URL Coursework 2

StackGAN++: Realistic Image Synthesis with Stacked Generative Adversarial Networks [1]

Bruno Sánchez Gómez

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Introduction

Area of Research of the Paper

Generative Adversarial Networks (GANs) for Image Generation

- **StackGAN++** focuses on:
  - High-resolution images (256×256 pixels)
  - Two tasks:
    - *Unconditional Image Generation*
    - *Text-to-Image Synthesis* (Conditional Image Generation)

Introduction

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Generative Adversarial Networks (GANs) for Image Generation

- **StackGAN++** focuses on:
  - High-resolution images (256×256 pixels)
  - Two tasks:
    - *Unconditional Image Generation*
    - *Text-to-Image Synthesis* (Conditional Image Generation)
- **Limitations of prior work with GANs:**
  - Training instability
  - Mode collapse
  - Difficulty in generating high-resolution images

Contributions by StackGAN++

- **Conditioning Augmentation (CA):** Improve sample diversity by augmenting the image-text pairs.
- **StackGAN:** Two GAN frameworks for conditional and unconditional image synthesis with high resolution (256×256):
  - **StackGAN-v1:** Two-stage GAN
  - **StackGAN-v2:** Multi-stage GAN with a tree-like structure

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Conditioning Augmentation (CA)

Core Idea

Augment the text conditioning to improve sample diversity and stabilize GAN training

- The latent space for text embeddings, ϕ_t, is high-dimensional
- Limited data causes discontinuity in the latent data manifold
- CA samples a new embedding $\hat{c}$ from a Gaussian distribution:

$$\hat{c} = N(\mu_\theta(\phi_t), \Sigma_\theta(\phi_t))$$

- To further enforce smoothness over the conditioning manifold and avoid overfitting, a regularization term is added to the loss:

$$\mathcal{L}_{\text{KL}} = D_{KL}\big(N(\mu_\theta(\phi_t), \Sigma_\theta(\phi_t)) \,||\, N(0, I)\big)$$

Core Idea

Decompose text-to-image generation into a sketch-refinement process

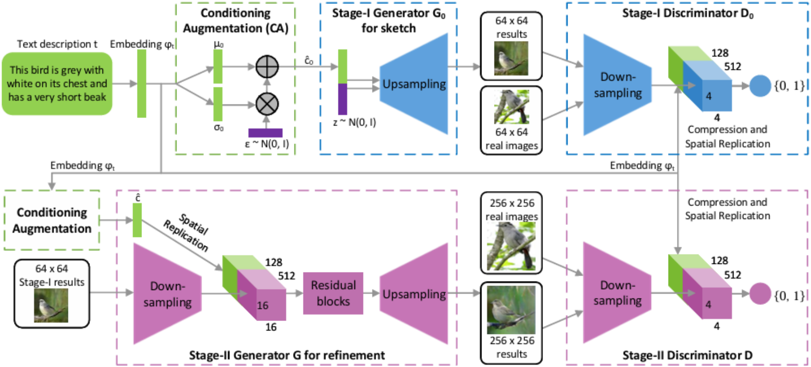

Figure: StackGAN-v1 Architecture (Source: [1])

Core Idea

A more general, end-to-end multi-stage framework with a tree-like structure

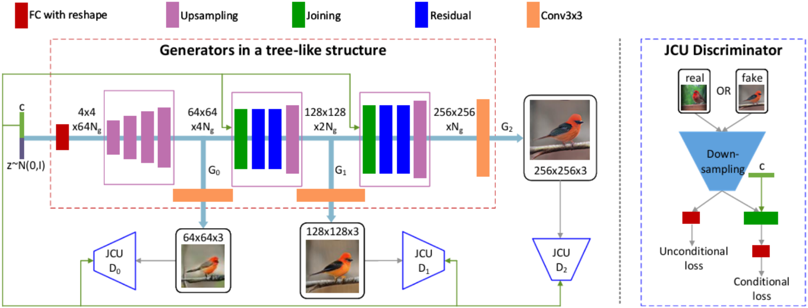

Figure: StackGAN-v2 Architecture and JCU Discriminators (Source: [1])

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Experimental Setup

	Unconditional	**Conditional**
Datasets	LSUN ImageNet	CUB-200-2011 Oxford-102 MS COCO
Competing Methods	DCGAN WGAN EBGAN-PT LSGAN WGAN-GP	GAN-INT-CLS GAWWN

Evaluation Metrics	*Inception Score (IS)* $\uparrow$
	Fréchet Inception Distance (FID) $\downarrow$
	Human Rank (HR) $\downarrow$

Quantitative Results

Metric	CUB			Oxford		COCO	
	GAN-INT-CLS	GAWWN	Our StackGAN-v1	GAN-INT-CLS	Our StackGAN-v1	GAN-INT-CLS	Our StackGAN-v1
FID ↓	68.79	67.22	**51.89**	79.55	**55.28**	**60.62**	74.05
FID* ↓	68.79	53.51	**35.11**	79.55	**43.02**	60.62	**33.88**
IS ↑	2.88 ± .04	3.62 ± .07	**3.70 ± .04**	2.66 ± .03	**3.20 ± .01**	7.88 ± .07	**8.45 ± .03**
IS* ↑	2.88 ± .04	**3.10 ± .03**	3.02 ± .03	2.66 ± .03	**2.73 ± .03**	7.88 ± .07	**8.35 ± .11**
HR ↓	2.76 ± .01	1.95 ± .02	**1.29 ± .02**	1.84 ± .02	**1.16 ± .02**	1.82 ± .03	**1.18 ± .03**

TABLE 2: Inception scores (IS), fréchet inception distance (FID) and average human ranks (HR) of GAN-INT-CLS [35], GAWWN [33] and our StackGAN-v1 on CUB, Oxford-102, and COCO. (* means that images are re-sized to 64×64 before computing IS* and FID*)

Dataset		CUB	Oxford-102	COCO	LSUN-bedroom	LSUN-church	ImageNet-dog	ImageNet-cat
FID ↓	StackGAN-v1	51.89	55.28	**74.05**	91.94	57.20	89.21	58.73
	StackGAN-v2	**15.30**	**48.68**	81.59	**35.61**	**25.36**	**44.54**	**28.59**
IS ↑	StackGAN-v1	3.70 ± .04	3.20 ± .01	**8.45 ± .03**	**3.59 ± .05**	**2.87 ± .05**	8.84 ± .08	**4.77 ± .06**
	StackGAN-v2	**4.04 ± .05**	**3.26 ± .01**	8.30 ± .10	3.02 ± .04	2.38 ± .03	**9.55 ± .11**	4.23 ± .05
HR ↓	StackGAN-v1	1.81 ± .02	1.70 ± .03	**1.45 ± .04**	1.95 ± .01	1.86 ± .02	1.90 ± .01	1.88 ± .02
	StackGAN-v2	**1.19 ± .02**	**1.30 ± .03**	1.55 ± .05	**1.05 ± .01**	**1.14 ± .02**	**1.10 ± .01**	**1.12 ± .02**

TABLE 3: Comparison of StackGAN-v1 and StackGAN-v2 on different datasets by inception scores (IS), fréchet inception distance (FID) and average human ranks (HR).

Figure: Tables of quantitative results (Source: [1])

Qualitative Results: Unconditional Image Generation

Figure: Comparison of generated samples from LSUN Bedroom (Source: [1])

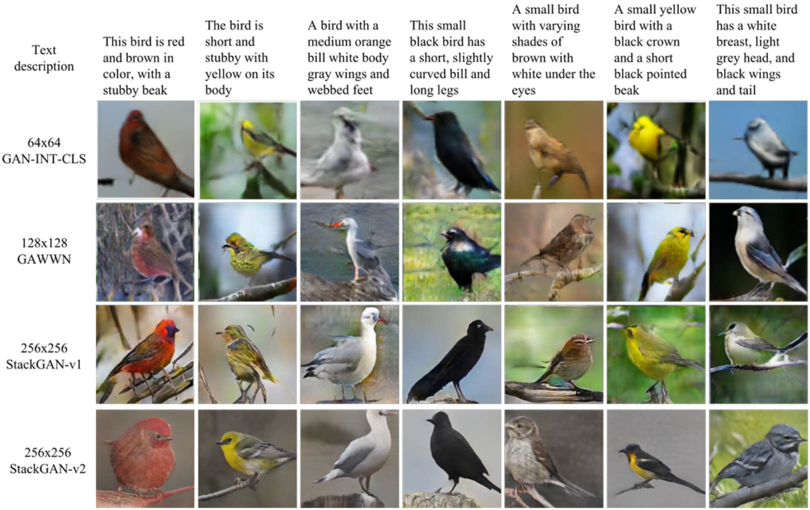

Figure: Comparison of generated samples with text descriptions from CUB (Source: [1])

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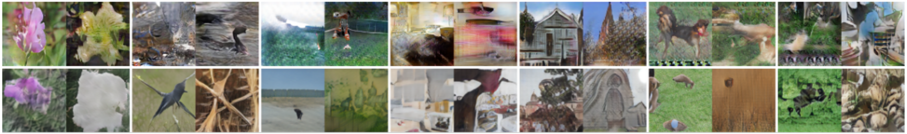
Limitations: StackGAN-v1 Mode Collapse

(a) StackGAN-v1 has two collapsed modes (in red rectangles). (b) StackGAN-v2 contains no collapsed nonsensical mode.

Fig. 5: Utilizing t-SNE to embed images generated by our StackGAN-v1 and StackGAN-v2 on the CUB test set.

Figure: StackGAN-v1 suffers from mode collapse (Source: [1])

Limitations: Failure Cases



Oxford-102 CUB COCO LSUN-bedroom LSUN-church ImageNet-dog ImageNet-cat

Fig. 9: Examples of failure cases of StackGAN-v1 (top) and StackGAN-v2 (bottom) on different datasets.

Figure: Failure cases of both StackGAN-v1 and StackGAN-v2 (Source: [1])

Ablation Studies

Method	CA	Text twice	Inception score
64×64 Stage-I GAN	no	/	2.66 ± .03
	yes	/	2.95 ± .02
256×256 Stage-I GAN	no	/	2.48 ± .00
	yes	/	3.02 ± .01
128×128 StackGAN-v1	yes	no	3.13 ± .03
	no	yes	3.20 ± .03
	yes	yes	3.35 ± .02
256×256 StackGAN-v1	yes	no	3.45 ± .02
	no	yes	3.31 ± .03
	yes	yes	3.70 ± .04

Figure: Component analysis of StackGAN-v1 (Source: [1])

Model	branch G_1	branch G_2	branch G_3	JCU	inception score
StackGAN-v2	64×64	128×128	256×256	yes	4.04 ± .05
StackGAN-v2-no-JCU	64×64	128×128	256×256	no	3.77 ± .04
StackGAN-v2-G_3	removed	removed	256×256	yes	3.49 ± .04
StackGAN-v2-3G_3	removed	removed	three 256×256	yes	3.22 ± .02
StackGAN-v2-all256	256×256	256×256	256×256	yes	2.89 ± .02

Figure: Component analysis of StackGAN-v2 (Source: [1])

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Conclusions

- **Conditioning Augmentation** significantly improves sample diversity and training stability
- **StackGAN-v1** succeeds in generating high-resolution images with photo-realistic details
- **StackGAN-v2** improves robustness by jointly approximating:
  1. Multi-scale image distributions
  2. Conditional and unconditional image distributions
- **Quantitative and Qualitative Results** demonstrate superior performance over prior SOTA methods
- **Ablation Studies** validate the effectiveness of each component

Personal Comments

Cons

- **JCU Discriminators** could have also been used in **StackGAN-v1**
- The authors **did not include StackGAN-v2 in the quantitative analysis** against SOTA methods
- The improvement in **image quality** from the qualitative results is **not very significant**

Pros

- It mantains the **same level of quality** at **higher resolutions**
- The idea of progressive refinement as a way to tackle high-resolution image synthesis is **well-motivated**, **intuitive**, and **empirically validated**

- The paper was published in 2018, and since then, there have been **many advancements** in the field of GANs (e.g. *StyleGAN* [2])

References I

Han Zhang, Tao Xu, Hongsheng Li, Shaoting Zhang, Xiaogang Wang, Xiaolei Huang, and Dimitris Metaxas.
Stackgan++: Realistic image synthesis with stacked generative adversarial networks, 2018.

Tero Karras, Samuli Laine, and Timo Aila.
A style-based generator architecture for generative adversarial networks.
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