UNIVERSITÉ DE GENÈVE
Fachhochschule Nordwestschweiz

Information-theoretic stochastic contrastive conditional GAN (InfoSCC-GAN) for physical data generation

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Agenda

1. Problem formulation
2. Dataset
3. InfoSCC-GAN

    a) Self-Supervised encoder (SimCLR)

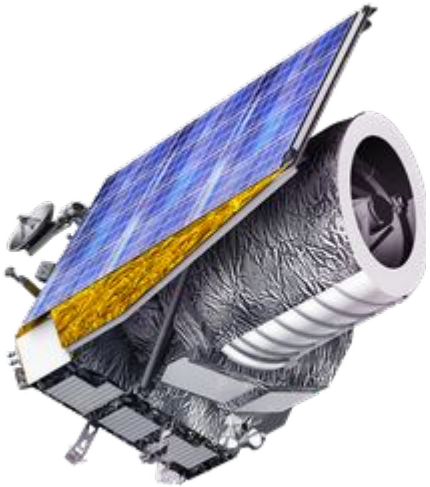
    b) Classifier

    c) Generator: EigenGAN

4. Ablations
5. Demo
6. Conclusions

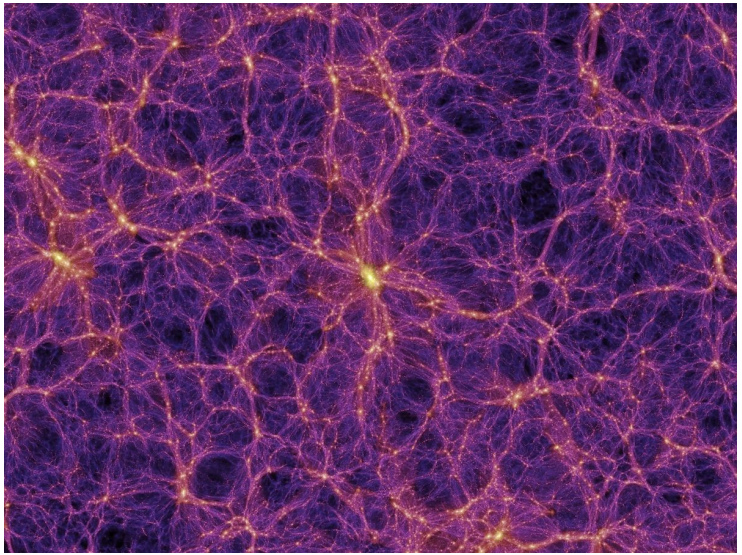
Problem formulation

Problem

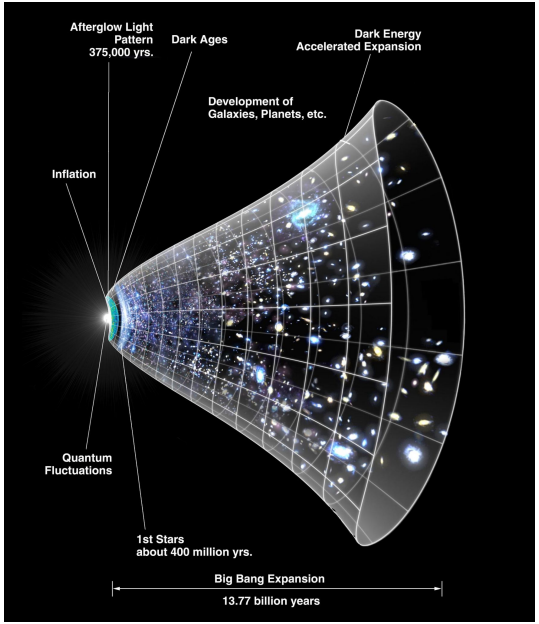


Billions of images

Research



- distribution of dark matter



- expansion of the Universe

Real and generated galaxies

1 

2 

3 

4 

5 

6 

Real and generated galaxies

1 

2 

3 

4 

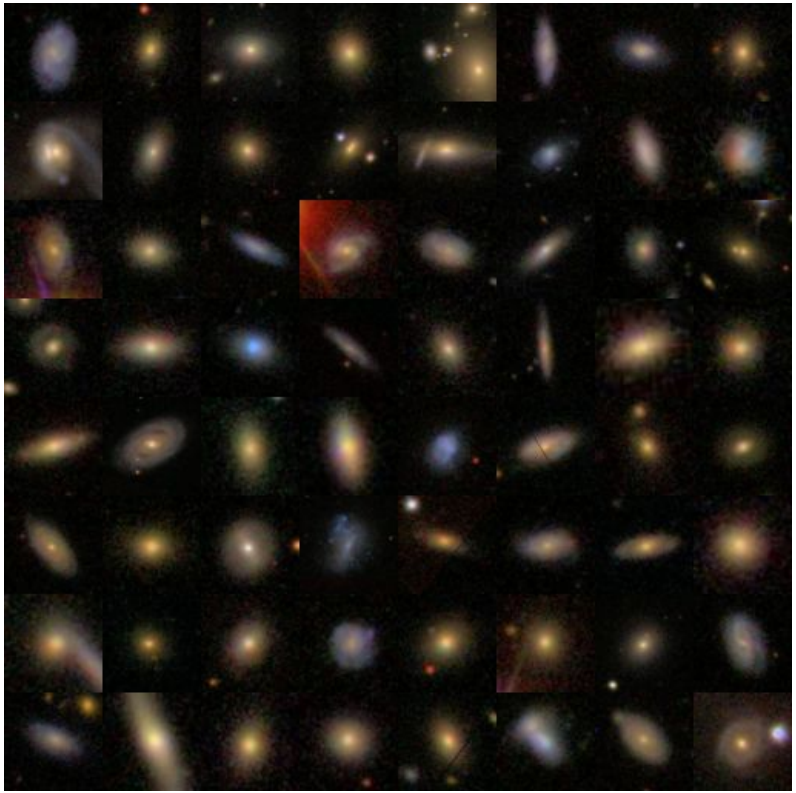
5 

6 

Dataset

Galaxy-Zoo dataset

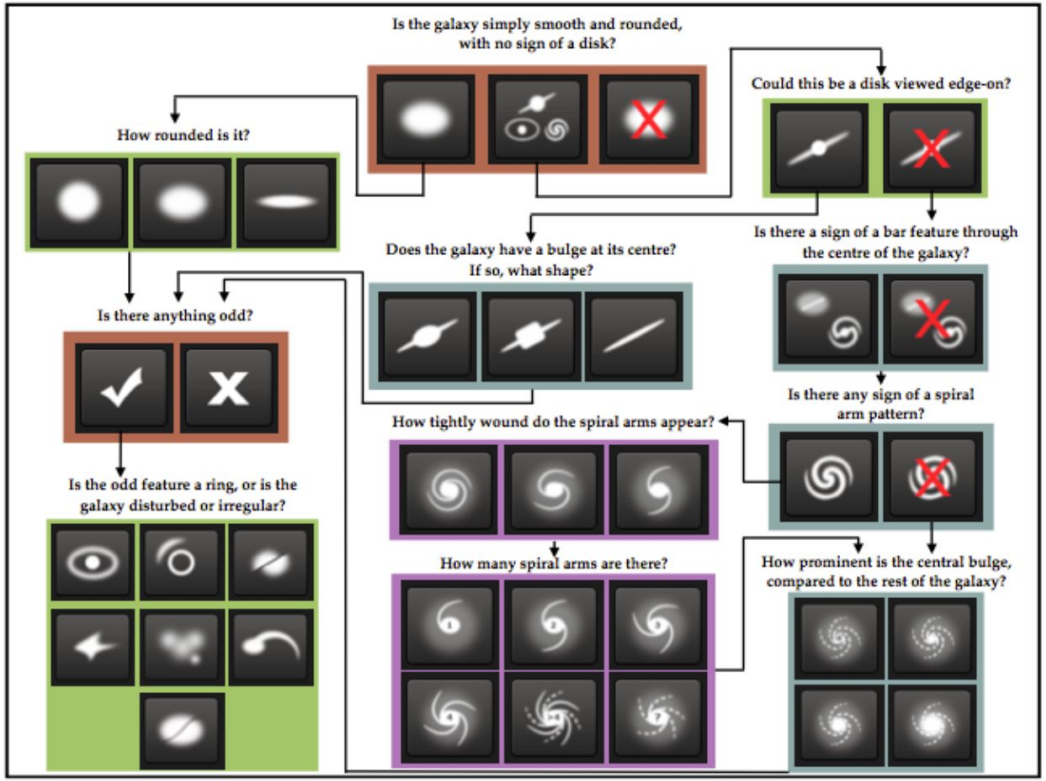
- RGB images
- more than 60’000 images
- 424x424 pixels each
- 37 crowdsourced label score for each image
- each label reflects the distribution of answers given by participants
- labels are hierarchical



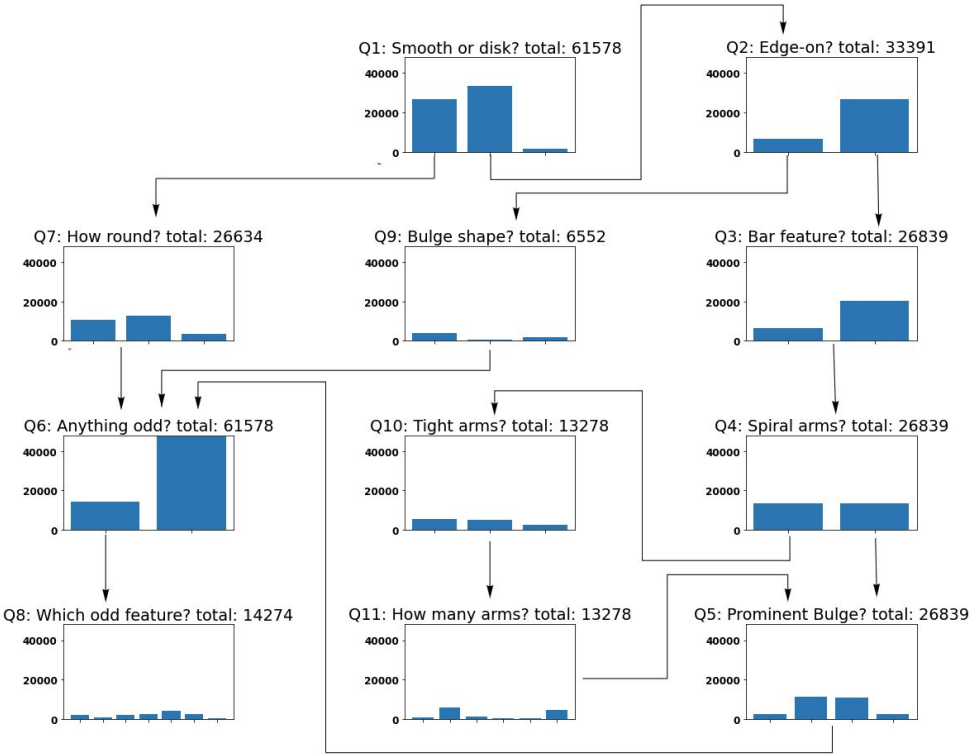
64 images from Galaxy Zoo dataset*

*kaggle.com/c/galaxy-zoo-the-galaxy-challenge

Galaxy Zoo dataset: questions

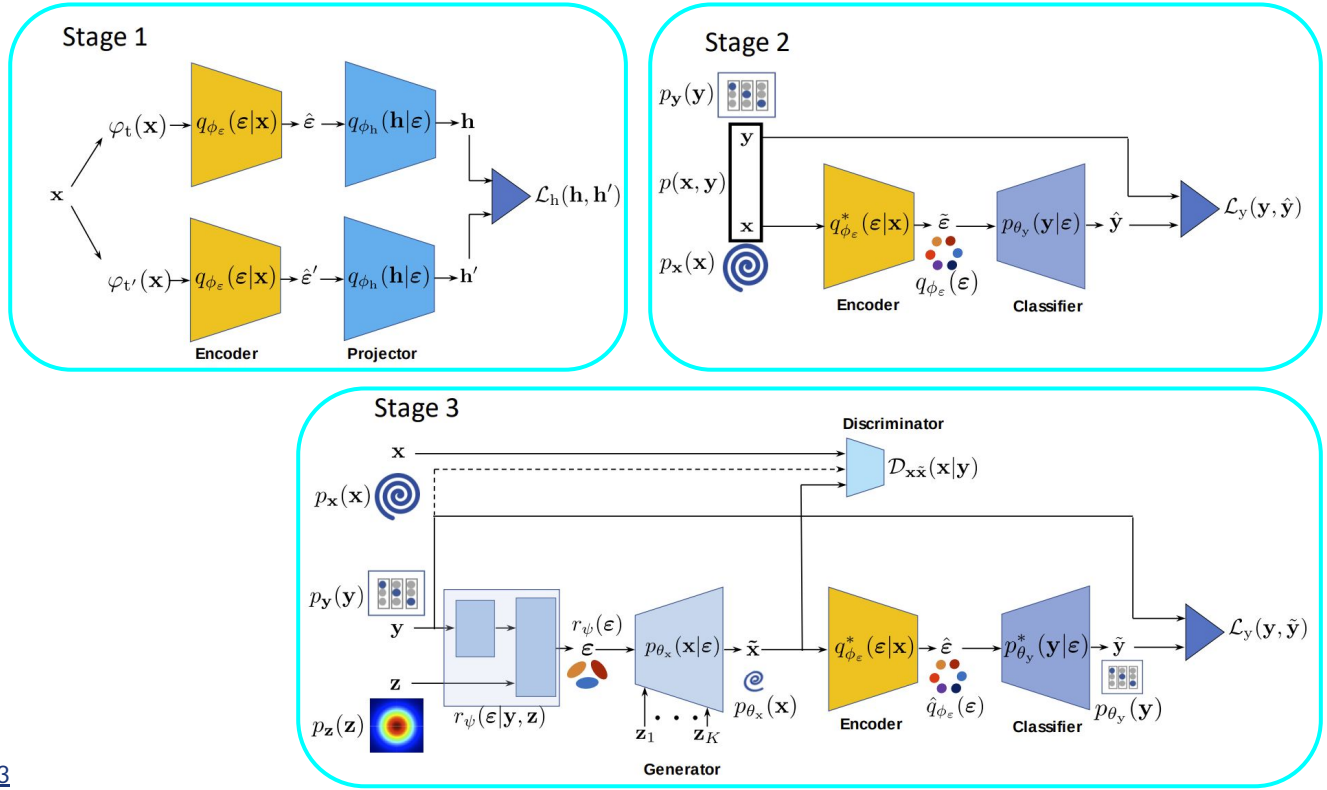


Galaxy Zoo dataset: label distribution



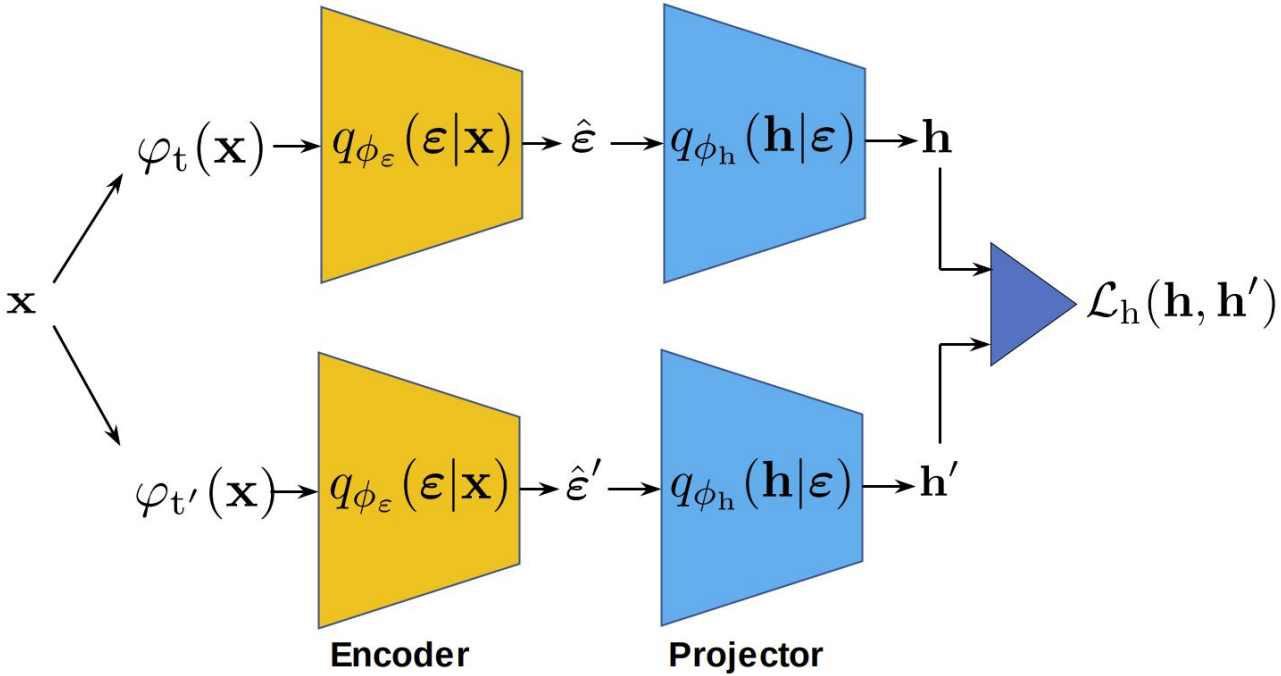
InfoSCC-GAN

InfoSCC-GAN



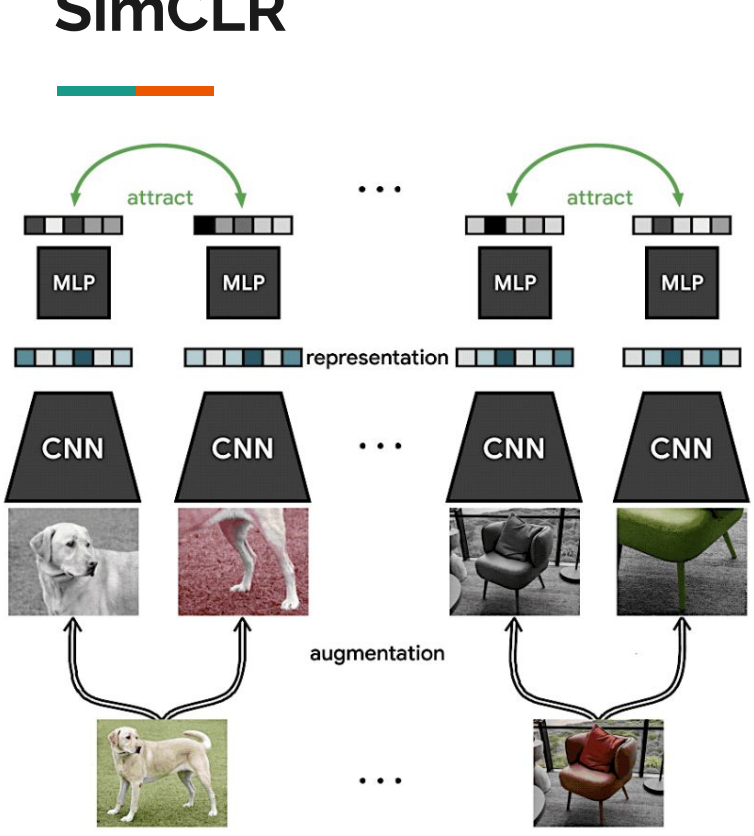
*arxiv.org/abs/2112.09653

SimCLR encoder

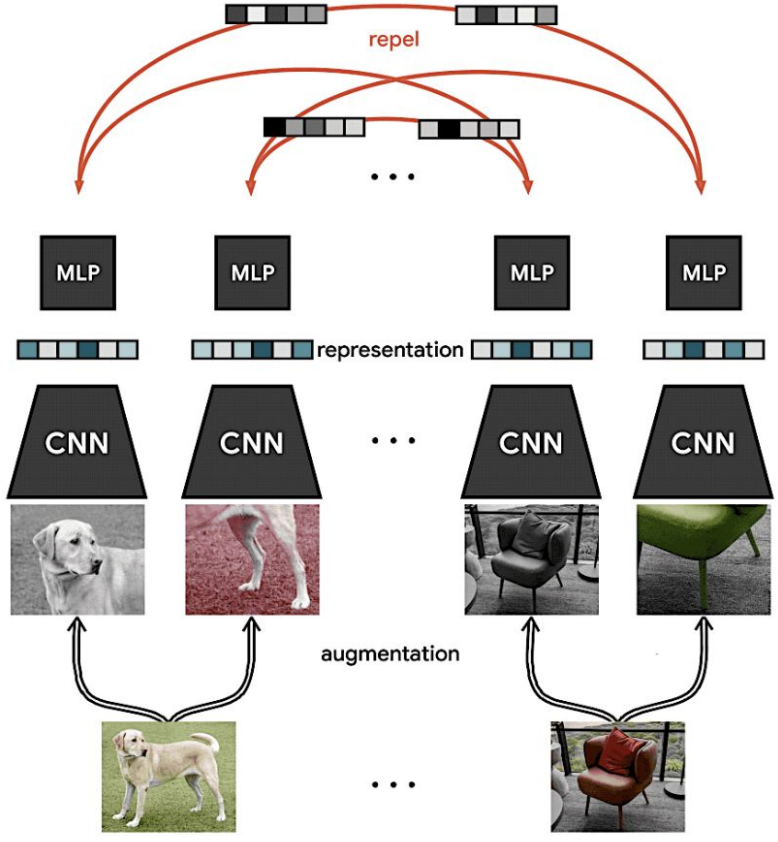


*arxiv.org/abs/2002.05709

SimCLR



Attract

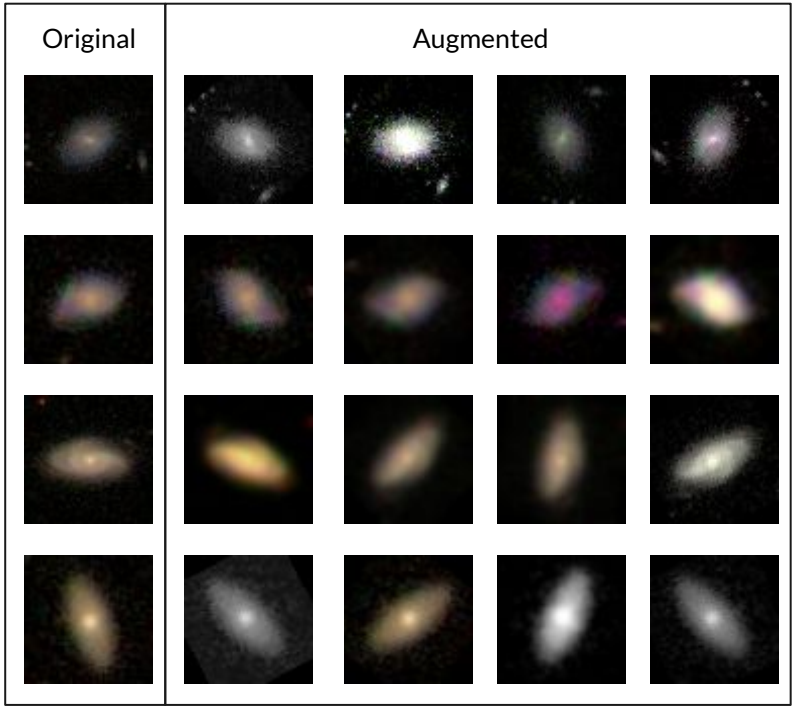


Repel

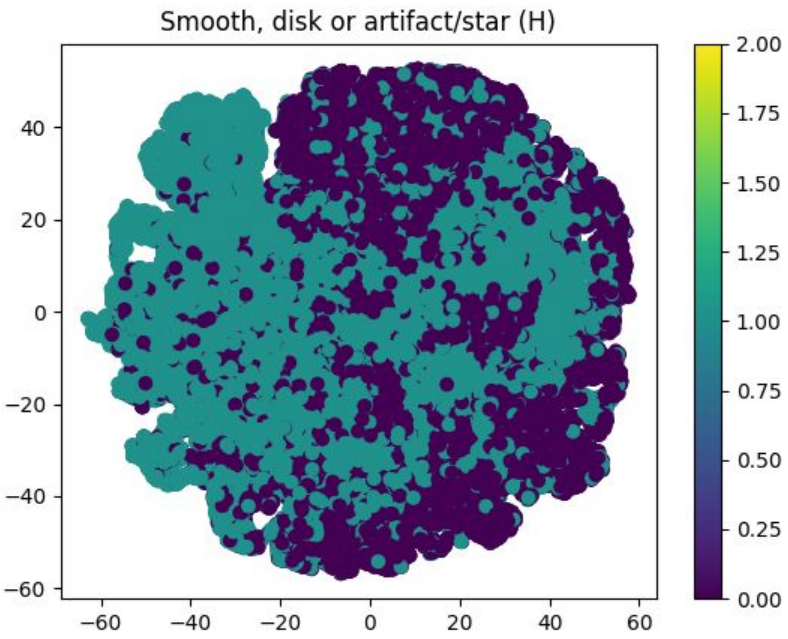
SimCLR augmentations

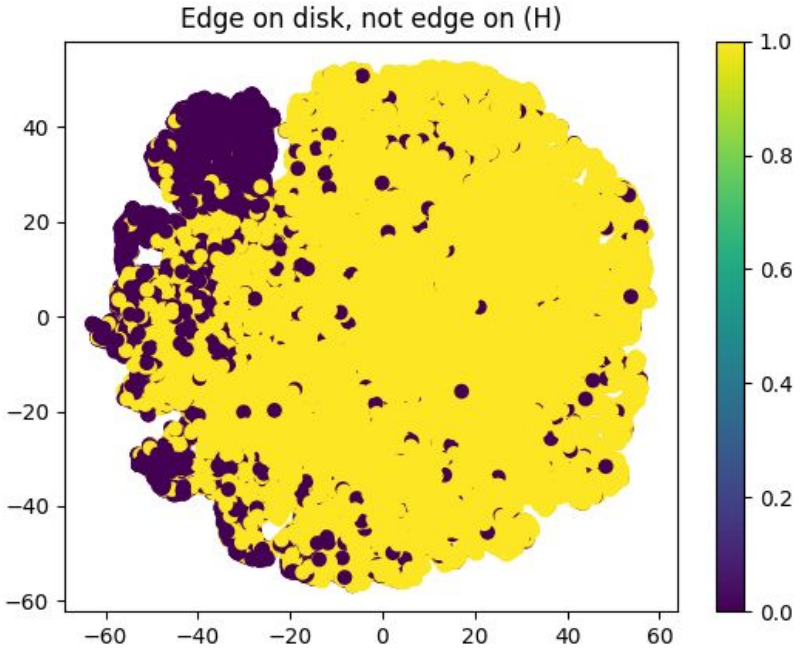
Augmentations for galaxies:

- random affine transform:
  - flipping
  - translation
  - rotation
- color jitter
- Gaussian blur

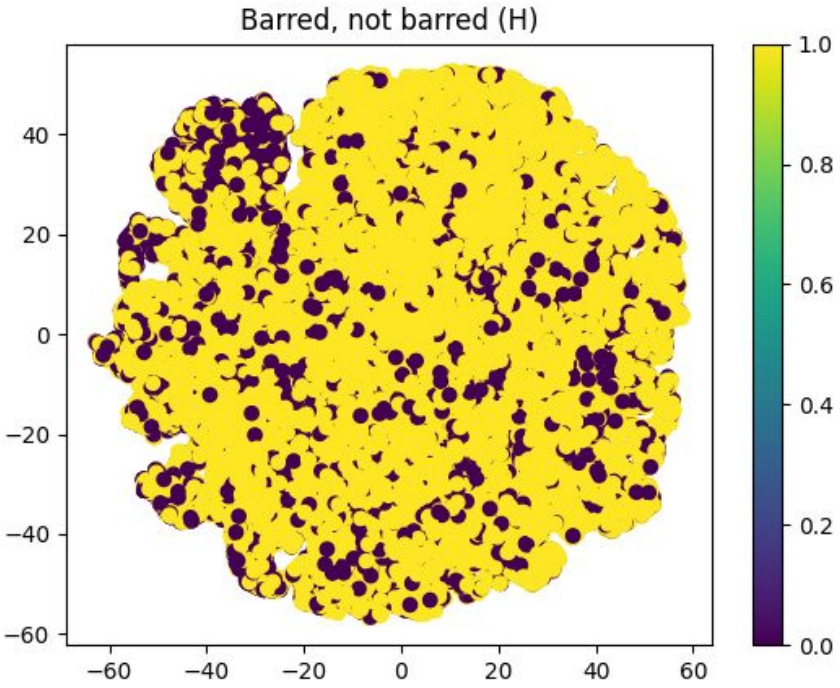


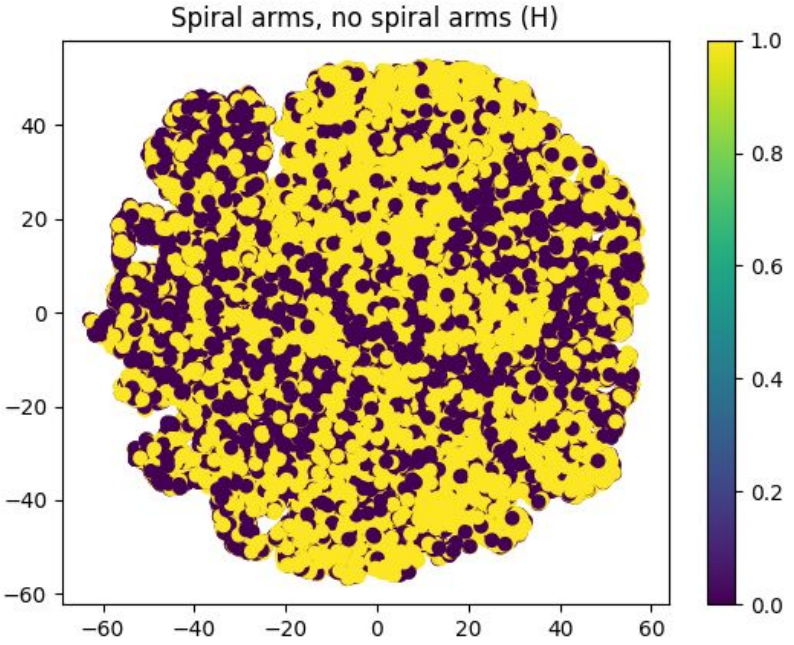
Latent embeddings



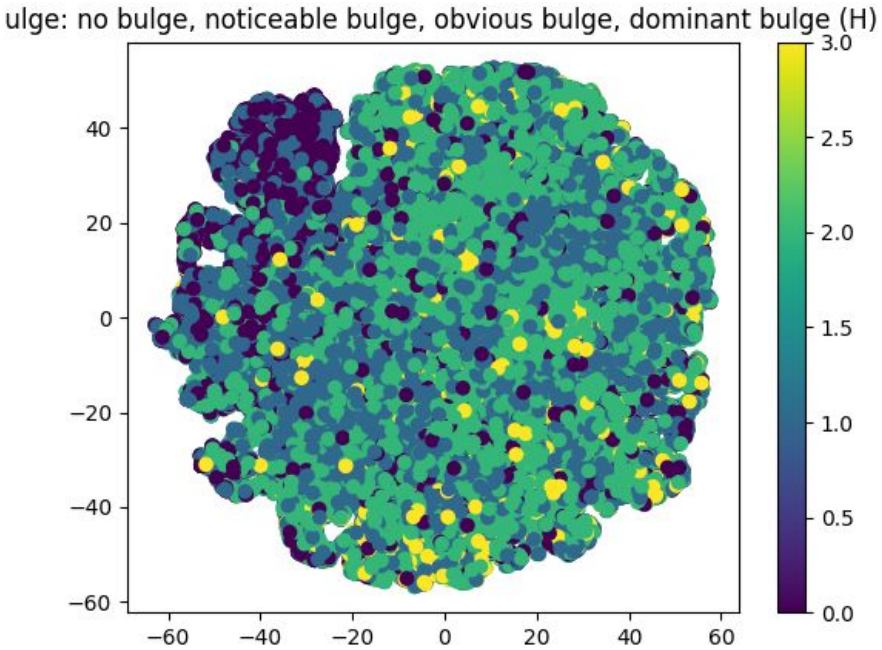


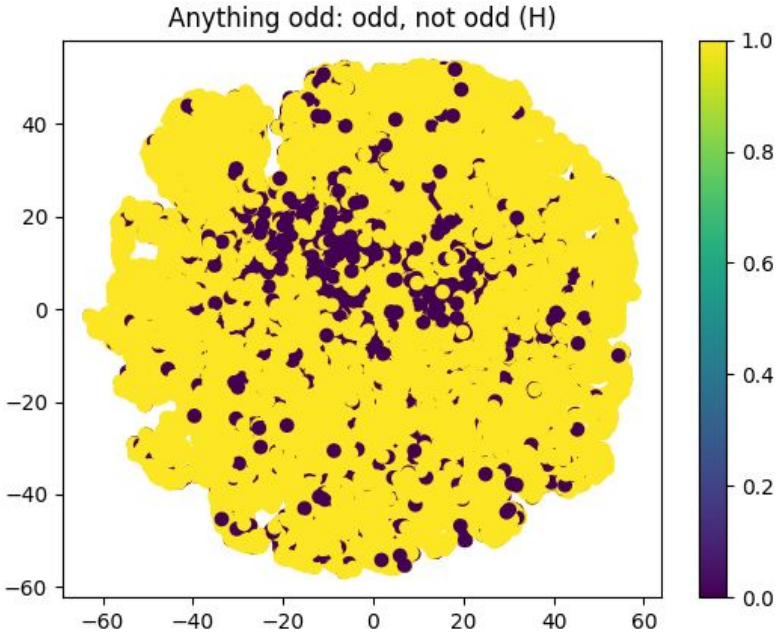
Latent embeddings



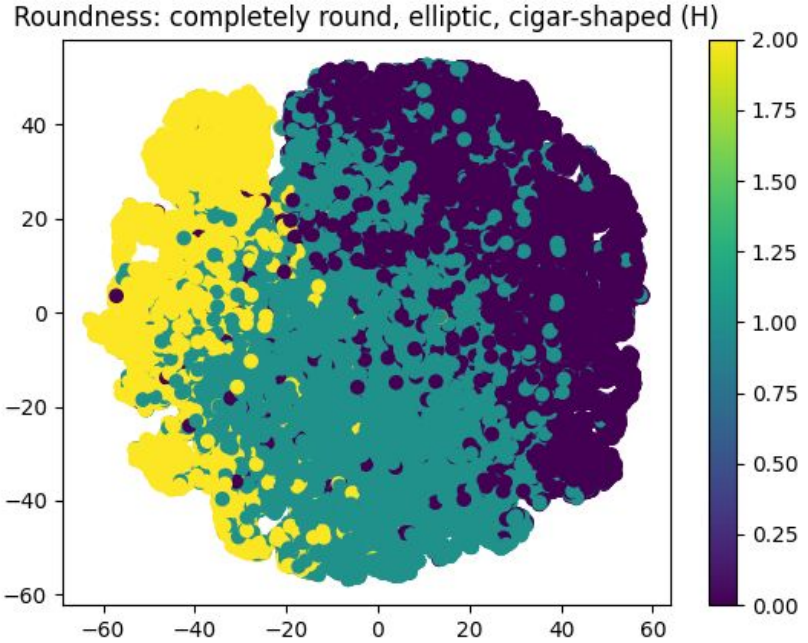


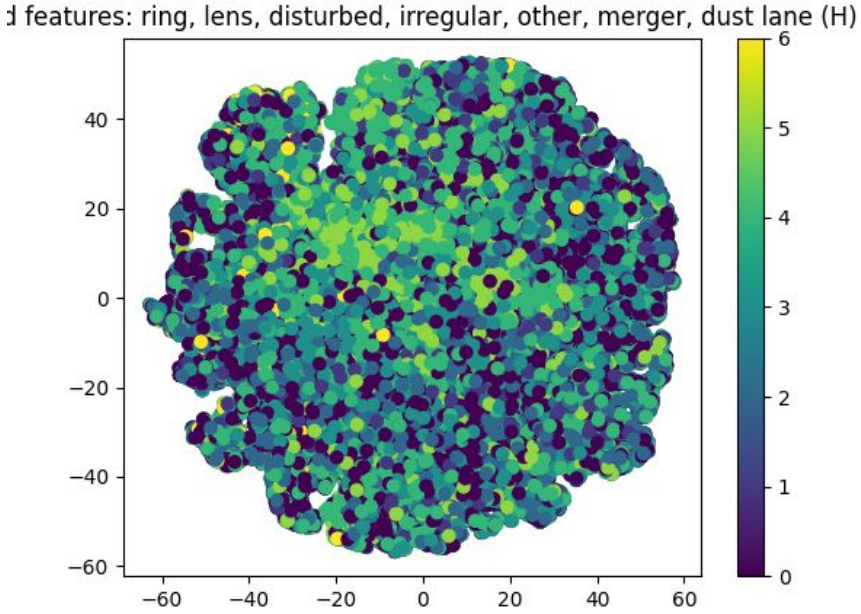
Latent embeddings



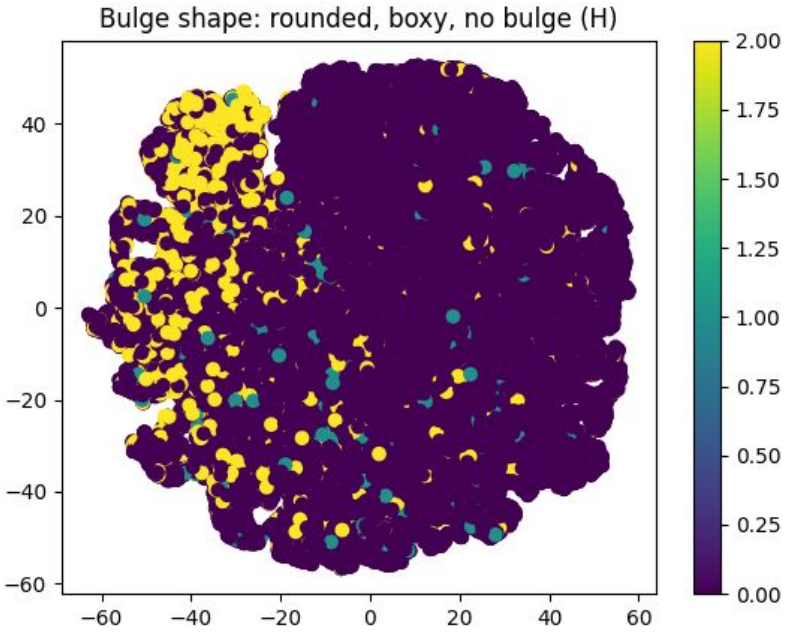


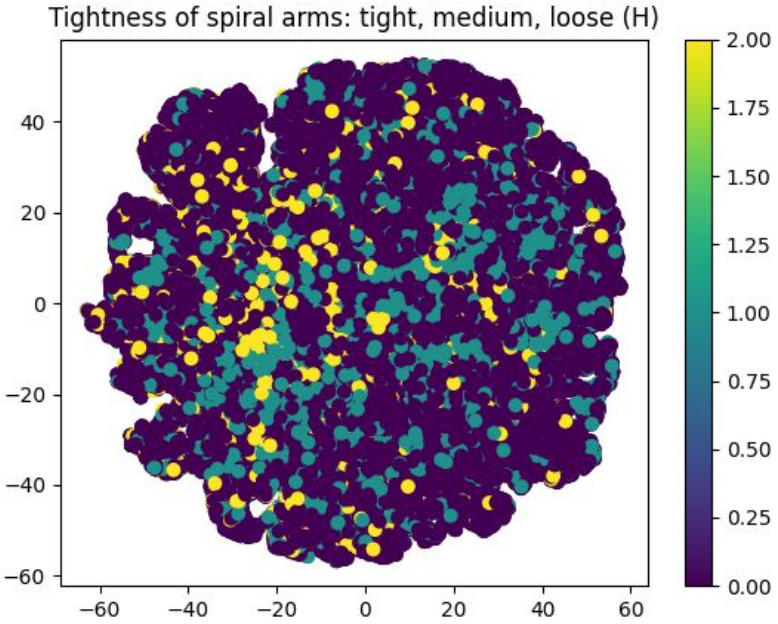
Latent embeddings



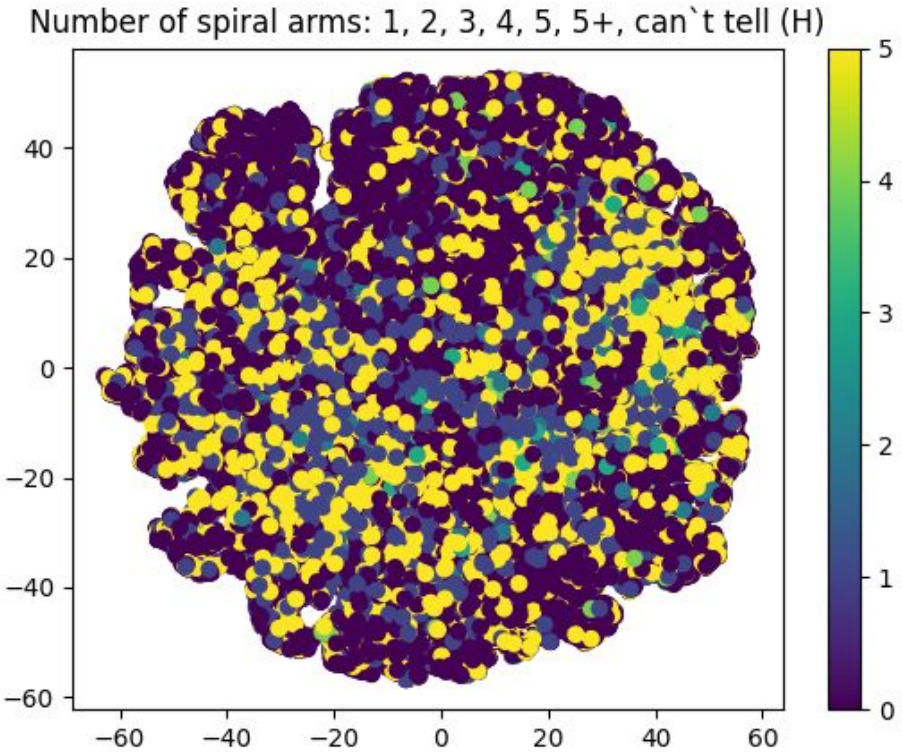


Latent embeddings

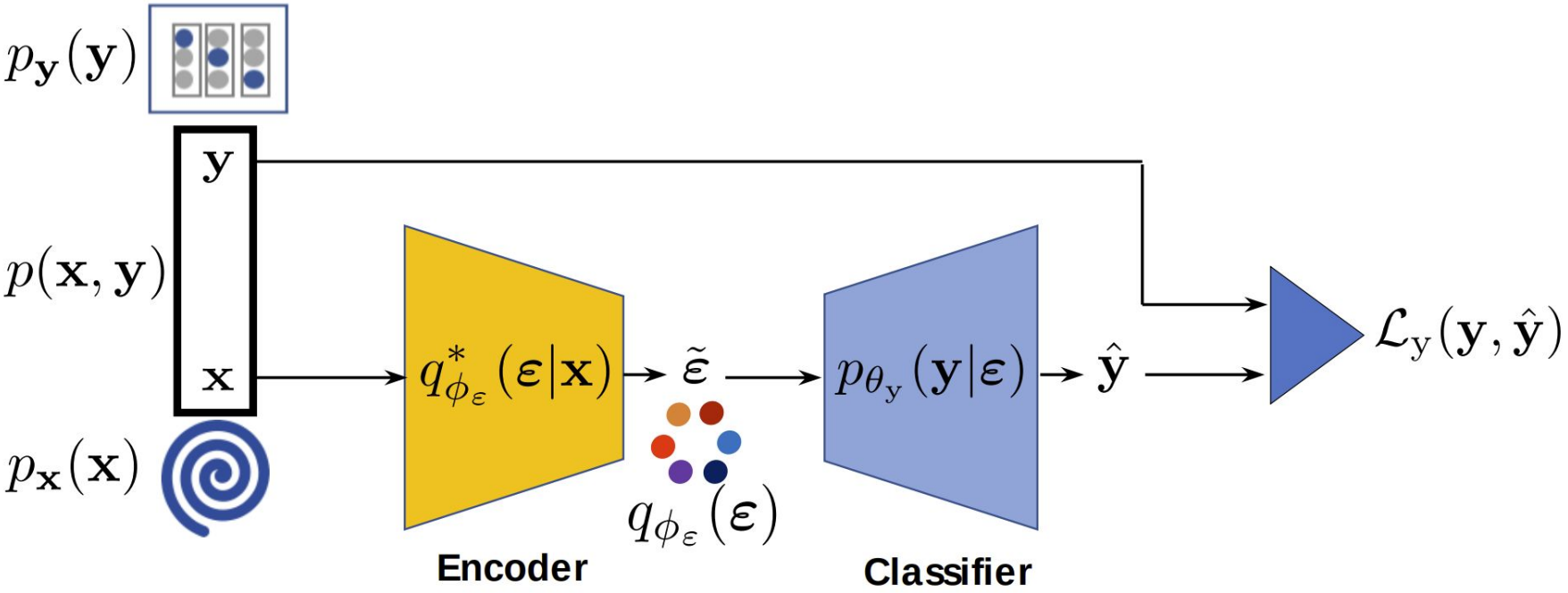




Latent embeddings

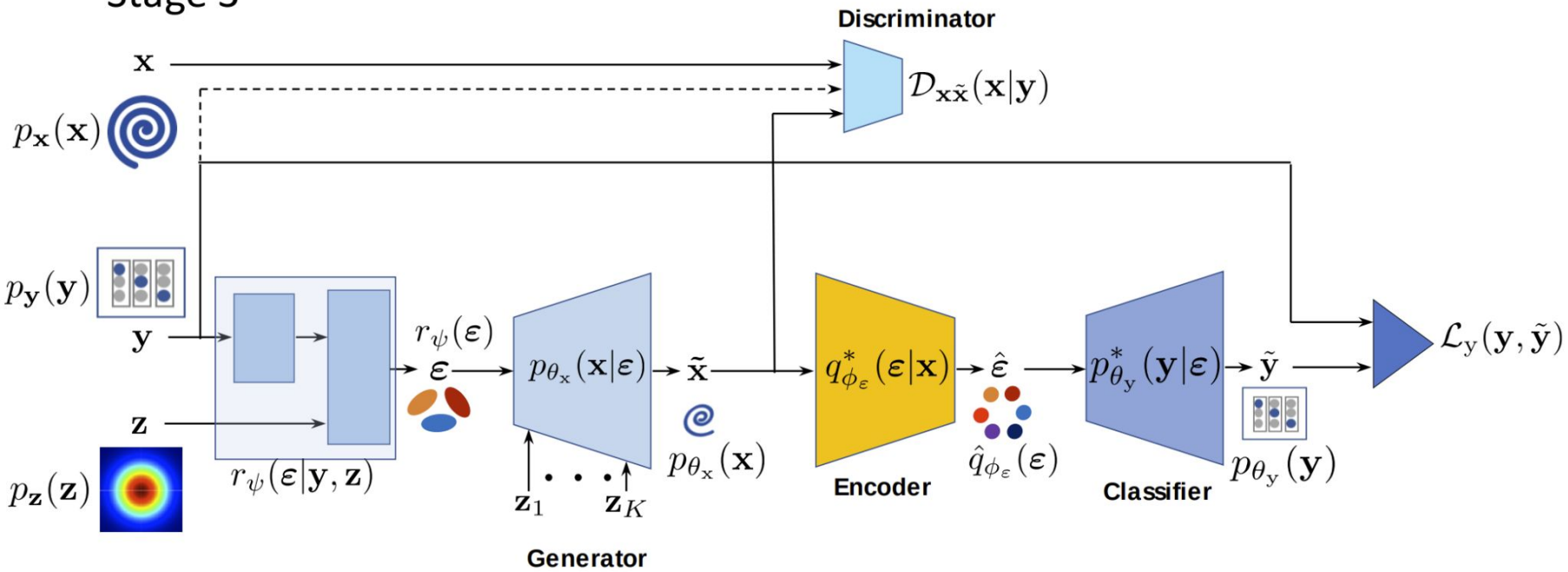


Classifier

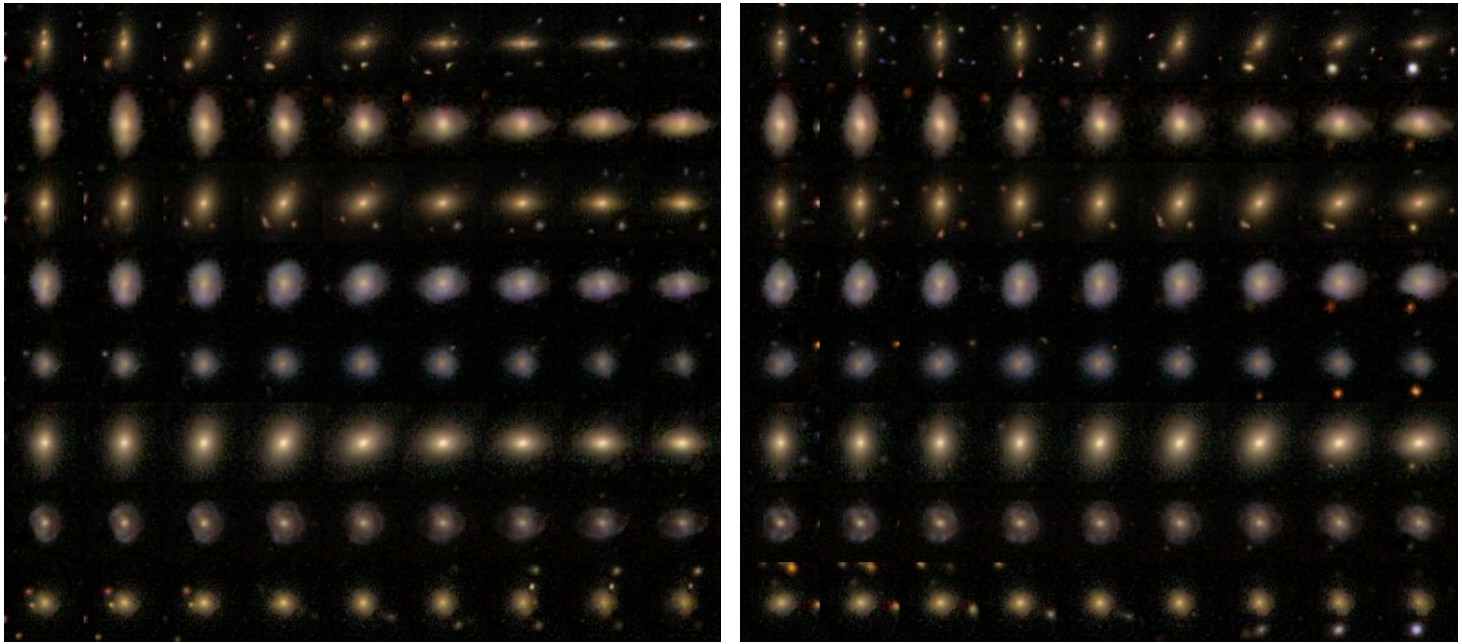

$p_{\mathbf{y}}(\mathbf{y})$
$p(\mathbf{x},\mathbf{y})$
$\mathbf{y}$
$\mathbf{x}$
$p_{\mathbf{x}}(\mathbf{x})$
$q^*_{\phi_\varepsilon}(\boldsymbol{\varepsilon}|\mathbf{x})$
$\tilde{\boldsymbol{\varepsilon}}$
$q_{\phi_\varepsilon}(\boldsymbol{\varepsilon})$
Encoder
$p_{\theta_{\mathrm{y}}}(\mathbf{y}|\boldsymbol{\varepsilon})$
$\hat{\mathbf{y}}$
Classifier
$\mathcal{L}_{\mathrm{y}}(\mathbf{y},\hat{\mathbf{y}})$

Generator

Stage 3



EigenGAN



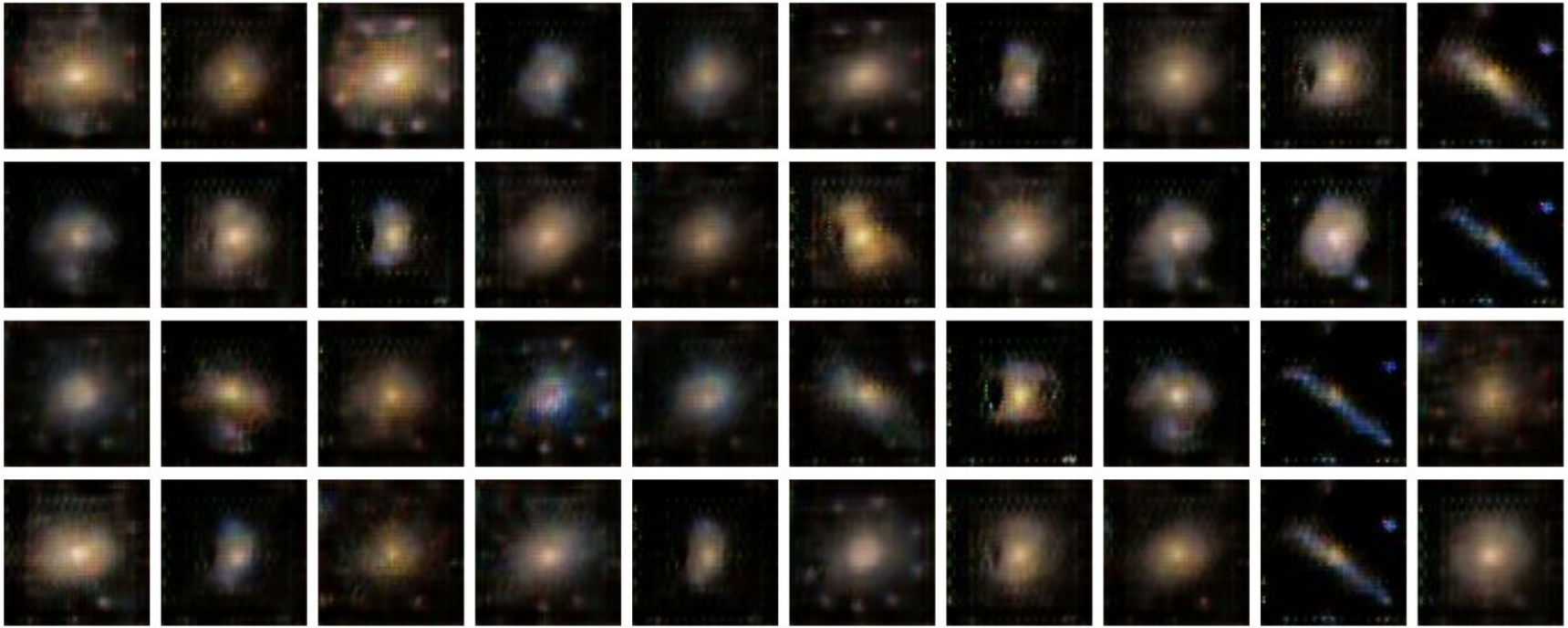
Ablations

Ablations

Global discriminator	
Loss	**FID**
Hinge loss	173.3
Non-saturating loss	115.6
Least-squared loss	117.5

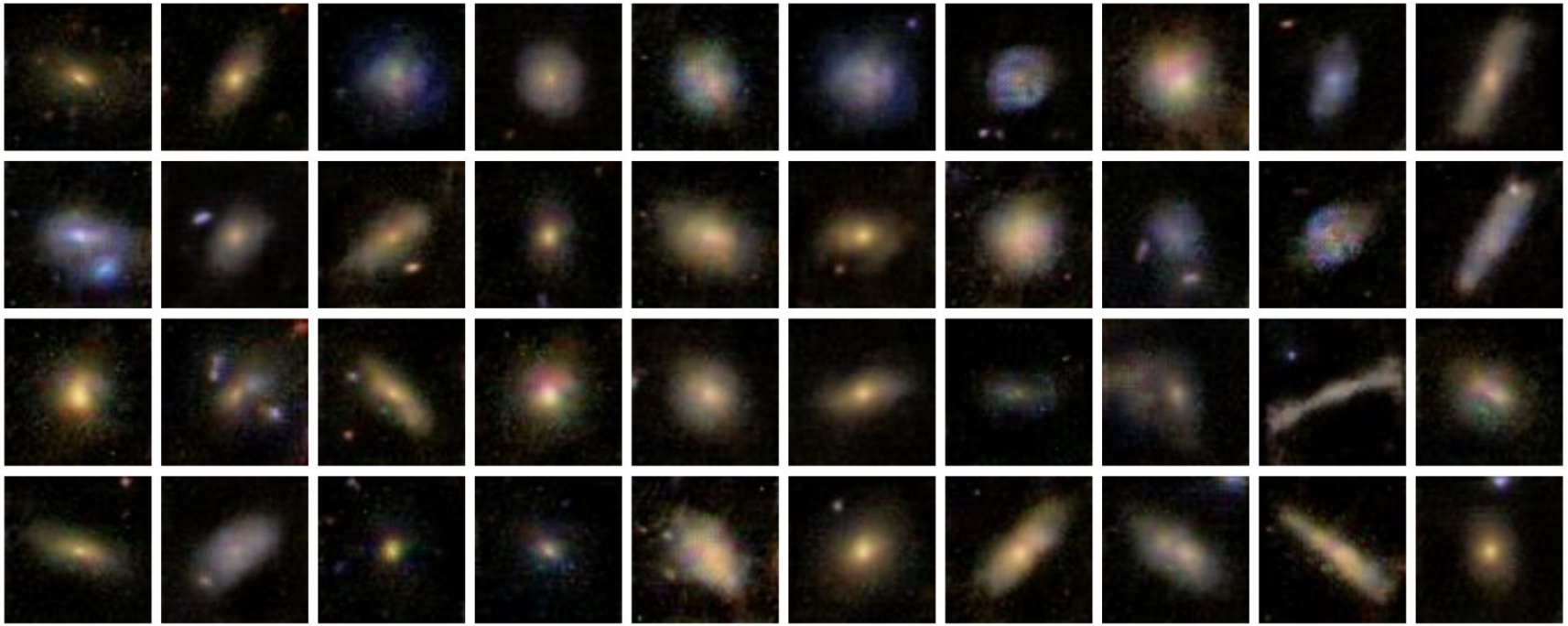
Patch discriminator	
Loss	**FID**
Hinge loss	117.5
Non-saturating loss	75.25
Least-squared loss	60.96

Global discriminator. Hinge loss



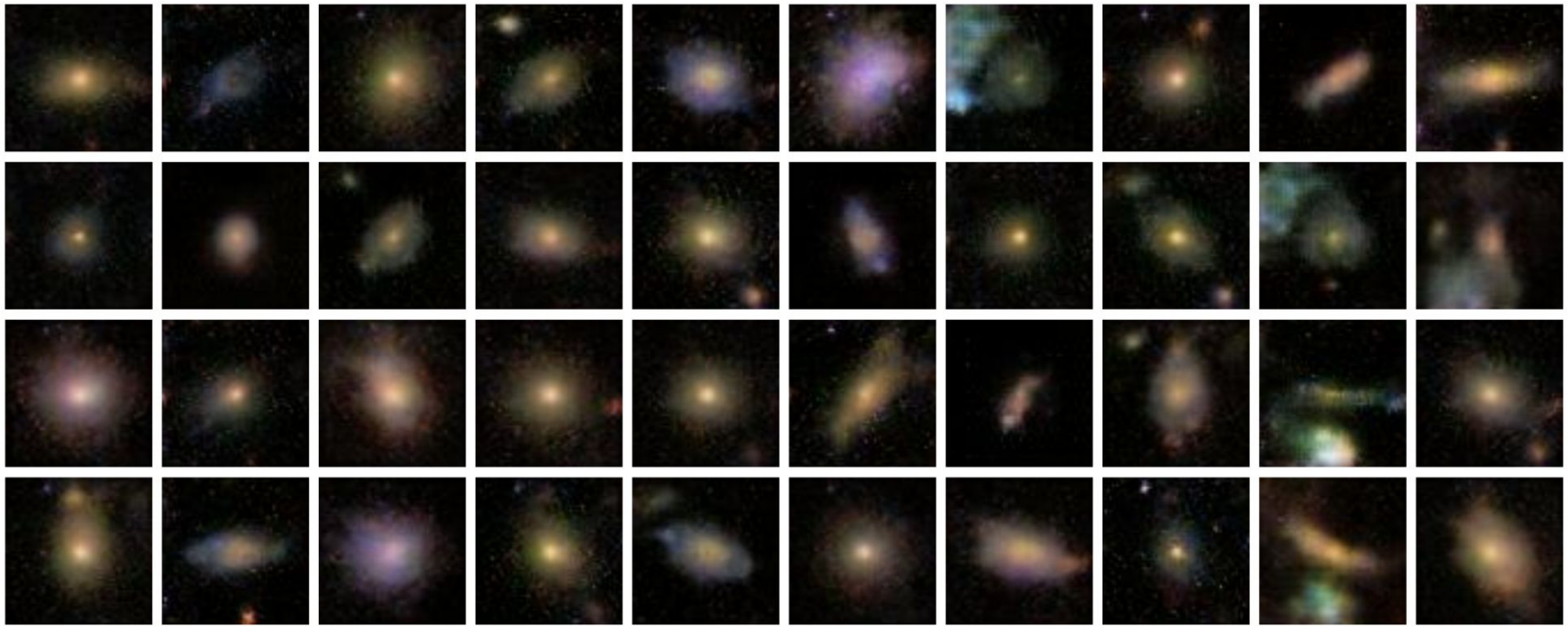
FID: 173.3

Global discriminator. Non-saturating loss



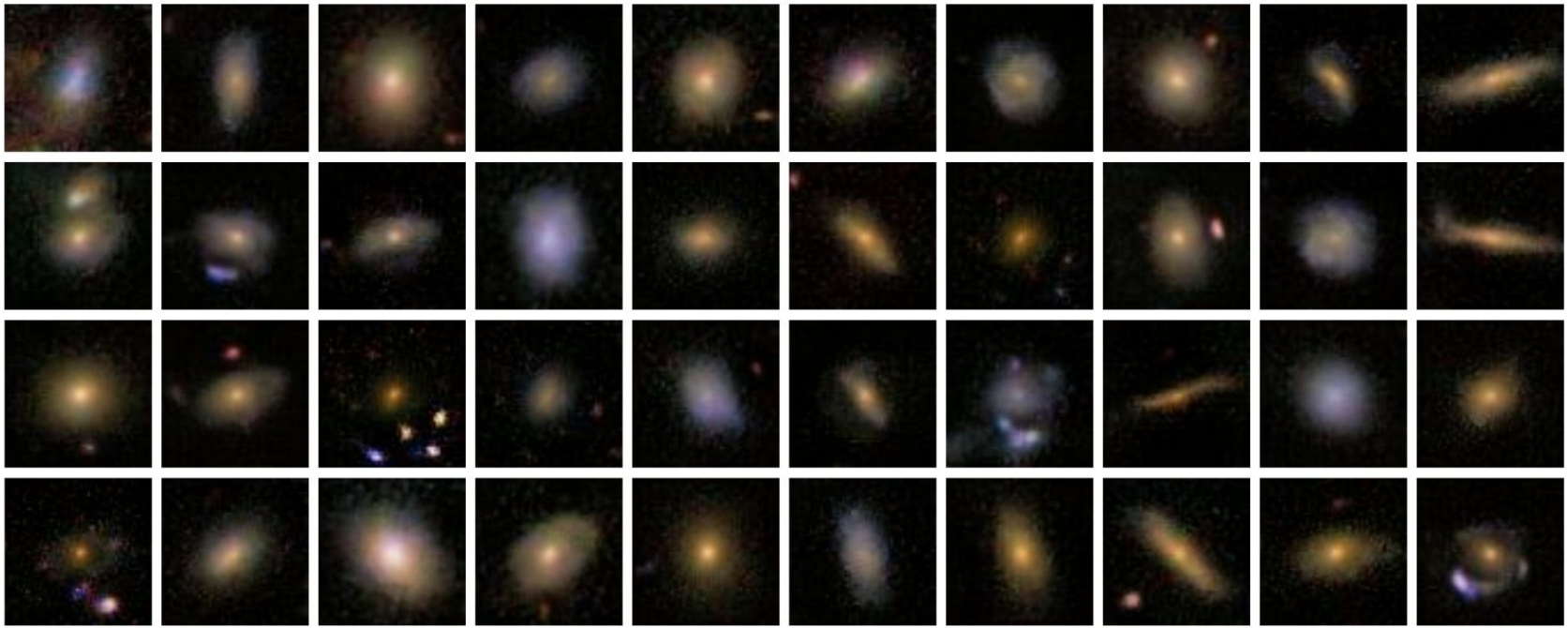
FID: 115.6

Patch discriminator. Hinge loss



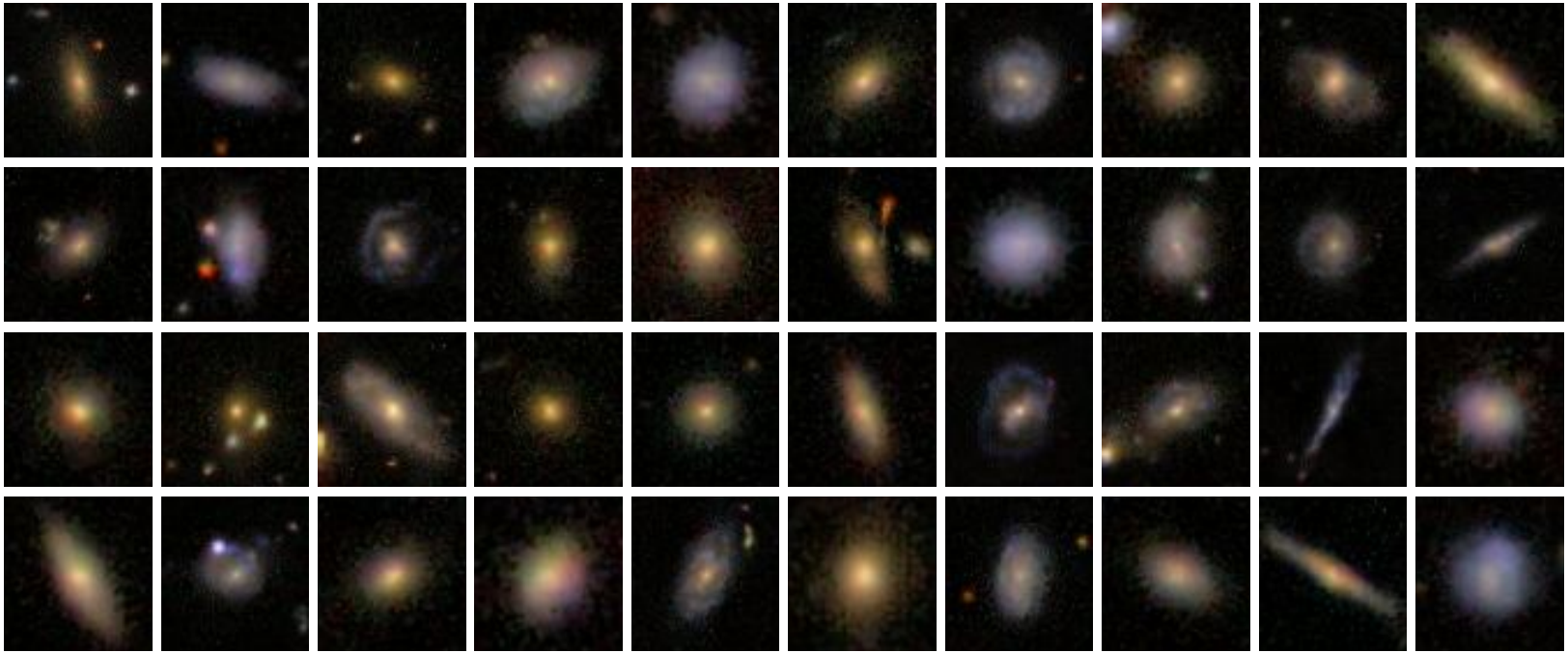
FID: 117.5

Patch discriminator. Non-saturating loss



FID: 75.25

Patch discriminator. Least-squared loss



FID: 60.96

Demo

Conclusions

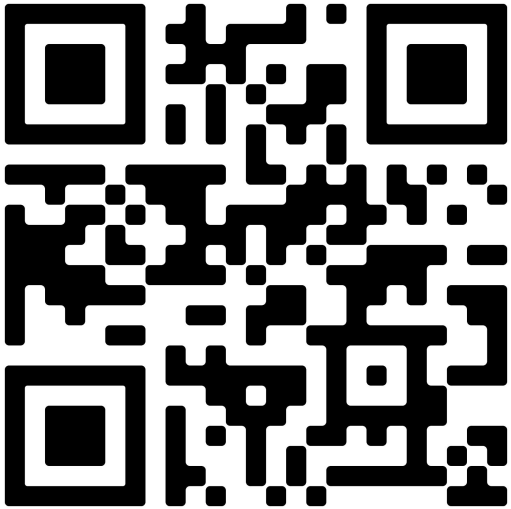
- SimCLR-based encoder produces interpretable latent space
- Embeddings from SimCLR encoder are suitable for classification of galaxies
- InfoSCC-GAN is capable of generating Galaxy Zoo images
- InfoSCC-GAN even generates rare galaxies, that are underrepresented in the dataset
- Eigen-GAN generator allows for the controllable generation in unsupervised way

Find our work online

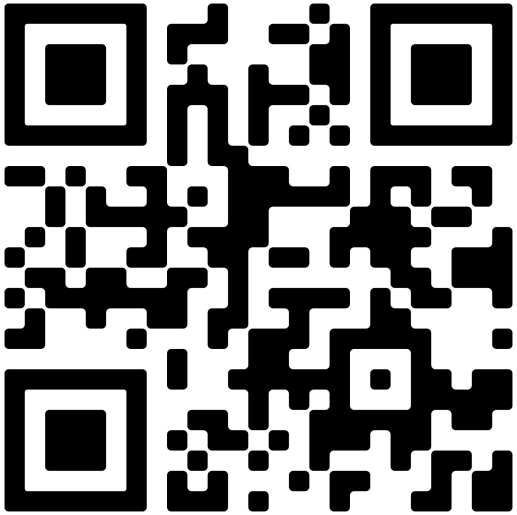
InfoSCC-GAN paper

Interactive demo

Find our work online



InfoSCC-GAN paper



Interactive demo