Studying data variability in variational autoencoders using a chain model

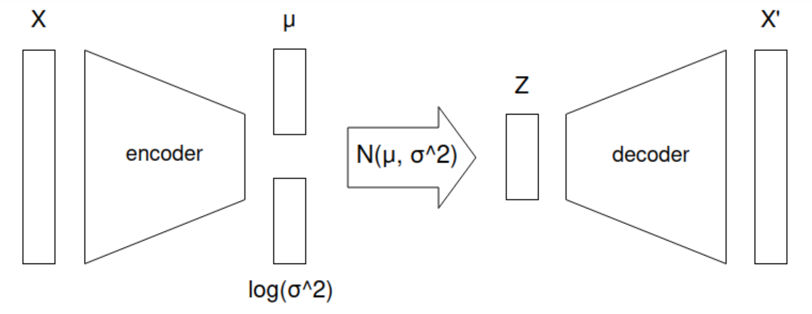
Tommaso Tarchi

January 29, 2024

University of Trieste

Introduction to VAEs

General architecture

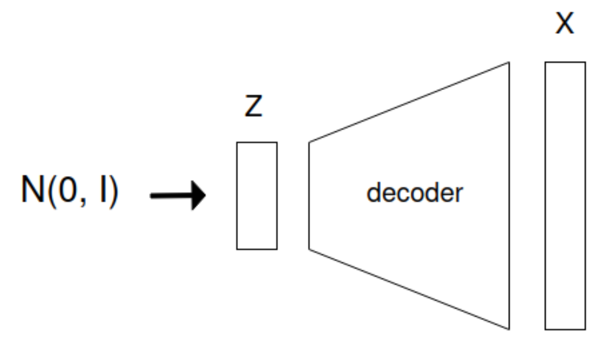


Loss function

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

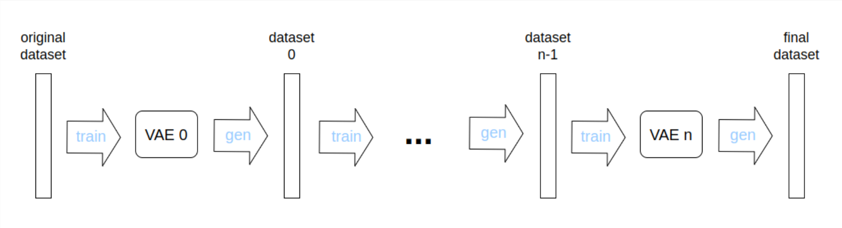
$$\text{with} \quad \mathrm{p}(z) = N\left(z|0, I\right)$$

Generative mode

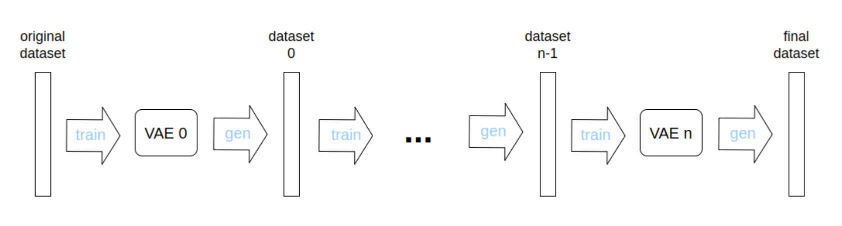


Chain model and initial dataset

VAEs chain

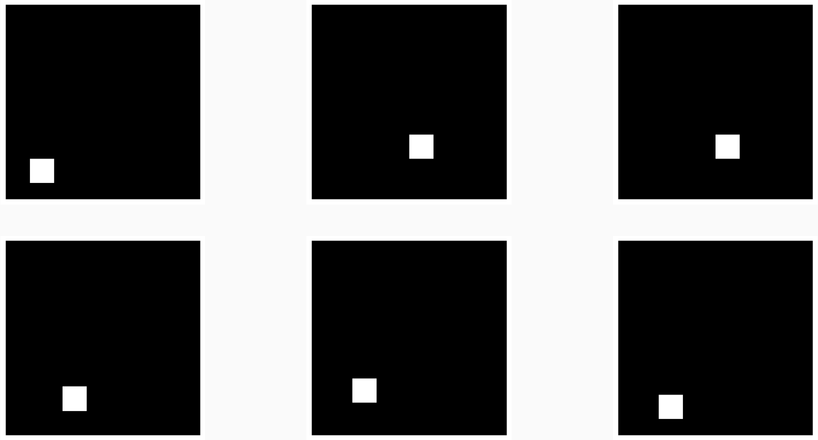

original
dataset
dataset
0
dataset
n-1
final
dataset
train
VAE 0
gen
train
...
gen
train
VAE n
gen

VAEs chain



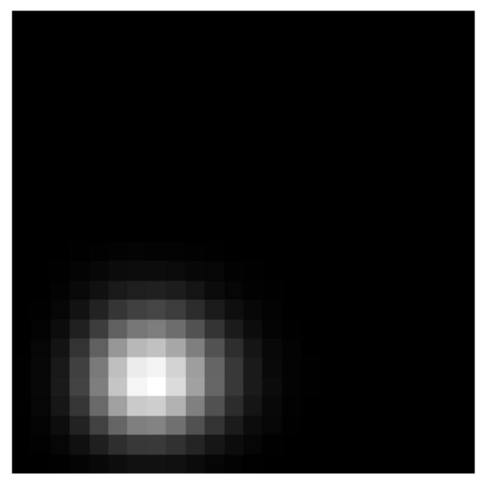
Possible systematic effects introduced by VAEs will be amplified.

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)

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)

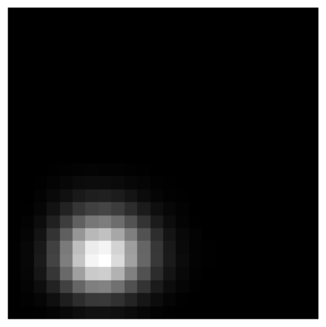
How to evaluate results

- **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)

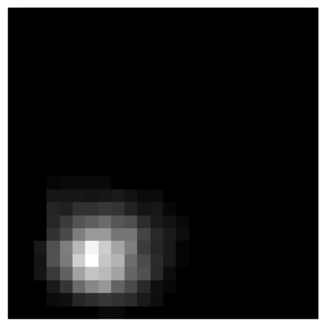
This method is NOT perfect!

Preliminary results

Distribution difference



(a) Distribution of original synthetic dataset



(b) Distribution of dataset generated by last model in chain (20 models)

Visual inspection

(a) Original dataset of the chain

(b) Dataset 1 of the chain

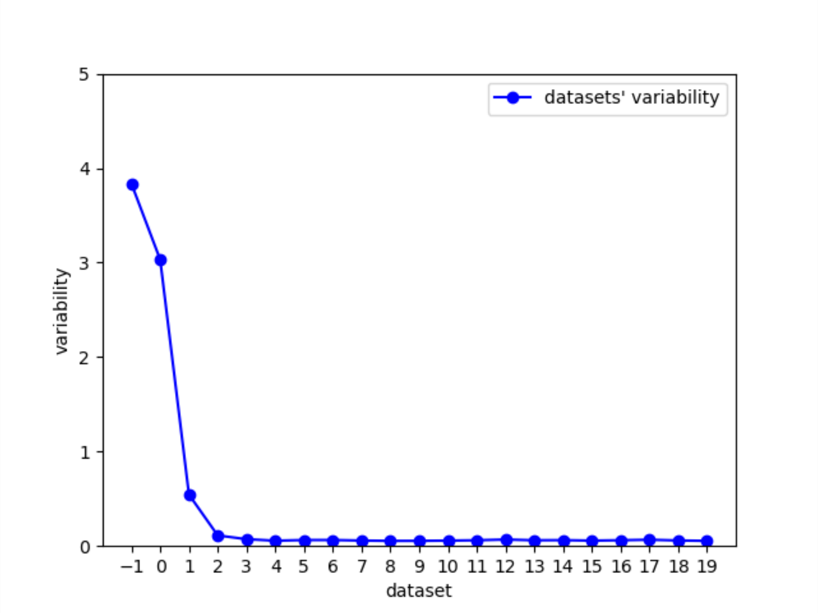
(c) Dataset 2 of the chain

(d) Dataset 3 of the chain

(e) Dataset 4 of the chain

(f) Final dataset of the chain (20-th)

Variability

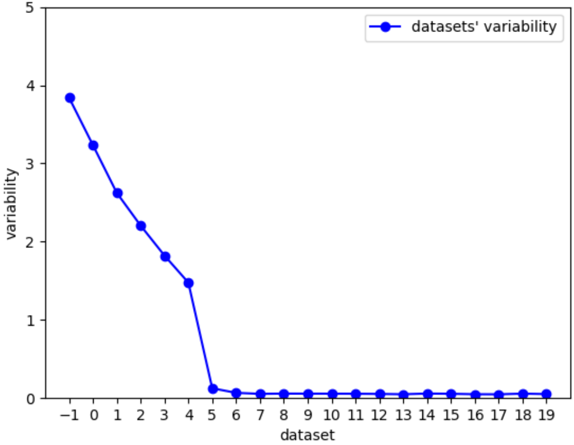


How can we fix this?

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:

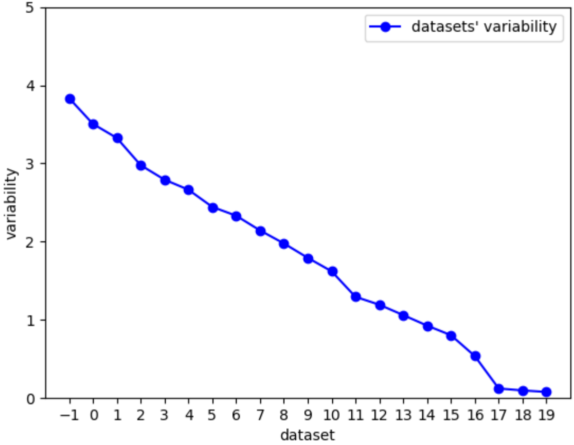
- **trade-off between variability and quality of data**
- eventually leads to zero variability

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**
- **higher-quality output data**

Cons:

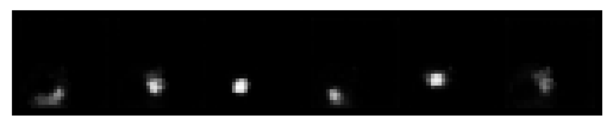
- still, eventually leads to zero variability

Denoising

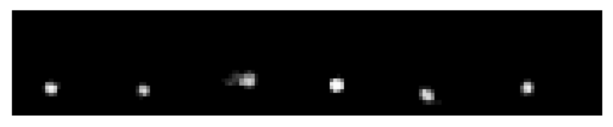
(a) Non-denoised data

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

Improving non-optimal parameters with denoising

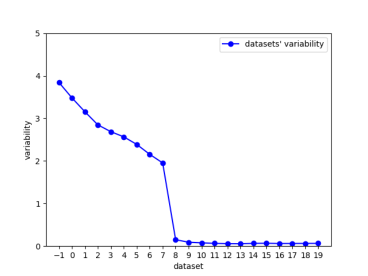


(a) Batch from fifth dataset without denoising ($\lambda = 0.7$ and $K = 10$)

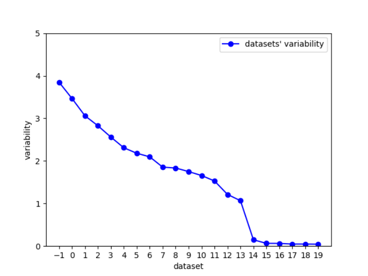


(b) Batch from fifth dataset with denoising ($\lambda = 0.7$ and $K = 10$, thres=5%)

Improving non-optimal parameters with denoising

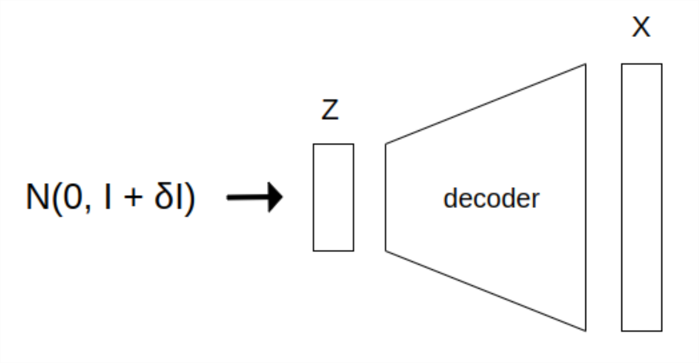


(a) Dataset variability without denoising ($\lambda = 0.7,\ K = 10$)

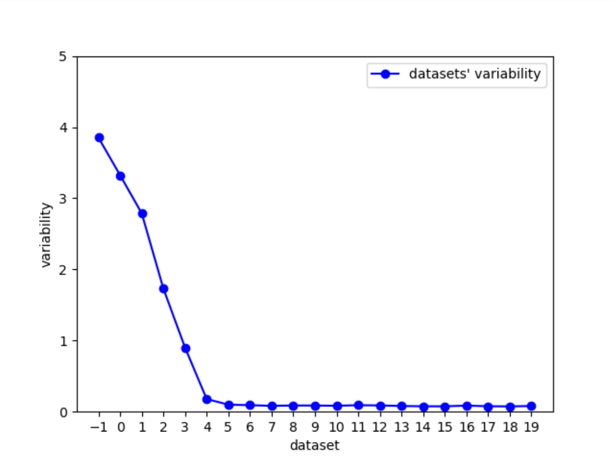


(b) Dataset variability with denoising ($\lambda = 0.7,\ K = 10$, thres=5%)

Wider distribution in generative mode

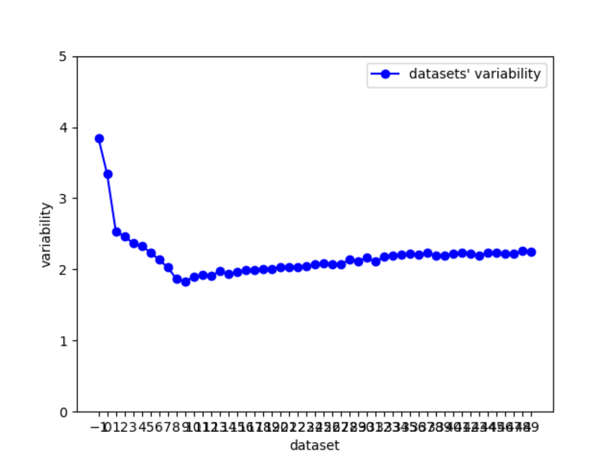


Wider distribution in generative mode - small increment



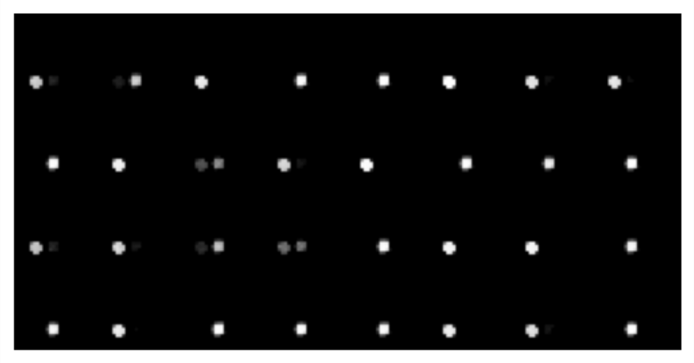
Dataset variability over models of the chain with $\delta = 0.3$, using denoising ($thres = 5\%$)

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 δ, 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.

References

- tutorial: https://medium.com/@sofeikov/implementing-variational-autoencoders-from-scratch-533782d8eb95
- article: https://mbernste.github.io/posts/vae/
- article: https://aimagazine.com/articles/research-finds-chatgpt-headed-for-model-collapse

Thank you!