

## Background and Context

Variational Autoencoders (VAEs) are widely used for generative modeling, but their basic design lacks supervised conditional generation capabilities.

A common approach adds a projection of one-hot labels  $OHE(y)$  via an MLP to the latent variable  $z$ , producing  $z + MLP(OHE(y))$ . While effective in some cases, this raises concerns about fully utilizing label information and ensuring that similar latents with slight label differences generate "close" outputs.

## Proposed solution

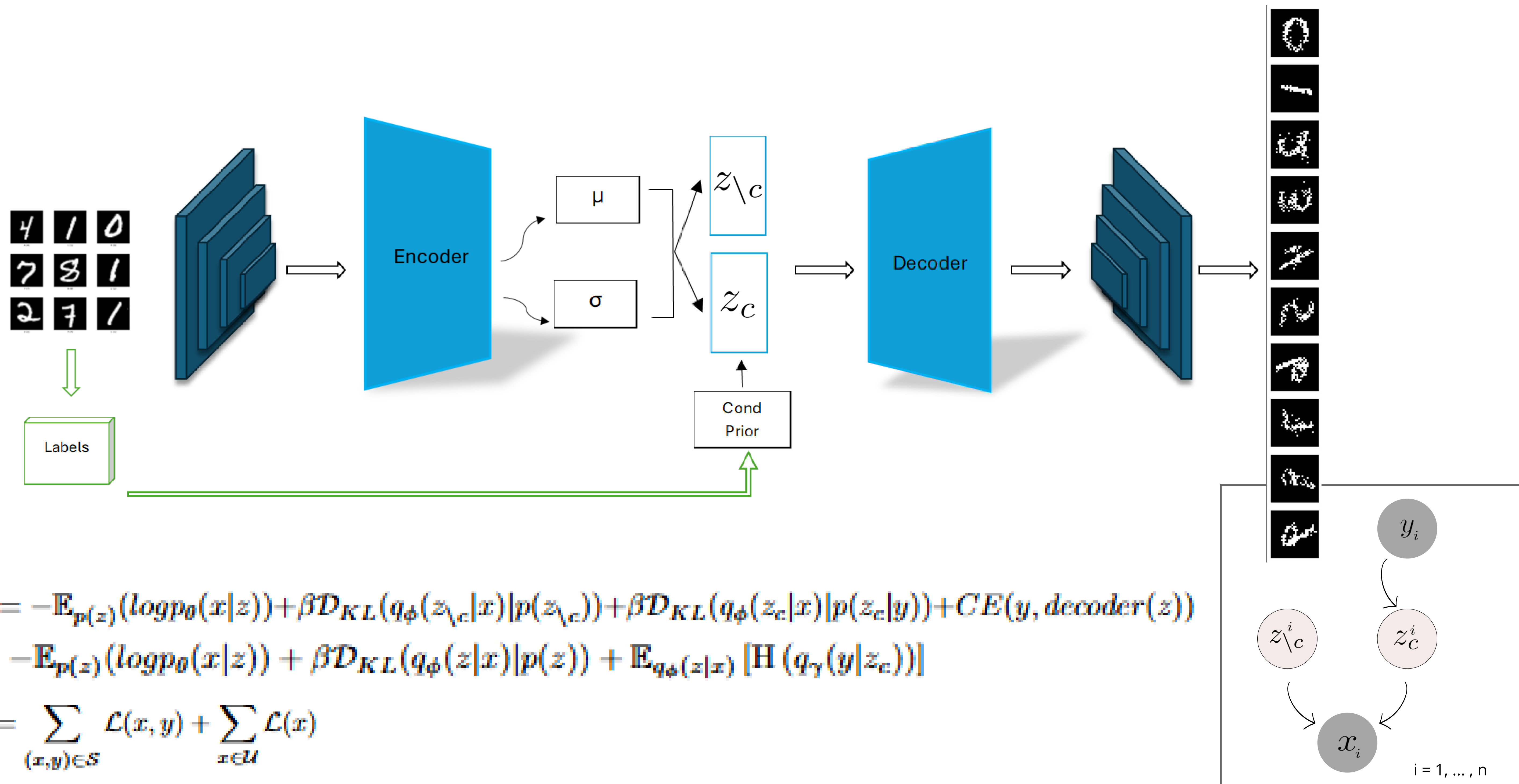
$$z = \{z_c, z_{\setminus c}\}$$

$z_c$  characteristical latent

$p_\psi(z_c|y)$  characteristic latent conditional distribution

$z_{\setminus c}$  style latent

## A Characteristic Capturing Variational AutoEncoders (CCVAEs)



## Our Personal Experiments

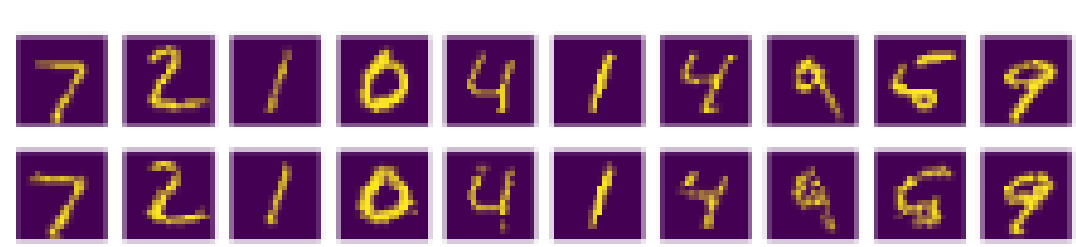


Figure 1: Reconstructed images  $\beta = 0.05$



Figure 2: Reconstructed images  $\beta = 0.4$

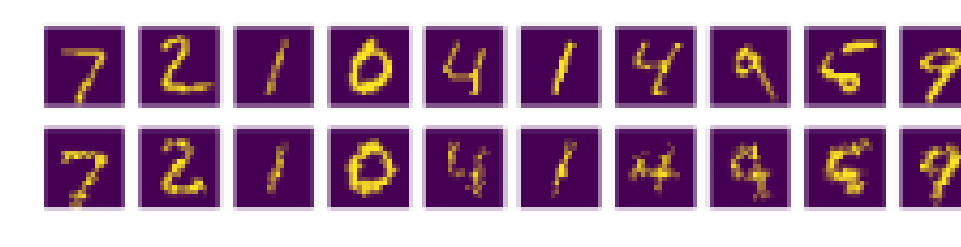


Figure 9: Reconstructed images latent dim = 16

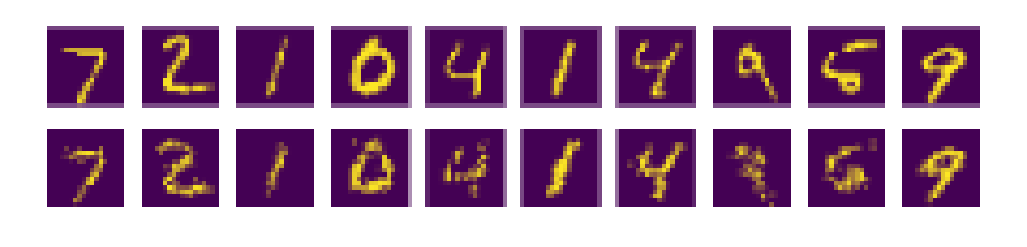


Figure 10: Reconstructed images latent dim = 128

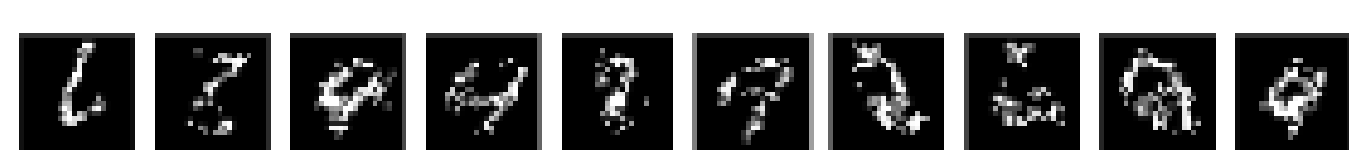


Figure 3: Conditionally generated images  $\beta = 0.001$



Figure 4: Conditionally generated images  $\beta = 0.05$

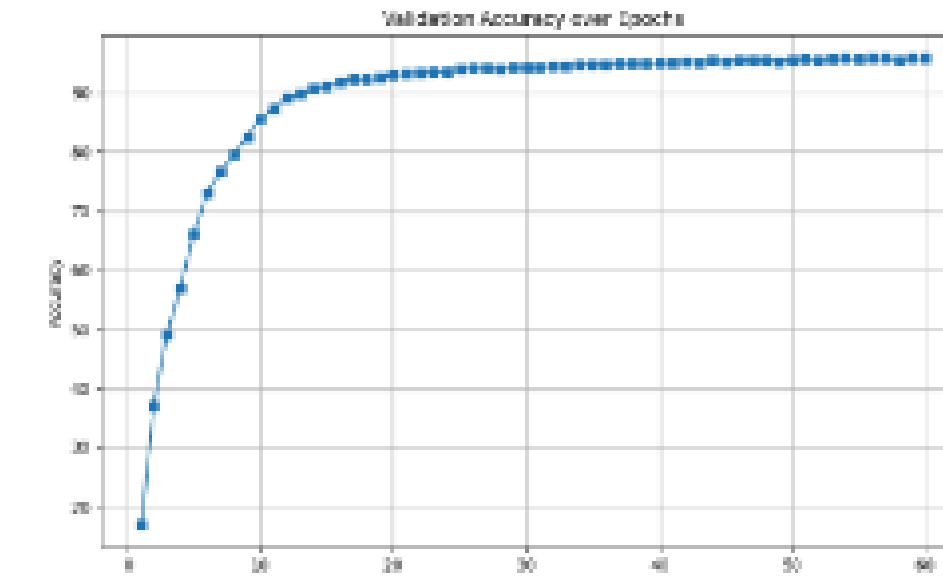


Figure 11: Validation accuracy  $\beta = 0.05$

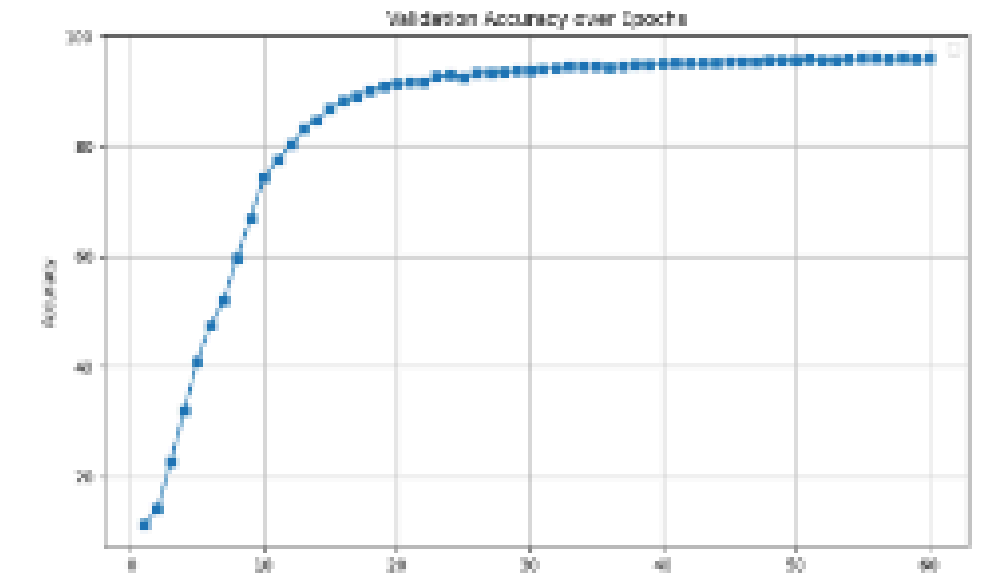


Figure 12: Validation accuracy  $\beta = 0.4$

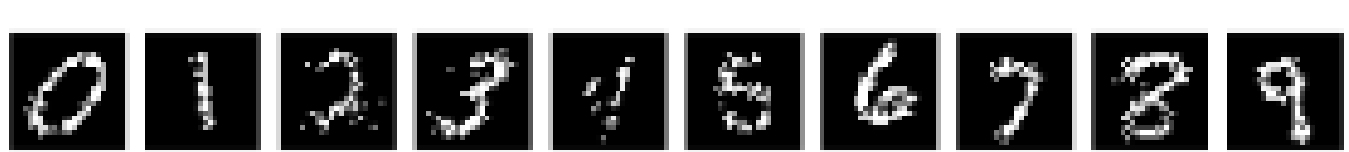


Figure 5: Conditionally generated images  $\beta = 0.2$

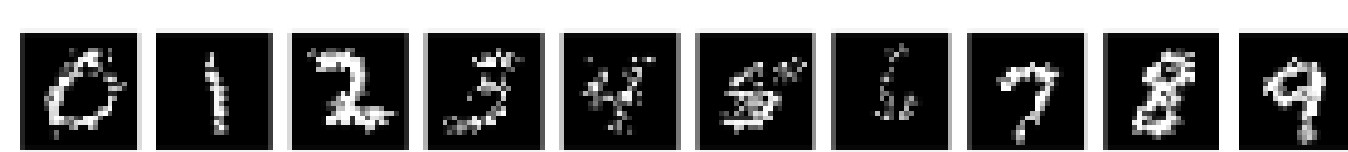


Figure 6: Conditionally generated images  $\beta = 0.4$

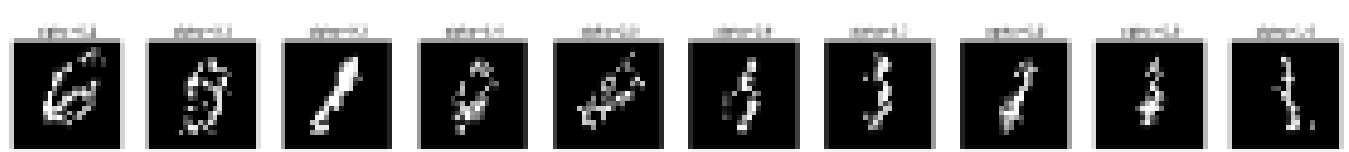


Figure 7: Interpolated images  $\beta = 0.05$

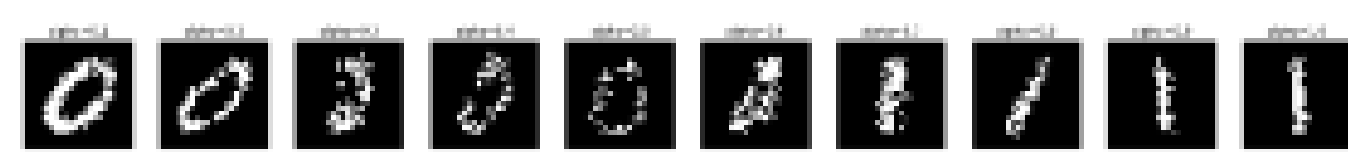


Figure 8: Interpolated images  $\beta = 0.4$

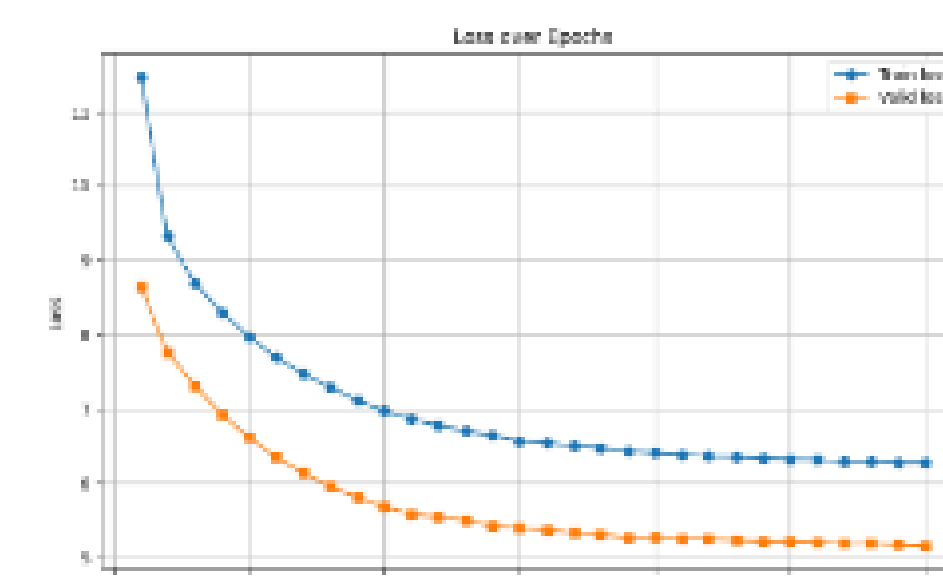


Figure 13: Train and Validation losses latent dim = 16

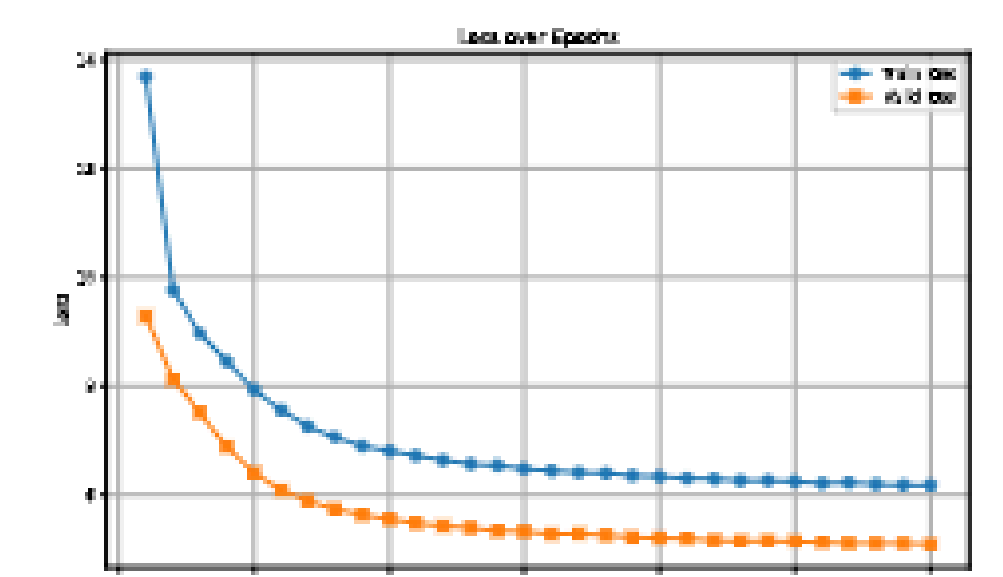


Figure 14: Train and Validation losses latent dim = 128