# Latent space representation

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### Introduction

First approaches

II. Cluster based method: ClusterGAN

**III.** Results and improvements

### **Problem Setting**

Standard Generative Adversarial Networks minimax objective:

$$\mathcal{L}_{adv} = \min_{\Theta_G} \max_{\Theta_D} \mathbb{E}_{x \sim P_x^r} \left[ q(D(x)) \right] + \mathbb{E}_{z \sim P_z} \left[ q(1 - D(G(z))) \right]$$

where q(.) = log for the Vanilla GAN

Two main drawbacks:

- mode collapse → we try enforcing mode diversity explicitly
- non-convergence

### **Perceptual Loss**

**Intuition**: increase the **precision** by changing the loss as follows

$$\mathcal{L}_{adv} + \beta_p \cdot \mathcal{L}_{perceptual}$$
 with 
$$\mathcal{L}_{perceptual}(x, \hat{x}) = \sum_{l=1}^{L} \lambda_l \left\| \phi_l(x) - \phi_l(\hat{x}) \right\|_2^2$$
 we use VGG16 to extract the feature maps

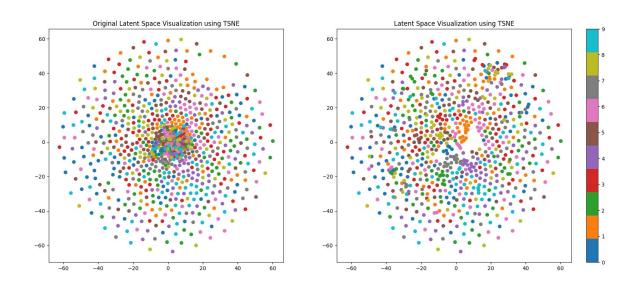
<u>Results</u>: slightly increased precision - strong decrease in **FID** value Method is **over-killing** for the MNIST dataset

**Non conclusive method** → next : clustering based approach

### **Latent Space Exploration**

Trained a classifier to retrieve labels (94% accuracy)

Performed **gradient** ascent on z



→ "explicitly" encode the class label in the latent space via **clustering** 

### **ClusterGAN**

#### **Generator** and **encoder** loss:

$$\mathcal{L}_{GE} = \mathcal{L}_{adv} + \beta_n \cdot \mathcal{L}_{zn} + \beta_c \cdot \mathcal{L}_{zc}$$

with

$$\mathcal{L}_{zn} = \|z_n - E(G(z))_n\|_2^2$$

$$\mathcal{L}_{zc} = -\sum_{i=1}^{10} z_{c,i} \log(E(G(z))_{c,i})$$

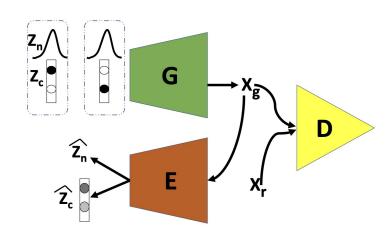
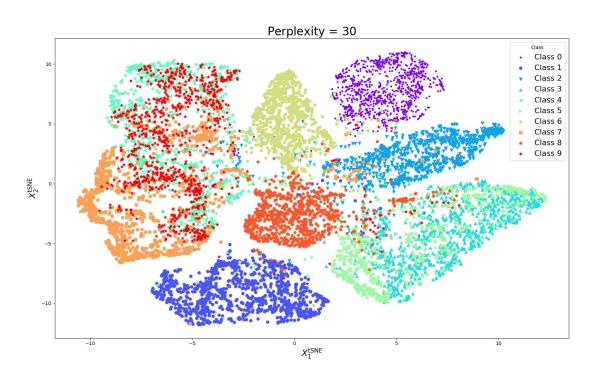


Figure 1: ClusterGAN Architecture

and the standard adversarial loss for the discriminator

### **Clustering Results**





## Improving the model

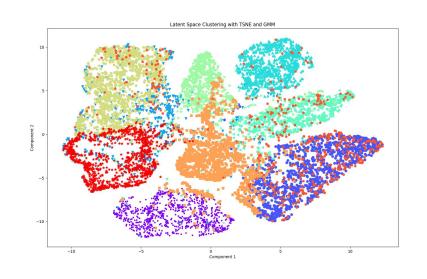
- Recall
- ⇒ focus on each specific **mode**
- **X** limited to fixed modes
- ✓ continuous Gaussian in the latent space mitigates coverage of the data distribution

- **GMM:** clustered the latent space

#### Latent space dimension

continuous sampled noise

one hot encoding of the class



## **Results and Analysis**

Metrics	FID	Precision	Recall
ClusterGAN (d=20)	9.60	0.77	0.32
ClusterGAN (d=100)	9.66	0.76	0.31
ClusterGAN (d=200)	12.61	0.65	0.41

Table 1: Metrics over the ClusterGAN model with different latent space dimensions

Metrics	FID	Precision	Recall
VanillaGAN	15.13	0.62	0.47
ClusterGAN (GMM)	14.0	0.8636	0.14
ClusterGAN	9.60	0.77	0.32
ClusterGAN with IR	10.06	0.76	0.33

Table 2: Metrics over the different models with d=20

# Thank you for listening!

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