Report for Preliminary Study

DQM-DC Patomporn (Jab) 21 June 2019

Outline

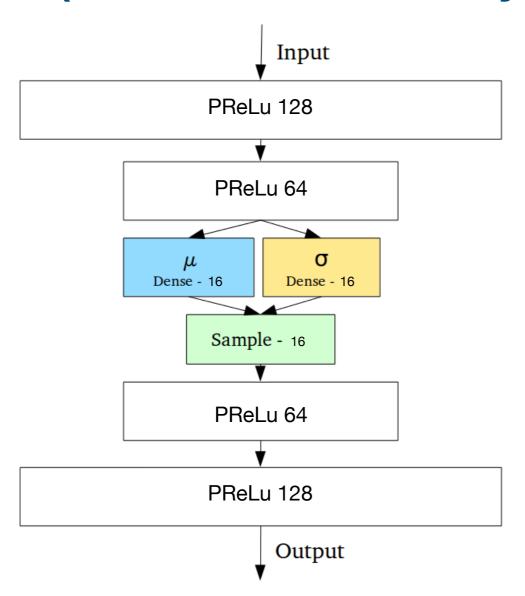
- Variational Autoencoder
 - Model
 - Training (Also include vanilla)



To sum up

Variational Model

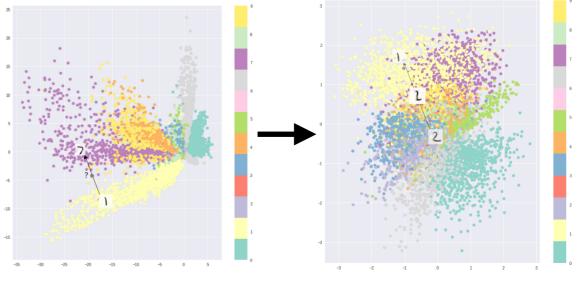
 Tweak by Random Sampling in Encoding vector (Remove discontinuity in Latent Space)



$$\mathcal{Z}_i \equiv \mathcal{N}(\mu_i, \sigma_i)$$

"Random new sampling by gaussian"

Ex: Latent space in MNIST



Variational Model

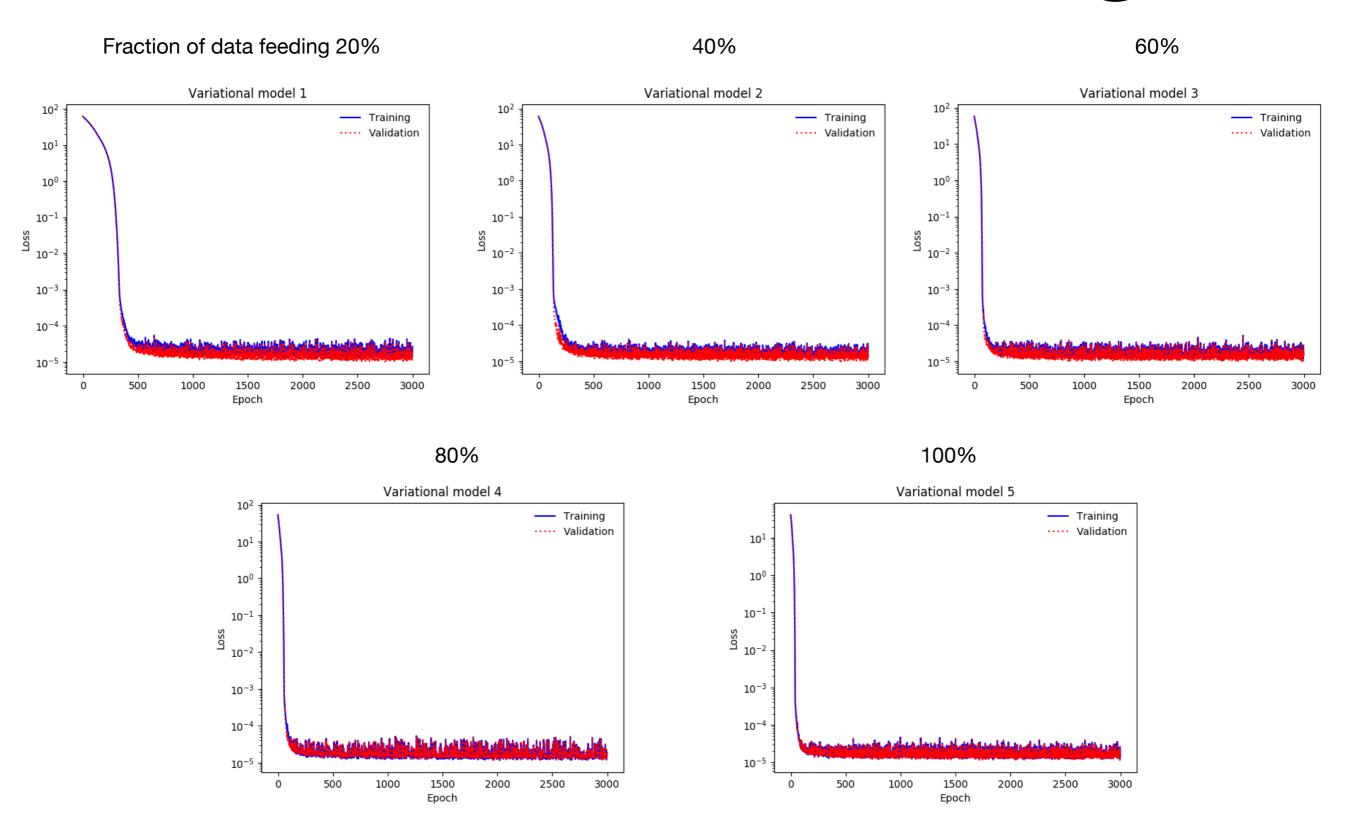
Kullback–Leibler divergence

$$\mathcal{D}_{\mathrm{KL}}(p|q) \equiv <\log p - \log q >$$

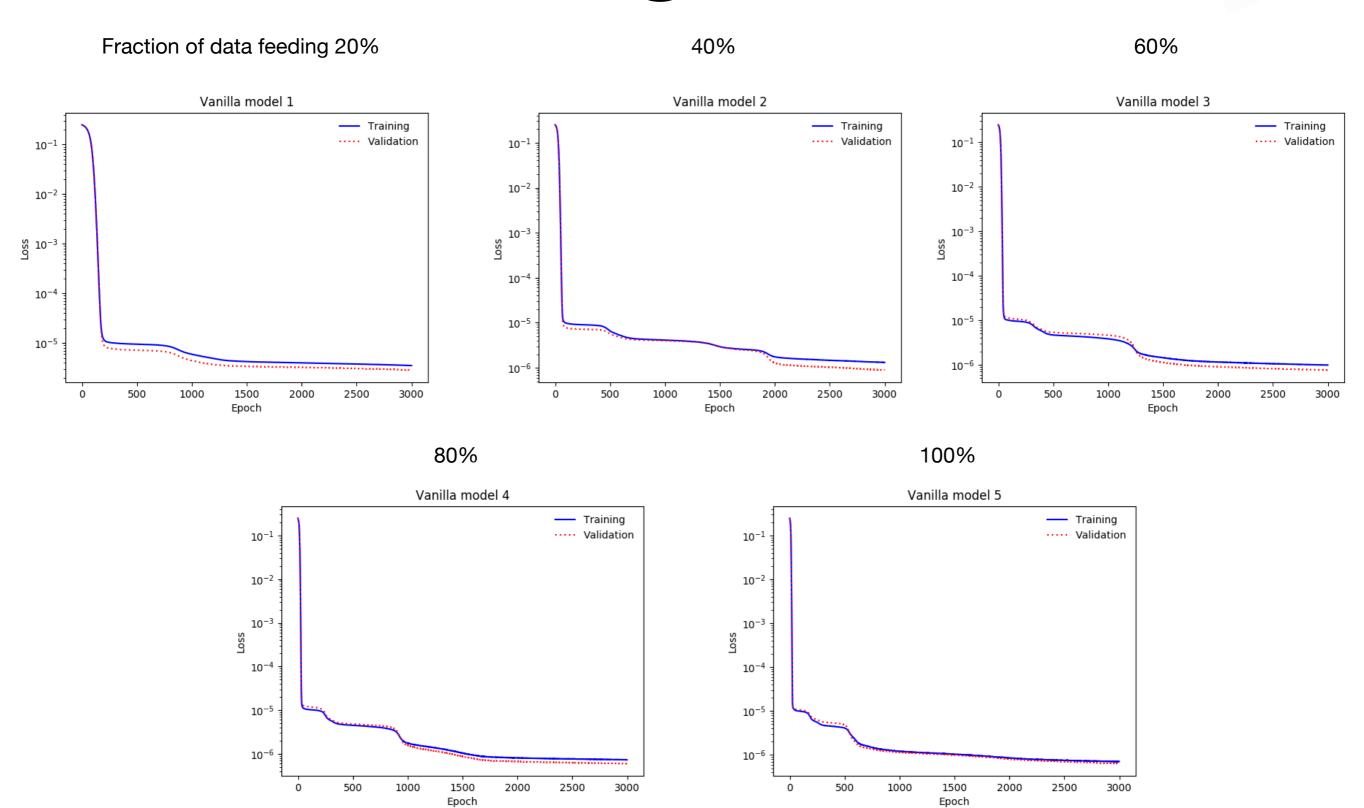
- where p is observed value, and q is approx. fn.
- Since our q is gaussian, then

$$\mathcal{L}_{\text{tot}} \equiv \mathcal{L}_{MSE} + \frac{1}{2} \sum_{i} (\mu_i^2 + \sigma_i^2 - \log(\sigma_i^2) - 1)$$

Variational Training



Don't forget Vanilla!

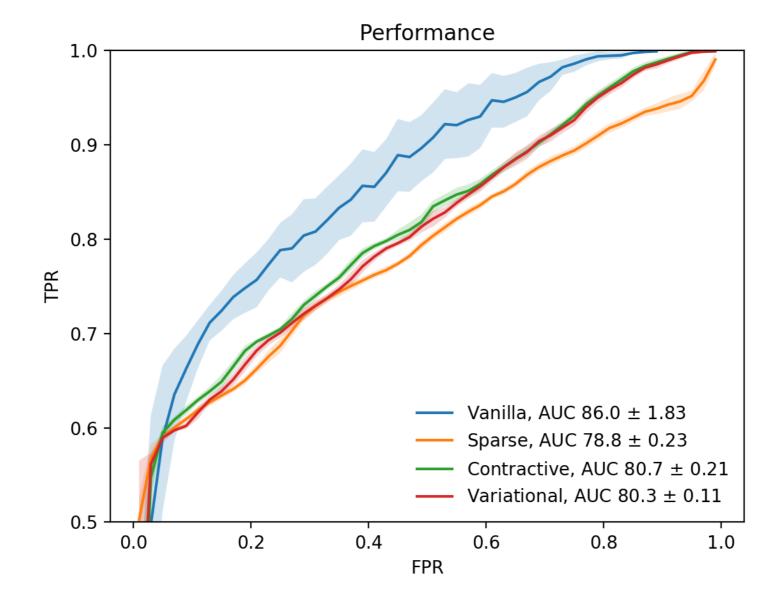


Finalize

- Reproducing new training for 4 flavours of ice-cream (Autoencoder) with
 - Reduced Features from 2806 => 259 (Take care only cumulative Jet)
 - Batch_size 256
 - EPOCHS 1200
 - SPLITTING DATASETS
 - 60% Training (Only good condition)
 - 20% Validation (Only good condition)
 - 20% Testing (Mix with bad)

Results

Repeat 10 times of process to measure robustness



Interesting Spots

AUC\Model	Vanilla	Sparse	Contractive	Variational
MEAN (%)	86.0	78.8	80.7	80.3
STD (±)	1.83	0.23	0.21	0.11

- Simplest one work best (doesn't mean that Vanilla would be best candidate for all 4 channels of Yandex's prototype)
- Variational is obvious to be most robust as loss value in training

Future work

- Anymore evaluation technique?
- Explore new thing (maybe construct new model if need)
- Get more familiar with big picture of DQM-DC and figure out how I could implement..

BTW, could checkout on https://github.com/calzonelover/CMS_DC_ANOMALY/