Language Technologies Institute

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Generative Adversarial Nets for Image Generation

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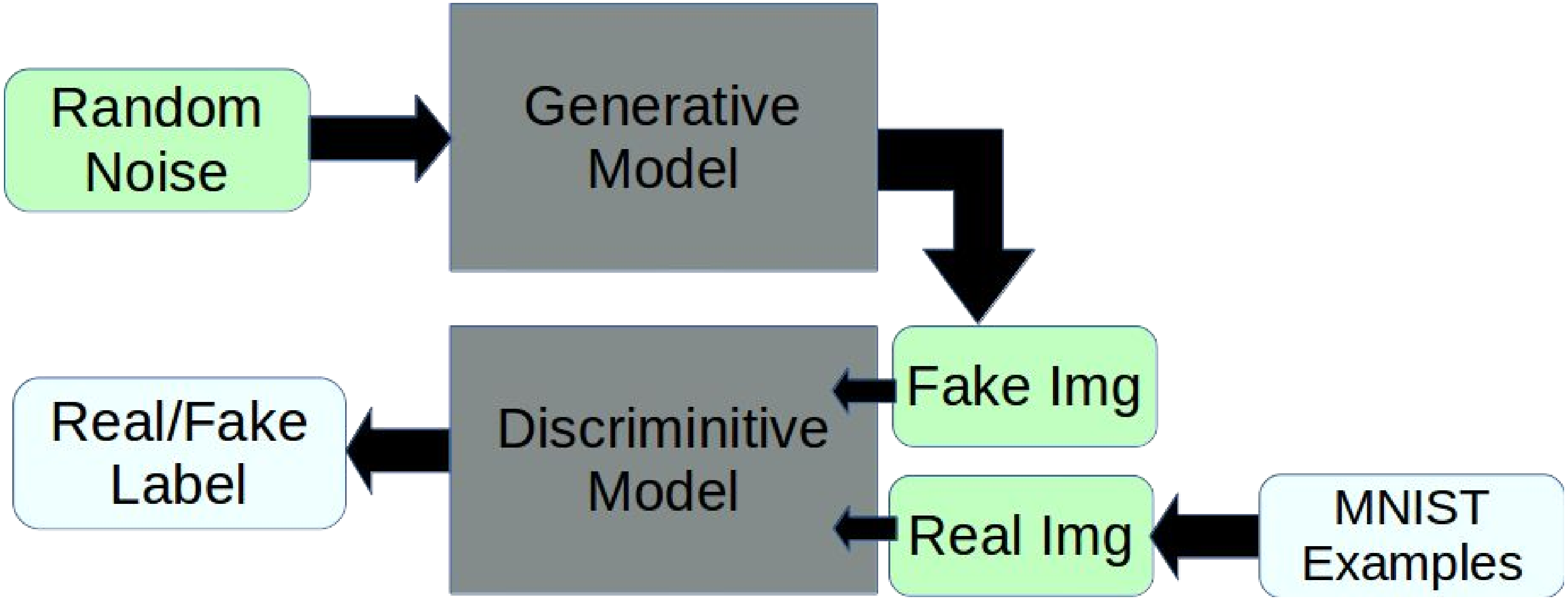
Introduction

- Generative Adversarial Nets
  - Discriminative Model $D(\boldsymbol{x}; \theta_d)$
    - Learn to determine whether a sample is from the data or the generative model
  - Generative Model $G(\boldsymbol{z}; \theta_g)$
    - Produce fake samples
    - $\boldsymbol{z}$: Noise variable
  - Prior of the noise variable $p_z(\boldsymbol{z})$

Introduction

- Generative Adversarial Nets



Introduction

- Generative Adversarial Nets
  - Two-player minmax game

$$\min_G \max_D V(D,G) = \boxed{\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})]} + \boxed{\mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]}.$$

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Generated samples $G(z)$ is not from the data

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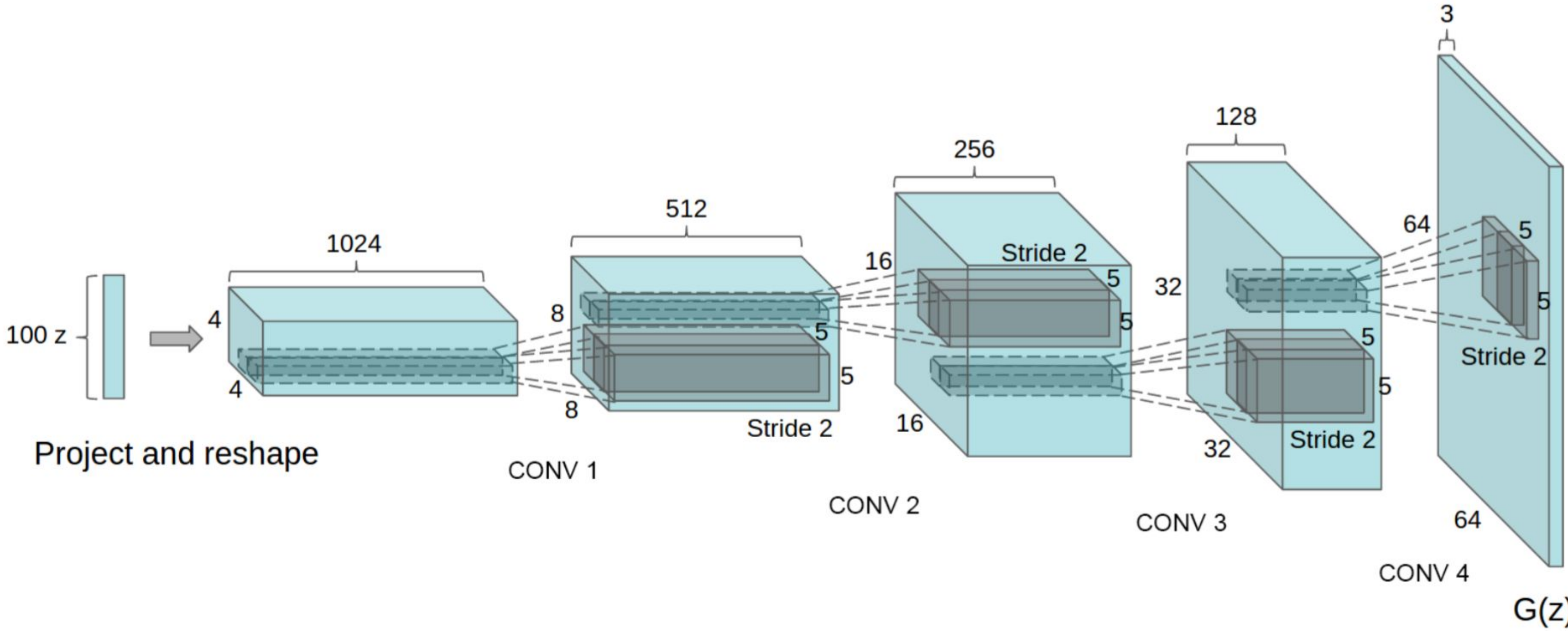
Generated samples $G(z)$ is not from the data

  - D Optimization
    - Maximize the probability of assign the correct labels
  - G Optimization
    - Minimize $\log(1\text{-}D(G(z)))$

Implementation

- Discriminator: ConvNets
- Generator: DeconvNets



Implementation

- Optimization: Minibatch Gradient Descent

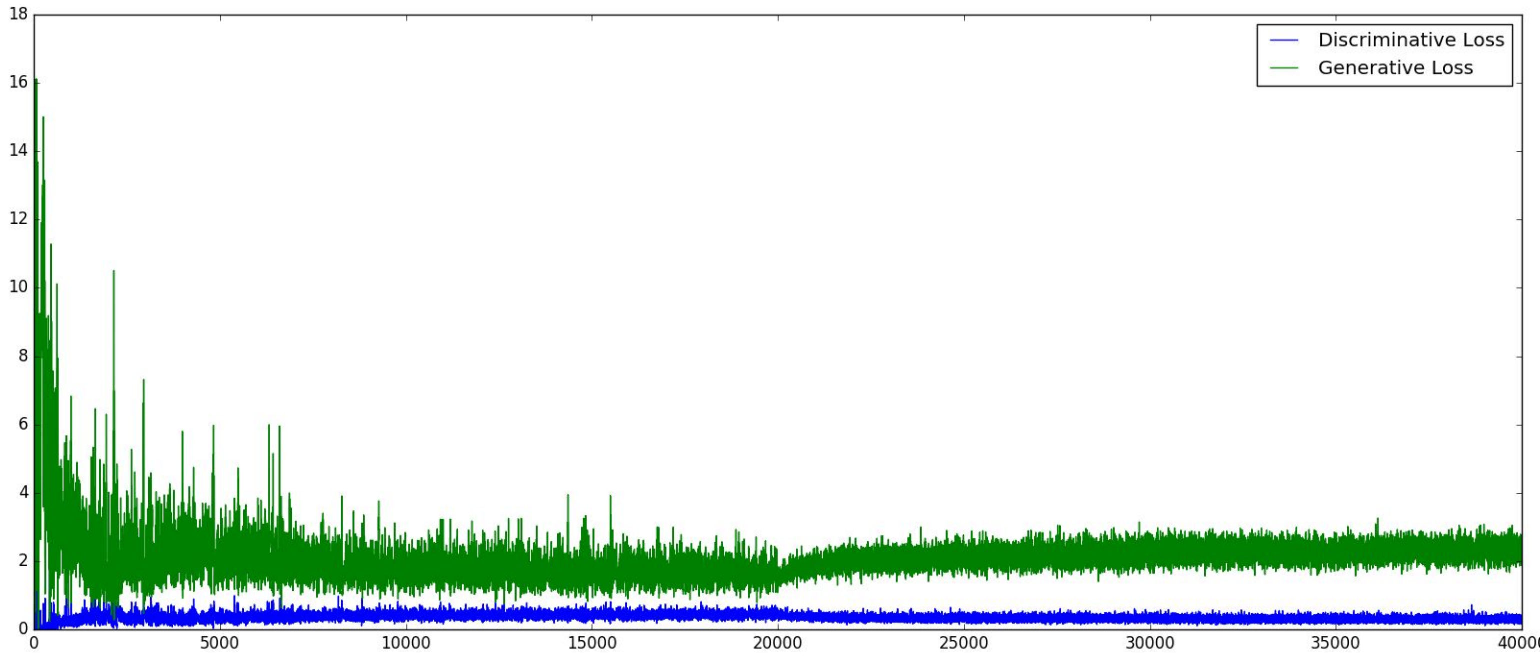
1. *Generate images using* $G(z)$
2. *Batch update of weights in* D *given* $G(z)$, $\boldsymbol{x}$, *and labels*
3. *Batch update of weights in* G *to minimize* $-\log(D(G(z)))$
4. Go to 1, Repeat …

Experiments

- Dataset
  - MNIST
    - 70,000 digits
  - CelebA
    - 202,599 face images
- Preprocess
  - Resize the images in CelebA dataset to 28 * 28
- Optimizer
  - Adam
  - Decrease the learning rate after predefined number of iterations

Experiments

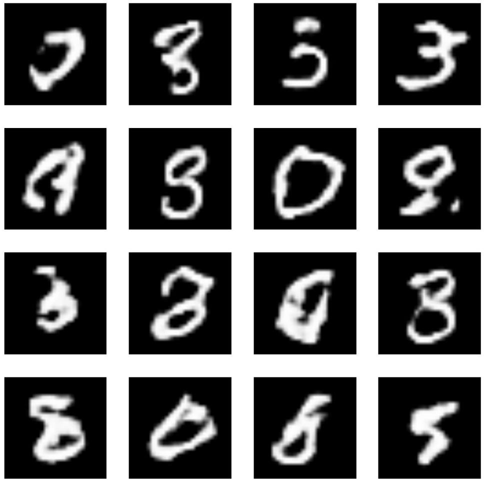
- Discriminator loss vs. generator loss (on CelebA dataset)



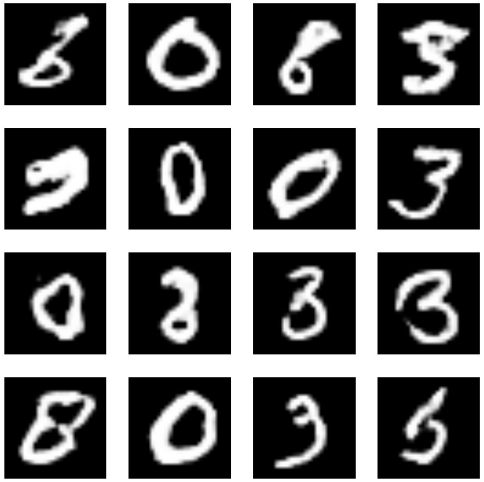
Experiments

- Visualization of MNIST

After 500 iterations



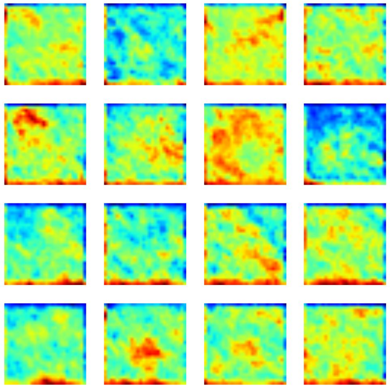
After 3000 iterations



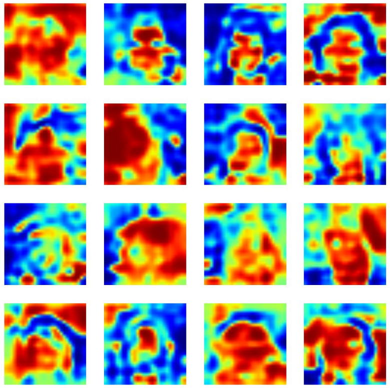
After 10000 iterations

Experiments

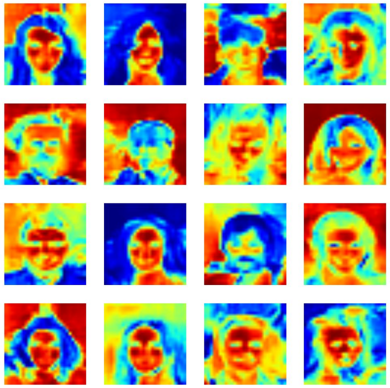
- Visualization of CelebA



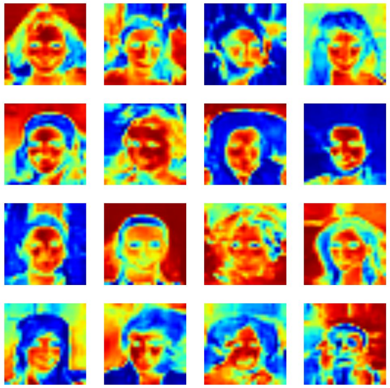
After 500 iterations



After 2000 iterations



After 20000 iterations



After 40000 iterations

InfoGAN

Motivation

Learning interpretable and meaningful representations

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Learning interpretable and meaningful representations

Main idea

Maximising the mutual information between a subset of the generators noise variables and observed data. These subset of variables are called latent codes.

InfoGAN

Mutual Information - Definition

The mutual information between random variables X and Y, I(X:Y) measures the "amount of information" learned about the variable X from the knowledge of variable Y

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$$I(X;Y) = H(X) - H(X|Y) = H(Y) - H(Y|X)$$

InfoGAN

Mutual Information - Interpretation

I(X;Y) represents the reduction of uncertainty in X when Y is observed.

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$I(X;Y)$ represents the reduction of uncertainty in X when Y is observed.

If X and Y are independent, $I(X;Y) = 0$.

If X and Y are related by a deterministic, invertible function, maximal mutual information is attained.

InfoGAN

Formulating loss

Given some $x \sim P_G(x)$, we'd like $P_G(c \mid x)$ to have a small entropy.

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Given some $x \sim P_G(x)$, we'd like $P_G(c \mid x)$ to have a small entropy.

Information regularized minimax game:

$$\min_G \max_D V_I(D, G) = V(D, G) - \lambda I(c; G(z, c))$$

Experiment Setup

Dataset: MNIST

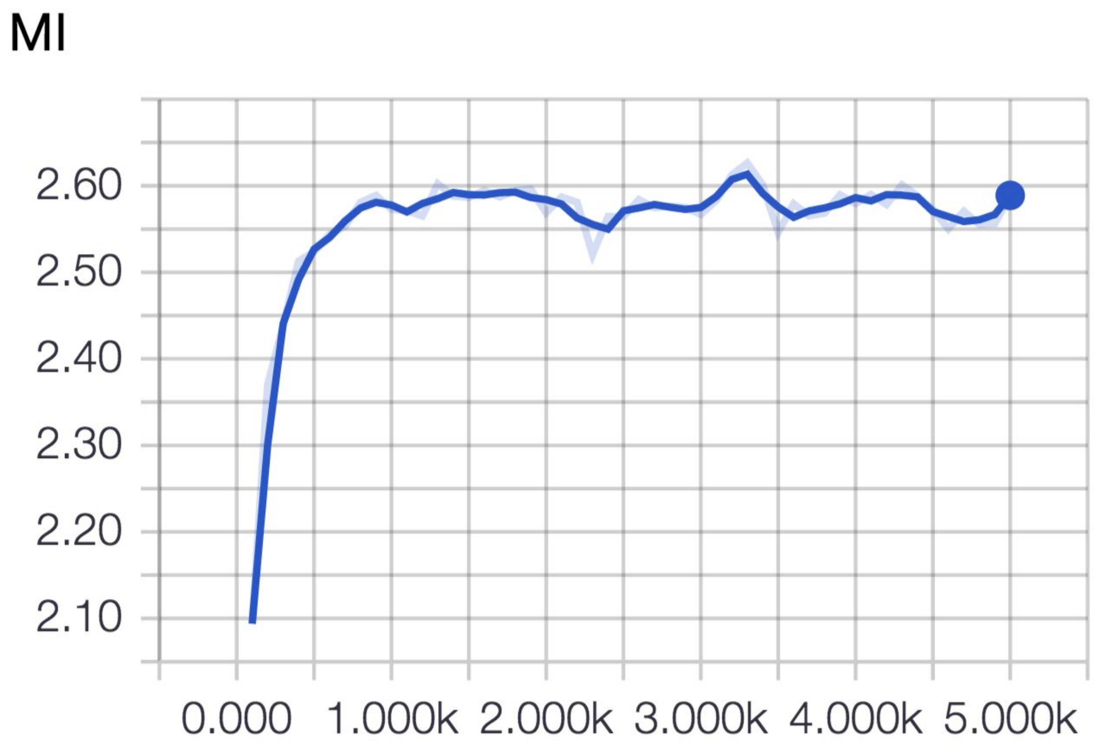
Latend codes setup:

One categorical code, $c1 \sim Cat(K = 10, p = 0.1)$, and two continuous codes: $c2$, $c3 \sim Unif(-1, 1)$.

Lamda: 1

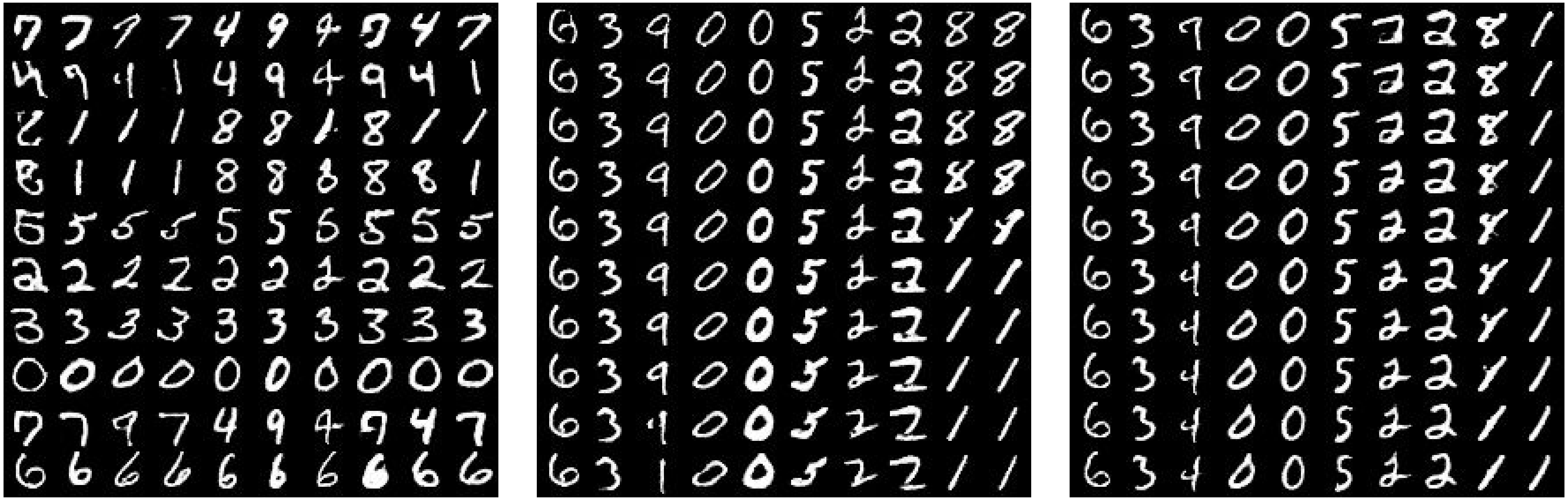
Results

Mutual Information during the training:



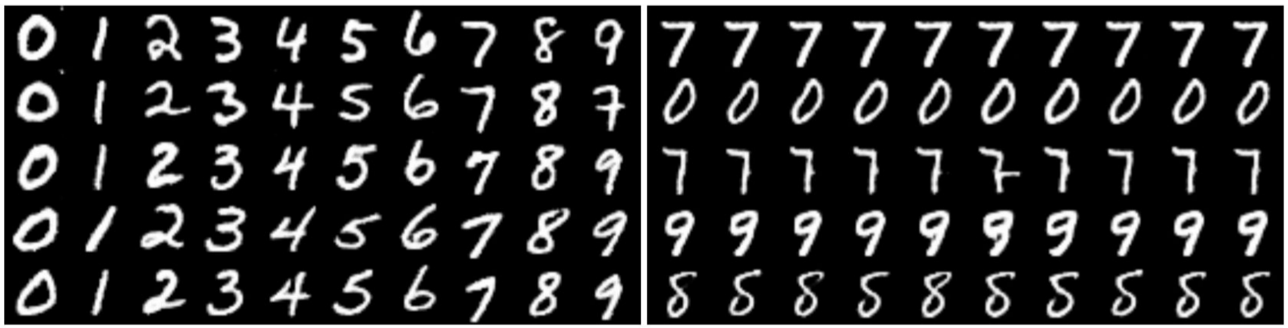
Results

Latent code manipulation results:

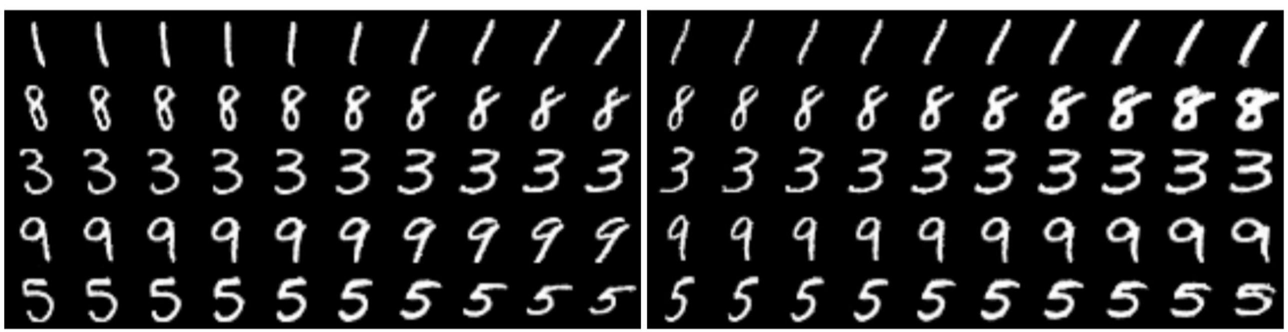


Results

Interpretation:



(a) Varying c_1 on InfoGAN (Digit type) (b) Varying c_1 on regular GAN (No clear meaning)



(c) Varying c_2 from -2 to 2 on InfoGAN (Rotation) (d) Varying c_3 from -2 to 2 on InfoGAN (Width)

Repository

InfoGAN : https://github.com/chiragraman/InfoGAN

Thank you!

Questions?