1, \ldots, z_n)$, while the decoder, given z, generates an output sequence $(y_1, \ldots, y_m)$ of symbols one element at a time. Each transformer module (encoder-decoder) is connected to each other via feed-forward layers.

The details about how an attention function works are reported in Appendix A.1.

Vaswani et al. [5] used multiple multi-head attentions, stacked on the top of each other, enabling to pass multiple input sequences simultaneously, instead of one at a time, allowing for more parallelisation and therefore reducing training times if you have access to sufficient computational resources.

3 Methodology: Generative Adversarial Transformers

The Generative Adversarial Transformers (GANsformer), introduced by Hudson and Zitnick [2], are models which combine GANs and the transformers to generate better and more realistic examples.

GANs, and in particular the StyleGAN2 model [3], presented in Section 2.2 and shown in Figure 6, is used as a starting point for the GANformer design for the properties it owns as CNN: they are powerful generators for the overall style of the image, since by nature they merge the local information of the pixels together with the general information regarding the image. However, they are less powerful with respect to small details of localised regions within the generate image itself, since they miss out on the long range interaction of the faraway pixel.

Accordingly, GANsformer take advantage of the transformers attention mechanism to make the StyleGAN2 architecture even more powerful: the integration of attention in the architecture allows the network to draw global dependencies between input and output, and understand the context of the image thanks to the transformer's strength for long-range interactions. Thus, rather than focusing on using global information and controlling all features globally, transformer use attention to propagate information from the local pixels to the global high-level representation and vice versa.

The *bipartite transformer* structure computes *soft attention*, iteratively aggregating and disseminating information between the generated image features and a compact set of *latent variables* enable bidirectional interaction between these dual representations. This architecture offers a solution to the StyleGAN limitation in its ability to perform spatial decomposition which leaded to the impossibility of controlling the style of a localised regions within the generated image. More details regarding the composition and functioning of the bipartite transformer and self-attention layers are thorough in Appendix A.2.

The *transformer network* corresponds to the *multi-layer bidirectional transformer encoder* (BERT), introduced by Devlin et al. [6], which interleaves *multi-head self-attention* and *feed-forward layers*.

The discriminator model performs multiple layers of convolution downsampling on the image, reducing the representation's resolution gradually until making final prediction. Optionally, attention can be incorporated into the discriminator as well where it has multiple k aggregator variables, that use attention to adaptively collect information from the image while being processed.

The generator likewise is composed of two parts, a mapping network and a synthesis network. The mapping network of a GANformer is the same as that of the StyleGAN2. In the synthesis network, while in the StyleGAN2, a single global w vector controls all the features equally, the GANformer uses attention so that the k latent components specialise to control different regions in the image to create it cooperatively, and therefore perform better especially in generating images depicting multi-object scenes, allowing also for a flexible and dynamic style modulation at the region level.

Hudson and Zitnick [2] have applied some adaptations to the structure of the GANformer as presented here, in order to foster an interesting communication flow. The details are provided later in Section 4.2. Rather than densely modelling interactions among all the pairs of pixels in the images, instead it supports *adaptive long-range interaction* between far away pixels in a moderated manner, passing through a compact and global latent bottleneck that selectively gathers information from the entire input and distributes it back to the relevant regions.

There are two attention operations that could be computed over the bipartite graph, depending on the direction in which information propagates, (1) *simplex attention* permits communication either in one way only, in the generative context, from the latents to the image features, and (2) *duplex attention* which enables it both top-down and bottom-up ways.

3.1 Simplex attention

As already mentioned, simplex attention distributes information in a single direction over the bipartite transformer graph.

Formally, let $X^{n \times d}$ denote an input set of n vectors of dimension d — where, for the image case, $n = W \times H$ — and $Y^{m \times d}$ denote a set of m aggregator variables — the latents, in the generative case. Specifically, the attention is computed over the derived bipartite graph between these two groups of elements, as in Equation (7), moreover:

$$a(X, Y) = \mathsf{Attention}(q(X), k(Y), v(Y)), \tag{1}$$

where $q(\cdot), k(\cdot), v(\cdot)$ are functions that respectively map elements into queries, keys, and values, all maintaining dimensionality d. The mappings are provided with positional encodings to reflect the distinct position of each element (e.g. in the image). This bipartite attention is a generalisation of self-attention, where $Y = X$.

Standard transformers implement an additive update rule of the form:

$$u^a(X, Y) = \mathsf{LayerNorm}(X + a(X, Y)), \tag{2}$$

however, [2] used the retrieved information to control both the scale as well as the bias of the elements in X, in line with the practice promoted by the StyleGAN model [4]:

$$u^s(X, Y) = \gamma(a(X, Y)) \odot \omega(X) + \beta(a(X, Y)), \tag{3}$$

where $\gamma(\cdot), \beta(\cdot)$ are mappings that compute multiplicative and additive styles (gain and bias), maintaining dimensionality d, and $\omega(X) = X - \mu(X)$ normalises each element with $\sigma(X)$ respect to the other features. By normalising X (image features), and then letting Y (latents) control the statistical tendencies of X, the information propagation from Y to X is enabled, allowing the latents to control the visual generation of spatial attended regions within the image, so as to guide the synthesis of objects or entities. The multiplicative integration permits significant gains in the model performance.

3.2 Duplex attention

Duplex attention can be explained by taking into account the variables Y to set their own key-value structure: $Y = (K^{n \times d}, V^{n \times d})$, where the values store the content of the Y variables, as before (e.g. the randomly sampled latent vectors in the case of GANs) while the keys track the centroids K of the attention-based assignments between Y and X, which can be computed as $K = a(Y, X)$ — namely, the weighted averages of the X elements using the bipartite attention distribution derived through comparing it to Y. Consequently, the new update rule is defined as follows:

$$u^d(X, Y) = \gamma(A(X, K, V)) \odot \omega(X) + \beta(A(X, K, V)), \tag{4}$$

where, two attention operations are compound on top of each other: first compute the *soft attention* assignments between X and Y, by $K = a(Y, X)$, and then refine the assignments by considering their centroids, by $A(X, K, V)$. This is

analogous to the *k-means algorithm* and works more effectively than the simpler update u^a defined above in Equation (3).

Finally, to support bidirectional interaction between X and Y (the image and the latents), two reciprocal simplex attentions are chain from X to Y and from Y to X, obtaining the duplex attention, which alternates computing $Y := u^a(Y, X)$ and $X := u^d(X, Y)$, such that each representation is refined in light of its interaction with the other, integrating together bottom-up and top-down interactions.

4 Implementation

The code from the authors' has been merged with the code provided by StyleGAN2 to obtain a hybrid version of the StyleGAN2 and the GANformer. In addition, we created a simplified version of the code which removed unnecessary operations in the creation of the network that were used for other model architectures. Furthermore, we implemented a Google Colab Pro version of the authors' code, as we had access to a more powerful GPU.

4.1 Datasets

The original paper [2] explored the GANformer model on four datasets for images and scenes: CLEVR [7], LSUN-Bedrooms [8], Cityscapes [9] and FFHQ [4].

Initially, we tried to use the Cityscapes dataset, since it is the smaller among the four: it contains 24998 images with 256x256 resolution. However, the memory required to complete the training was too high on this dataset (more than 25Gb). Even if we had more memory available, Colab Pro's limitation of 24 hours sessions would have interrupted our experiments prematurely.

For this reason, we switch to another dataset, the Google Cartoon Set [10][1], containing 10k 2D cartoon avatar images with 64x64 resolution, composed of 16 components that vary in 10 artwork attributes, 4 colour attributes, and 4 proportion attributes (see Table 5 in Appendix A.3).

4.2 Hyper-parameters

In this section we present the relevant hyper-parameters used in our experimentation, both for training and also in terms of layer sizes and technical choices.
Table 1 contains a comparison between Stylegan2(the baseline) and the novel networks proposed in the original paper. Note that in the code provided by the author [2], the hyper-parameters are not the same mentioned in the article.

Table 1: Hyperparameters (Including comparison between given code and paper statements)

	Stylegan2	GANformer simplex	GANformer duplex	GANformer simplex (PAPER)	GANformer duplex (PAPER)
latent_size	/	32	32	32	32
dlatent_size	/	32	32	32	32
components_num	/	16	16	16	16
beta1	0.0	0.0	0.0	0.9	0.9
beta2	0.99	0.99	0.99	0.999	0.999
epsilon	1e-8	1e-8	1e-8	1e-3	1e-3

Network choices

A *kernel size* of $k = 3$ is used after each application of the attention, together with a *Leaky ReLU non-linearity* after each convolution and then upsample or downsample the features X, as part of the generator or discriminator respectively, as in e.g. StyleGAN2 [3]. To account for the features location within the image, we use a sinusoidal positional encoding along the horizontal and vertical dimensions for the visual features X, and trained positional embeddings for the set of latent variables Y. Overall, the bipartite transformer is thus composed of a stack that alternates attention (simplex or duplex), convolution, and upsampling layers, starting from a 4×4 grid up to the desirable resolution.

Both the simplex and the duplex attention operations enjoy a bilinear efficiency of $\mathcal{O}(mn)$ thanks to the network's bipartite structure that considers all pairs of corresponding elements from X and Y. Since, as we see below, we maintain

[1] `https://google.github.io/cartoonset`

Y to be of a fairly small size, choosing m in the range of 8–32, this compares favourably to the prohibitive $\mathcal{O}(n^2)$ complexity of self-attention, which impedes its applicability to high-resolution images.

As to the loss function, optimisation and training configurations, we adopt the settings and techniques used in StyleGAN2 [3], including in particular style mixing, stochastic variation, exponential moving average for weights, and a non-saturating logistic loss with a lazy R1 regularisation.

4.3 Experimental setup

The source code of our work is available at the following GitHub repository: `https://github.com/GiorgiaAuroraAdorni/gansformer-reproducibility-challenge`.

The approaches proposed in both the original paper codebase by Karras et al. [3] and by Hudson and Zitnick [2] have been implemented in Python using TensorFlow [11], so, according to that, we used the same setup. We created a Jupyter Notebook which runs all the experiments in Google Colaboratory, which allows us to write and execute Python in the browser.

All the models have been trained on a Tesla P100-PCIE-16GB (GPU) provided by Google Colab Pro.

4.4 Computational requirements

In the original paper [2], they evaluate all models under comparable conditions of training scheme, model size, and optimisation details, implementing all the models within the codebase introduced by the StyleGAN authors [3]. All models have been trained with images of 256 x 256 resolution and for the same number of training steps, roughly spanning a week on 2 NVIDIA V100 GPUs per model (or equivalently 3-4 days using 4 GPUs).

Considered that we had available just one GPU and not enough time to reproduce this settings, we decided to resize the images from 256x256 to 64x64 resolution.

For the GANformer we select k = 32 number of latent variables.

All models have been trained for the same number of steps, 300 000 image training samples (300 kimg) while the paper present results after training 100, 200, 500, 1000, 2000, 5000 and 10000 kimg samples

For the StyleGAN2 model we present results after training 300 kimg, obtaining good results. Note that the original StyleGAN2 model has been trained by its authors [3] for up to 70000 kimg samples, which is expected to take over 90 GPU-days for a single model.

For the GANformer, the authors [3] show impressive results, especially when using duplex attention: the model manages to learn a lot faster than competing approaches, generating astonishing images early in the training. This model is expected to take 4 GPU-days.

However, we are not able to replicate this achievements, first because this model learns significantly slower than the StyleGAN2, which is able to train approximately 1.3 times faster than the GANformer in terms of time per kimg. (in the paper they reach better results with the GANformer with 3-times less training steps than the StyleGAN2, but they don't specify the time required for a step) Secondly, the GANformer with simplex attention seems to be as slow if not slower to achieve qualitative results in terms of training steps when compared to StyleGAN2 and if Duplex attention is selected, qualitative results are never obtained.

As previously mentioned we trained using Colab Pro which enabled us to access a Tesla P100 GPU by Nvidia with 16Gb of vram and 25Gb of RAM.

For StyleGAN2, with the given resources, for 300 kimg, training took around 8h while for all variations of the GANformer, training took around 10 h.

5 Results

In this section we show and comment our results while also comparing them to the original GANformer paper. We start by evaluating the 2 presented variations of the GANformer and StyleGAN2 over a set of four metrics: Frechet Inception Distance (FID), Inception Score (IS), Precision and Recall.

The FID is one of the most popular metrics for evaluating GANs, which provides stable and reliable indications of *image fidelity* and *diversity*. It is a measure of similarity between curves that takes into account the location and ordering of the points along the curves. For this specific application, FID is used to measures the feature distance between the

real and the generated images, but it can be used for measuring the distance between two distributions as well. For this reason, we have decided to use it as a reference metric for all the following analyses.

In Table 2, we compared the GANformer (Simplex and Duplex) with the competing StyleGAN2 model. To have a fair comparison, the three image synthesis methods are run for the same amount of iterations and the same dataset. To express the improvement over StyleGAN2, a difference factor of FID is positioned alongside the scores.

Table 2: **Comparison between the GANformer (Simplex and Duplex) and competing StyleGAN2**. In the last column, is reported the percentage of improvement all the models, in terms of FID score, with respect to the baseline StyleGAN2 architecture.

Model	FID ↓	IS ↑	Precision↑	Recall ↑	FID Improvement (%)
StyleGAN2	24.77	2.50	0.00	0.02	0 %
GANformer, Simplex attention	28.11	2.58	0.00	0.01	-13.47 %
GANformer, Duplex attention	374.18	1.40	0.00	0.00	-1410.47 %

Unexpectedly, the novel GANformer with Duplex attention, is considerably worse than the baseline on all aspects with a staggering -1410.47 % deterioration in FID score. To investigate this further, a similar representation is recreated in Table 3 using the original paper findings for the same metrics and with a mean of the scores spanning the four used datasets.

Table 3: **Original paper's reported results (mean of results over the 4 datasets used by the authors)**. In the last column, is reported the percentage of improvement all the models, in terms of FID score, with respect to the baseline StyleGAN2 architecture.

Model	FID ↓	IS ↑	Precision ↑	Recall ↑	FID Improvement (%)
StyleGAN2	11.29	2.74	52.02	23.98	0 %
GANformer, Simplex attention	10.29	2.82	56.76	18.21	+8.86 %
GANformer, Duplex attention	7.22	2.78	55.45	33.94	+36.11 %

It is noteworthy to state that in the code given by the authors, attention seems to be only optionally used in the discriminator and when analysing the pre-trained models provided, it is never used, prompting us to implement two variations of the GANformer not openly discussed in [2]. We use the GANformer paradigm for the generator and a vanilla StyleGAN2 discriminator and obtain the results visible in Table 4.

Table 4: **Comparison between the GANformer (Simplex and Duplex) both with and without attention on the Discriminator and competing StyleGAN2**. In the last column, is reported the percentage of improvement all the models, in terms of FID score, with respect to the baseline StyleGAN2 architecture.

Model	FID ↓	IS ↑	Precision ↑	Recall ↑	FID Improvement (%)
StyleGAN2	24.77	2.50	0.00	0.02	0 %
GANformer, Simplex attention	28.11	2.58	0.00	0.01	-13.47 %
GANformer, Duplex attention	374.18	1.40	0.00	0.00	-1410.47 %
GANformer, Simplex attention (StyleGAN2 disc.)	19.09	2.62	0.00	0.05	+22.93 %
GANformer, Duplex attention (StyleGAN2 disc.)	24.81	2.62	0.00	0.02	-0.14 %

Due to the relevance of the FID metric, we compare all the created models score over iterations number to both show quality of results over training steps in Figure 1.

As mentioned before, unexpectedly, the model that yields the better results in the original paper, is overall the worst in our experiments. Not only the FID score is worse than the baseline StyleGAN2 at the final training step both for simplex and duplex attention implementations but also claims about efficiency can not be verified. Models that include attention on the Generator only, instead, are faster in terms of steps to reach a qualitative results when compared to the baseline. We believe that this behaviour explains the choices made by the authors in their GitHub publication of the code. Moreover a comment has to be made on the claim of efficiency; both with and without attention on the discriminator, a

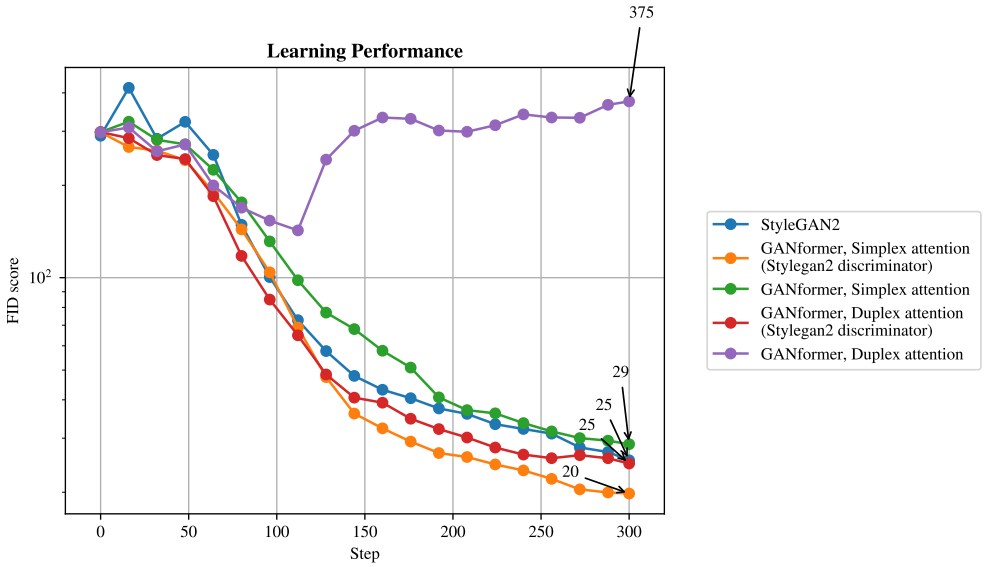


Figure 1: **Comparison between the StyleGAN2 and the GANformer models.** We evaluate the models according to FID score along 300k image samples. The score is computed every sixteen checkpoints.

training step is considerably slower to be completed on the same resources when compared to StyleGAN2. While the latter is capable of having a training speed of 10.9 images generated a second, all flavours of the GANformer, in the best case, only yield 8.3 images generated a second.

Finally, to visualise our findings in a less empirical fashion, we have used random seeds to create latent inputs and shown the resulting images generated by the baseline StyleGAN2 and all four presented variations of the GANformer in Figures 2 and 3.

It is blatantly obvious that the Duplex GANformer implementation is not capable of performing the task at hand, while all other models are at least able to produce visually compelling results. ADD MORE COMPREHENSIVE COMMENT

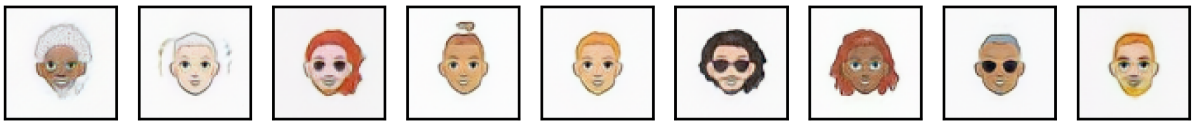
6 Discussion and conclusion

In this project we have discussed the replication of "*Generative adversarial Transformers*" by Hudson and Zitnick [2]. Contrary to our initial expectations, in our opinion, some of the claims made by the authors were misleading or unproven in a scientific manner. Once we made this realisation, our methodology shifted from a pure reproduction of the results to a search of undisclosed variations of the novel GANformer system in the published material trying to obtain results that were comparable to the given ones. As mentioned in paragraph 4.4, our limited resources forced us to reduce the depth of our experiments compared to the authors'. We had to shift from four datasets to a single, size-reduced one: Forrester et al. [10], significantly decreasing the time of execution and the complexity of our research. For the same reasons, we have discarded four out of the five baselines: GAN, k-GAN, SAGAN and VQGAN in favour of just StyleGAN2. The choice of StyleGAN2 as the baseline was prompted by a similarity of its execution to the novel GANformer, where parts of the author's code are a carbon copy of the StyleGAN2 implementation first proposed in Karras et al. [4].
In this study, we have firstly implemented a Google Colab Pro compatible version of the authors code, enabling us to train and test StyleGAN2 and the two flavours of GANformer (Duplex and Simplex attention) in less than 54 hours in total. As presented in section 5, we were not able to achieve the improvements declared by the authors but instead found a decrease both in time performance and quality. Believing it was an error arised by our adaptation we have analysed the pre-trained models provided and noticed an alarming discrepancy between the code and the methodology discussed in the paper. In "*Generative adversarial Transformers*" by Hudson and Zitnick [2], the attention component is said to be placed both on the generator and the discriminator sub-networks, while in all the pre-trained models provided, it seems to never be used on the discriminator.
Believing that all of the authors experiments were performed on a different network than the one presented in the publication, we have tried to recreate the structure that could have yielded the claimed qualitative results. To perform such a task we have decomposed the GANformer network in two sections by keeping the presented Generator but substituting the hypothetically valid discriminator network with a vanilla StyleGAN discriminator. To our surprise the StyleGAN/GANformer hybrid did perform significantly better than the baseline, proving, in our opinion the suspected behaviour of the original code.
In conclusion we have succesfully reproduced the "*Generative adversarial Transformers*" by Hudson and Zitnick [2] and found unexpected results. We have then modified the proposed methodologies to obtain an image generation network that takes inspiration from the novel GANformer and adapts it to produce images that score significantly higher than the baseline over four quality metrics.

7 Authors contribution

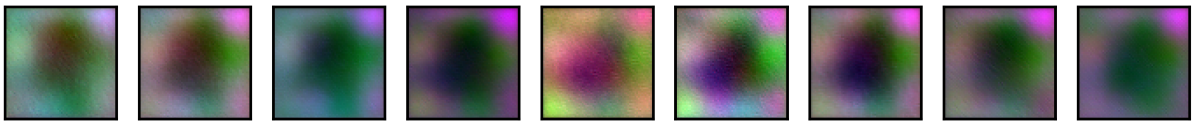
(a) StyleGAN2.

(b) GANformer with Simplex attention and vanilla StyleGAN2 discriminator.



(c) GANformer with Simplex attention.

(d) GANformer with Duplex attention and vanilla StyleGAN2 discriminator.



(e) GANformer with Duplex attention.

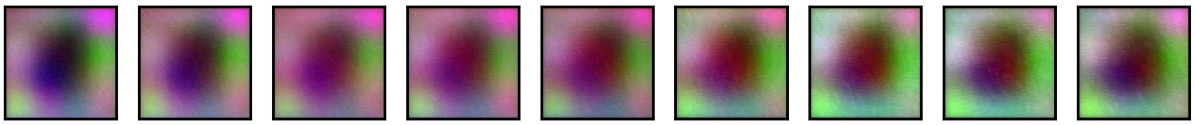
Figure 2: **Visualisation of 9 images generated with the various models**.

(a) StyleGAN2.

(b) GANformer with Simplex attention and vanilla StyleGAN2 discriminator.

(c) GANformer with Simplex attention.

(d) GANformer with Duplex attention and vanilla StyleGAN2 discriminator.



(e) GANformer with Duplex attention.

Figure 3: **Simple z interpolation using of the various models**.

A Appendix

A.1 Methodology background

As aforementioned in Section 2.1, GANs [1], are deep-learning-based generative models composed by two main neural networks: the *generator* $G(z)$, which take as input a sample from the latent space z, or a vector drawn randomly from a Gaussian distribution, and use it to generate new plausible examples in the problem domain — images in our case — , and the *discriminator* $D(x)$, which takes an example from the domain as input, and predicts a binary class label which classify the examples as real (coming from the training dataset) or fake (generated by G).

The two models are trained together: the discriminator D estimates the probability that sample x is generated by G or is a real sample, and aims at maximising the probability of assigning the correct label to both real and fake samples, while the generator G is trained to maximise the probability of the discriminator D making a mistake, so it aims to minimise $\log(1 - D(G(z)))$.

Combining the two objectives for $G(z)$ and $D(x)$ we get the *GAN min-max game* with the value function $V(G, D)$:

$$\min_G \max_D V(G, D) = \mathbb{E}_{x \sim p*(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))] \tag{5}$$

GANs typically work with images, as in our case, for this reason, both the generator and discriminator models use Convolutional Neural Networks (CNNs).

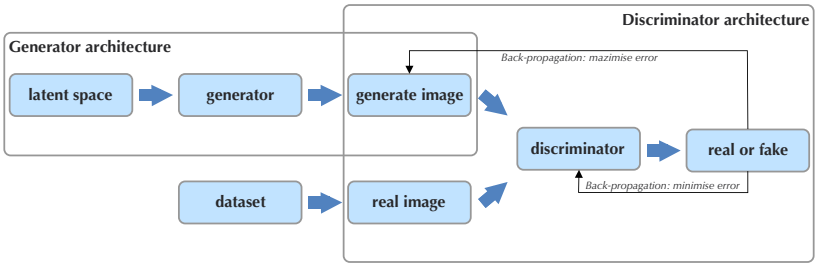


Figure 4: **GAN architecture.** Visualisation of the two components of a GAN: generator and discriminator.

In this paper, we exploited StyleGAN2 architecture, the second version of the StyleGAN model, introduced in Section 2.2, which is a re-design of the GANs generator architecture. The aim of the StyleGAN is to control the image synthesis process [4]. The architecture is illustrated in Figure 5.

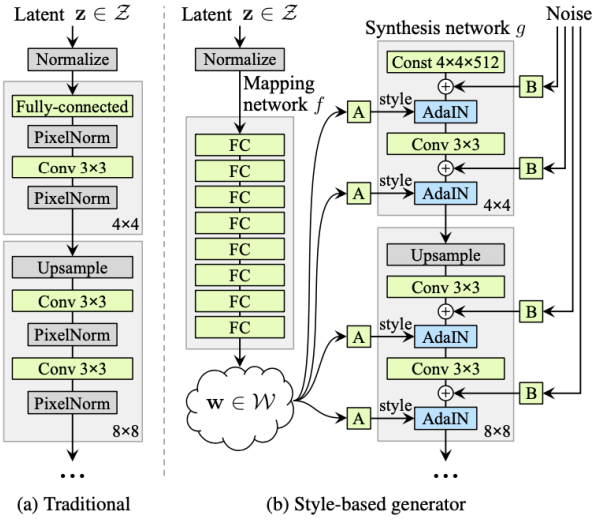


Figure 5: **StyleGAN architecture.** Re-design of the traditional GAN generator into a style-based generator.

The StyleGAN approach departs from the design of a common generator network, consisting in a multi-layer CNN. A traditional GAN generator feeds the latent code z though the input layer only, to start the up-sampling process. Karras et al. [4] introduce a feed-forward mapping network $f : Z \to W$ which processes the latent code z in the input latent space Z, and output an intermediate latent vector $w \in W$. w, in turn, interacts directly with each convolution through the synthesis network g and, in particular, with the *Adaptive Instance Normalisation (AdaIN)* [12] aligns the mean and variance of the content features with those of the style features, meaning that is able to globally controls these parameters and so the strength of image features at different scales.

The *AdaIN* operation is defined as:

$$\mathsf{AdaIN}(x, y) = \sigma(y)\left(\frac{x - \mu(x)}{\sigma(x)}\right) + \mu(y), \tag{6}$$

where x is the content input, y a style input, and the channel-wise mean and variance of x are aligned to match those of y.

Karras et al. [4] provided the generator with a direct means to generate stochastic details by introducing explicit Gaussian noise inputs after each convolution: an automatic and unsupervised separation of high-level attributes (e.g., pose, identity) from stochastic variation (e.g., freckles, hair) is obtained in the generated images, and intuitive scale-specific mixing and interpolation operations are enabled.

StyleGAN2 [3] are a revisiting of the architecture of the StyleGAN synthesis network. Figure 6 shows the various changes made to the original architecture up to the final network.

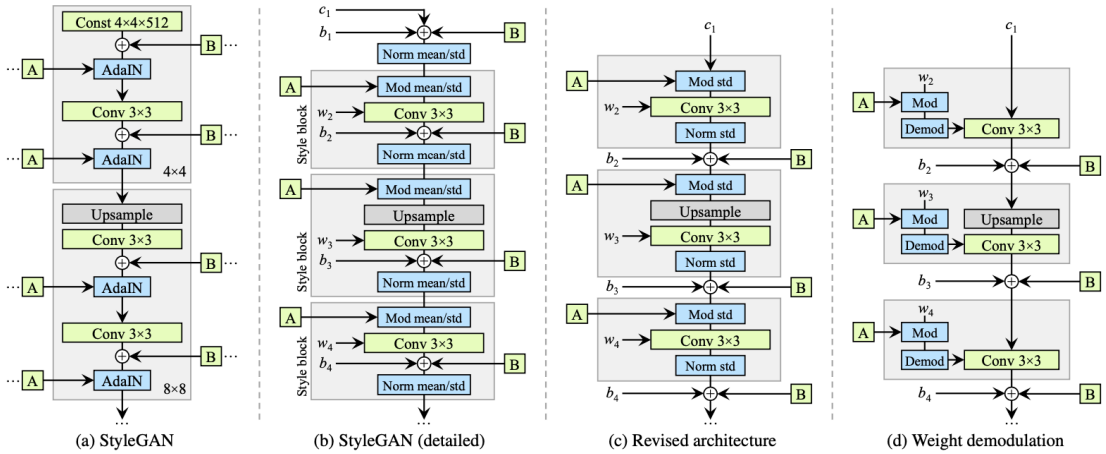


Figure 6: **StyleGAN2 architecture.** Evolution from a StyleGAN to a StyleGAN2 synthesis network.

In particular, some redundant operations have been removed from the original StyleGAN architecture. Bias and noise are operations which might have conflicting interests, and their application within the style block caused their relative impact to be inversely proportional to the current style's magnitudes. For this reason, they have been moved outside the style block and separated, allowing to obtain more predictable results. Furthermore, after this change, the mean is no longer necessary, but it is sufficient for the normalisation and modulation to operate on the standard deviation alone. Moreover, the application of bias, noise, and normalisation to the constant input has been safely removed.

When the style block consists in a modulation, a convolution, and a normalisation operation, it is possible to restructure the AdaIN has a demodulation operation, which is applied to the weights associated with each convolution layer. AdaIN uses different scale and shift parameters to align different areas of w — the activations of intermediate activations — with different regions of the feature map (either within each feature map or via grouping features channel-wise by spatial location), while weight demodulation takes the scale and shift parameters out of a sequential computation path, instead baking scaling into the parameters of convolutional layers.

Also transformers are an important deep-learning model exploited in this work and introduced in Section 2.3. An *attention function* [5], can be described as mapping a query and a set of key-value pairs to an output, where the query, keys, values, and output are all vectors. The output is computed as a weighted sum of the values, where the weight assigned to each value is computed by a compatibility function of the query with the corresponding key.

The input consists of queries and keys of dimension d_k, and values of dimension d_v. The dot products of the query with all keys is computed, each divided by $\sqrt{d_k}$ and then a softmax function is applied to obtain the weights on the values. In practice, the attention function is computed on a set of queries simultaneously, packed together into a matrix Q. The keys and values are also packed together into matrices K and V.

$$\mathsf{Attention}(Q, K, V) = \mathsf{softmax}(\frac{QK^T}{\sqrt{d_k}})V \tag{7}$$

Instead of performing a single attention function, transformers use multiple self-attentions, called *multi-head attention*, allowing the model to jointly attend to information from different representation subspaces at different positions, learning attention relationship independently [5]. As mentioned in Section 2.3, Vaswani et al. [5] used multiple multi-head attentions, which are defined as follows.

$$\mathsf{MultiHead}(Q, K, V) = \mathsf{Concat}(\mathsf{head}_1 \ldots, \mathsf{head}_h)W^O, \tag{8}$$

where $\mathsf{head}_i = \mathsf{Attention}(QW_i^Q, KW_i^K, VW_i^V)$, and the projections are parameter matrices $W_i^Q \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^K \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^V \in \mathbb{R}^{d_{\text{model}} \times d_v}$ and $W^O \in \mathbb{R}^{hd_v \times d_{\text{model}}}$.

As reported by [5], transformer uses multi-head attention in three different ways:

1. In "encoder-decoder attention" layers, the queries come from the previous decoder layer, and the memory keys and values come from the output of the encoder. This allows every position in the decoder to attend over all positions in the input sequence.
2. The encoder contains self-attention layers, in which all of the keys, values and queries come from the output of the previous layer in the encoder. Each position in the encoder can attend to all positions in the previous layer of the encoder.
3. Similarly, self-attention layers in the decoder allow each position in the decoder to attend to all positions in the decoder up to and including that position. We need to prevent leftward information flow in the decoder to preserve the auto-regressive property. We implement this inside of scaled dot-product attention by masking out (setting to $-\infty$) all values in the input of the softmax which correspond to illegal connections.

A.2 Generative Adversarial Transformers in details

In this Section we dive into the details of Generative Adversarial Transformers [2], introduced in Section 3.

The BERT *transformer network* [6] interleaves *multi-head self-attention* and *feed-forward layers*. Each pair of self-attention and feed-forward layers is intended as a *transformer layer*, hence, a transformer is a stack of several such layers.

The *self-attention layer* considers all pairwise relations among the input elements, so to update each single element by attending to all the others. The *bipartite transformer* generalises this formulation, featuring instead a bipartite graph between two groups of variables — in the GAN case, latents and image features.

In particular, the attention layers are added in between the convolutional layers of both the generator and discriminator.

Instead of controlling the style of all features globally, the new attention layer is used to perform *adaptive region-wise modulation*. The latent vector z is split into k components, $z = [z_1, \ldots, z_k]$ and, as in StyleGAN [4], pass each of them through a shared mapping network, obtaining a corresponding set of intermediate latent variables $Y = [y_1, ..., y_k]$.

During synthesis, after each CNN layer in the generator, the feature map X and latents Y play the roles of the two element groups, mediating their interaction through our new attention layer (either simplex or duplex). This setting thus allows for a flexible and dynamic style modulation at the region level.

Since soft attention tends to group elements based on their proximity and content similarity, the transformer architecture naturally fits into the generative task and proves useful in the visual domain, allowing the model to exercise finer control in modulating local semantic regions. This capability turns to be especially useful in modelling highly-structured scenes.

For the discriminator, attention is applied after every convolution using trained embeddings to initialise the aggregator variables Y, which may intuitively represent background knowledge the model learns about the task. At the last layer are concatenated these variables Y to the final feature map X to make a prediction about the identity of the image source. This structure empowers the discriminator with the capacity to likewise model long-range dependencies, which can aid it in its assessment of the image fidelity, allowing to acquire a more holistic understanding of the visual modality.

A.3 Datasets

The dataset used in this work is the Google Cartoon Set [10] introduced in Section 4.1, containing 10k 2D cartoon avatar. These images are composed of 16 components that vary in 10 artwork attributes, 4 colour attributes, and 4 proportion attributes (see Table 5).

Table 5: Attributes of the Cartoon Set.

		# Variants	Description
Artwork	`chin_length`	3	Length of chin (below mouth region)
	`eye_angle`	3	Tilt of the eye inwards or outwards
	`eye_lashes`	2	Whether or not eyelashes are visible
	`eye_lid`	2	Appearance of the eyelids
	`eyebrow_shape`	14	Shape of eyebrows
	`eyebrow_weight`	2	Line weight of eyebrows
	`face_shape`	7	Overall shape of the face
	`facial_hair`	15	Type of facial hair (type 14 is no hair)
	`glasses`	12	Type of glasses (type 11 is no glasses)
	`hair`	111	Type of head hair
Colors	`eye_color`	5	Color of the eye irises
	`face_color`	11	Color of the face skin
	`glasses_color`	7	Color of the glasses, if present
	`hair_color`	10	Color of the hair, facial hair, and eyebrows
Proportions	`eye_eyebrow_distance`	3	Distance between the eye and eyebrows
	`eye_slant`	3	Similar to eye_angle, but rotates the eye and does not change artwork
	`eyebrow_thickness`	4	Vertical scaling of the eyebrows
	`eyebrow_width`	3	Horizontal scaling of the eyebrows

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