GIRAFFE: Representing Scenes as Compositional Generative Neural Feature Fields

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Controllable Image Generation needs disentanglement







GIRAFFE

- Controlling a single object in the image should not change irrelevant objects
- Disentanglement is hard in 2D generative models

GIRAFFE: Construction



- Represent a scene as compositional generative neural feature fields
- (N 1) foreground feature fields
- One background feature field

GIRAFFE Architecture



Generative Neural Feature Fields from GRAF



Generative Neural Feature Fields from GRAF



Composition of objects by summation



$$C(\mathbf{x}, \mathbf{d}) = \left(\sigma, \frac{1}{\sigma} \sum_{i=1}^{N} \sigma_i \mathbf{f}_i\right), \text{ where } \sigma = \sum_{i=1}^{N} \sigma_i \quad (8)$$

3D Volume Rendering in feature space



2D Neural Rendering

1



$$\pi_{\theta}^{\text{neural}} : \mathbb{R}^{H_V \times W_V \times M_f} \to \mathbb{R}^{H \times W \times 3}$$
(11)

Feature space to image space, achieved by 2D CNN

GIRAFFE is better, lighter, and faster at generation

	Cats	CelebA	Cars	Chairs	Churches
2D GAN [58]	18	15	16	59	19
Plat. GAN [32]	318	321	299	199	242
BlockGAN [64]	47	69	41	41	28
HoloGAN [63]	27	25	17	59	31
GRAF [77]	26	25	39	34	38
Ours	8	6	16	20	17

Table 1: Quantitative Comparison. We report the FID score (\downarrow) at 64² pixels for baselines and our method.

	CelebA-HQ	FFHQ	Cars	Churches	Clevr-2
HoloGAN [63]	61	192	34	58	241
w/o 3D Conv	33	70	49	66	273
GRAF [77]	49	59	95	87	106
Ours	21	32	26	30	31

Table 2: Quantitative Comparison. We report the FID score (\downarrow) at 256² pixels for the strongest 3D-aware baselines and our method.

2D GAN	Plat. GAN	BlockGAN	HoloGAN	GRAF	Ours
1.69	381.56	4.44	7.80	0.68	0.41

Table 3: **Network Parameter Comparison.** We report the number of generator network parameters in million.

- Better FID score for all resolutions
- Much less parameters
- Rendering time reduced from 1595.0 ms to 5.9 ms from [77] with 256² pixels

Scene disentanglement learned w/o supervision



- Represents foreground and background as separate objects
- Learns to generate
 background although no
 complete background is in
 the dataset (in-painting)

Results: Rotation



Rotation

Results: Translation



Horizontal Translations



Vertical Translations

Results: Changing Foreground / Background





Changing Object Appearance

Changing Background

Results: Adding Objects





Adding Objects in CLEVR

Adding Object in Cars (OOD)

Limitation: Bias of Dataset



Rotation in CelebA