# Studying data variability in variational autoencoders using a chain model

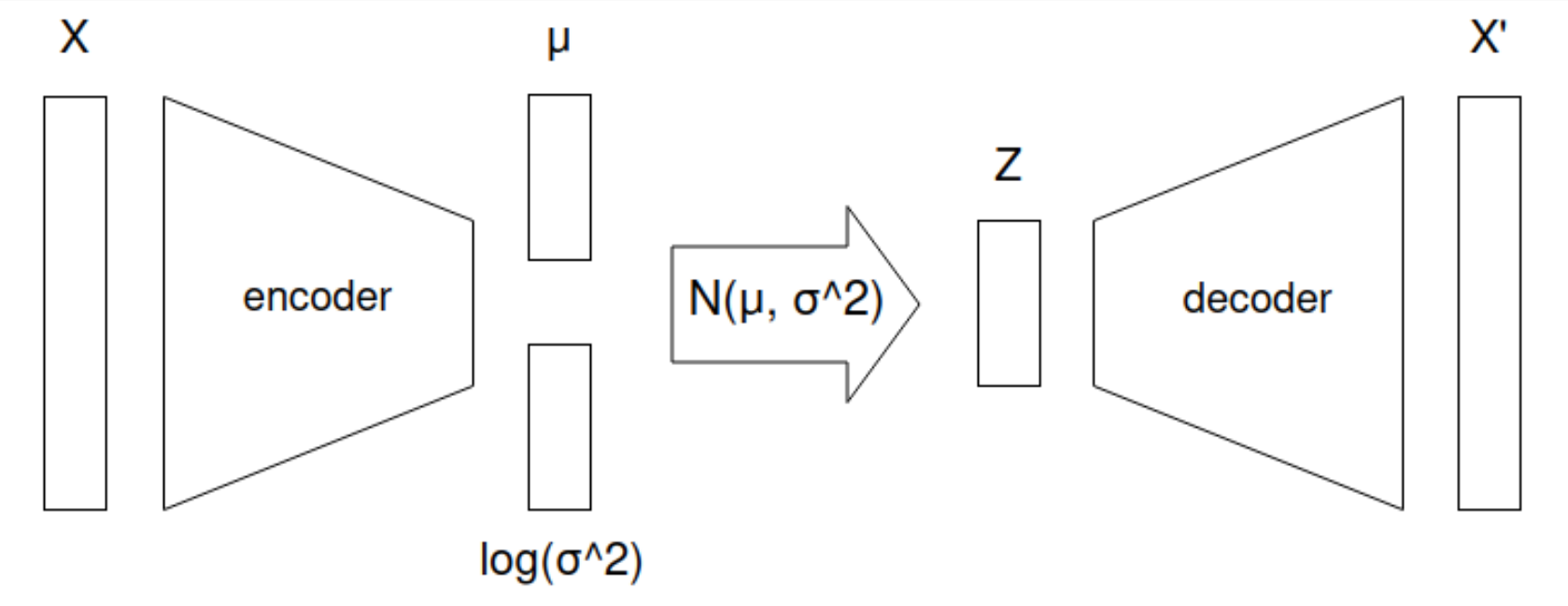
Tommaso Tarchi

January 16, 2024

University of Trieste

# Introduction

# General architecture of a VAE

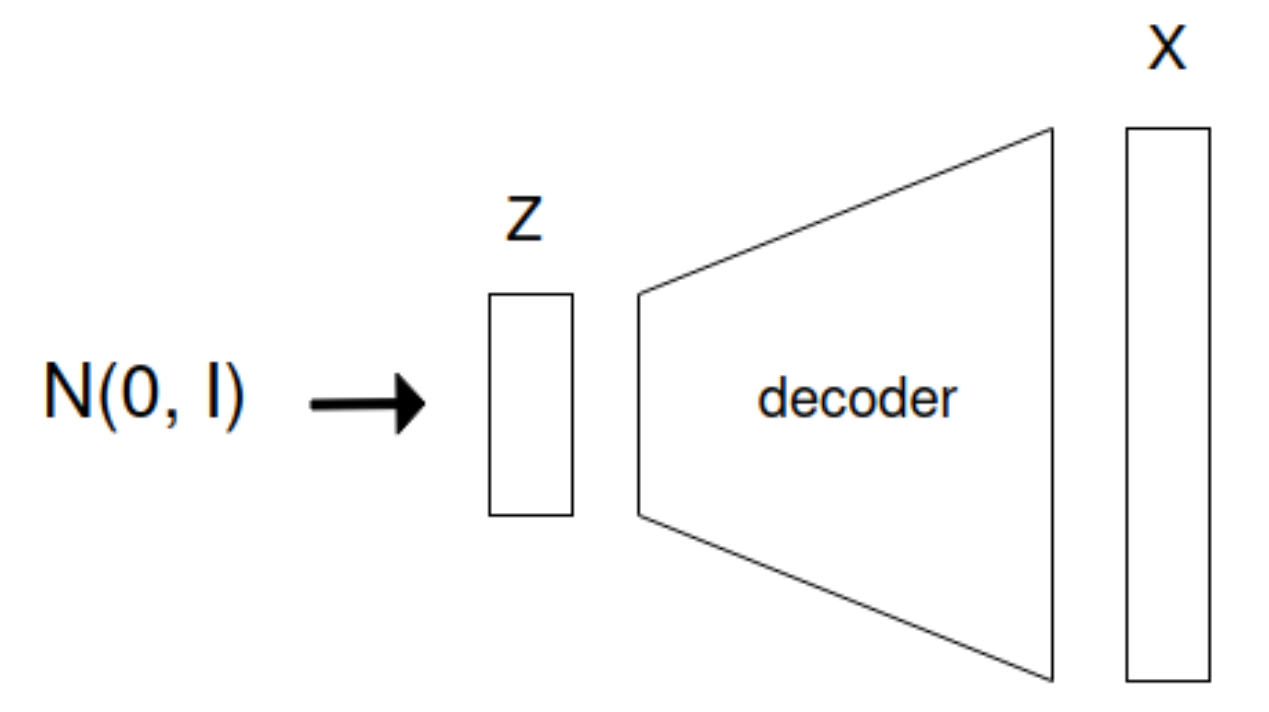


# Loss function

$$\text{LOSS}(\theta) = MSE_\theta\left(x, x_{recon}\right) + KL\left[q_\theta\left(z|x\right)||p\left(z\right)\right],$$

$$\text{with} \quad \text{p}(z) = N\left(z|0, I\right)$$

# Generative mode



# What if...

**But, what if we train a VAE on a dataset that was generated by another VAE?**

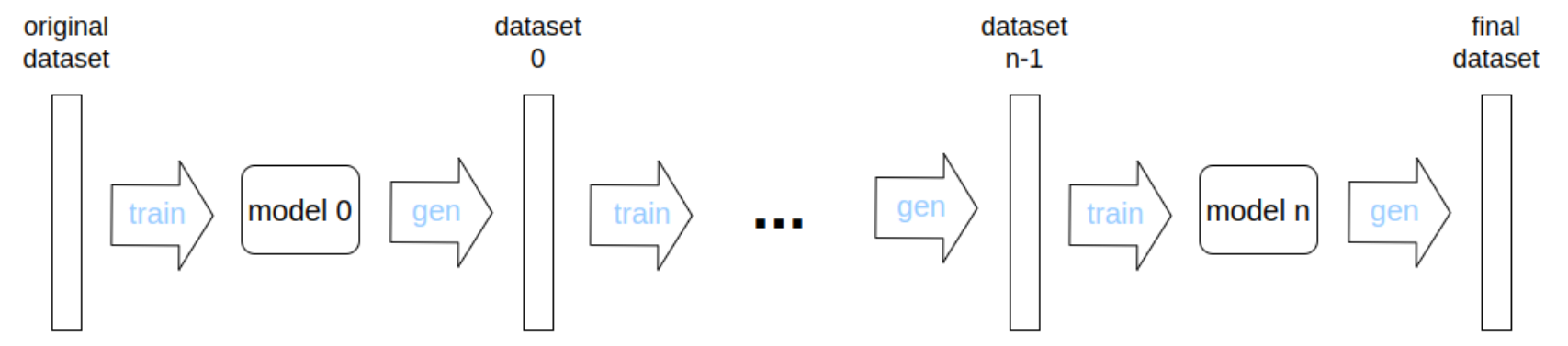
# What if...

**But, what if we train a VAE on a dataset that was generated by another VAE?**

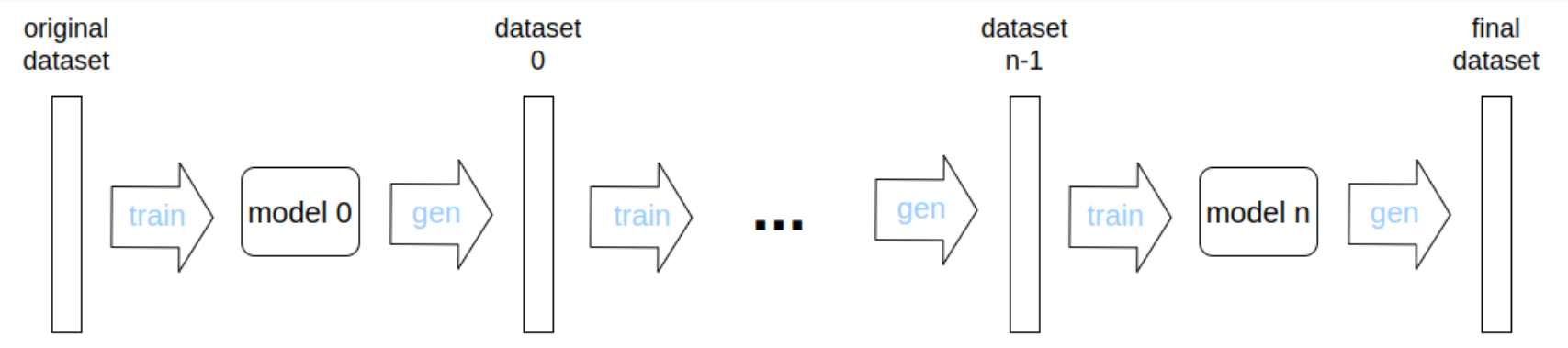
Possible questions:

- Is the new dataset still representative of the original dataset the first model was trained on?
- Are any bias introduced by this process?
- Will the new dataset have the same variability of the one it was trained on?

# VAEs chain


original dataset
train
model 0
gen
dataset 0
train
...
gen
dataset n-1
train
model n
gen
final dataset

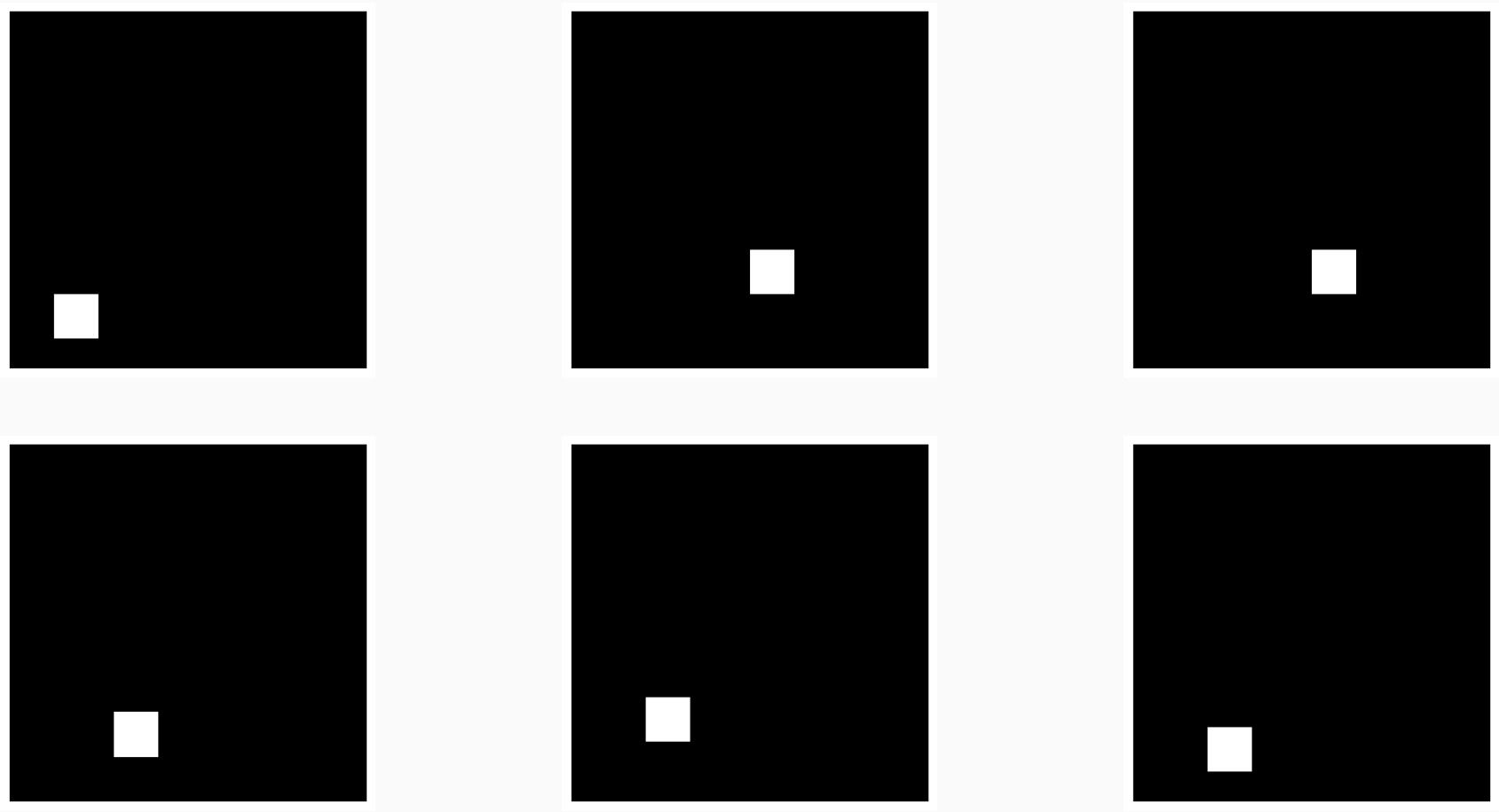
# VAEs chain




Possible systematic effects introduced by VAEs will be amplified.

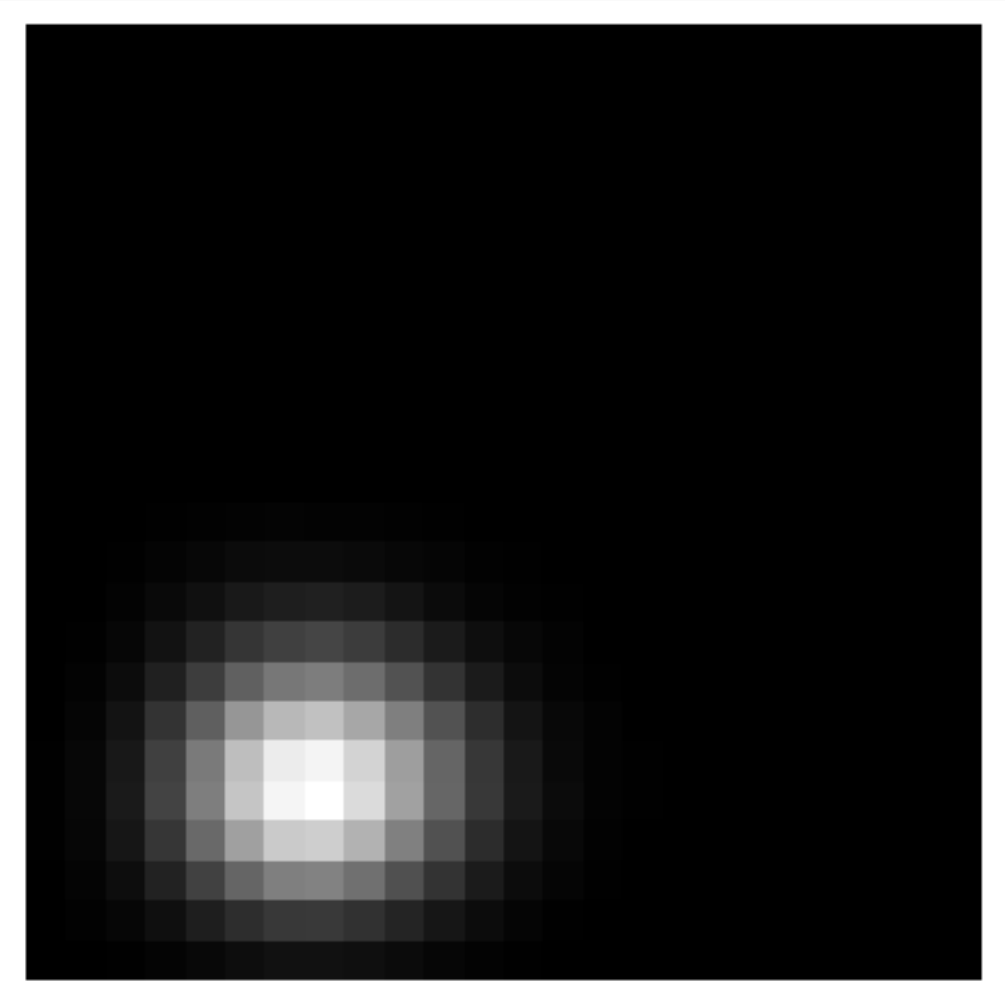
# Our implementation

# Initial dataset



24x24 grids, x-distribution: Binom(24,0.3), y-distribution: Binom(24,0.8)

# Dataset's distribution



24x24 grids, x-distribution: Binom(24,0.3), y-distribution: Binom(24,0.8)

# NN architectures

- One-layer fully connected (*FC1*)
- Two-layers fully connected (*FC2*)
- Convolutional with max-pooling (*Conv*)

# How to evaluate results

- **Distribution difference**: difference between train dataset's and generated dataset's distributions (checks for biases)

# How to evaluate results

- **Distribution difference**: difference between train dataset's and generated dataset's distributions (checks for biases)
- **Variability**: diversity of datasets (checks for variability reductions)

# How to evaluate results

- **Distribution difference**: difference between train dataset's and generated dataset's distributions (checks for biases)
- **Variability**: diversity of datasets (checks for variability reductions)
- **Visual inspection**: checking random images visually (checks images to be of the right kind)

# How to evaluate results

- **Distribution difference**: difference between train dataset's and generated dataset's distributions (checks for biases)
- **Variability**: diversity of datasets (checks for variability reductions)
- **Visual inspection**: checking random images visually (checks images to be of the right kind)

**This method is NOT perfect!**

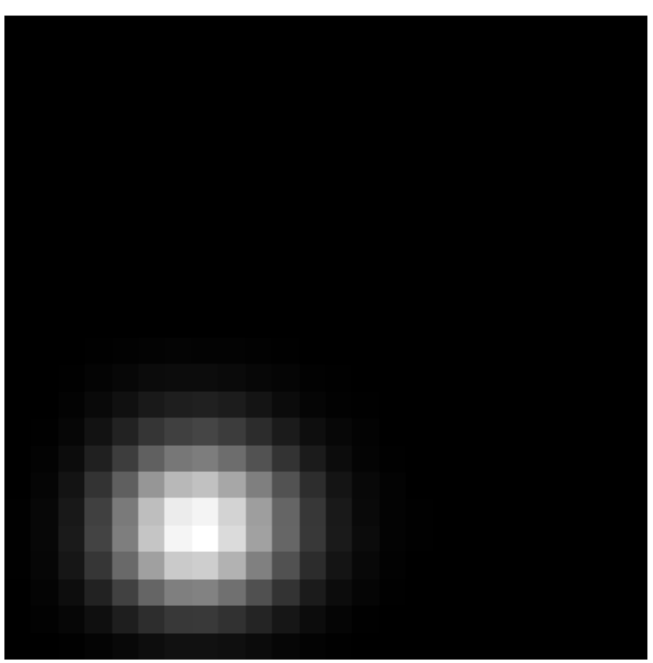
# Results

# Single model

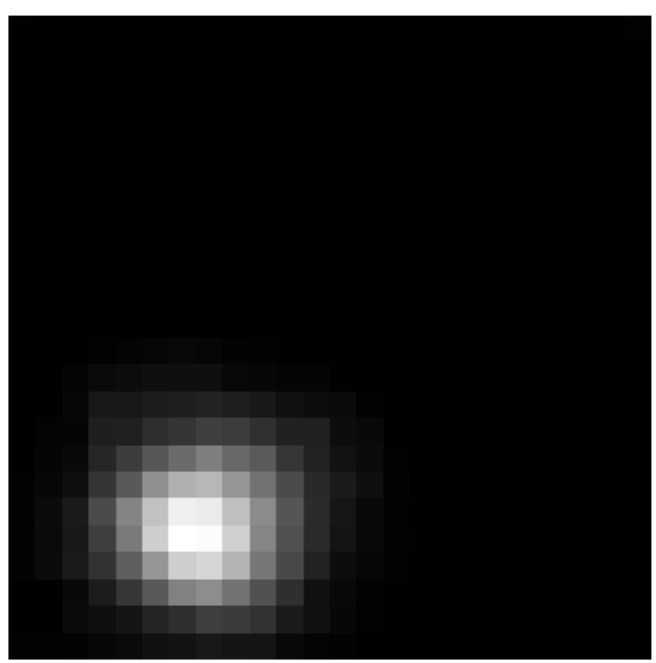
**(a)** Batch from original synthetic dataset

**(b)** Batch from dataset generated by VAE

# Single model



**(a)** Distribution of original synthetic dataset



**(b)** Distribution of dataset generated by VAE

# Whole chain

**(a)** Original dataset of the chain

**(b)** Dataset 1 of the chain

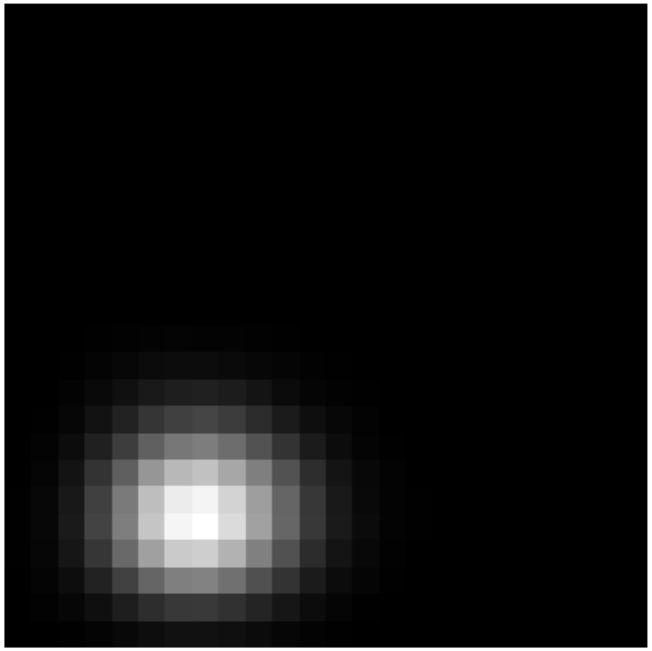
**(c)** Dataset 2 of the chain

**(d)** Dataset 3 of the chain

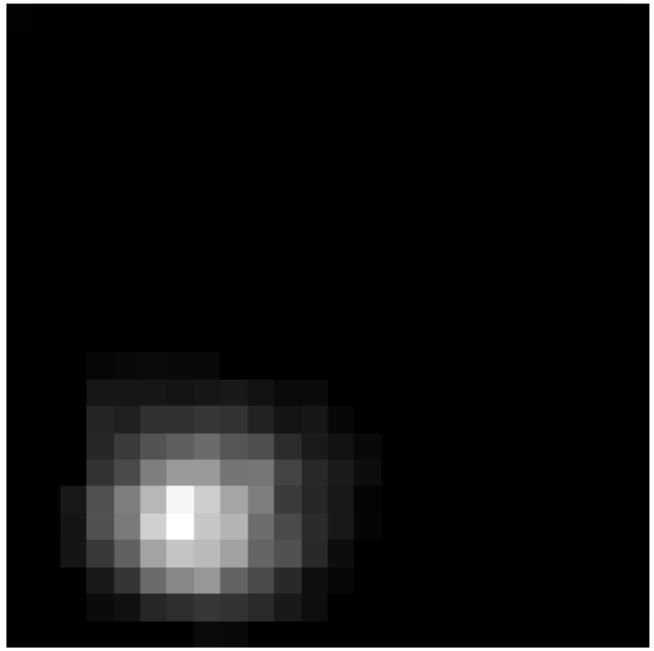
**(e)** Dataset 4 of the chain

**(f)** Final dataset of the chain

# Whole chain

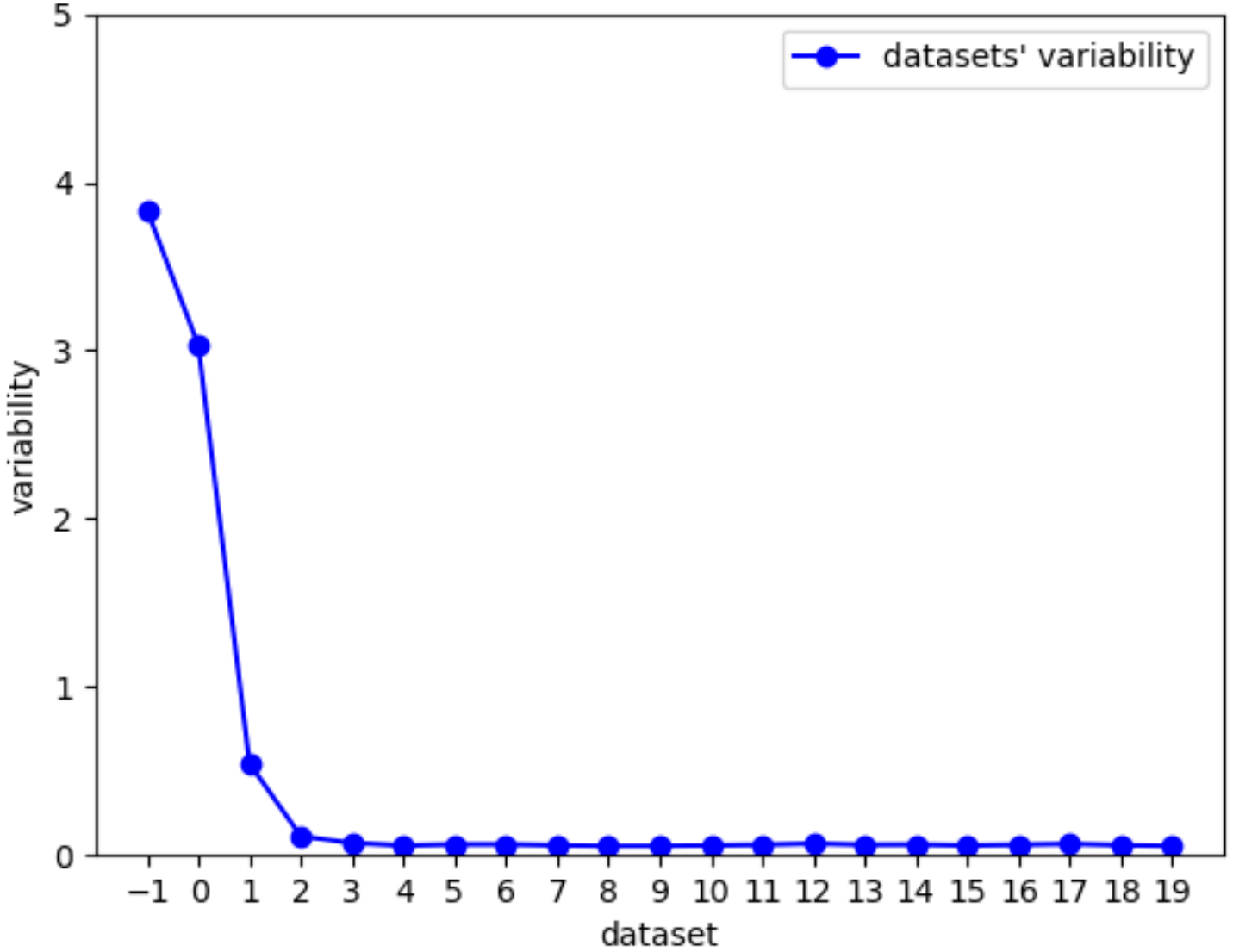


**(a)** Distribution of original synthetic dataset



**(b)** Distribution of dataset generated by last model in chain

# Whole chain


datasets' variability
variability
dataset
0
1
2
3
4
5
−1 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19

# Observations

- Images get lighter and more spread
- No evident bias is introduced in the data distribution (the data distribution is well "captured")
- **Variability is lost**

# How can we fix this?

# Possible causes

# Possible causes

- **Regularization term**: the distribution in the latent space is forced to be close to a standard normal

# Possible causes

- **Regularization term**: the distribution in the latent space is forced to be close to a standard normal
- **Dimensionality reduction**: less fundamental features are lost in latent space representation

# Possible causes

- **Regularization term**: the distribution in the latent space is forced to be close to a standard normal
- **Dimensionality reduction**: less fundamental features are lost in latent space representation
- **Noisy reconstruction**: noise causes images to be more and more spread, may leading to more and more similar reconstructions

# Possible causes

- **Regularization term**: the distribution in the latent space is forced to be close to a standard normal
- **Dimensionality reduction**: less fundamental features are lost in latent space representation
- **Noisy reconstruction**: noise causes images to be more and more spread, may leading to more and more similar reconstructions
- **Autoencoders' symmetry**: using mirror architectures for encoders and decoders may lead to unpredicted systematic patterns and behaviour

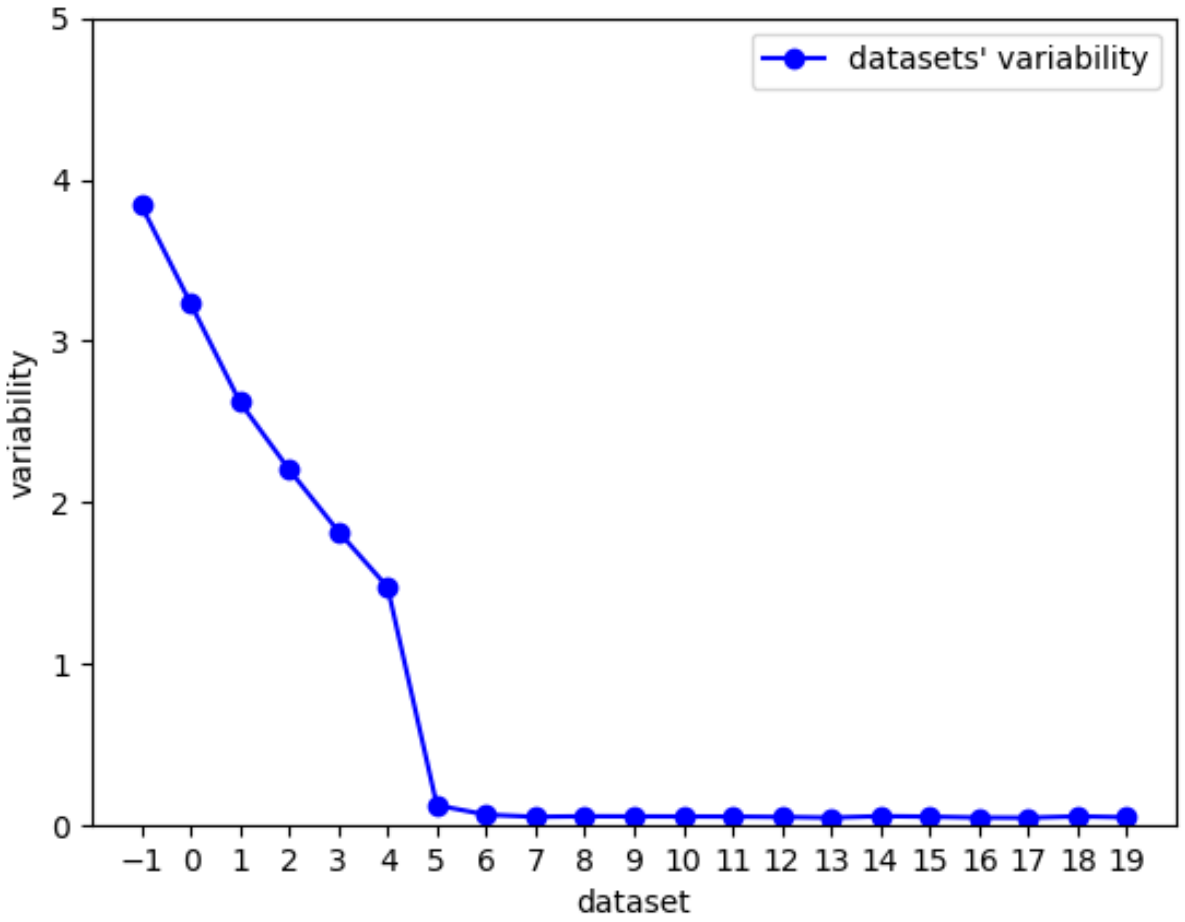
# Possible causes

- **Regularization term**: the distribution in the latent space is forced to be close to a standard normal
- **Dimensionality reduction**: less fundamental features are lost in latent space representation
- **Noisy reconstruction**: noise causes images to be more and more spread, may leading to more and more similar reconstructions
- **Autoencoders' symmetry**: using mirror architectures for encoders and decoders may lead to unpredicted systematic patterns and behaviour
- **All (or some) of them combined**

# Regularization constant tuning

$$\text{LOSS}(\theta) = MSE_\theta\left(x, x_{recon}\right) + \lambda KL\left[q_\theta\left(z|x\right)||p\left(z\right)\right]$$

# Regularization constant tuning - results




Variability over models of the chain using $\lambda = 0.3$

# Regularization constant tuning - results

**(a)** Batch from dataset generated by last model of the chain with $\lambda = 1$ (**untuned model**)

**(b)** Batch from dataset generated by last model of the chain with $\lambda = 0.3$ (**tuned model**)

# Regularization constant tuning - conclusion

**Pros:**

- helps maintaining variability longer
- easy to implement
- easy to tune ("linear" behaviour)

**Cons:**

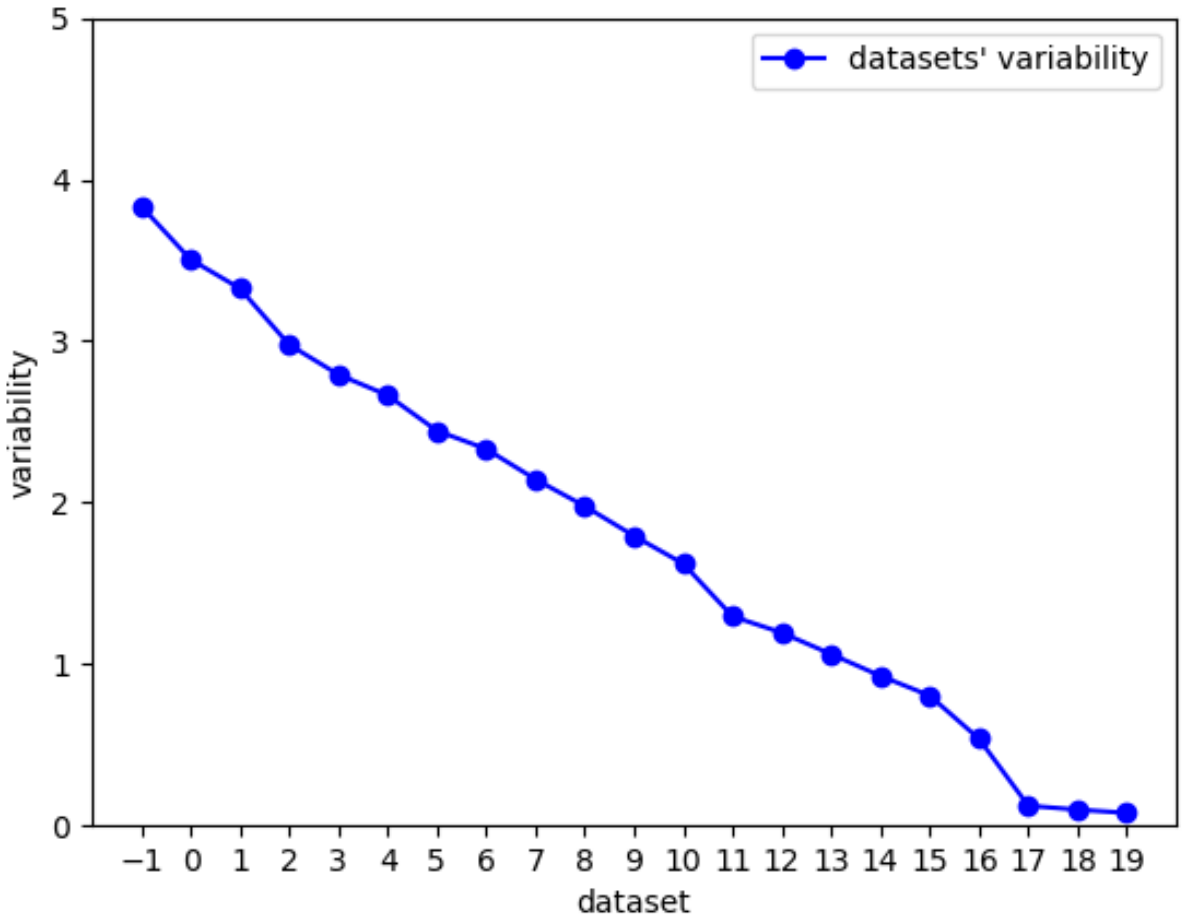
- less precise outputs (latent space distribution less close to a standard normal)
- eventually leads to zero variability

# Variability loss term

$$\mathrm{LOSS}_{batch}(\theta) = \sum_i MSE_\theta\left(x_i, x_i^{recon}\right) + \sum_i KL\left[q_\theta\left(z_i|x_i\right)||p\left(z_i\right)\right]$$

$$+ \mathrm{K}\left|\sum_{i,j} MSE\left(x_i, x_j\right) - \sum_{i,j} MSE_\theta\left(x_i^{recon}, x_j^{recon}\right)\right|$$

# Variability loss term - results

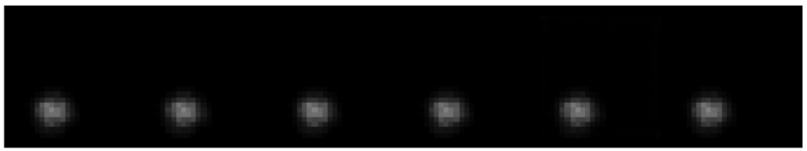



Dataset variability over models of the chain using $K = 10$

# Variability loss term - results

**(a)** Batch from dataset generated by last model of the chain with $\lambda = 1$ and $K = 0$ (**no tuning**)

**(b)** Batch from dataset generated by last model of the chain with $\lambda = 0.3$ and $K = 0$ (**regularization tuning**)



**(c)** Batch from dataset generated by last model of the chain with $\lambda = 1$ and $K = 10$ (**variability loss tuning**)

# Variability loss term - conclusion

**Pros:**

- helps maintaining variability longer
- easy to tune
- **better variability-precision trade-off than regularization term tuning**
- **less light images**

**Cons:**

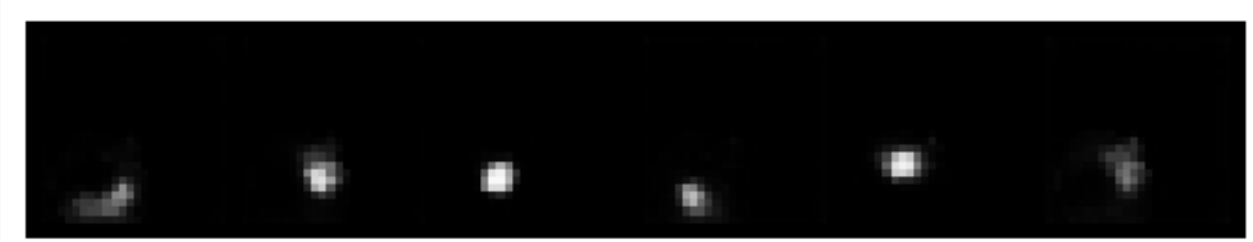
- still, eventually leads to zero variability

# Denoising

**(a)** Non-denoised data

**(b)** Denoised data ($thres = 50\%$)

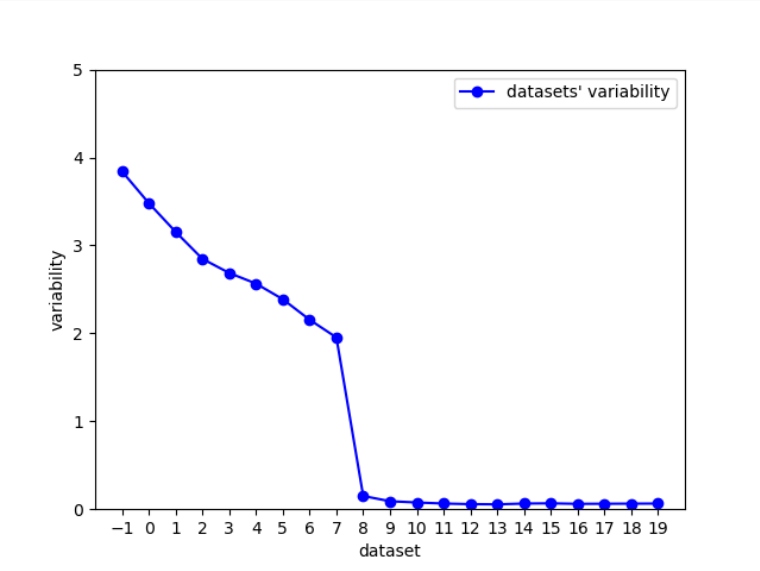
# Improving non-optimal parameters with denoising



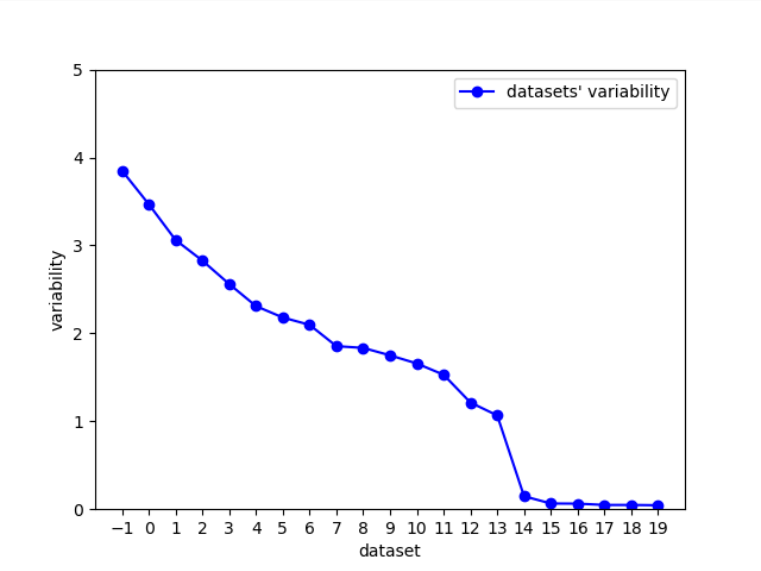
**(a)** Batch from fifth dataset without denoising ($\lambda = 0.7$ and $K = 10$)

**(b)** Batch from fifth dataset with denoising ($\lambda = 0.7$ and $K = 10$, thres=5%)

# Improving non-optimal parameters with denoising

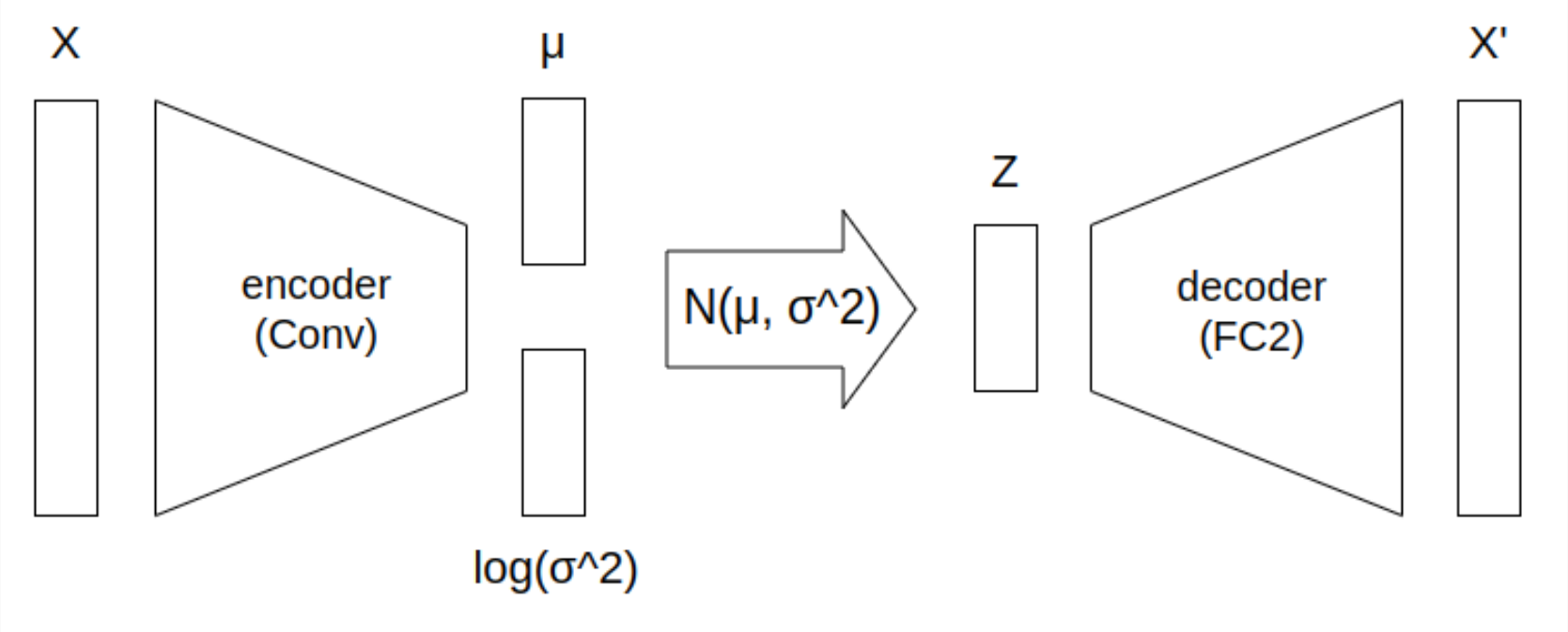



**(a)** Dataset variability without denoising ($\lambda = 0.7$, $K = 10$)

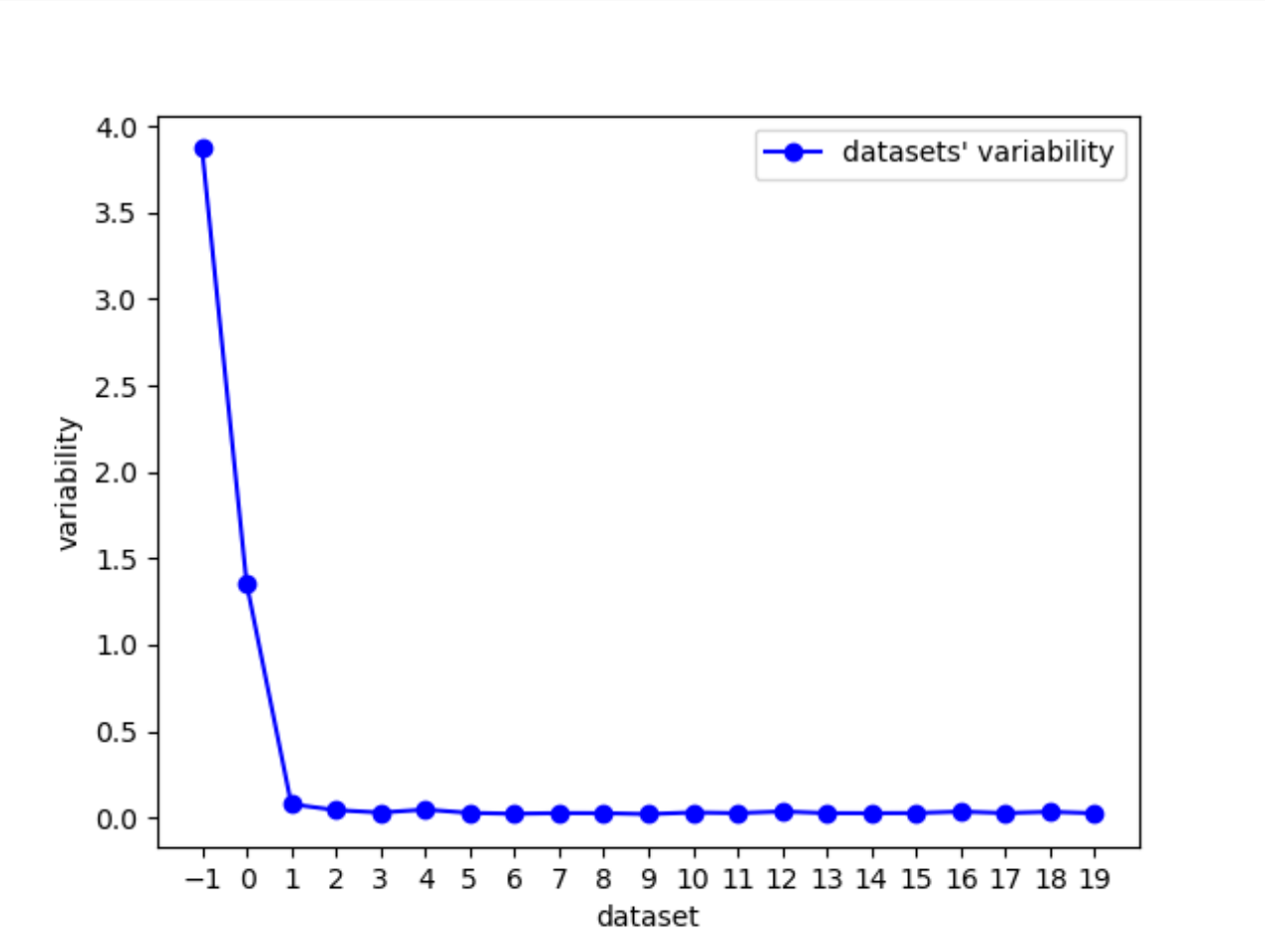



**(b)** Dataset variability with denoising ($\lambda = 0.7$, $K = 10$, thres=5%)

# Asymmetric architecture

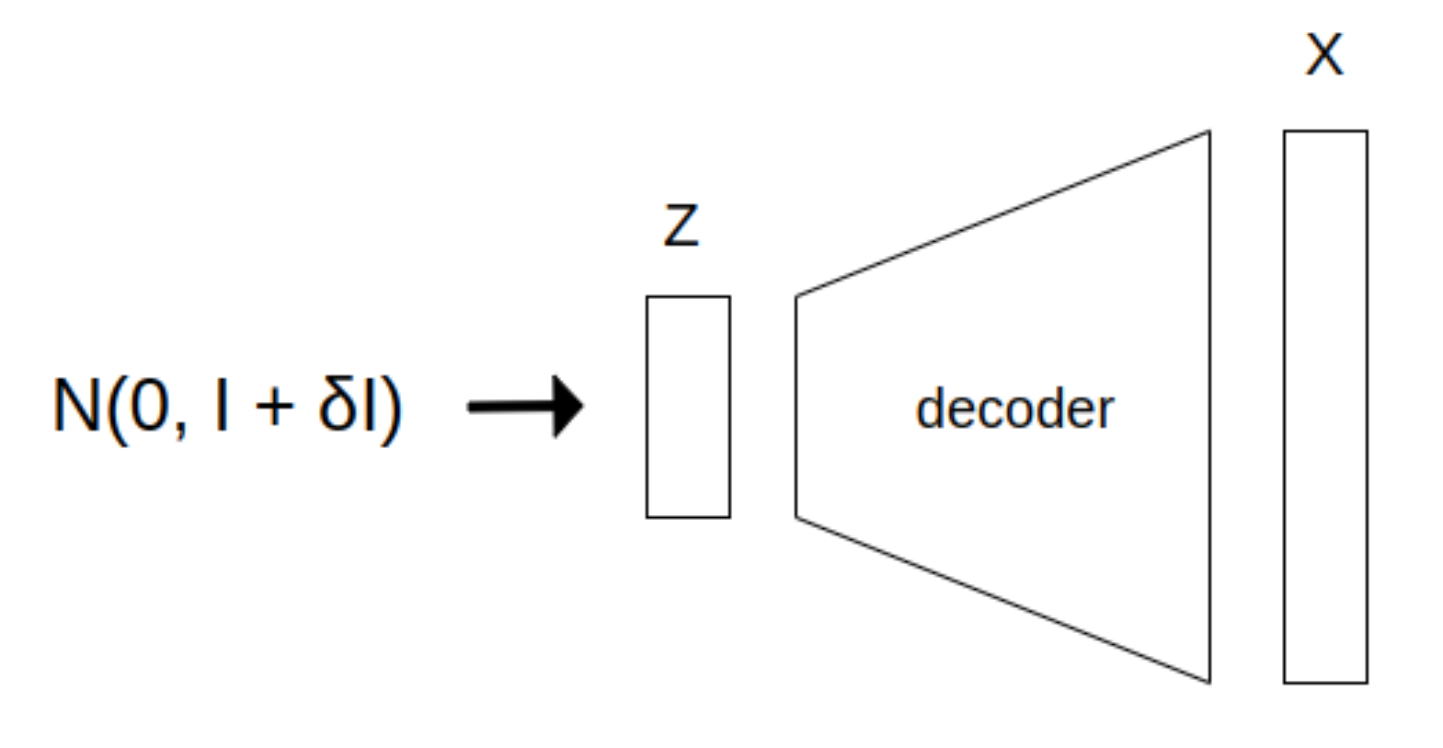


# Asymmetric architecture - results

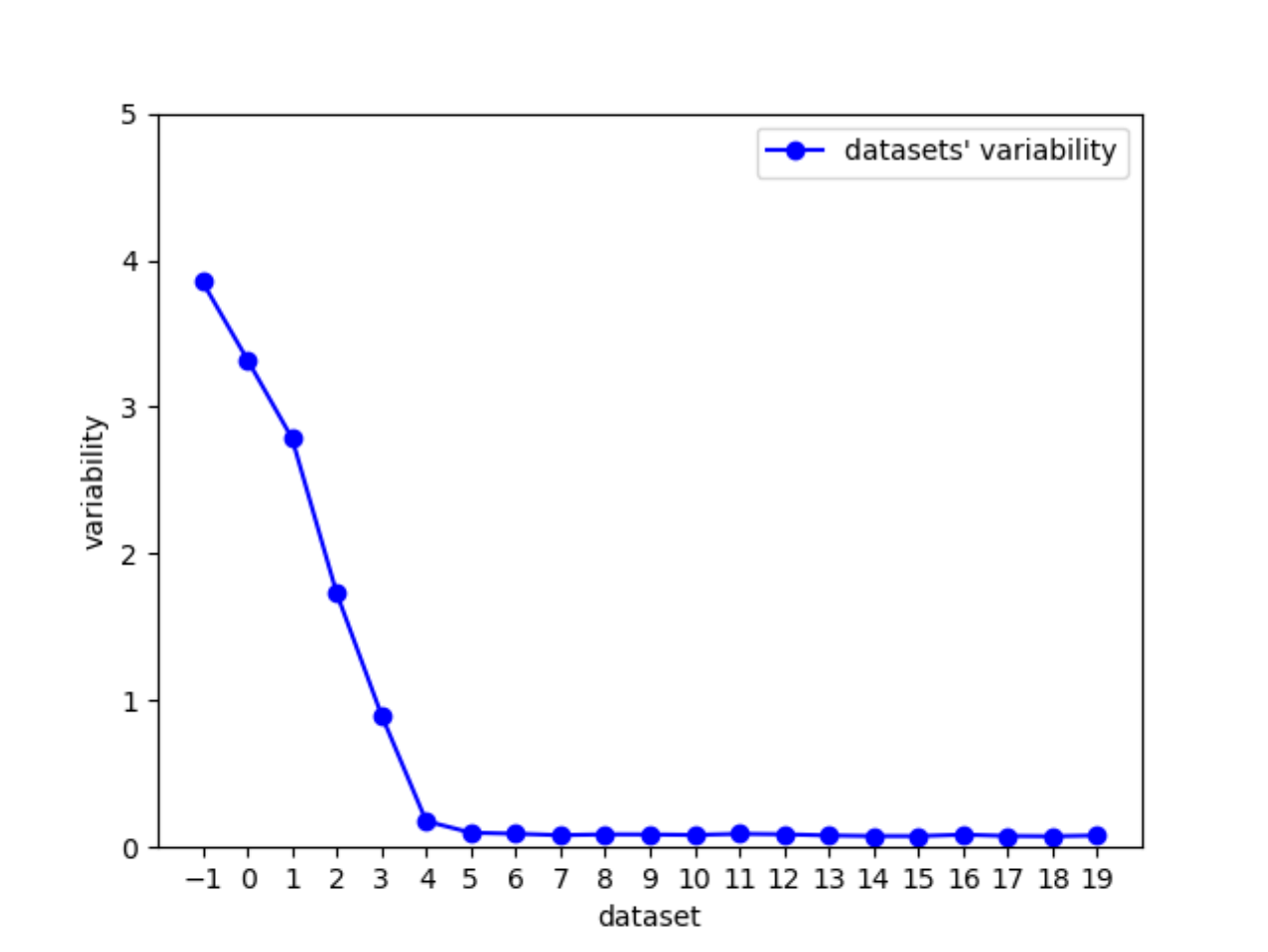



Dataset variability over models of the chain with asymmetric architecture

# Wider distribution in generative mode

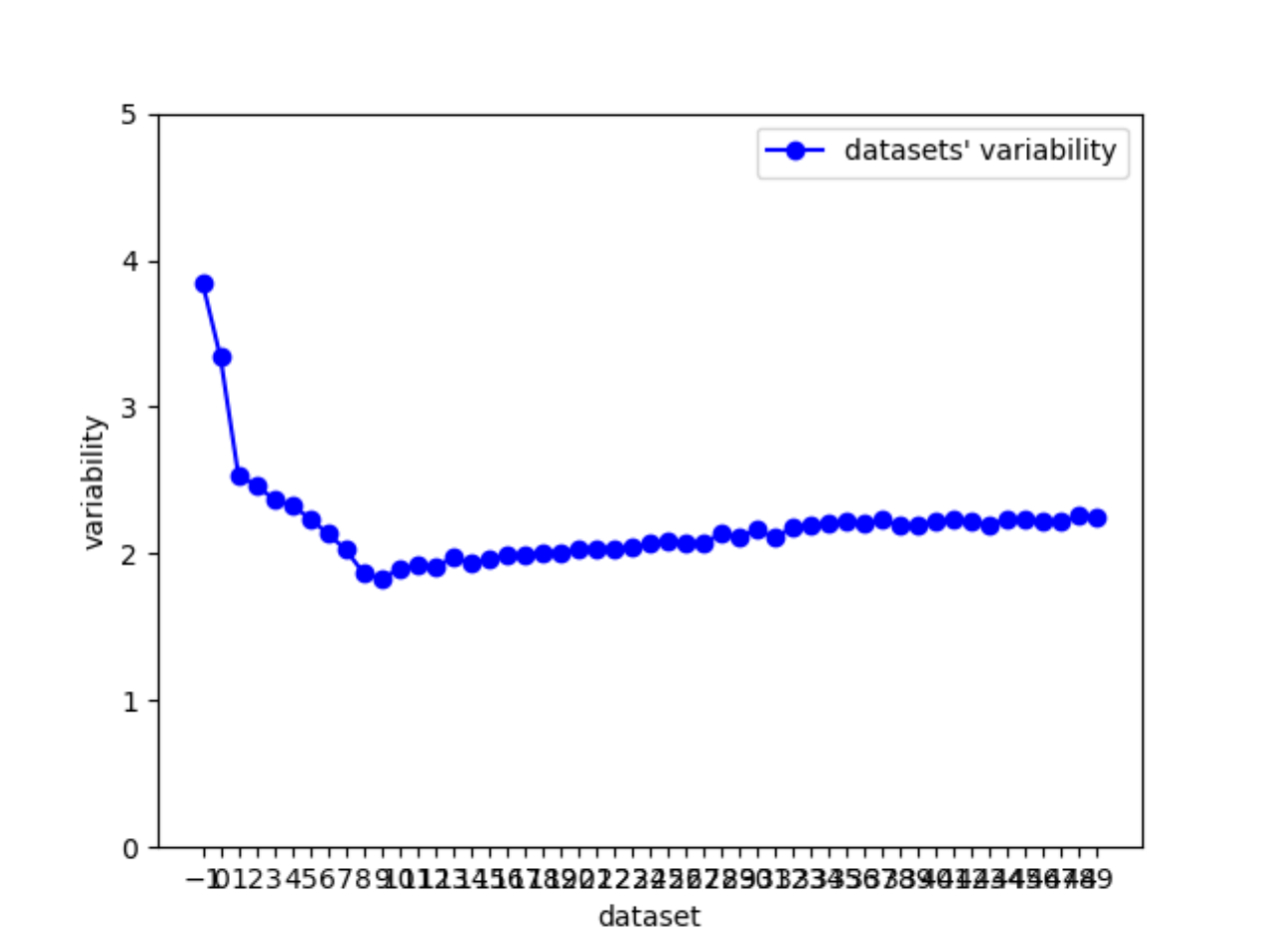


# Wider distribution in generative mode - small increment



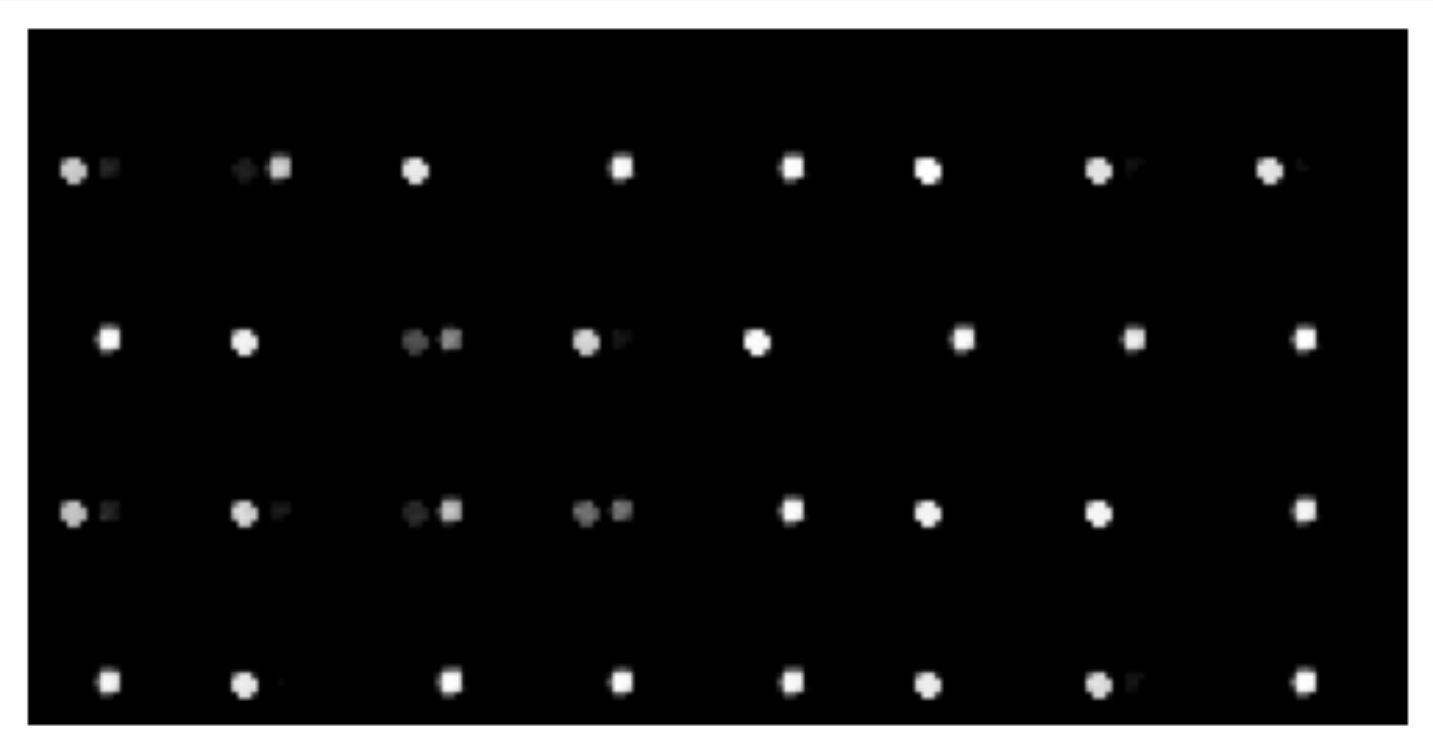

Dataset variability over models of the chain with $\delta = 0.3$, using denoising ($thres = 5\%$)

# Wider distribution in generative mode - large increment




Dataset variability over models of the chain with $\delta = 0.7$, using denoising ($thres = 5\%$)

# Wider distribution in generative mode - large increment



Batch from dataset generated by last model of the chain with $\delta = 0.7$, using denoising ($thres = 5\%$)

# Wider distribution in generative mode - conclusion

**Pros:**

- helps maintaining variability longer
- **for some values of $\delta$, keeps variability different from zero indefinitely**

**Cons:**

- **"classes formation"**
- may change distribution slightly
- very hard to tune (strongly non-linear behaviour)
- **unpredictable outcome on more complex datasets**
- may need denoising to work

# Can we really fix this problem?

# Can we really fix this problem?

**Probably not!** Due to information loss in latent space representation.

# Can we really fix this problem?

**Probably not!** Due to information loss in latent space representation.

We can only either mitigate this effect or introduce "artificial" variability.

# More general issue

This is just a very simple example of a much larger and fundamental problem:

**AI models trained on AI-generated data.**

Thank you!