Experiments with DaGMM and VAE

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1. VAE with Batch Norm

We tried to use only a variational autoencoder for distinguishing between normal and anomaly class.

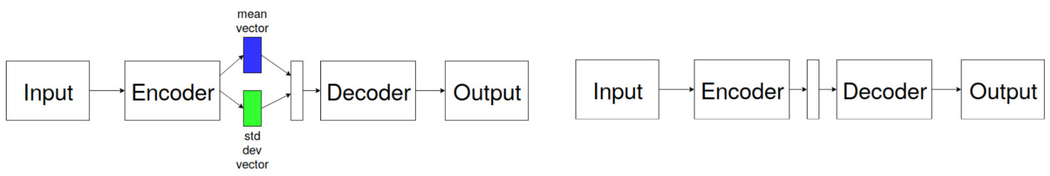
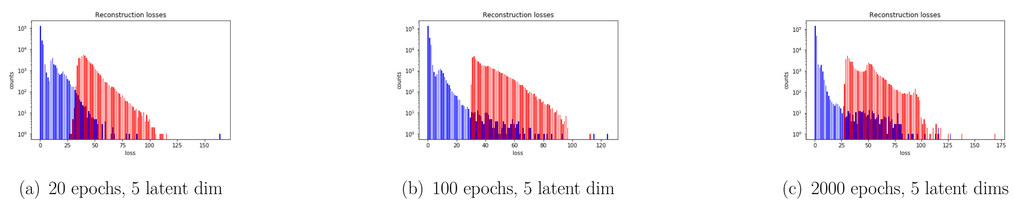
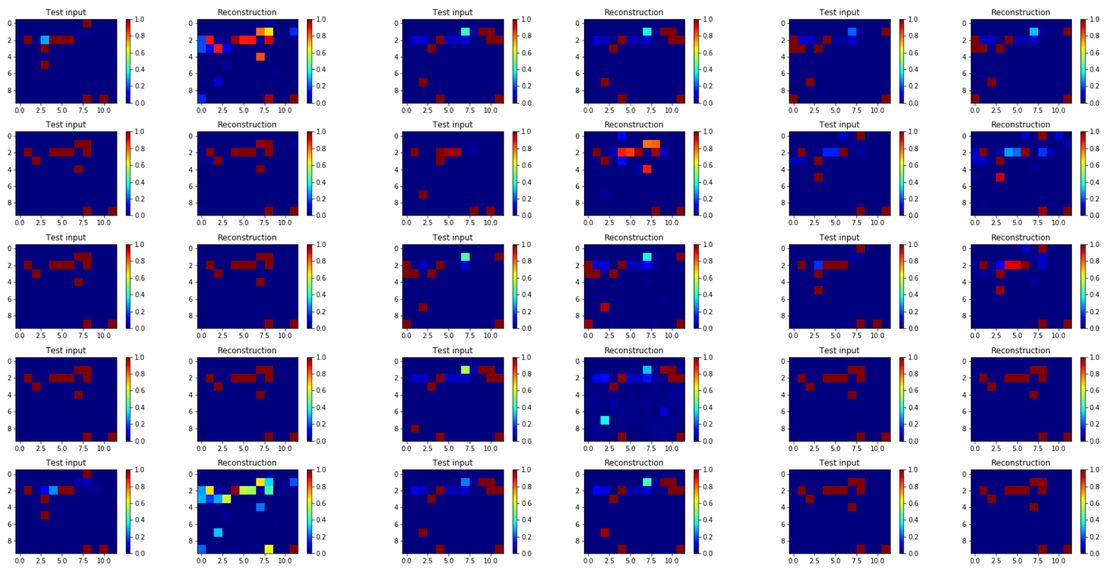


Figure 1: Variational and normal autoencoder



(a) 20 epochs, 5 latent dim (b) 100 epochs, 5 latent dim (c) 2000 epochs, 5 latent dims

Figure 2: Reconstruction losses with different epochs



(a) 20 epochs, 5 latent dim (b) 100 epochs, 5 latent dim (c) 2000 epochs, 5 latent dims

Figure 3: Reconstruction visualizations with different epochs

2. DaGMM with VAE

We tried replacing the autoencoder with an equivalent variational autoencoder. We couldn't obtain good results. It is not able to separate between the anomaly and normal class.

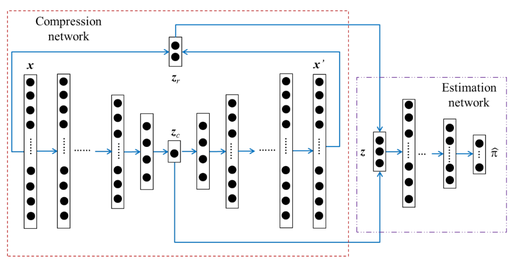
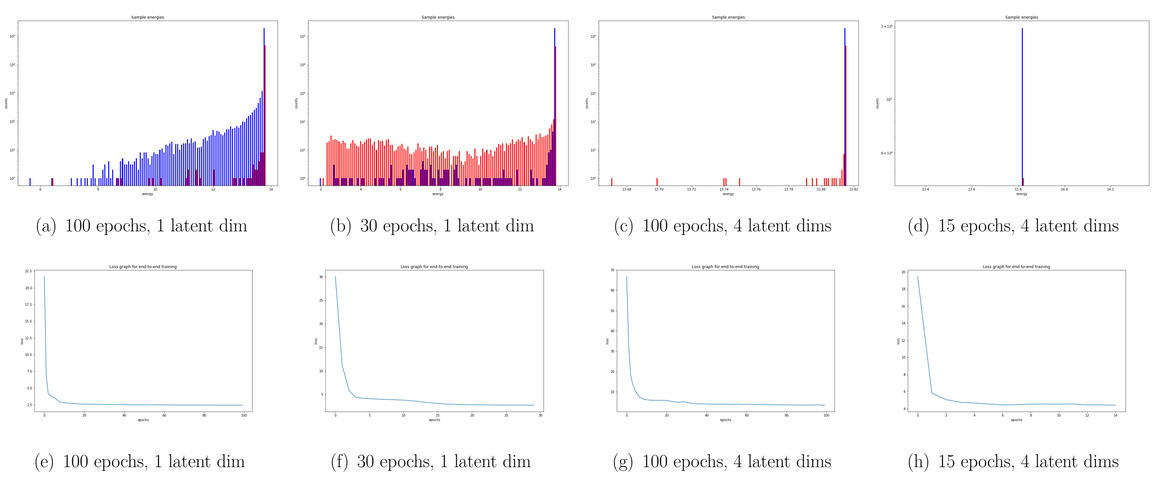


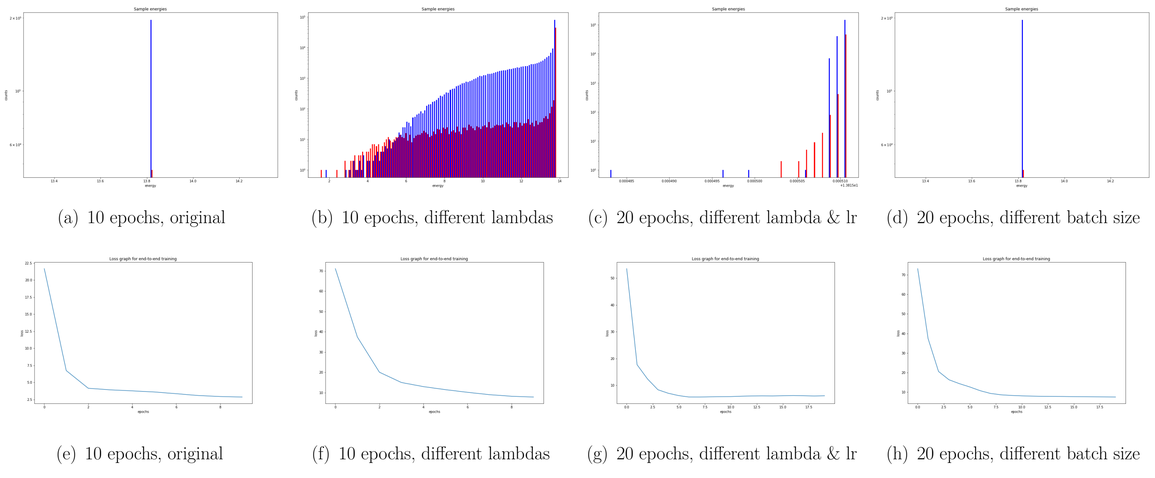
Figure 4: DaGMM original architecture



(a) 100 epochs, 1 latent dim (b) 30 epochs, 1 latent dim (c) 100 epochs, 4 latent dims (d) 15 epochs, 4 latent dims

(e) 100 epochs, 1 latent dim (f) 30 epochs, 1 latent dim (g) 100 epochs, 4 latent dims (h) 15 epochs, 4 latent dims

Figure 5: Experimental results with different latent sizes



(a) 10 epochs, original (b) 10 epochs, different lambdas (c) 20 epochs, different lambda & lr (d) 20 epochs, different batch size

(e) 10 epochs, original (f) 10 epochs, different lambdas (g) 20 epochs, different lambda & lr (h) 20 epochs, different batch size

Figure 6: Experimental results with different settings

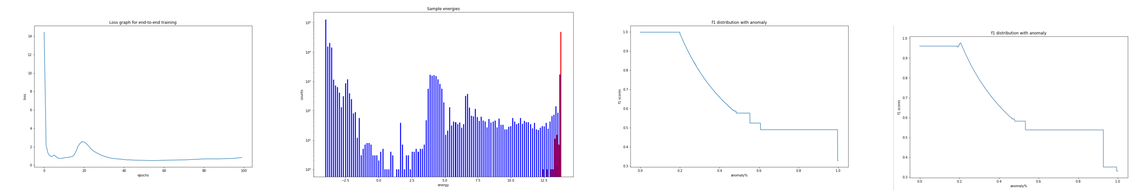
3. DaGMM Experiments with Other Dataset

We execute old model with new data-sets (Thyroid and Arrhythmia) and analysed their result and energy distribution.

We also try to use all given features (21 instead of 6 used in paper) for thyroid data-set and the model performance increased, but shows unstable behavior many a times.

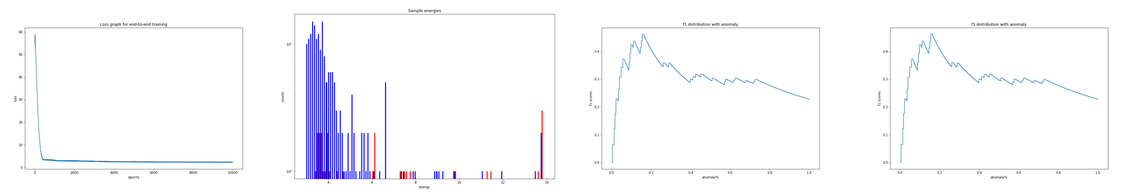
With proper observation, we come up with Auto-threshold idea to choose optimum anomaly percentage for current execution.

Though, we got unstable model behavior in many cases, where it gives single energy for all points.



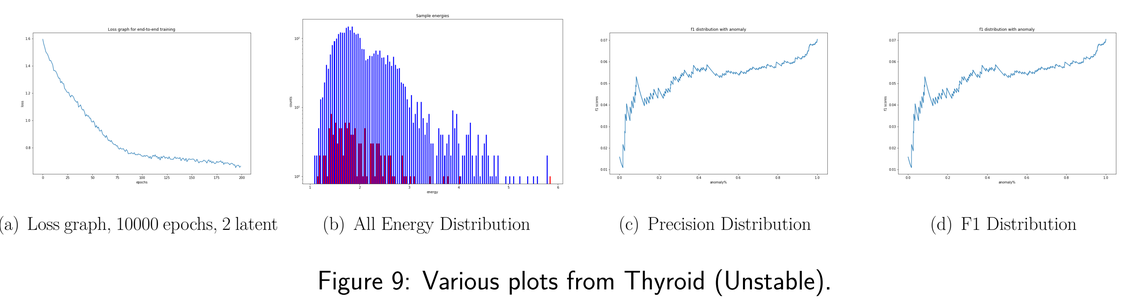
(a) Loss graph, 100 epochs, 4 latent (b) All Energy Distribution (c) Precision Distribution (d) F1 Distribution

Figure 7: Various plots from KDDCUP.



(a) Loss graph, 10000 epochs, 2 latent (b) All Energy Distribution (c) Precision Distribution (d) F1 Distribution

Figure 8: Various plots from Arrhythmia.



(a) Loss graph, 10000 epochs, 2 latent (b) All Energy Distribution (c) Precision Distribution (d) F1 Distribution

Figure 9: Various plots from Thyroid (Unstable).

4. Auto Threshold

We try to automate the anomaly percentage in current test data instead of using given anomaly percentage from paper and find out improved percentage with good F1 and precision score.

We plot anomaly percent vs F1 and precision plot and find out that there are more optimum percentage, which can be taken for higher separatedness of anomaly and normal data.

The jump in KDDCUP F1 distribution is a good example to visualize the behavior.

Methods	Datasets	Old Result		New Result	
		Precision	F1	Precision	F1
Naive Auto-Threshold	KDDCUP	0.9600	0.9674	0.9999	0.9584
	Thyroid	0.4766	0.4782	0.9687(u)	0.9435(u)
	Arrhythmia	0.4909	0.4983	0.4137	0.4138
Robust Auto-Threshold	KDDCUP	0.9600	0.9674	0.9999	**0.9768**
	Thyroid	0.4766	0.4782	0.9687(u)	0.9435(u)
	Arrhythmia	0.4909	0.4983	**0.6666**	0.4615

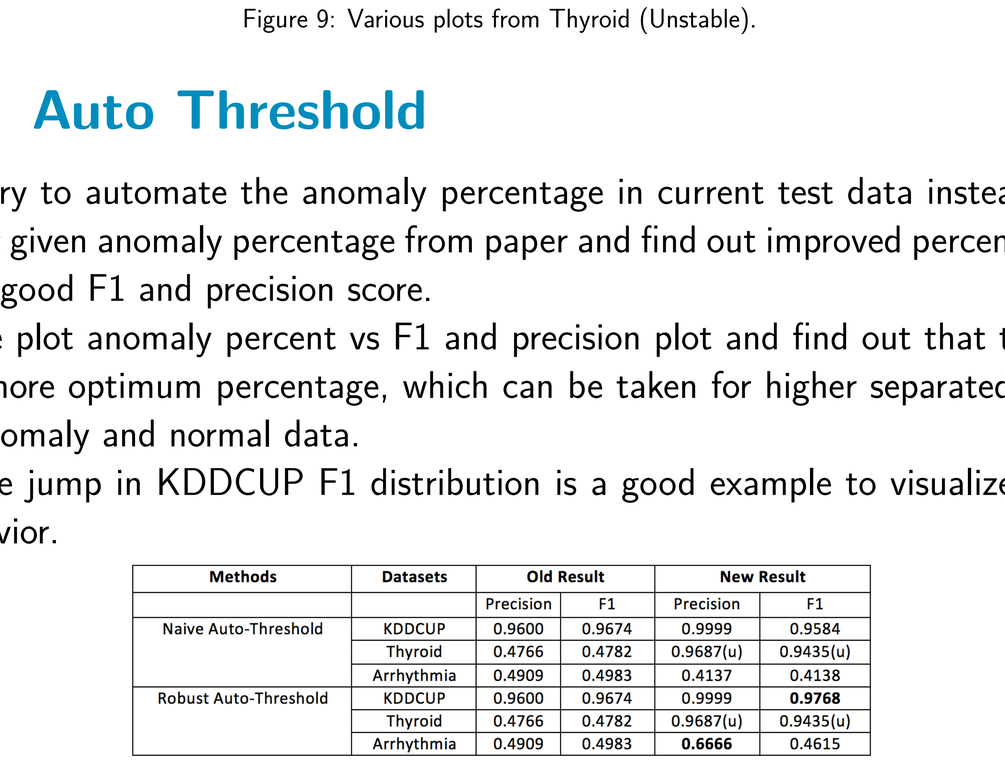


Figure 10: Experiment Results

References:

An, Jinwon and Sungzoon Cho. "Variational Autoencoder based Anomaly Detection using Reconstruction Probability." (2015).
Sønderby et. al "How to Train Deep Variational Autoencoders and Probabilistic Ladder Networks." (2016).
Zong, Bo et al. "Deep Autoencoding Gaussian Mixture Model for Unsupervised Anomaly Detection." (2018).
VAE code: https://jmetzen.github.io/2015-11-27/vae.html