Diffusion Models Beat GANs on Image Synthesis

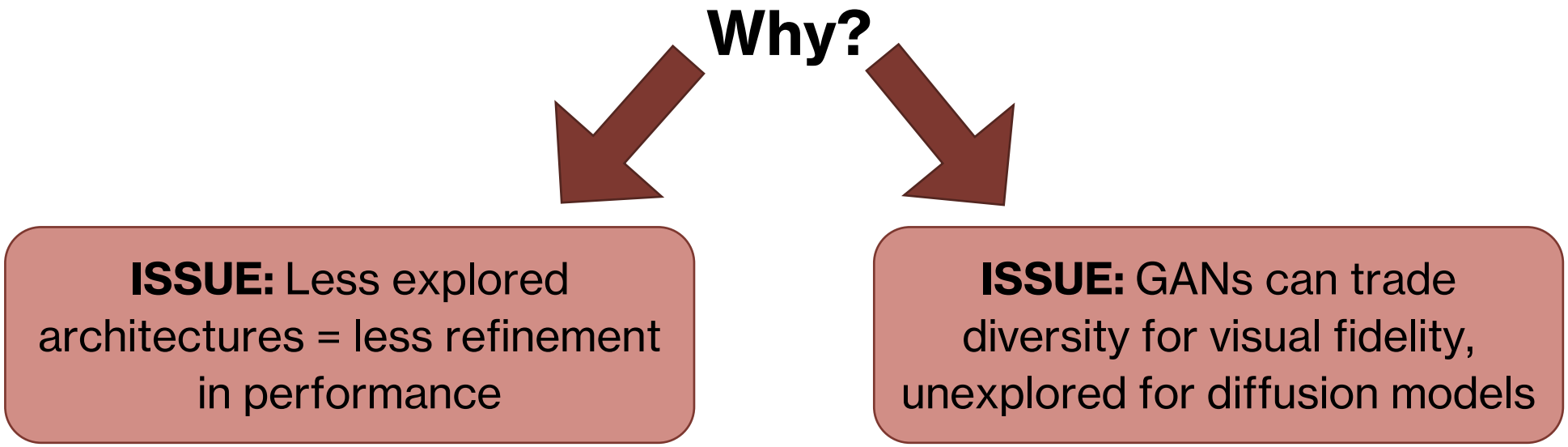
Dhariwal & Nichol (2021)

Background

- At the time, GANs were considered the state-of-the-art method for image generation tasks
  - BUT:
    - GANs captured less diversity in image synthesis then likelihood-based models
    - GANs are difficult to train and prone to collapse
    - Consequently, difficult to scale and apply to new domains
- Competing likelihood-based models captured more diversity and were easier to train
  - BUT:
    - Worse visual fidelity compared to GANs
    - Apart from VAEs, slower to sample than GANs

Diffusion Models (at the time)

- Pros: high quality images, good distribution coverage, stationary training objective, easy scalability
- At the time, held best performance on CIFAR-10, but lagged behind GANs for more difficult datasets (LSUN, ImageNet)



Brief Refresher on Diffusion Models...

- Sample from a distribution by learning to reverse a gradual noising process

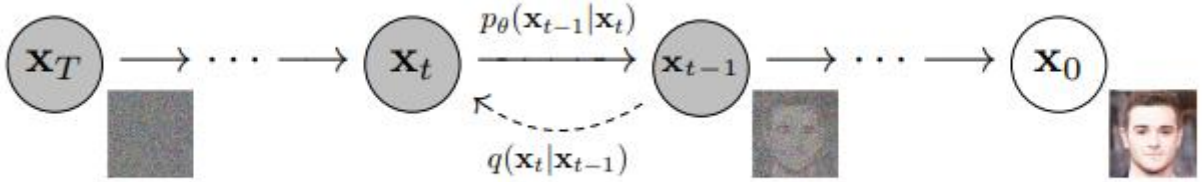


Figure 2: The directed graphical model considered in this work.

- DDIM (Song et al., 2020): Alternative non-Markovian noising process
  - Same forward marginals
  - Changes variance of reverse noise to produce different reverse samplers
  - Setting noise to 0 creates deterministic mapping from latent variables to images -> fewer sampling steps needed

Model Architecture

ISSUE: Less explored architectures = less refinement in performance

- UNet Base (as with prior diffusion models)
- Added multi-resolution attention (32 x 32, 16 x 16, 8 x 8)-> Better capture long-range relationships like object shape/symmetry
- Stronger residual blocks for better up/down sampling and stable gradients -> refined details and sharper images
- Adaptive group Normalization (AdaGN) to inject class information and timestep into normalization layers -> network can adapt processing depending on denoising stage
- Attention head tuning -> stable training and finer-grained attention patterns

FIX: Finetuned architecture to narrow engineering gap between diffusion and GANs

Classifier Guidance

ISSUE: GANs can trade diversity for fidelity, unexplored in diffusion models

- Train a classifier on noisy images and use it gradients to steer the diffusion process toward a target class
  - Classifier: $p_\theta(y|x_t, t)$
  - Modify the revere diffusion step using $\nabla_{xt} \log p_\theta\,(y|x_t, t)$
- Guidance Scaling:
  - Introduce a scaling factor s to control strength of steerage of classifier gradient
    - Low s -> higher diversity, lower fidelity
    - High s -> higher fidelity, lower diversity
- This is actually an improvement over GANs:
  - Single parameter that can tune trade-off

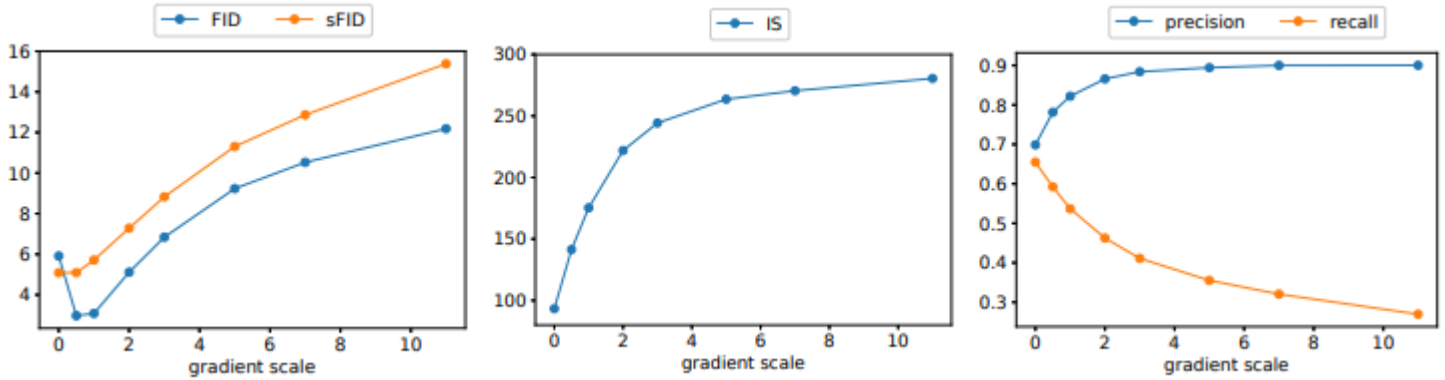
FIX: Implemented classifier guidance for tunable fidelity-diversity trade-off

CODE DEMONSTRATION

Prompt: “Pembroke Welsh Corgi

Classifier scale 1.0: More diverse samples, but less convincing

Classifier scale 10.0: Less diverse samples, but more convincing



- FID: *captures both fidelity and diversity*
- sFID: *captures spatial relationships within image*
- Precision: *proxy for separate measure of fidelity*
- Inception Score (IS): *proxy for fidelity*
- Recall: *proxy for separate measure of diversity*

Performance Comparisons

Table 4: Sample quality comparison with state-of-the-art generative models for each task. LSUN diffusion models are sampled using 1000 steps (see Appendix L). ImageNet diffusion models are sampled using 250 steps, except when we use the DDIM sampler with 25 steps. *No BigGAN-deep model was available at this resolution, so we trained our own. †Values are taken from a previous paper, due to lack of public models or samples. ‡Results use two-resolution stacks. §Results use compute-intensive classifier rejection sampling.

Model	FID	sFID	Prec	Rec
LSUN Bedrooms 256×256				
DCTransformer† [48]	6.40	6.66	0.44	**0.56**
DDPM [31]	4.89	9.07	0.60	0.45
IDDPM [49]	4.24	8.21	0.62	0.46
StyleGAN [33]	2.35	6.62	0.59	0.48
ADM (dropout)	**1.90**	**5.59**	**0.66**	0.51
LSUN Horses 256×256				
StyleGAN2 [34]	3.84	6.46	0.63	0.48
ADM	2.95	**5.94**	0.69	**0.55**
ADM (dropout)	**2.57**	6.81	**0.71**	**0.55**
LSUN Cats 256×256				
DDPM [31]	17.1	12.4	0.53	0.48
StyleGAN2 [34]	7.25	**6.33**	0.58	0.43
ADM (dropout)	**5.57**	6.69	**0.63**	**0.52**

Model	FID	sFID	Prec	Rec
ImageNet 128×128				
BigGAN-deep [8]	6.02	7.18	**0.86**	0.35
LOGAN† [74]	3.36			
ADM	5.91	**5.09**	0.70	**0.65**
ADM-G (25 steps)	5.98	7.04	0.78	0.51
ADM-G	**2.97**	**5.09**	0.78	0.59
ImageNet 256×256				
DCTransformer† [48]	36.51	8.24	0.36	**0.67**
VQ-VAE-2†‡ [57]	31.11	17.38	0.36	0.57
VQ-VAE-2 (RS)†‡§ [57]	∼ 10			
VQ-GAN‡ [21]	15.97	19.05	0.63	0.58
VQ-GAN (RS)‡§ [21]	5.06	7.34	0.79	0.48
IDDPM‡ [49]	12.26	5.42	0.70	0.62
SR3†‡ [60]	11.30			
BigGAN-deep [8]	6.95	7.36	**0.87**	0.28
ADM	10.94	6.02	0.69	0.63
ADM-G (25 steps)	5.44	5.32	0.81	0.49
ADM-G	**4.59**	**5.25**	0.82	0.52
ImageNet 512×512				
BigGAN-deep [8]	8.43	8.13	**0.88**	0.29
ADM	23.24	10.19	0.73	**0.60**
ADM-G (25 steps)	8.41	9.67	0.83	0.47
ADM-G	**7.72**	**6.57**	0.87	0.42

Unconditional image generation: Trained 3 separate diffusion models on bedroom, horse, and cat LSUN classes

Classifier guidance: trained conditional diffusion models on ImageNet 128x128, 256x256, and 512x512 resolutions

Guidance comparisons: trained two-stage diffusion models by combining a low-resolution diffusion model with a corresponding up-sampling diffusion model

Table 5: Comparing our single, upsampling and classifier guided models. The upsamplers are 64→256 and 128→512. When combining guidance with upsampling, we only guide the lower resolution model. All models are sampled using 250 sampling steps.

Model	FID	sFID	IS	Prec	Rec
ImageNet 256×256					
ADM	10.94	6.02	100.98	0.69	**0.63**
ADM, ADM-U	7.49	**5.13**	127.49	0.72	**0.63**
ADM-G	4.59	5.25	186.70	0.82	0.52
ADM-G, ADM-U	**3.94**	6.14	**215.84**	**0.83**	0.53

Model	FID	sFID	IS	Prec	Rec
ImageNet 512×512					
ADM	23.24	10.19	58.06	0.73	0.60
ADM, ADM-U	9.96	**5.62**	121.78	0.75	**0.64**
ADM-G	7.72	6.57	172.71	**0.87**	0.42
ADM-G, ADM-U	**3.85**	5.86	**221.72**	0.84	0.53

Results

Samples speak for themselves:

Figure 4: Samples from BigGAN-deep with truncation 1.0 (FID 6.95, left) vs samples from our diffusion model with guidance (FID 4.59, middle) and samples from the training set (right).

Critical Reflection

Limitations:

- Still much slower than GANs
- Implicit latent representation => unclear semantic meaning
  - Difficult to guide these models for user-prompted generation like image editing
  - Limited to labelled datasets

Impact:

- HUGE!!! Pivotal paper for image generation and predecessor of classifier-free guidance (e.g., Dall-E 2)
- Created more accessible, cost-efficient generation model that outperforms GANs on complex datasets
- Increasing danger of fake news and doctored photos

References

- Ho, J., Jain, A., & Abbeel, P. (2020). Denoising diffusion probabilistic models. *Advances in neural information processing systems*, *33*, 6840-6851.
- **Dhariwal, P., & Nichol, A. (2021). Diffusion models beat gans on image synthesis. *Advances in neural information processing systems*, *34*, 8780-8794.**
- Song, J., Meng, C., & Ermon, S. (2020). Denoising diffusion implicit models. *arXiv preprint arXiv:2010.02502*.
- Many thanks to this Kaggle Notebook: https://www.kaggle.com/code/vikramsandu/guided-diffusion-by-openai-from-scratch/notebook#Generate