Gaussian Mixtures for Generative Adversarial Networks in Unsupervised Learning Scenarios

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Introduction

- Vanilla GAN pre-training on MNIST dataset
- Gaussian Mixture GAN (GM-GAN)
- Hyper-parameter exploration
- Explored Unsupervised GM-GAN

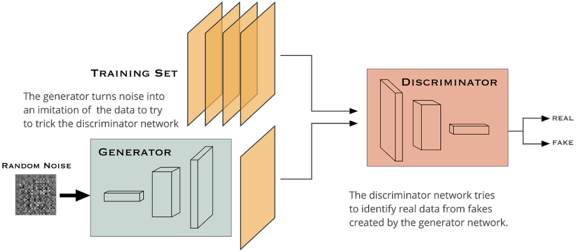


Figure 1: Generator and Discriminator building blocks [4]

Methodology & Results

- Ran multitple vanilla GAN models with a singular different hyper-parameter at a time to tune
- Allowed us to find best possible vanilla GAN to serve as a pretraining basis for our Gaussian Mixture models

- Best metric results:

GAN	FID	Precision	Recall
Platform Vanilla GAN	39.45	0.53	0.23
Platform Static GM-GAN	43.67	0.47	0.22
Local Static GM-GAN	19.02	-	-

Table 1: Results of our GANs and Gaussian Mixture Methods

Hyper-parameter Exploration

- Final Pre-trained Vanilla GAN Model:
  - Batch size $= 64$
  - learning rate $= 0.0002$
  - Starting epoch $= 50$
- FID $=$ 39.45

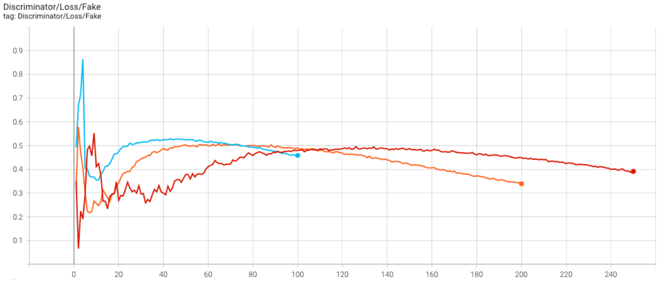


Figure 2: Discriminator loss of different Vanilla GANs

Unsupervised Gaussian Mixtures

- K - the number of Gaussians in the mixture.
- c - defines the range from which the Gaussians' means are sampled.
- σ - scaling factor for the covariance matrices.
- γ - the learning-rate.

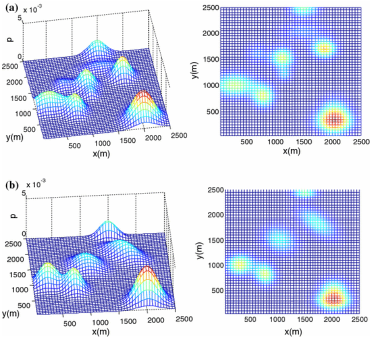
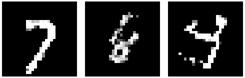


Figure 3: Gaussian Mixtures [3]

Fine-tuning Unsupervised Static GM-GAN - Part 1/2

- Hyper-parameter ranges:
  - $c \in [1; 5]$,
  - n $\in [10; 15]$ (number of gaussians)
  - $\sigma \in [0.01; 0.05]$,
  - $\gamma \in [5e-5; 8e-5]$



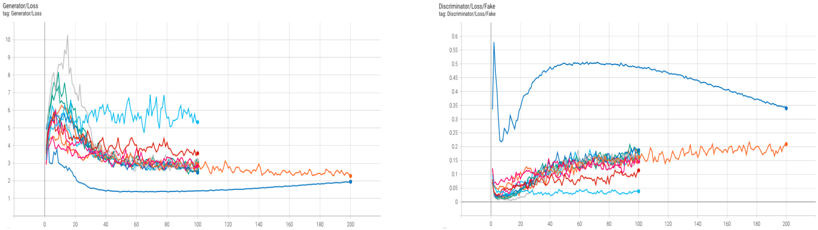
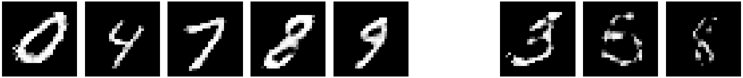


Figure 4: Generator loss & Discriminator fake loss

Fine-tuning Unsupervised Static GM-GAN - Part 2/2

- ★ RED: c$= 0.1, \sigma = 0.15$, batch$= 64, \gamma = 2e-4$, FID $= 17.02$ (ep 90)
  - ◀ BLUE: c$= 0.1, \sigma = 0.15$, batch$= 64, \gamma = 8e-05$, FID $= 42.48$ (ep 60)
  - ◀ PINK: c$= 0.467, \sigma = 0.7$, batch$= 64, \gamma = 2e-4$, FID $= 16.12$ (ep 150)
  - ◀ GREEN: c$= 0.467, \sigma = 0.7$, batch$= 64, \gamma = 8e-05$, FID $= 19.30$ (ep 30)



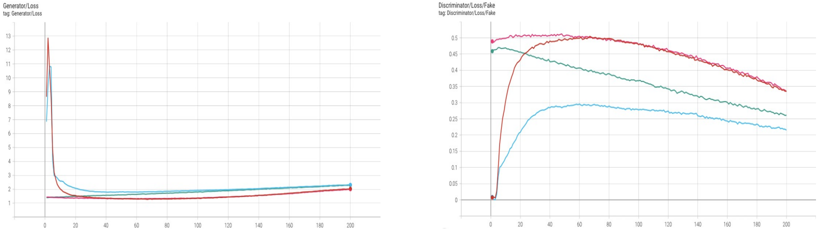


Figure 5: Better Generator loss & Better Discriminator fake loss

Conclusion & Next Steps

Guassian Mixture GAN when finetuned on an improved Vanilla GAN produced better metric results and more digit diversity

Next Steps:

- Testing dynamic Gaussian Mixture
- Supervised Gaussian Mixture
- Discriminative Rejection Sampling

Publication and References

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4. Yalçın, O, (2020). "Image Generation in 10 Minutes with Generative Adversarial Networks." Towards Data Science. https://towardsdatascience.com/image-generation-in-10-minutes-with-generative-adversarial-networks-c2afc56bfa3b