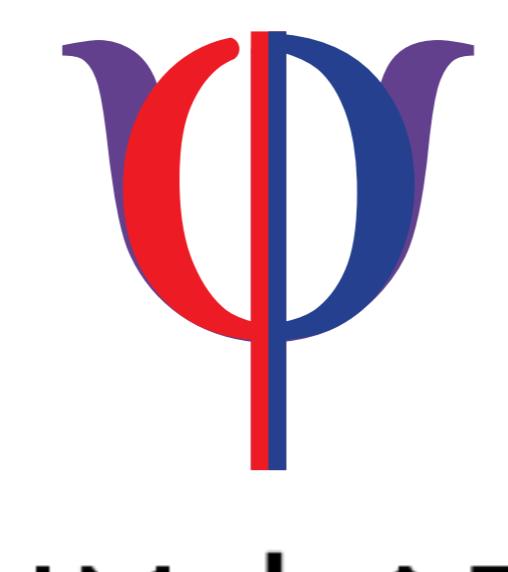
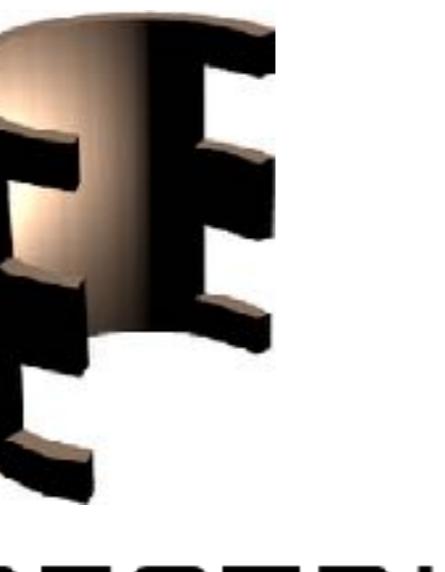


Spider GANs: Leveraging Friendly Neighbors to Accelerate GAN Training

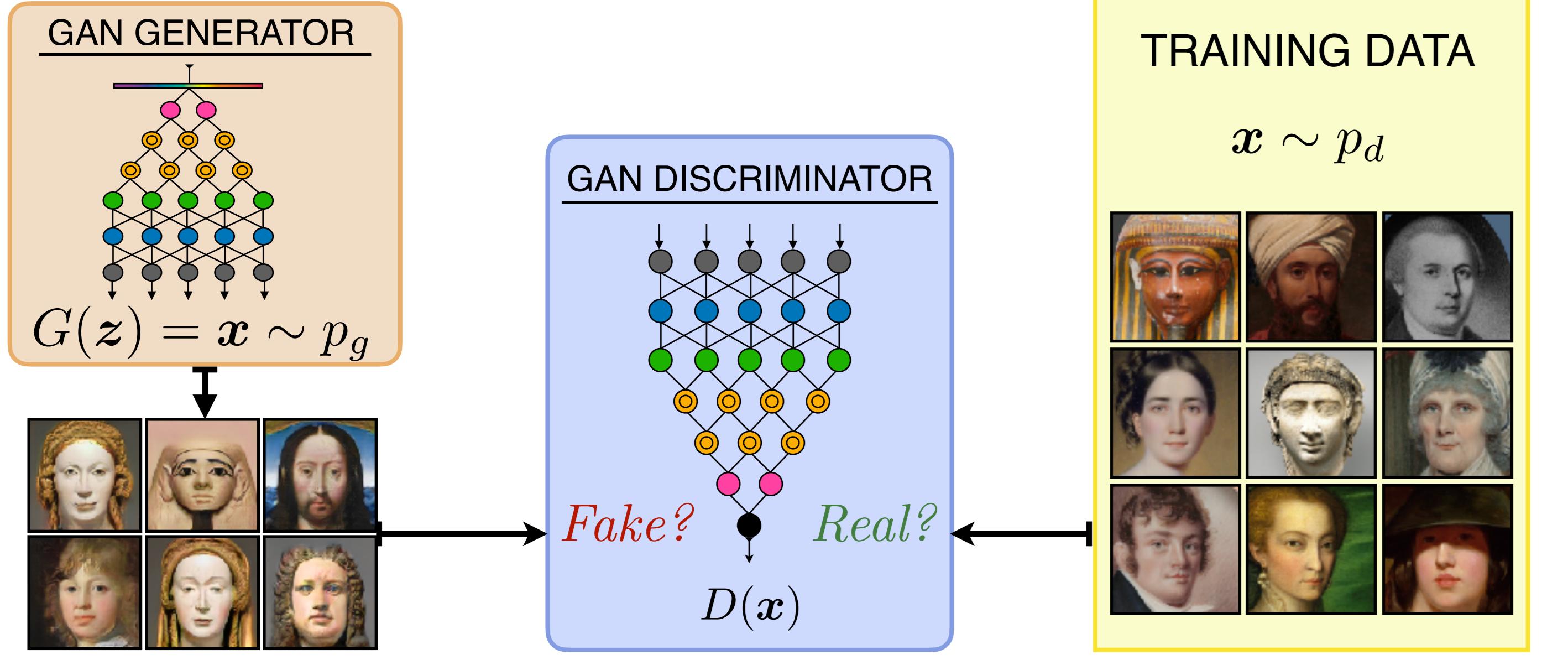


Siddarth Asokan¹ and Chandra Sekhar Seelamantula²
¹Robert Bosch Centre for Cyber-Physical Systems,
²Department of Electrical Engineering
 Indian Institute of Science, Bangalore, India

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1. Generative Adversarial Networks

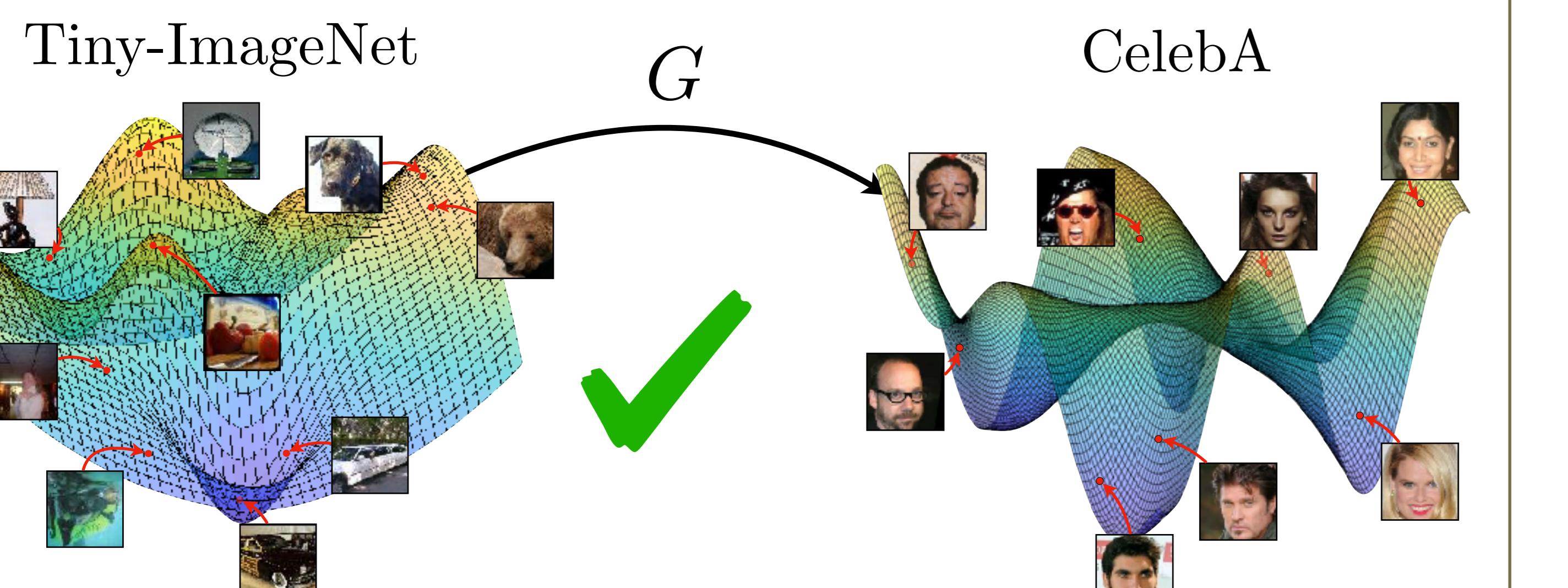


- The generator G transforms noise $z \sim \mathcal{N}(\mathbf{0}, \mathbb{I})$ into fake samples $x = G(z)$.
- The GAN^[1] discriminator D classifies x as real or fake.
- The optimal generator learns to confuses the discriminator!

^[1]Goodfellow et al., NeurIPS 14

2. The Spider GAN Philosophy

- n -D Gaussian
-
- Standard GANs provide high-dimensional Gaussian noise as input to the generator.
 - In Spider GANs we propose to provide images drawn from closely-related *friendly neighborhood* datasets as input!



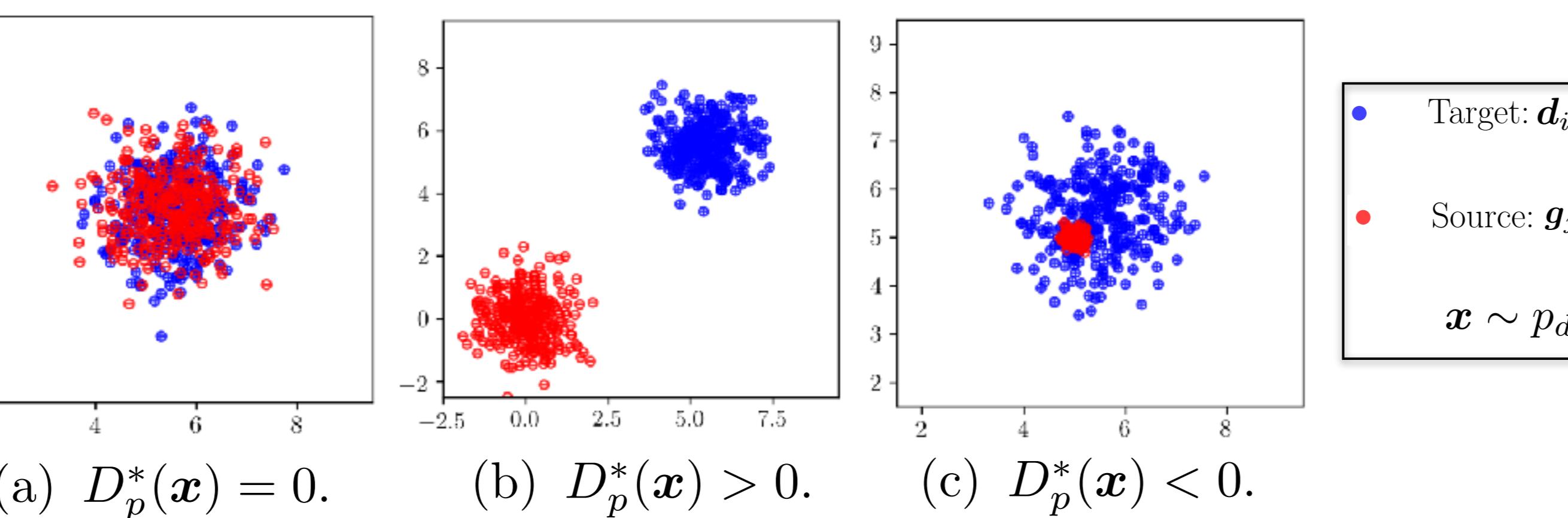
^[2]Asokan and Seelamantula, INTERPOLATE @ NeurIPS 22

3. The Signed Inception Distance (SID)

- The polyharmonic spline interpolator or order m in n -D^[2]:

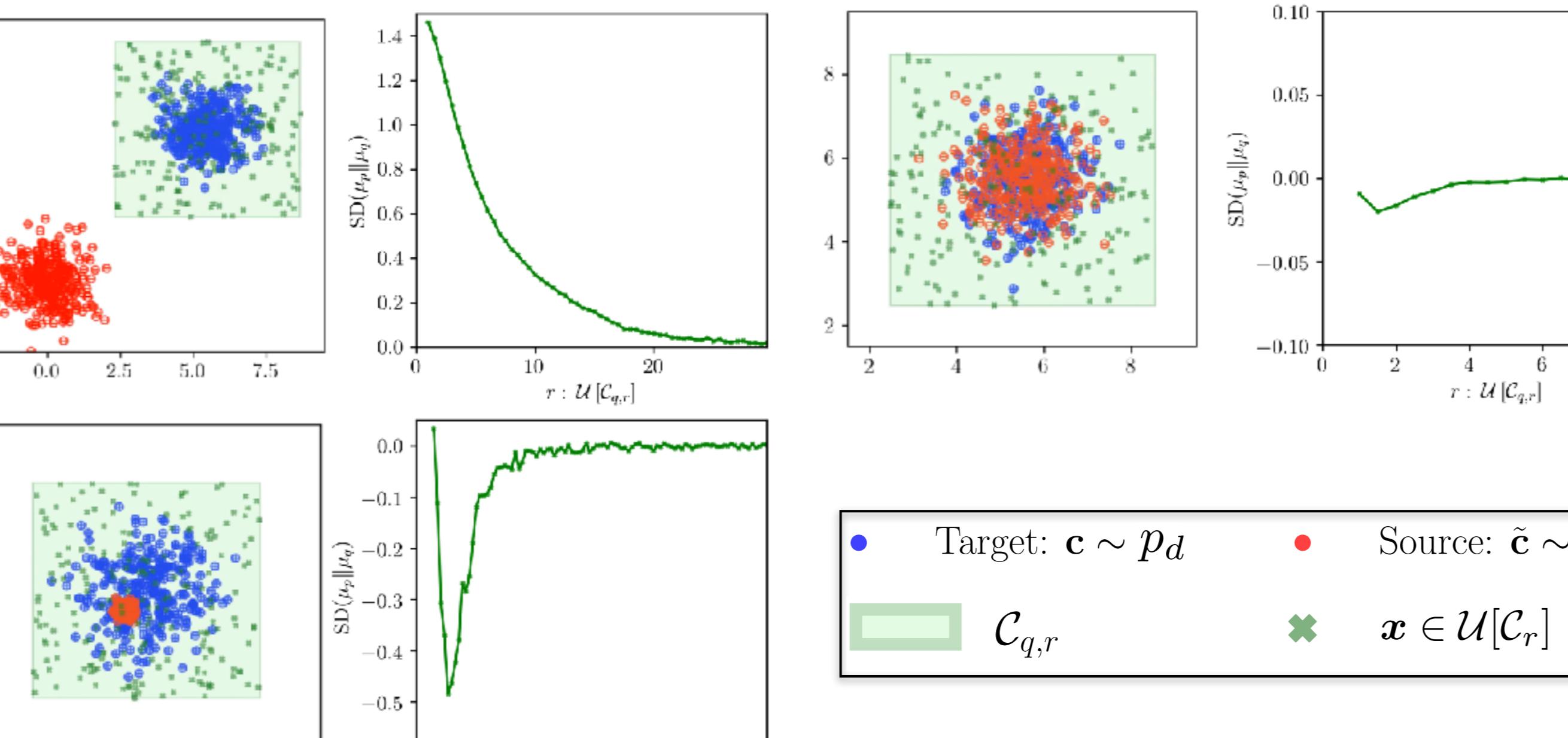
$$\tilde{D}_p^*(\mathbf{x}) = \frac{\kappa_{m,n}}{N} \left(\sum_{g_j \sim p_g} \psi_{m,n}(\mathbf{x} - \mathbf{g}_j) - \sum_{d_i \sim p_d} \psi_{m,n}(\mathbf{x} - \mathbf{d}_i) \right),$$

where $\psi_{m,n}(\mathbf{x}) = \begin{cases} \|\mathbf{x}\|^{2m-n} & \text{if } 2m-n < 0 \\ \|\mathbf{x}\|^{2m-n} \ln(\|\mathbf{x}\|) & \text{if } 2m-n \geq 0 \text{ and } n \text{ is even.} \end{cases}$



- The signed distance ($SD(p_s \| p_t)$): Average $D_p^*(\mathbf{x})$ over \mathbf{x} .

$$SD(p_s \| p_t) = \sum_{\mathbf{x} \in \mathcal{U}[\mathcal{C}_r]} \left(\sum_{d_i \sim p_s} \psi_{m,n}(\mathbf{x} - \mathbf{d}_i) - \sum_{g_j \sim p_t} \psi_{m,n}(\mathbf{x} - \mathbf{g}_j) \right)$$



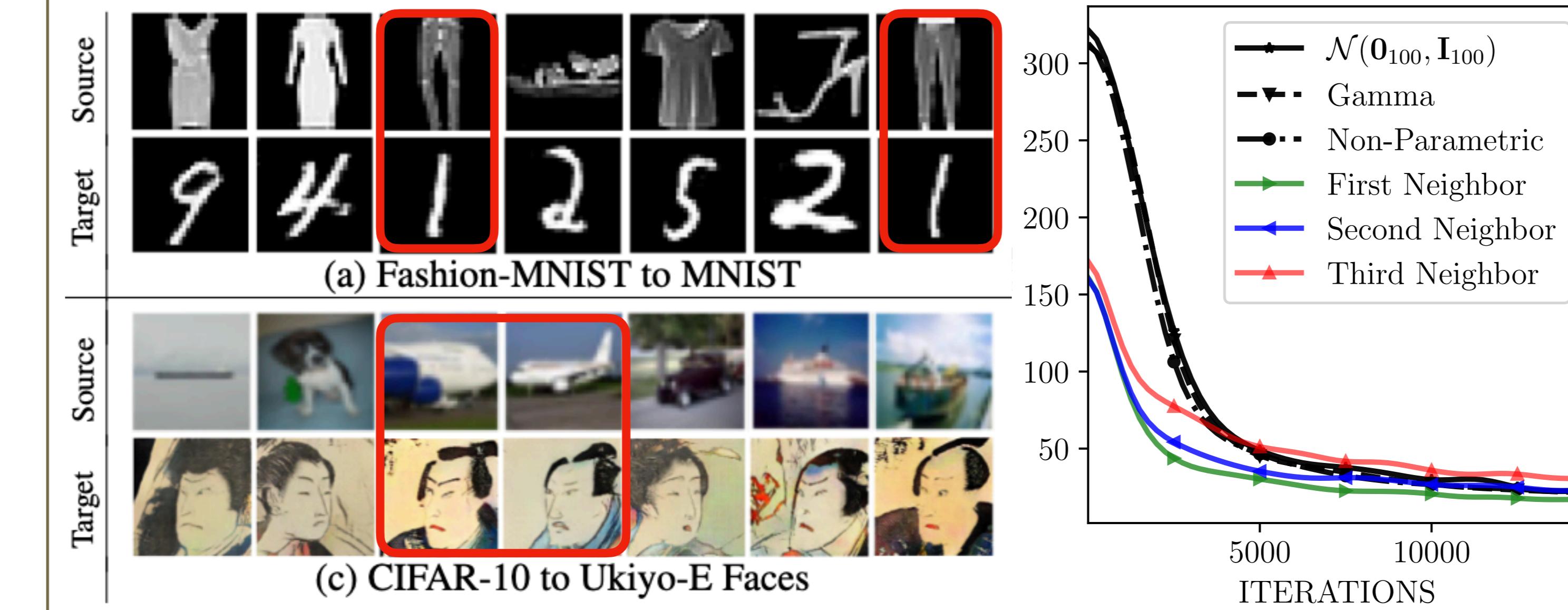
- The signed Inception distance, $SID(p_s \| p_t)$: Compute $SD(p_s \| p_t)$ over Inception embeddings.

Table: Comparing FID and area under the SID curve (CSID) in identifying friendly neighbors of target datasets in terms of the first, second and third “friendliest neighbors.”

Target Source	FID (Source, Target)				CSID _m (Source Target)			
	MNIST	CIFAR-10	TinyImageNet	Ukiyo-E	MNIST	CIFAR-10	TinyImageNet	Ukiyo-E
MNIST	1.2491	258.246	264.250	398.280	0.1863	29.298	9.436	201.550
F-MNIST	176.813	188.367	197.057	387.049	162.962	19.051	-2.5571	191.010
SVHN	236.707	168.615	189.133	327.444	212.473	34.534	21.668	214.507
CIFAR-10	259.045	5.0724	64.3941	303.694	221.337	-7.109	198.991	
TinyImageNet	264.309	64.0312	6.4854	257.078	230.916	12.892	0.6743	197.447
CelebA	360.773	303.490	250.735	301.108	204.794	23.685	8.829	184.170
Ukiyo-E	396.791	300.511	254.102	5.9137	250.226	39.793	18.727	0.5494
Church	350.708	294.982	254.991	267.638	212.452	-4.655	-23.115	198.750

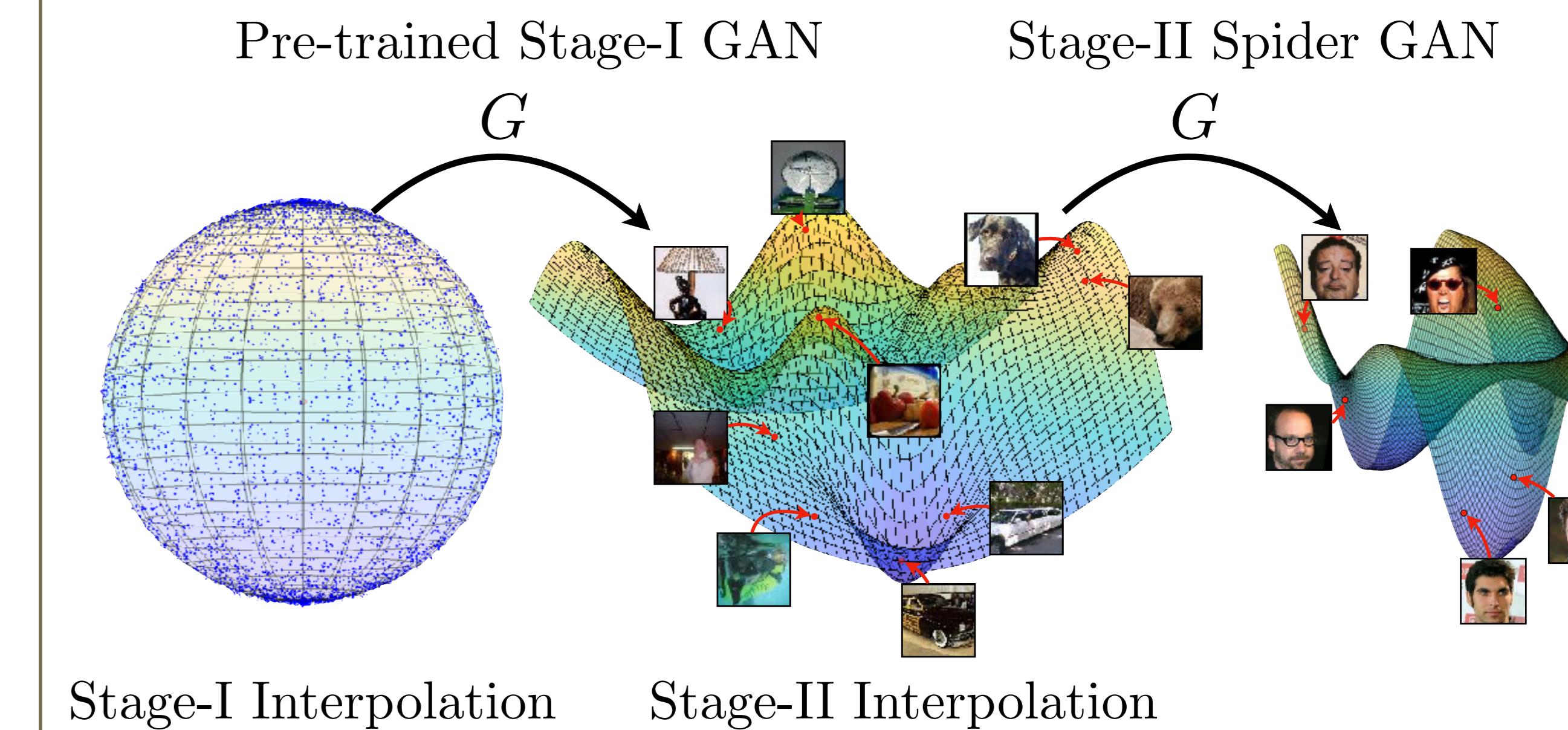
4. Experiments on Spider GANs

- Visual correspondence is not necessary! Spider GANs leverage underlying structural similarity between datasets.



5. Novel Transfer Learning — Cascaded Spider GANs

- The output of a **Stage-one pre-trained GAN** can be used as the input to a **Stage-two Spider GAN**.



6. Experimental Validation on Cascaded Spider StyleGANs

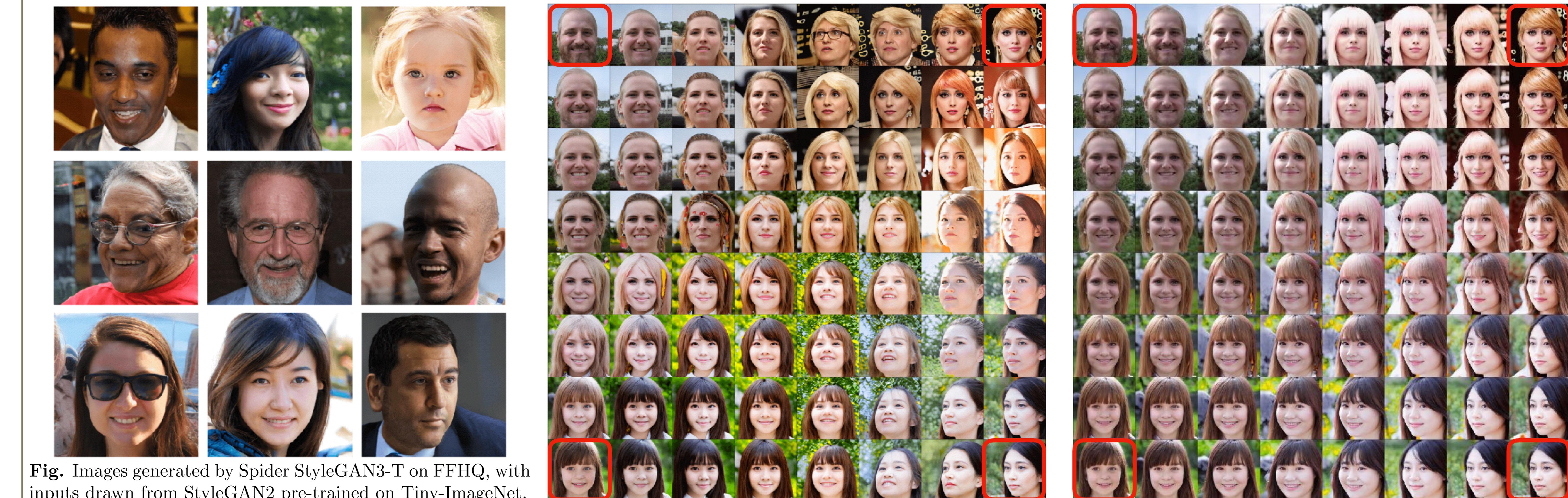


Fig. Images generated by Spider StyleGAN3-T on FFHQ, with inputs drawn from StyleGAN2 pre-trained on Tiny-ImageNet.

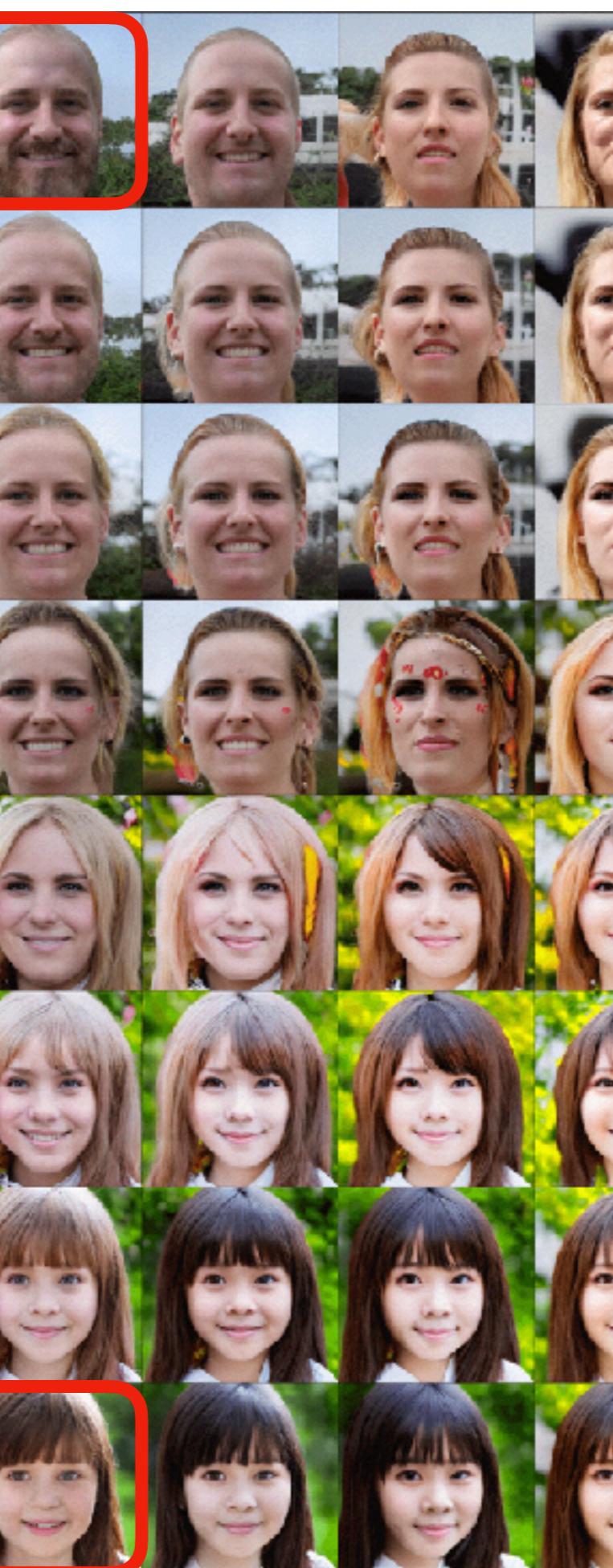


Fig. Interpolations on Stage-I Spider StyleGAN2-ADA



Fig. Interpolations on Stage-II Spider StyleGAN2-ADA

7. Take-home Message

- Trained the generator with inputs from closely related datasets.
- SID can identify friendly neighbors and quantify diversity.
- Spider StyleGANs achieved state-of-the-art performance in a fraction of the training time.

Acknowledgements

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