Anomaly Detection by ADGM / LVAE

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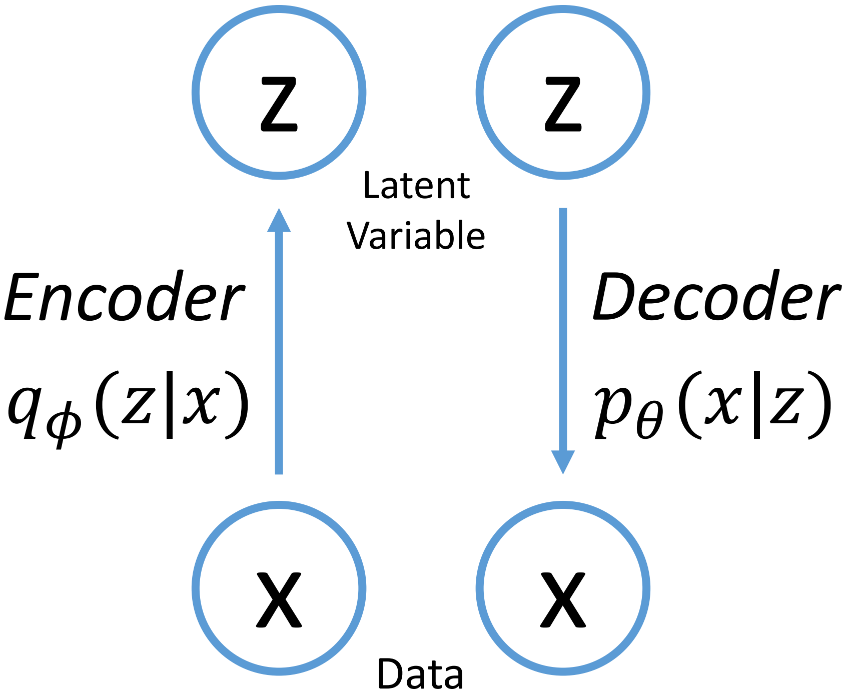
Introduction

- Anomaly detection
- Data
  - NAB Dataset (Artificial)
  - (Other data are not open to this presentation)
- Model
  - Auxiliary VAE (ADGM)
  - Ladder VAE
  - VAE (previous work)

Variational Auto-Encoder (VAE)

- We assume that the data x are generated from the latent variables z.
- We use neural network as encoder and decoder.



VAE

- We use lower bound of $\log p_\theta(x)$ as loss function.

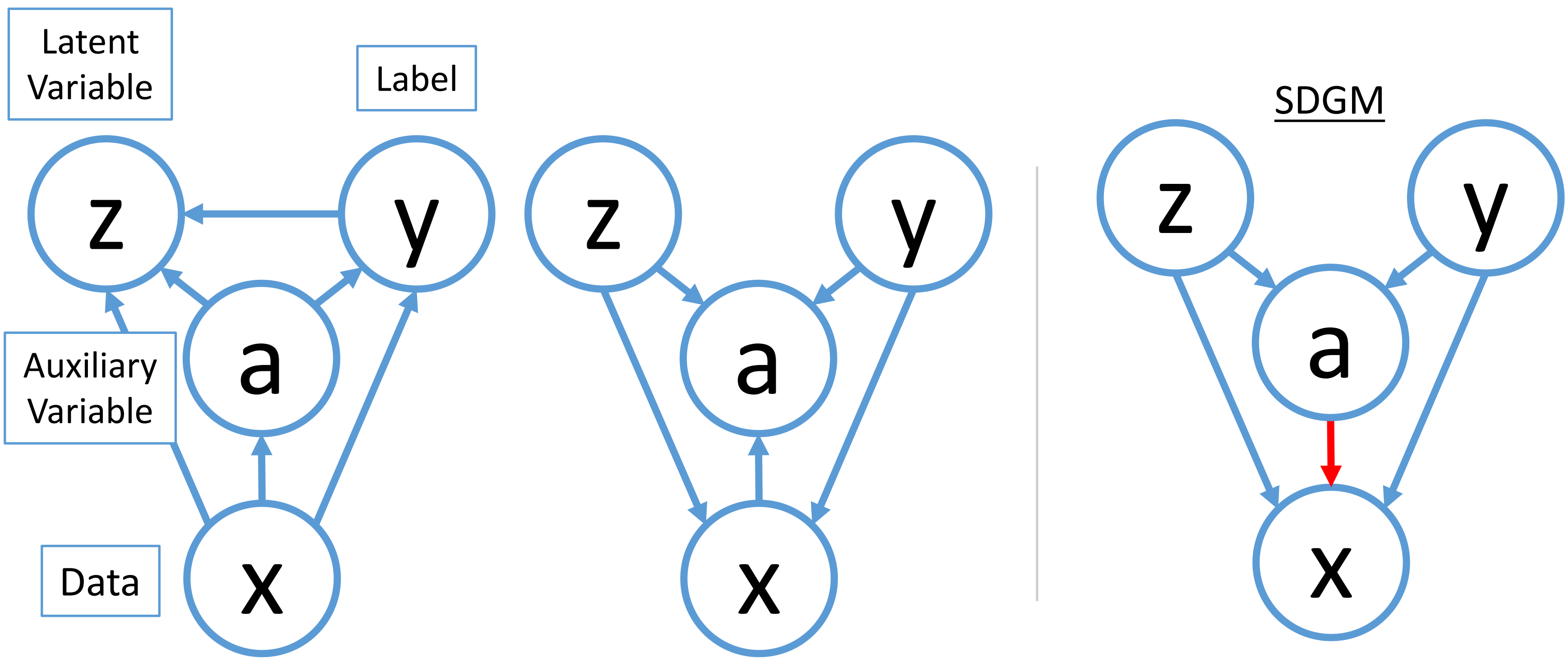
$$\log p_\theta(x) \geq E_{q_\phi(z|x)}\left[\log \frac{p_\theta(x,z)}{q_\phi(z|x)}\right]$$

$$p_\theta(x,z) = p_\theta(x|z)p_\theta(z)$$

- $p_\theta(z)$: Standard normal distribution
- In training, z is chosen from $q_\phi(z|x)$.

ADGM

- Semi-supervised Learning
- Detect label y and reconstruct data x.
- Auxiliary variable increase the flexibility of the model.



Objective function of ADGM

- For labeled data
  - Lower bound + classification loss

$$L(x,y) = -E_{q_\phi(a,z|x,y)}\left[\log \frac{p_\theta(x,y,a,z)}{q_\phi(a,z|x,y)}\right] - \alpha E_{q_\phi(a|x)}\left[\log q_\phi\,(y|a,x)\right]$$

- For unlabeled data

$$U(x) = -E_{q_\phi(a,y,z|x)}\left[\log \frac{p_\theta(x,y,a,z)}{q_\phi(a,y,z|x)}\right]$$

- Total

$$J = \sum_{x_l,y_l} L(x_l,y_l) + \sum_{x_u} U(x_u)$$

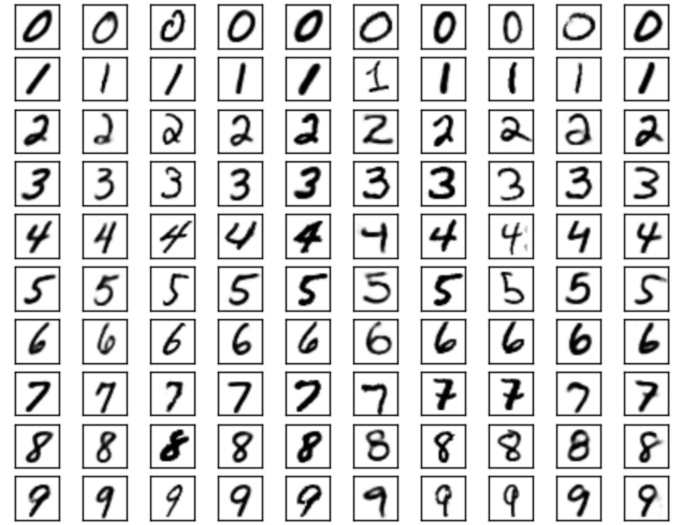
ADGM for MNIST

- Semi-supervised learning
  - 100 labeled, 60000 unlabeled
  - Test error

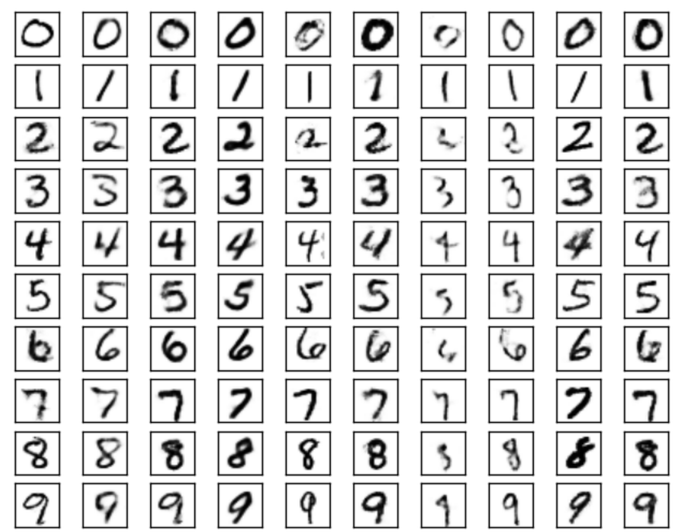
    ADGM : 0.96 %

    SDGM : 1.32%

- Generate image
  - Choosing z from Gaussian
  - Generate with each y



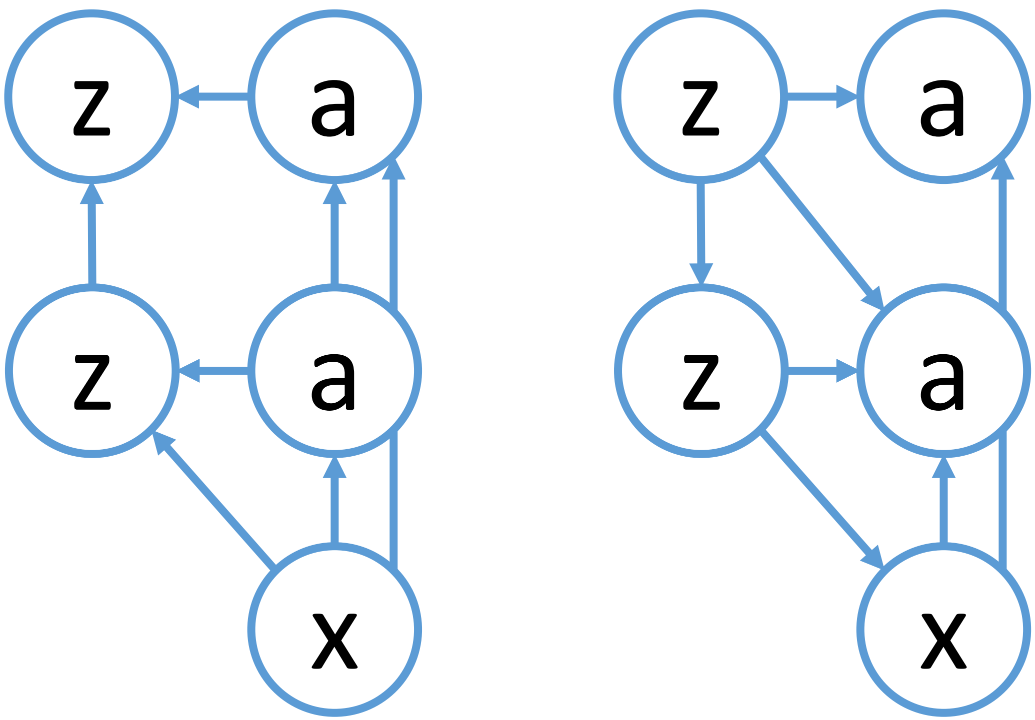
SDGM



Without auxiliary variable

Auxiliary VAE

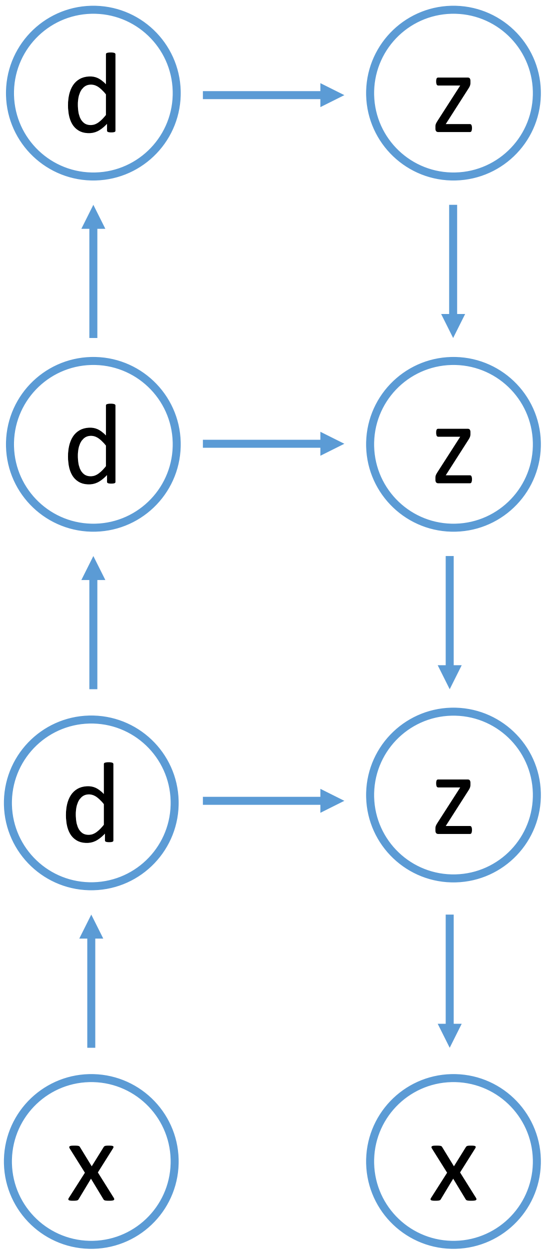
- Unsupervised Learning
- Several sampling layers (1 or 2)



Ladder VAE

- Several sampling layers (~5)
  - VAE with several sampling layers is difficult to train.

- Sharing the information between decoder and encoder.

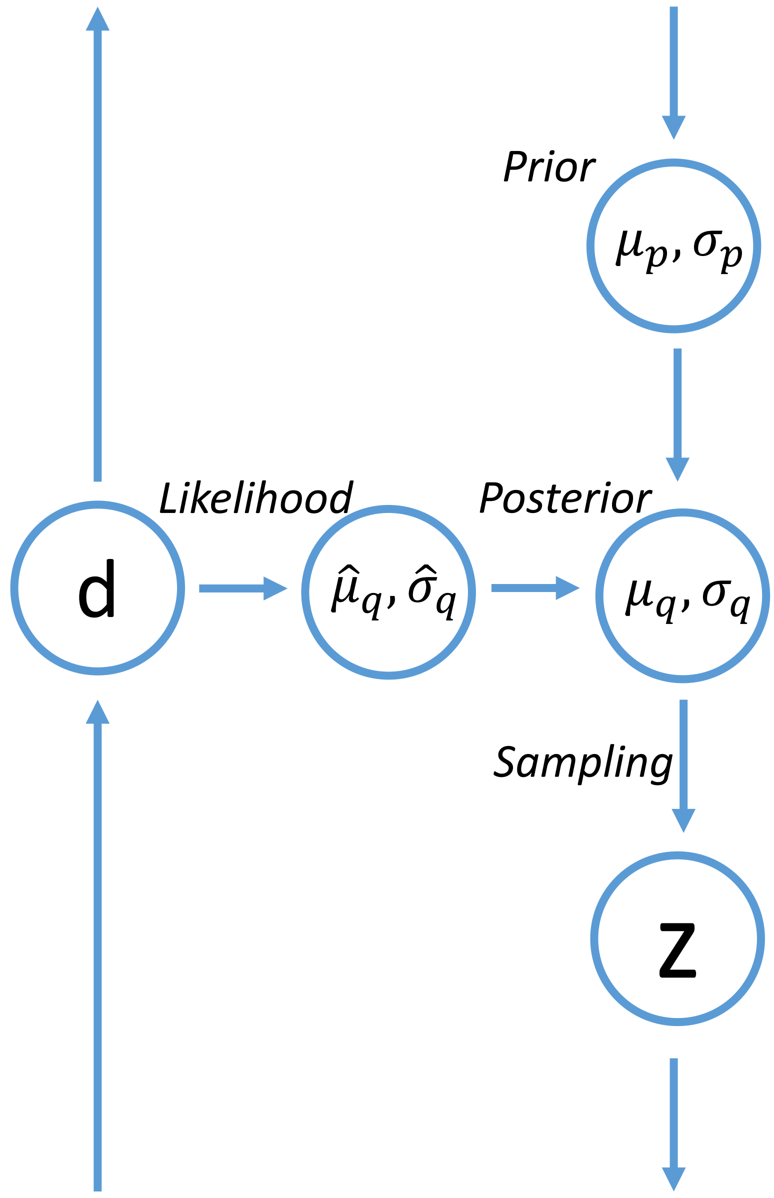


Ladder VAE

- Encoder use decoder output as prior.

$$\sigma_q^2 = \frac{1}{\hat{\sigma}_q^{-2} + \sigma_p^{-2}}$$

$$\mu_q = \frac{\hat{\mu}_q \hat{\sigma}_q^{-2} + \mu_p \sigma_p^{-2}}{\hat{\sigma}_q^{-2} + \sigma_p^{-2}}$$

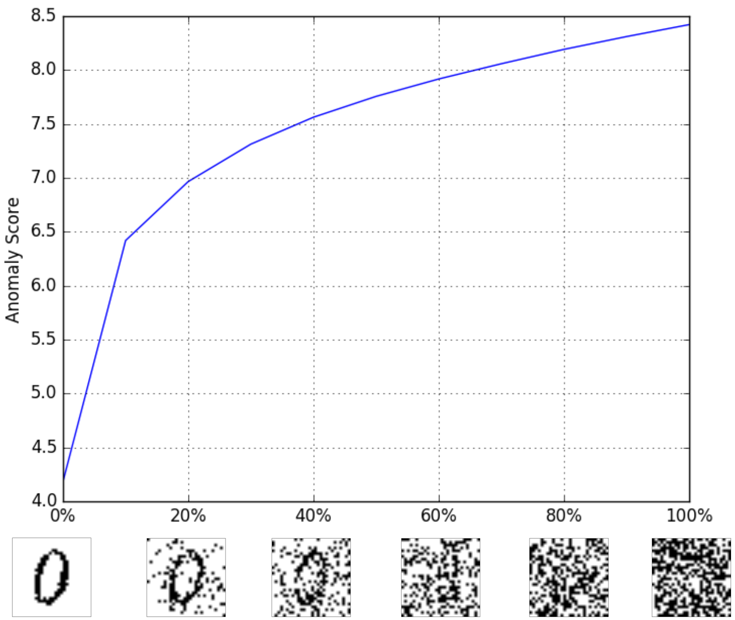


Anomaly detection

- Model is trained without anomaly data.
- Model cannot reconstruct anomaly data .

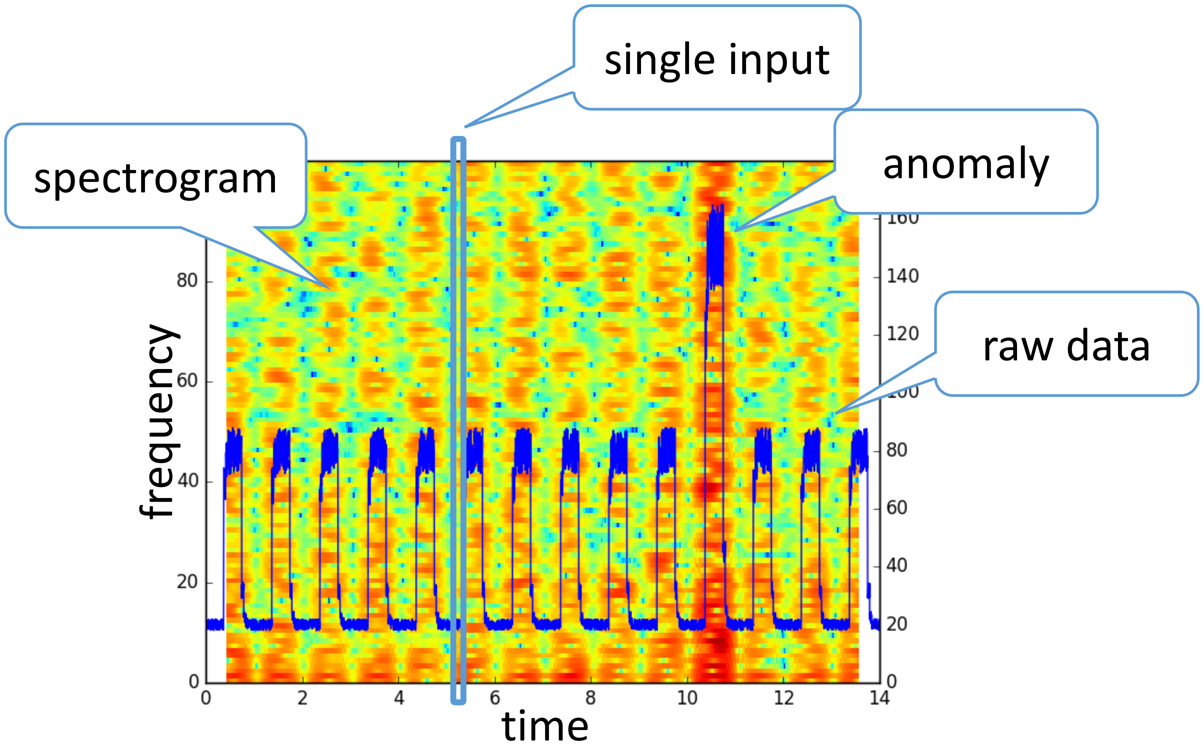
$$Anomaly\ Score = \log E[\log p_\theta(x|z)]$$

- MNIST with noise

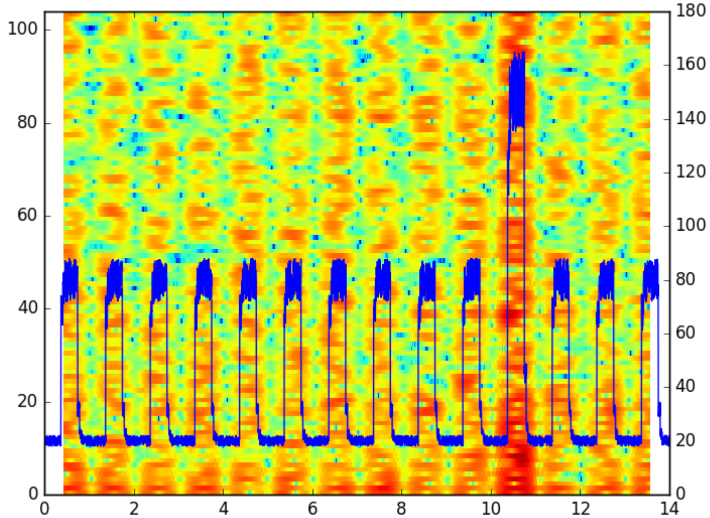


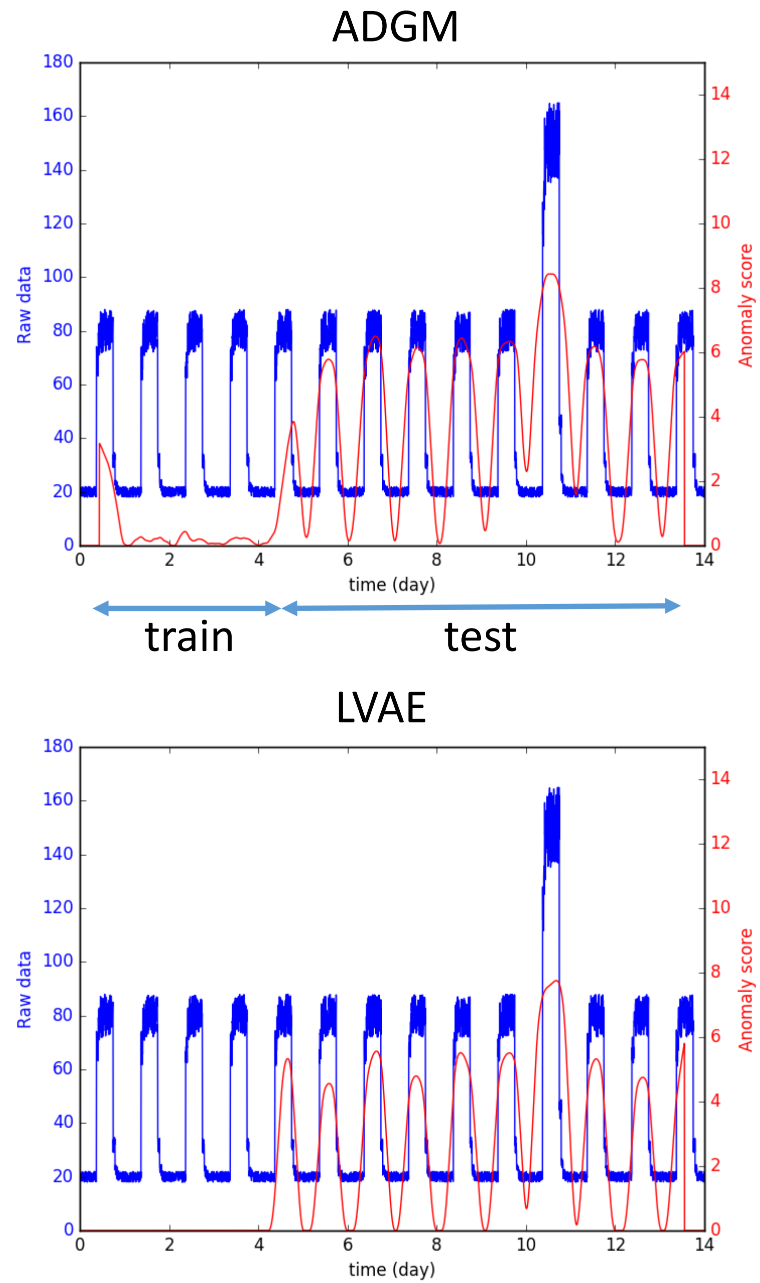
NAB Dataset (Artificial)

- We convert raw data to spectrogram.
  - Spectrogram : the amplitudes at a particular frequency and time.
- Input : the amplitudes at a time.



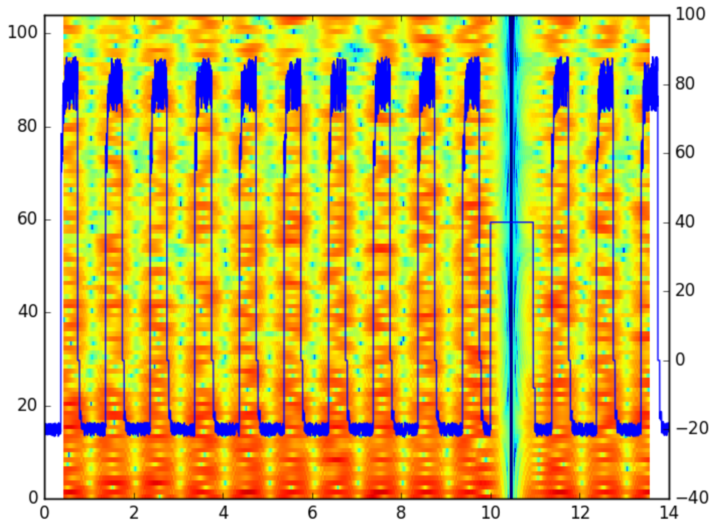
NAB

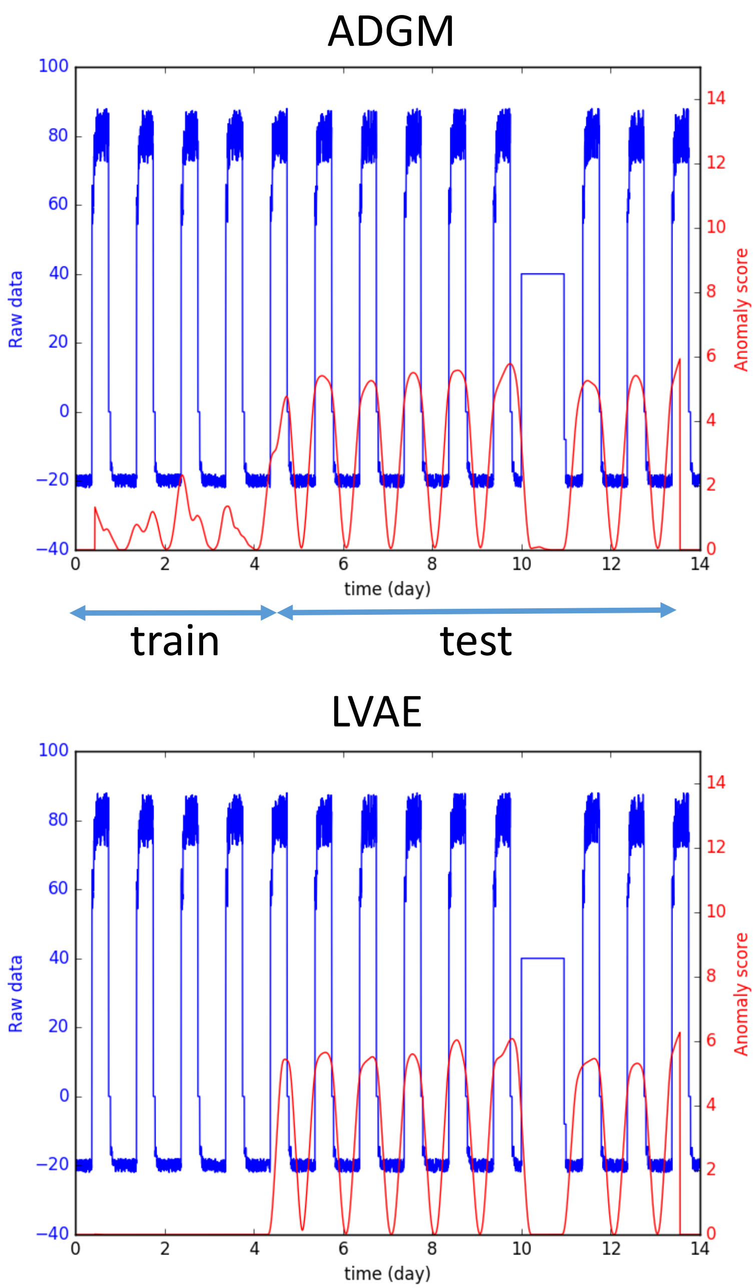




- Scores increase at anomaly.

NAB





- In this case models cannot detect anomaly.
- Small input value tends to result in small score.

Conclusion

- Anomaly detection using ADGM / LVAE.
  - Anomaly is detected as low probability data.

- Performances are almost same as VAE.
  - Many sampling layers are better (?)