Information-theoretic stochastic contrastive conditional GAN (InfoSCC-GAN)

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NEURAL INFORMATION PROCESSING SYSTEMS

Introduction

Conditional image generation is the task of generating image based on some attributes. We propose a new stochastic contrastive conditional generative adversarial network. InfoSCC-GAN consists of:

- Stochastic generator
- Controllable generator
- Explorable and interpretable latent space

and is based on:

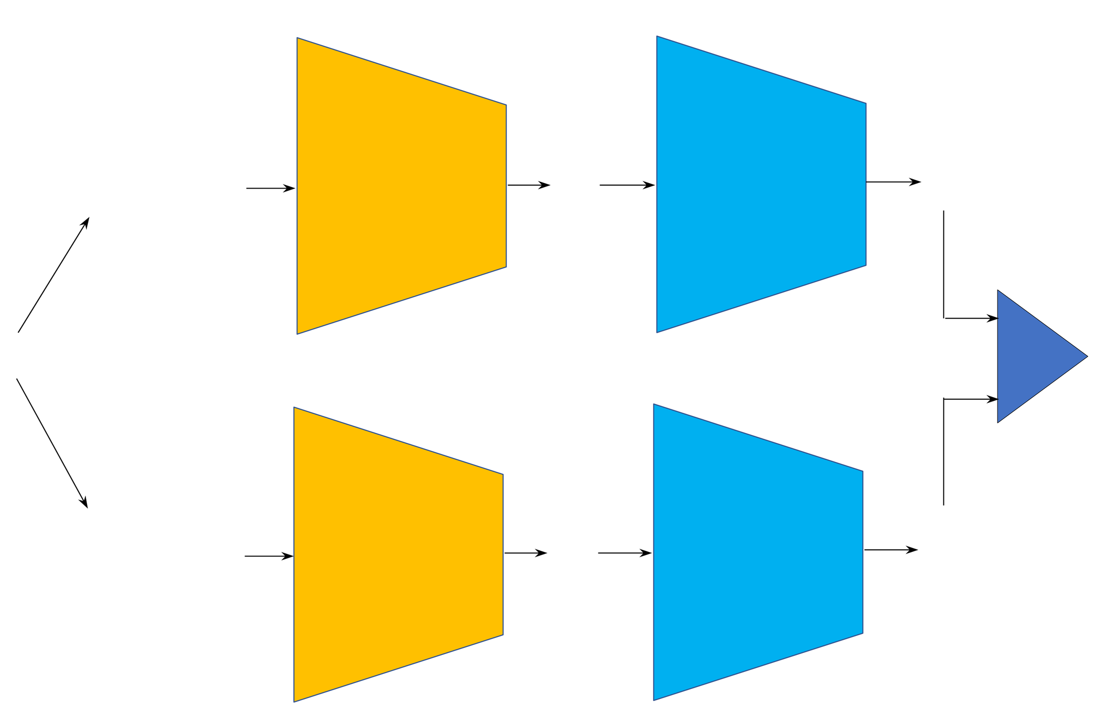
- Unsupervised contrastive encoder (SimCLR)
- Independent attribute classifier
- EigenGAN generator with explorable latent space
- Novel training approach with pre-trained encoder and classifier.

Contributions

- Propose a novel Stochastic Contrastive Conditional Generative Adversarial Network (InfoSCC-GAN) for stochastic conditional image generation with controllable and interpretable latent space
- Introduce a novel classification regularization technique, which is based on updating the generator with classification loss each n-th iteration
- Propose novel method for attribute selection, based on the clustering embeddings, computed using pre-trained encoder
- Provide an information-theoretic interpretation of the proposed system
- Perform experiments on AFHQ and CelebA datasets

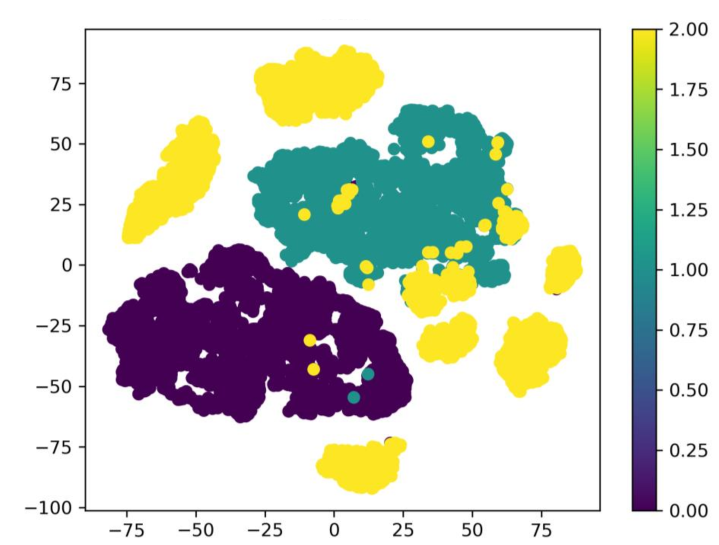
Approach

Stage 1

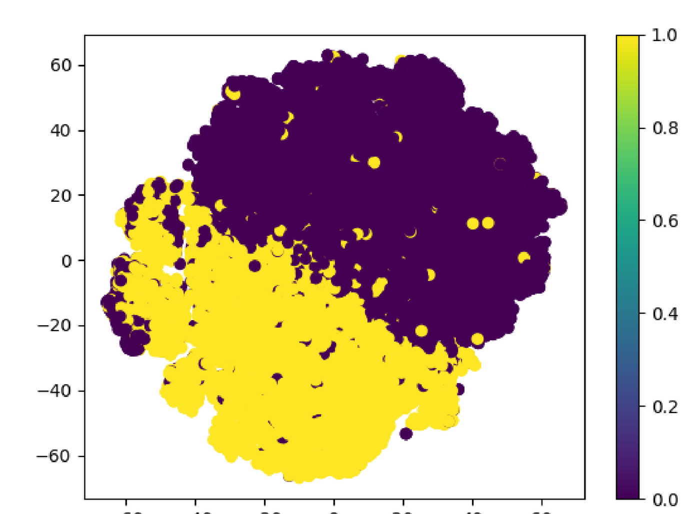


Stage 1. Training of the encoder

The encoder training is based on the maximization problem:

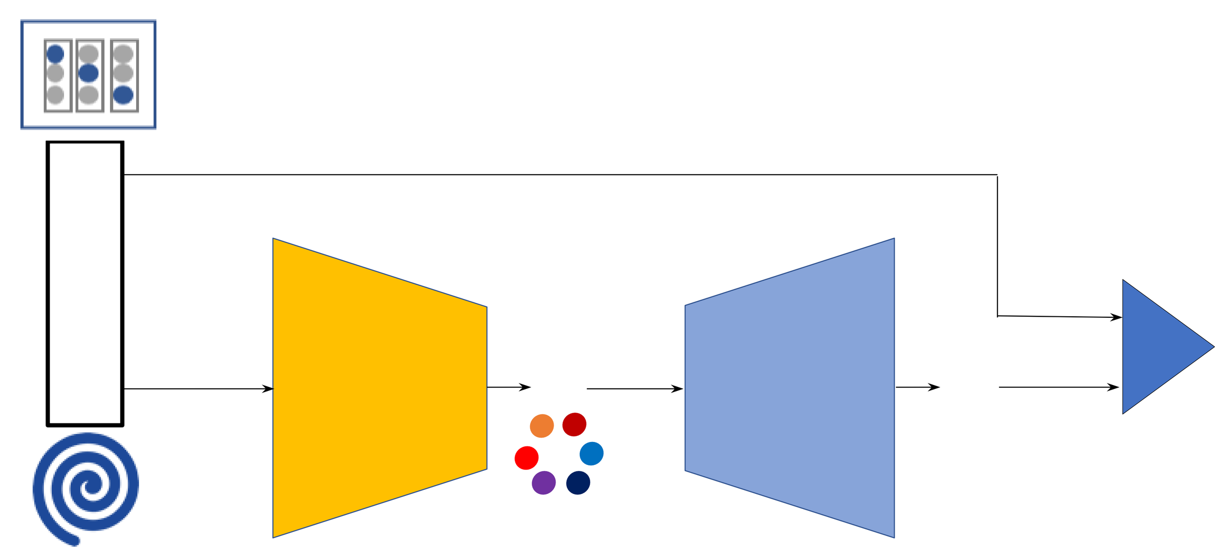


2D t-SNE of the computed features from the AFHQ dataset. Color represents the class in the dataset: yellow - cat; green - dog; dark violet - wild animal



2D t-SNE of the computed features from the CelebA dataset. Color represents the attribute in the dataset: yellow – male, dark violet – not male

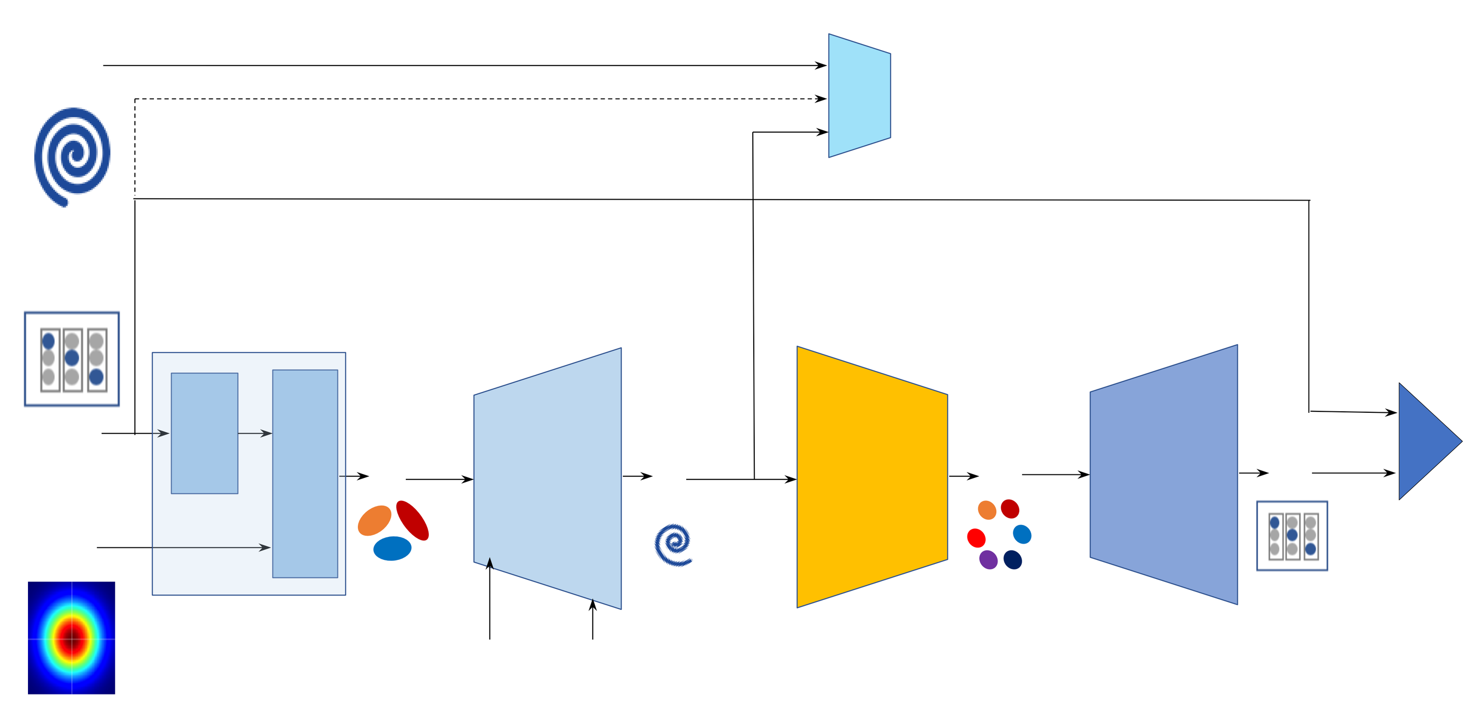
Stage 2



Stage 2. Training of the attribute classifier

The class attribute classifier training is based on the maximization problem:

Stage 3



Stage 3. Training of the conditional generator

The generator is trained first to maximize the mutual information between class attributes predicted from the generated images and true class attributes:

Ablation studies

Discriminator architecture and training loss ablation studies

Discriminator	**Loss**	**FID**	**IS**	**Chamfer distance**
Global	Hinge	13.08	10.71	4030
Global	Non saturating	25.62	10.33	28595
Global	LSGAN	29.02	9.89	45583
Patch	Hinge	15.95	10.51	7327
Patch	Non saturating	14.83	10.21	5114
Patch	LSGAN	**11.59**	**11.06**	**3645**

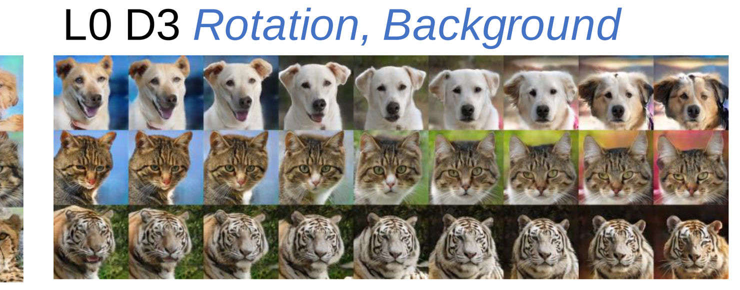
Features exploration

L0 D0 *Animal type*

L0 D1 *Animal type*

L0 D2 *Animal type, Background*

L0 D3 *Rotation, Background*



L0 D4 *Rotation, Background*

L2 D0 *Fur color*

L2 D1 *Light*

L2 D2 *Light*

References

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Code