Milky Way Challenge

Group 4

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Dataset Exploration

Our first studies

- All images cropped to 64x64
- Therefore, compress milky way image as well to perform meaningful comparison

reduced milky way

Minimizing a metric

- First naive approach used a metric to compare milky way against all images
- Pixelwise MSE | minimal maximum difference | sorted by label

Closest image from MSE

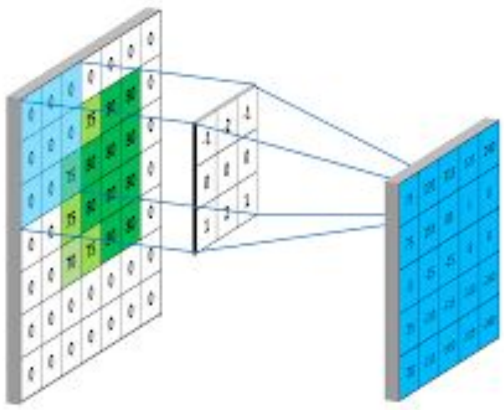
Closest image from Group: Unbarred Loose Spiral

- Not working well enough -> needing more sophisticated approach

Neural Network Architecture

CNN classifier

- Performance was better on pre-selected data
- Idea: Train convolutional neural network as image classifier
  - Using the fact that we have a lot of labeled images
- Network should be able to learn the important features separating different galaxies
- Afterwards, can produce score for each image and find the most similar classified to our milky way
- Improving labeling images into similar groups results in better training set for next approaches



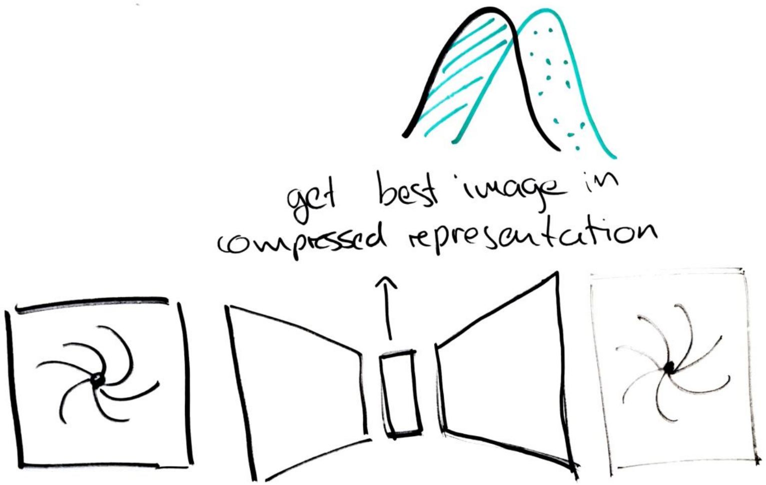
CNN Structure

- CNN approach similar to what Jonas explained monday
- Using convolutional layers to reduce dimensionality of inputs
- Classification in last layer

```
Layer (type)                Output Shape              Param #
=================================================================
input_1 (InputLayer)        [(None, 64, 64, 3)]       0

conv2d (Conv2D)             (None, 64, 64, 32)        896

max_pooling2d (MaxPooling2D  (None, 32, 32, 32)       0
)

dropout (Dropout)           (None, 32, 32, 32)        0

conv2d_1 (Conv2D)           (None, 32, 32, 32)        9248

max_pooling2d_1 (MaxPooling  (None, 16, 16, 32)       0
2D)

dropout_1 (Dropout)         (None, 16, 16, 32)        0

conv2d_2 (Conv2D)           (None, 16, 16, 32)        9248

max_pooling2d_2 (MaxPooling  (None, 8, 8, 32)         0
2D)

dropout_2 (Dropout)         (None, 8, 8, 32)          0

flatten (Flatten)           (None, 2048)              0

dense (Dense)               (None, 64)                131136

dropout_3 (Dropout)         (None, 64)                0

dense_1 (Dense)             (None, 64)                4160

dropout_4 (Dropout)         (None, 64)                0

dense_2 (Dense)             (None, 5)                 325

=================================================================
Total params: 155,013
Trainable params: 155,013
Non-trainable params: 0
```

Autoencoder

- Idea: Condensing dimension of the images into latent space
- Find closest agreement to representation of milky way in latent space
- Latent features should be more meaningful than single pixel values and therefore allow for better image comparison



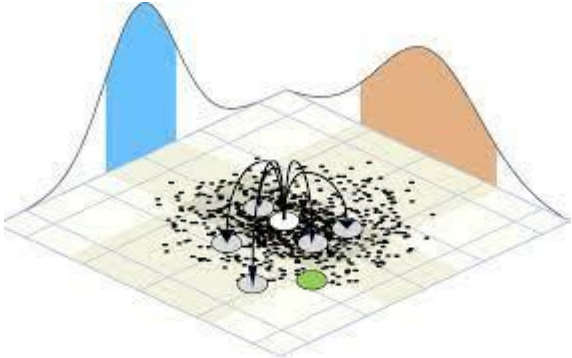
Autoencoder Structure

- Again, using convolutional layers similar to CNN approach
- After encoding an image into the latent space, second part decoding that representation back into full 64x64 image

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 64, 64, 3)]	0
conv2d (Conv2D)	(None, 64, 64, 32)	896
max_pooling2d (MaxPooling2D)	(None, 32, 32, 32)	0
conv2d_1 (Conv2D)	(None, 32, 32, 32)	9248
max_pooling2d_1 (MaxPooling 2D)	(None, 16, 16, 32)	0
conv2d_2 (Conv2D)	(None, 16, 16, 32)	9248
max_pooling2d_2 (MaxPooling 2D)	(None, 8, 8, 32)	0
conv2d_3 (Conv2D)	(None, 8, 8, 32)	9248
max_pooling2d_3 (MaxPooling 2D)	(None, 4, 4, 32)	0
flatten (Flatten)	(None, 512)	0
dense (Dense)	(None, 64)	32832
dense_1 (Dense)	(None, 512)	33280
reshape (Reshape)	(None, 4, 4, 32)	0
conv2d_transpose (Conv2DTra nspose)	(None, 8, 8, 32)	9248
conv2d_transpose_1 (Conv2DT ranspose)	(None, 16, 16, 32)	9248
conv2d_transpose_2 (Conv2DT ranspose)	(None, 32, 32, 32)	9248
conv2d_transpose_3 (Conv2DT ranspose)	(None, 64, 64, 32)	9248
conv2d_4 (Conv2D)	(None, 64, 64, 3)	867

Total params: 132,611
Trainable params: 132,611
Non-trainable params: 0

Variational Autoencoder

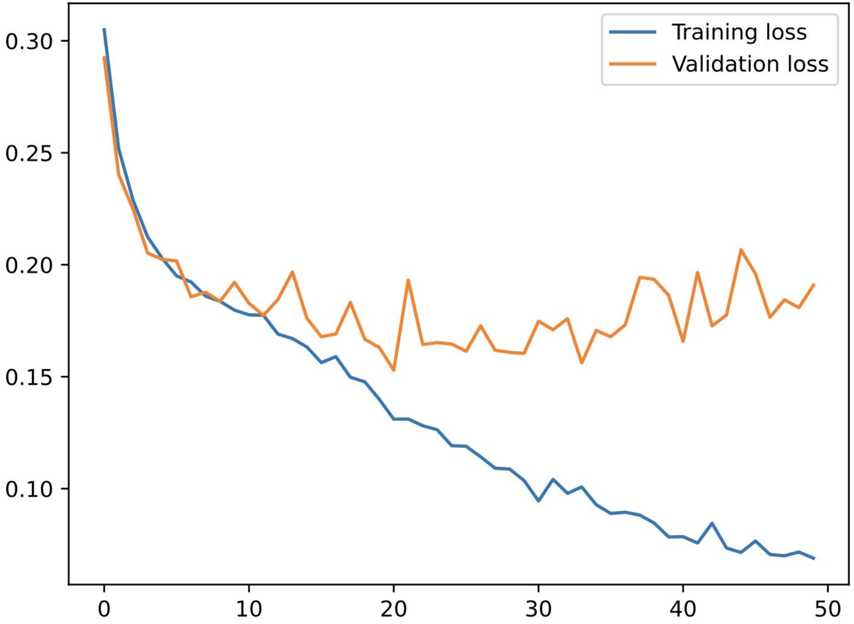


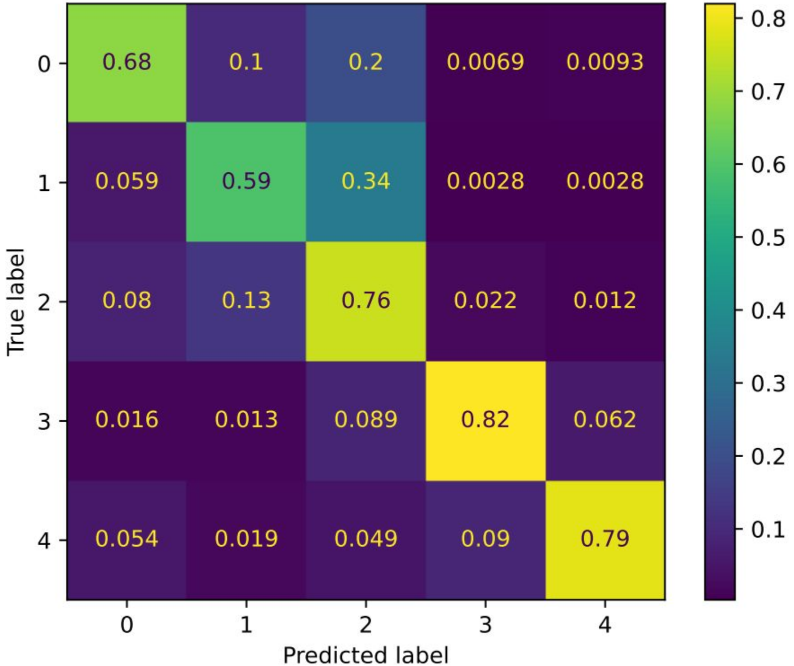
- Idea: Similar initial thought as the auto encoder
- Difference:
  - VAE enforces conditions on the latent variable to be independent gaussians
  - Random value of latent variable generates meaningful output at the decoder
- Therefore, we could use decoder to generate new images from gaussian noise
- Incorporating milky way-like images as a desired target should enable VAE to produce images of similar kind

VAE Structure

Network Training and Evaluation

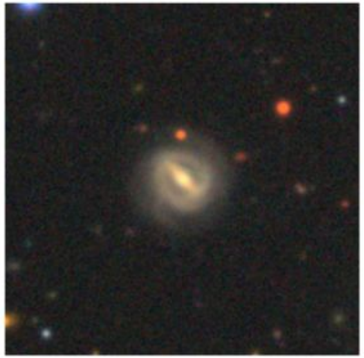
Performance plots for the CNN





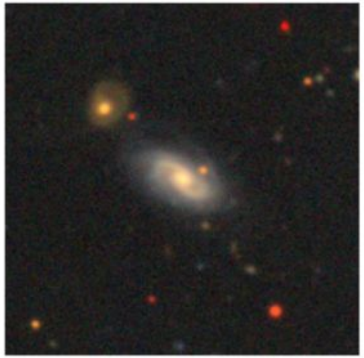
Milkyway image score

0.18
Barred Spiral



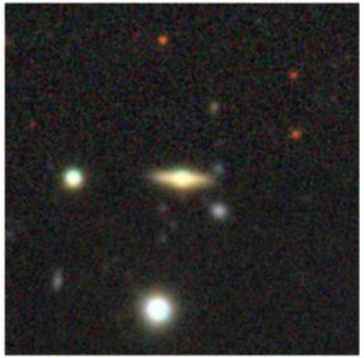
3.0e-04
Unbarred Tight Spiral

0.82
Unbarred Loose Spiral



4.5e-11
Edge-on without Bulge

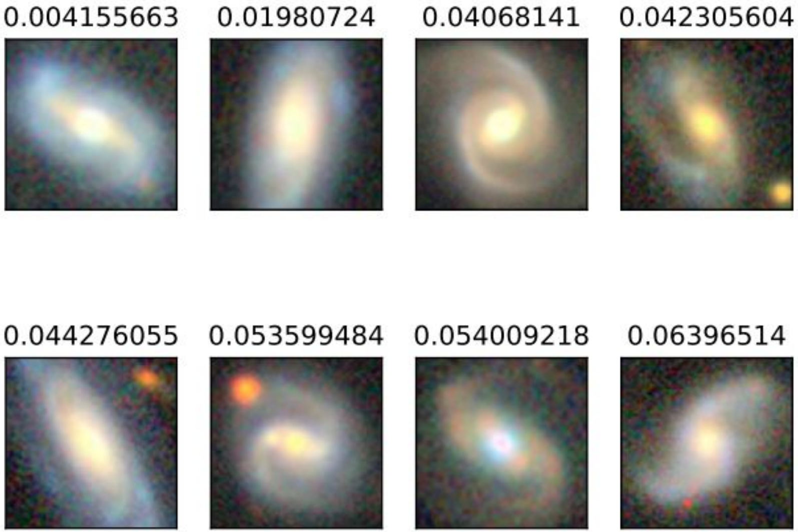
5.2e-11
Edge-on with Bulge



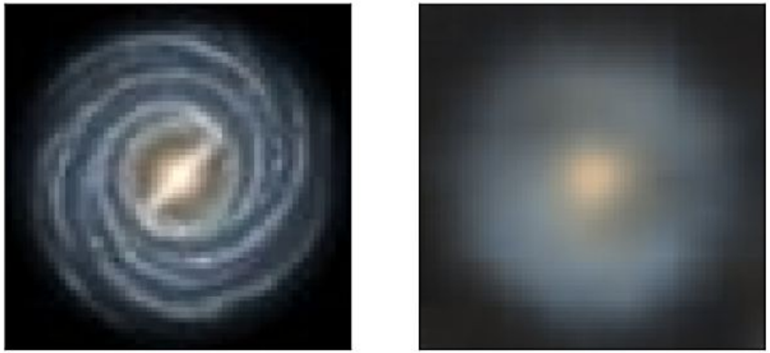
Minimum score distance

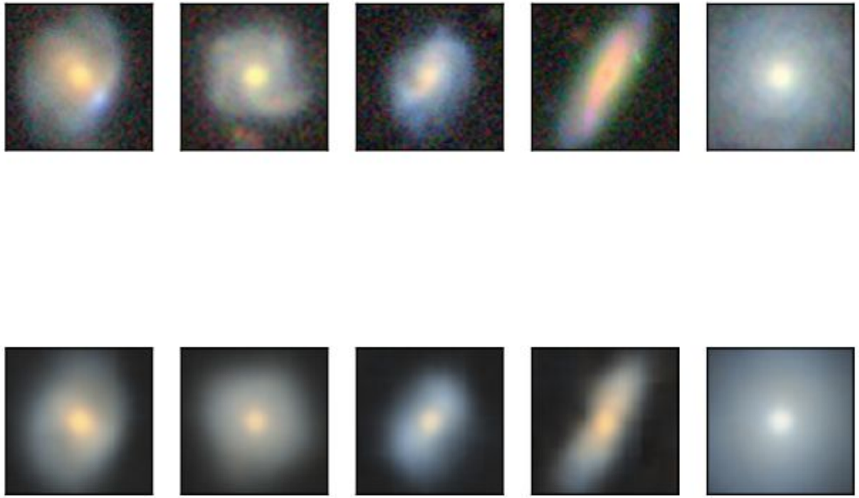
reduced milky way

MSE in score space

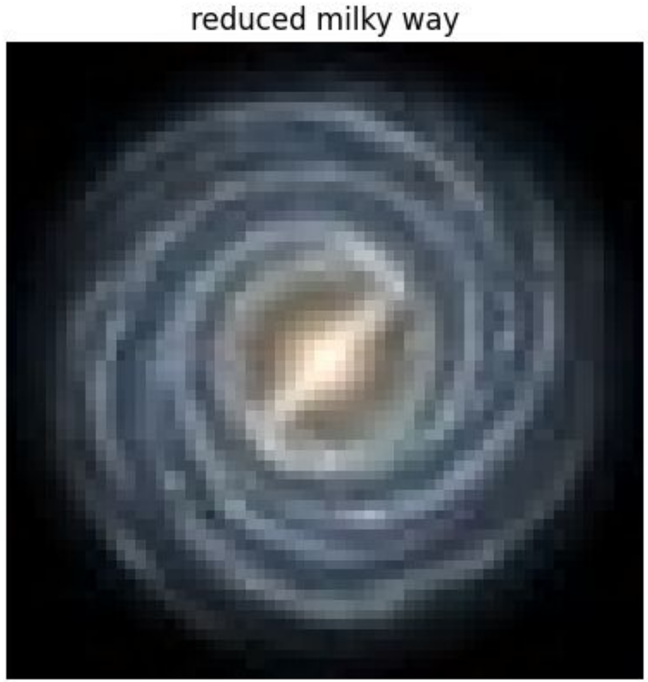


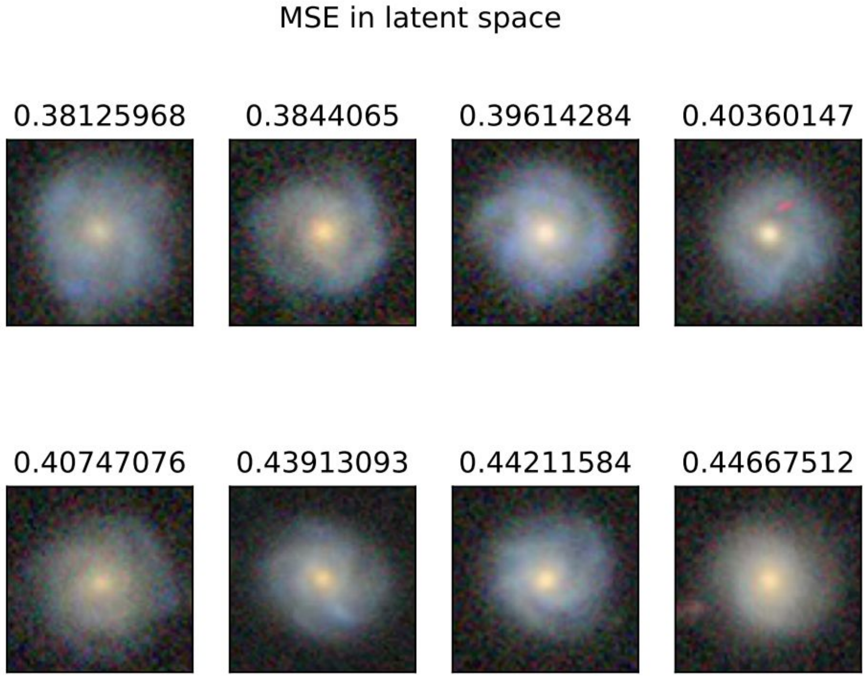
Autoencoder reconstruction





Minimum latent space distance





Generated images using the AE (Bonus task)

- Concept: use same architecture for both tasks
- Generate images by adding noise to milkyway latent space representation
- However, inability to reconstruct milkyway image well meant we did not perform this step