Deep Learning Project:

Generating Micro Doppler signatures with Conditional Generative Models: Challenges and Future Prospects

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Problems and solutions

Increasing sick people and insufficient caregivers

Use of video surveillance and **radar** surveillance systems instead of human operators

It takes a lot of time and human caregivers to analyze the footage and radar signals

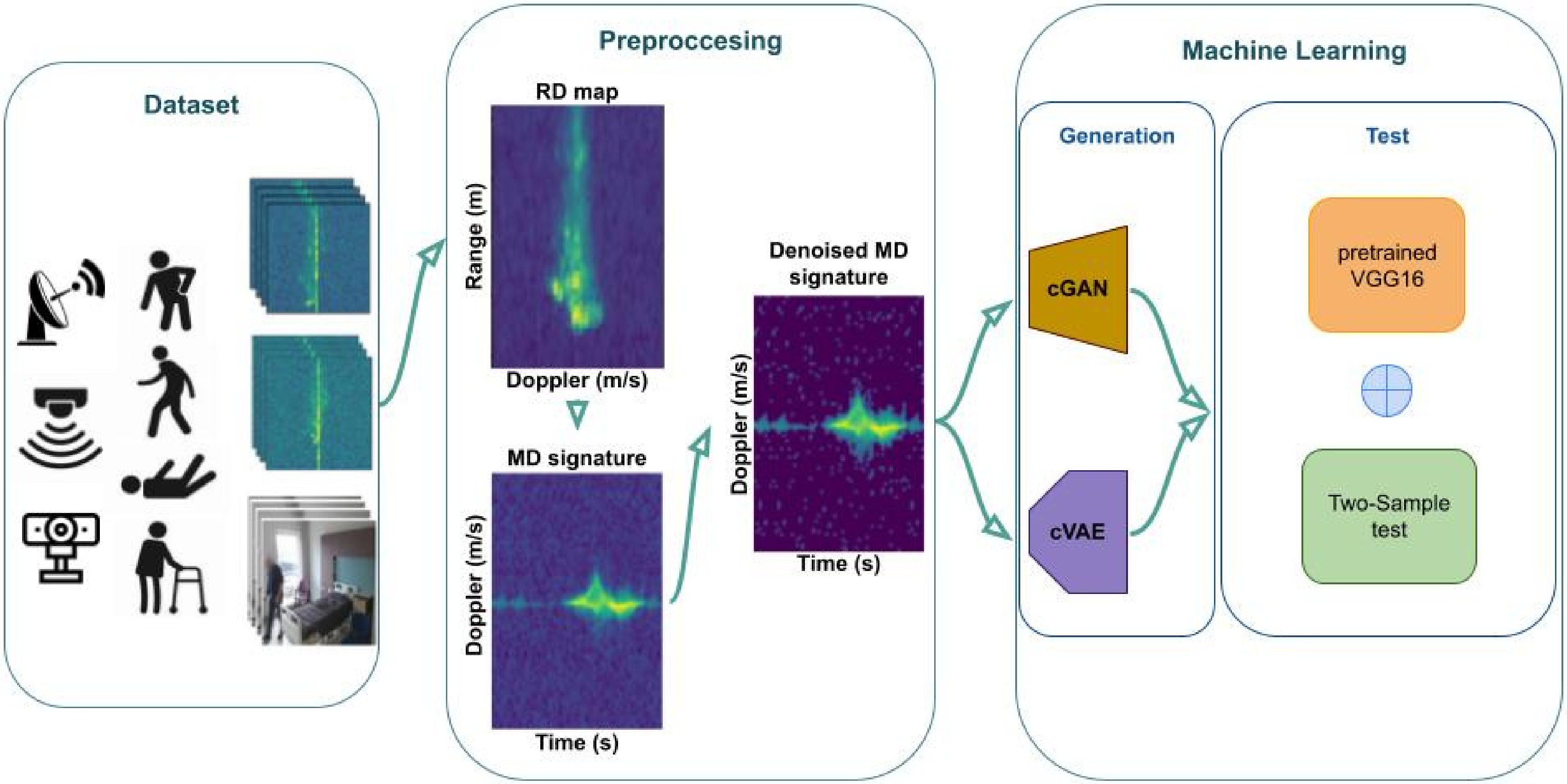
Using machine learning algorithms to automatically recognize patients' actions in real time

Machine learning algorithms require a lot of data, and health data are difficult to obtain

Our Task

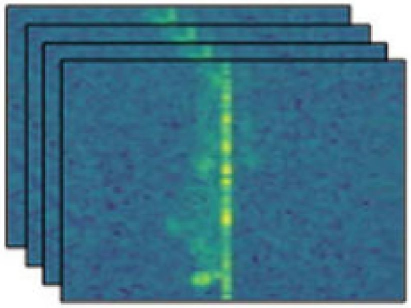
Using machine learning to generate lots of synthetic data from little real data

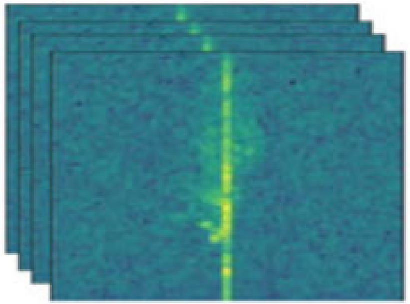
Workflow



Dataset
Preproccesing
RD map
Range (m)
Doppler (m/s)
MD signature
Doppler (m/s)
Time (s)
Denoised MD signature
Doppler (m/s)
Time (s)
Machine Learning
Generation
cGAN
cVAE
Test
pretrained VGG16
Two-Sample test

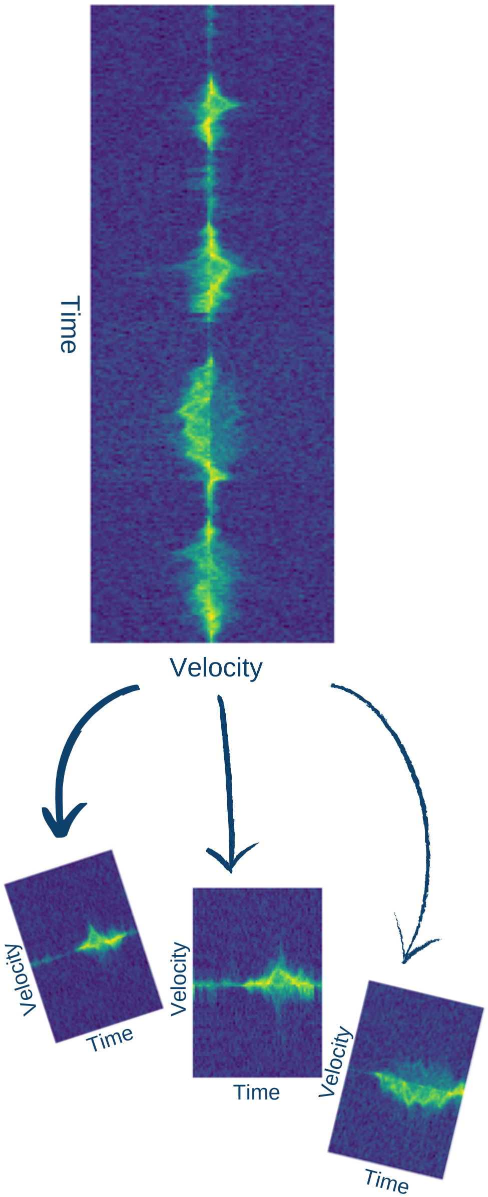
PARrad Dataset from UNIVERSITEIT GENT





- 77GHz, 60GHz radars and a webcam
- 24 subjects
- 14 activity classes
- 22 hours recordings at 11.1 fps ~ 1Tb

Pre-processing



- 77GHz
- 16 subjects
- 14 activity classes
- Cropped, resized and selected MD maps
  - remove 3 center bin
  - time cropping based on avarege duration of activites;

    64 frames   Δt ~ 6 s.
  - empirically crop the velocity axes to 96 bins;

    Velocity range ~ [-3 m/s; +3 m/s].
  - Wrap padding.
- 5570 samples ~ 270 Mb

Denoising

Algorithm 1 Denoising algorithm for MD maps

Require: $mDoppler \in \mathbb{R}^{X \times Y \times Z}$
Ensure: $mDoppler_{denoised}$

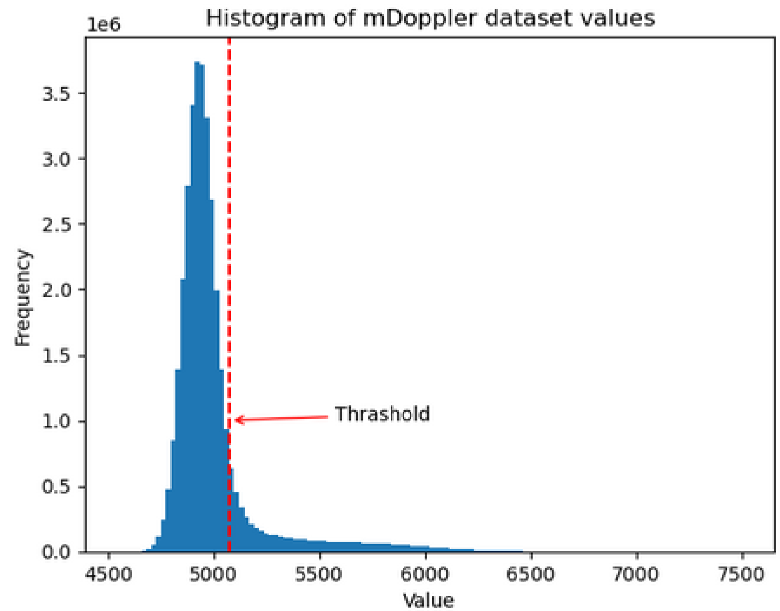
$$minimum \leftarrow \min_{i=1}^{X} \min_{j=1}^{Y} \min_{k=1}^{Z} mDoppler_{i,j,k}$$

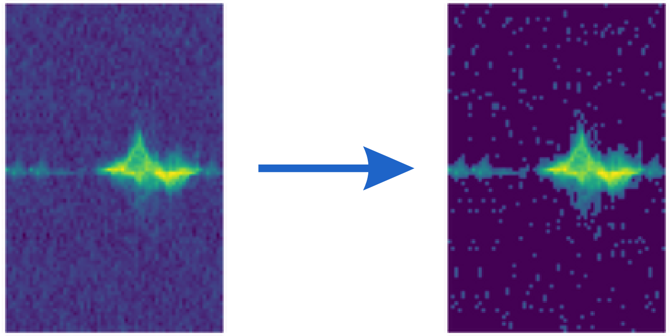
$$maxFirstRow \leftarrow \max_{i=1}^{Z} \max_{j=1}^{Y} mDoppler_{1,j,i}$$

$$threshold \leftarrow \max_{i=1}^{Z} maxFirstRow - 400$$

for $i = 1$ to X **do**
  for $j = 1$ to Y **do**
    for $k = 1$ to Z **do**
      if $mDoppler_{i,j,k} < threshold$ **then**
        $mDoppler_{i,j,k} \leftarrow minimum$
      end if
    end for
  end for
end for

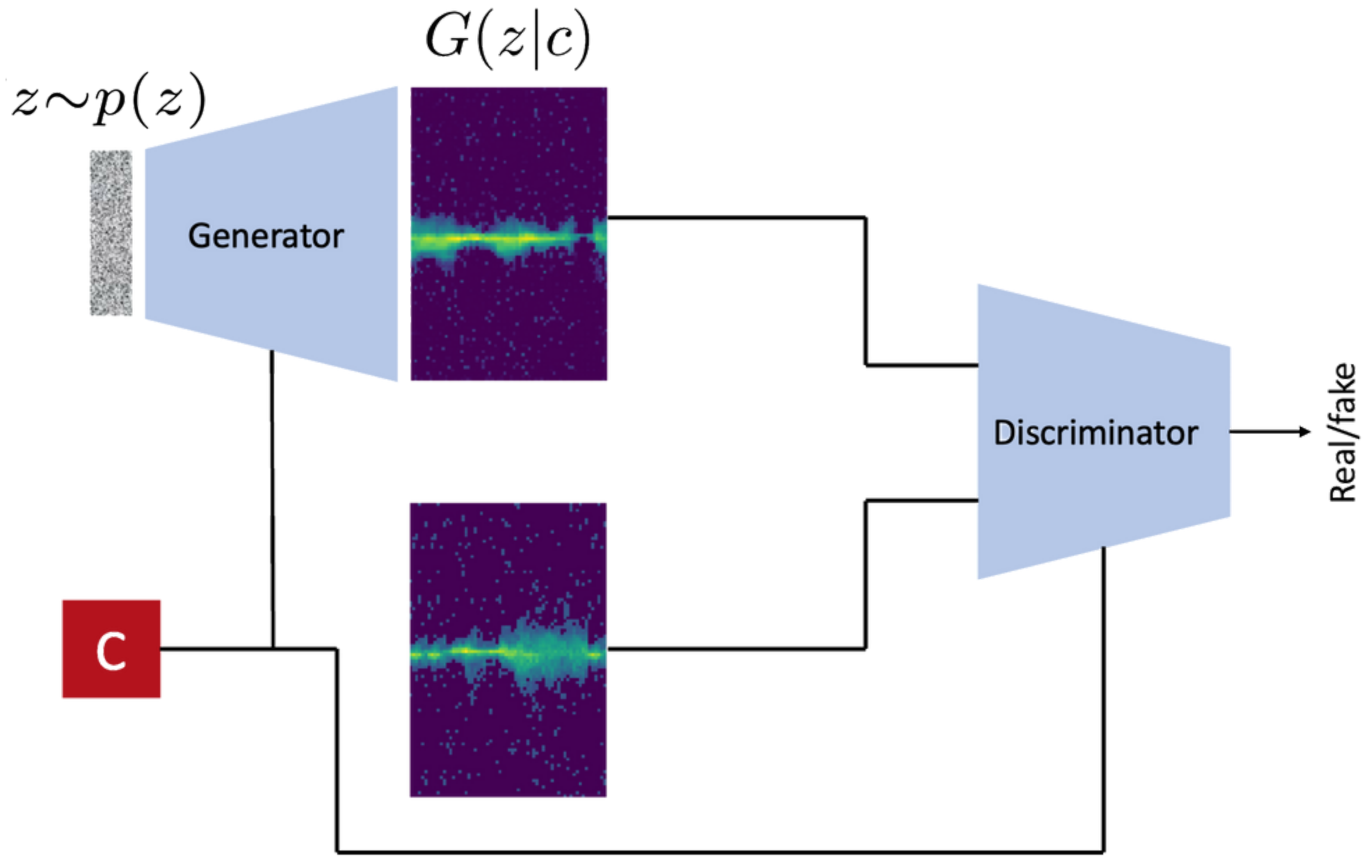
$mDoppler_{denoised} \leftarrow mDoppler$





1st approach: cGAN

cGAN
Intro



The Architecures

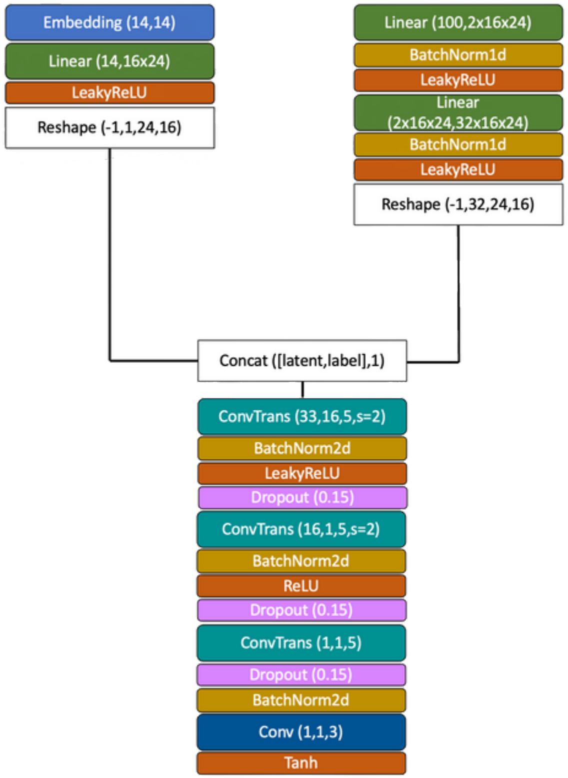
Overview

- **cGAN Simple & cGAN Refresh**
  - Similar architectures
  - trained for 2000 epochs
  - batch size = 32
  - Adam optimizer with l.r.= 0.0002, betas =(0.5,0.999)
- **cGAN Minibatch**
  - Deeper convolutional block
  - trained for 2000 epochs
  - batch size = 32
  - Adam optimizer with l.r. = 0.0001, betas = (0.5,0.999)

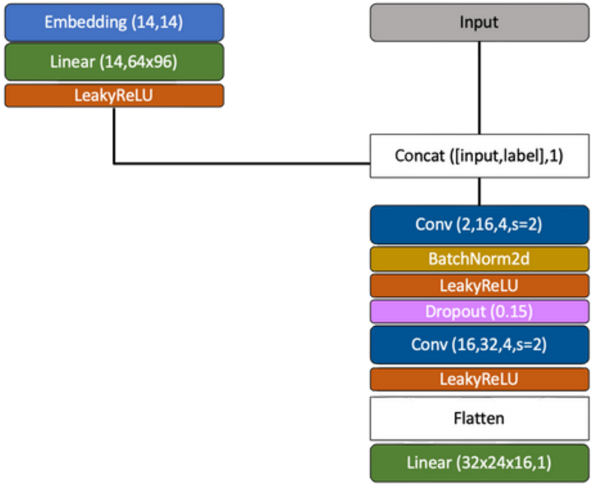
- All the architectures have been trained using:
  - One sided Label smoothing with α=0.1
  - Goodfellow training Trick on the generator loss

The Architecures
cGAN Simple

Generator

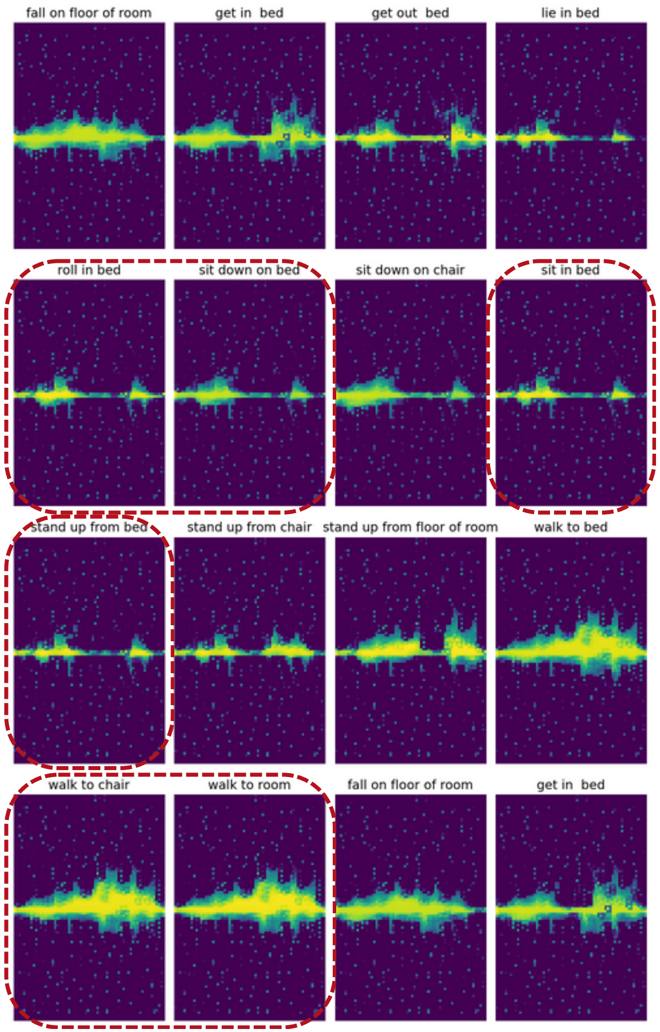


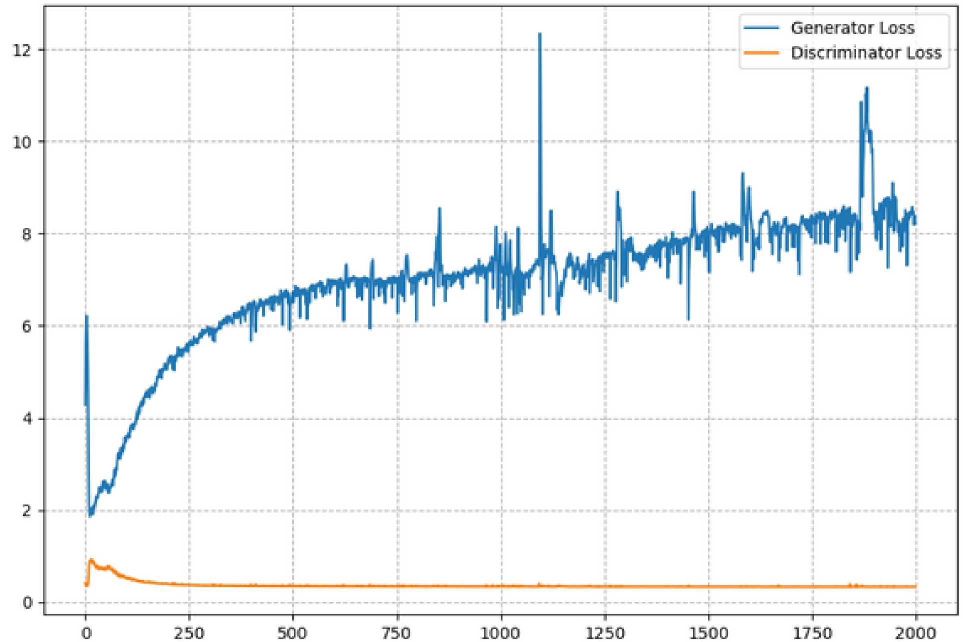
Discriminator

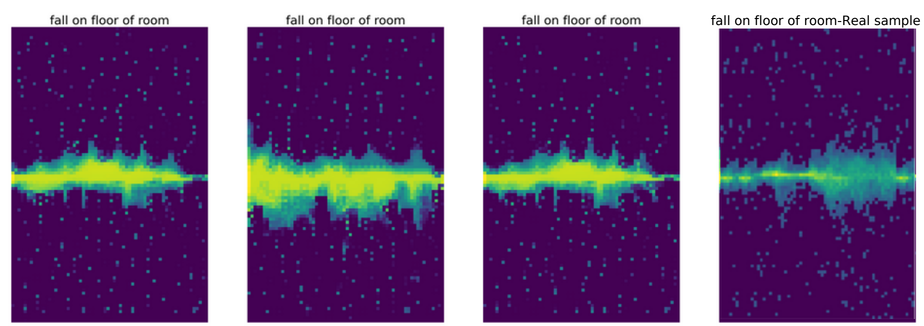


The Architecures

cGAN Simple - Results



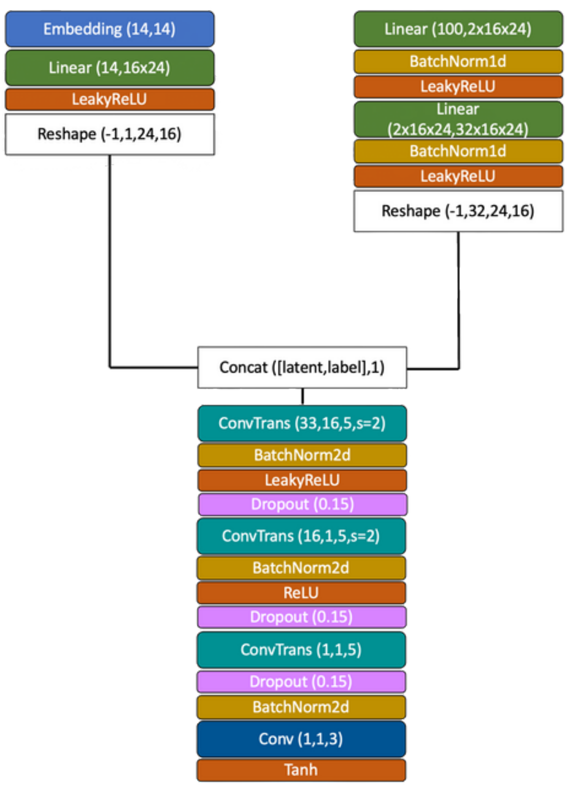




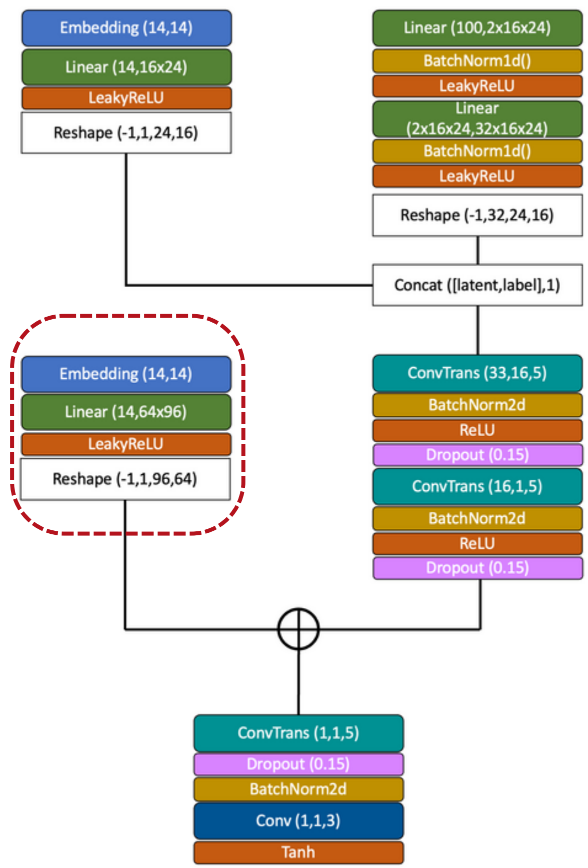
The Architecures

cGAN Refresh - Generator

cGAN Simple



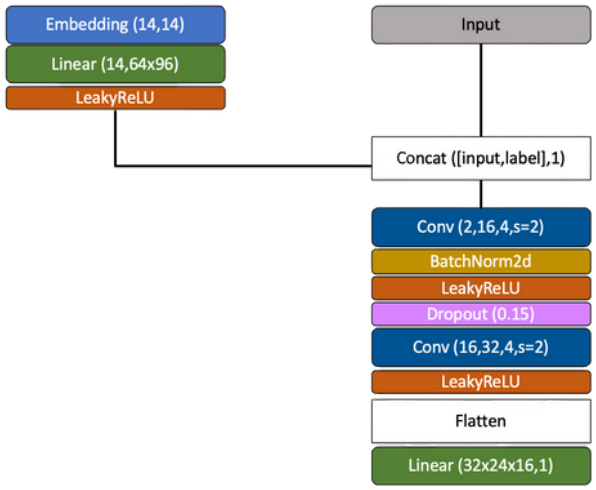
cGAN Refresh



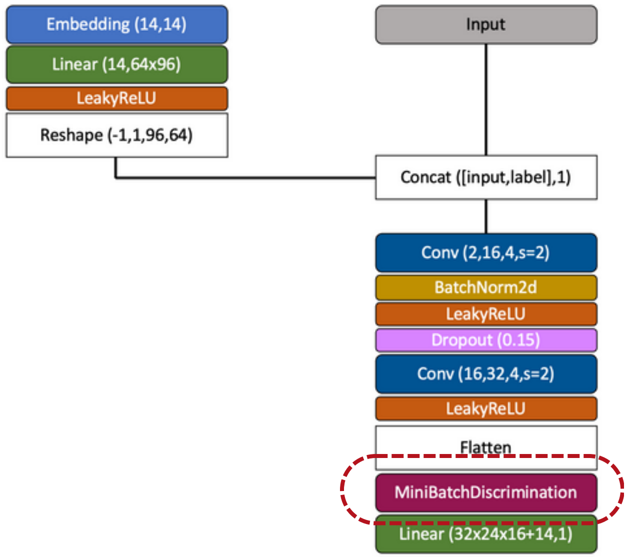
The Architecures

cGAN Refresh - Discriminator

cGAN Simple

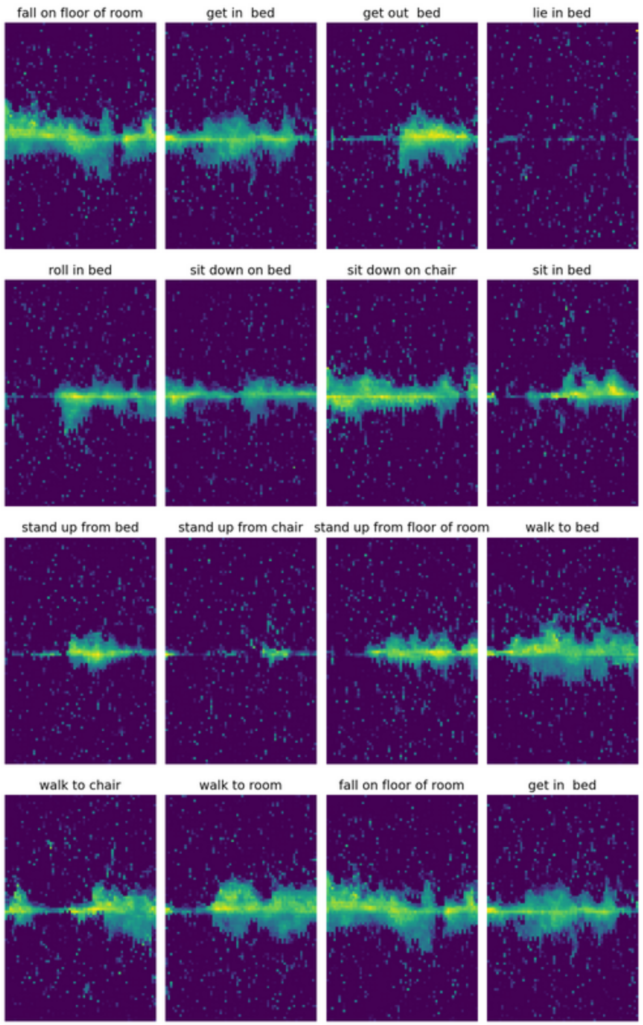


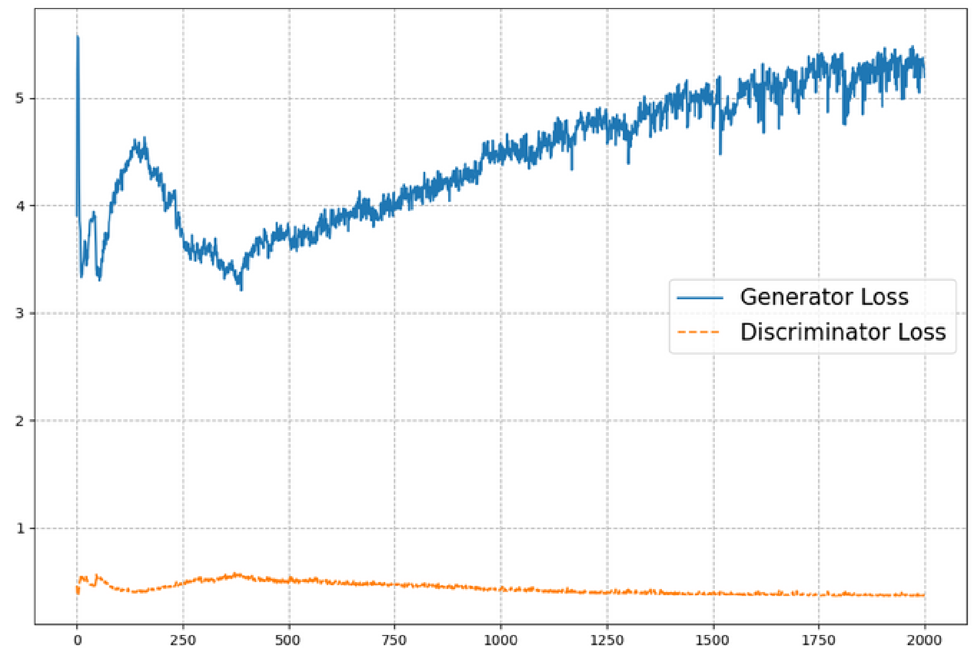
cGAN Refresh

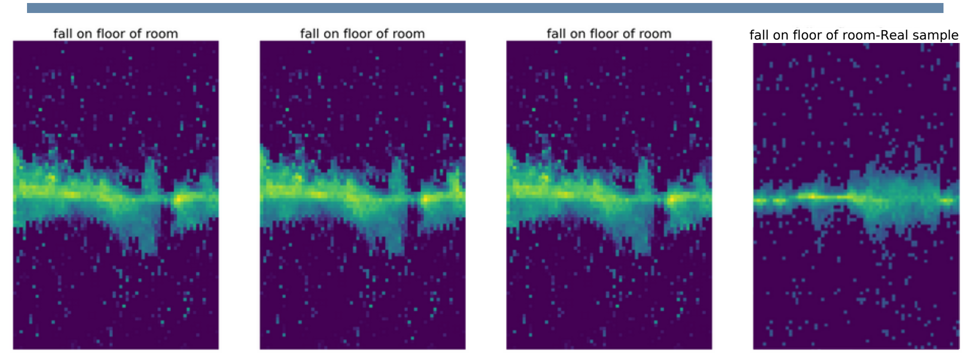


The Architecures

cGAN Refresh - Results

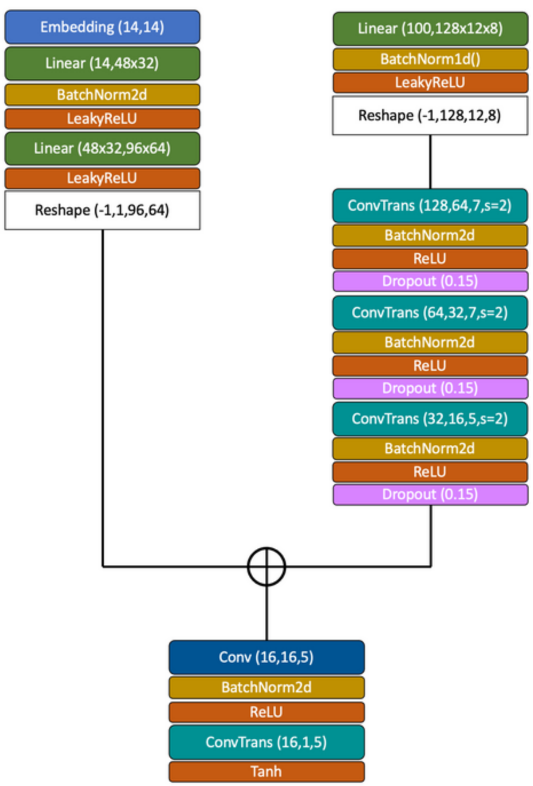




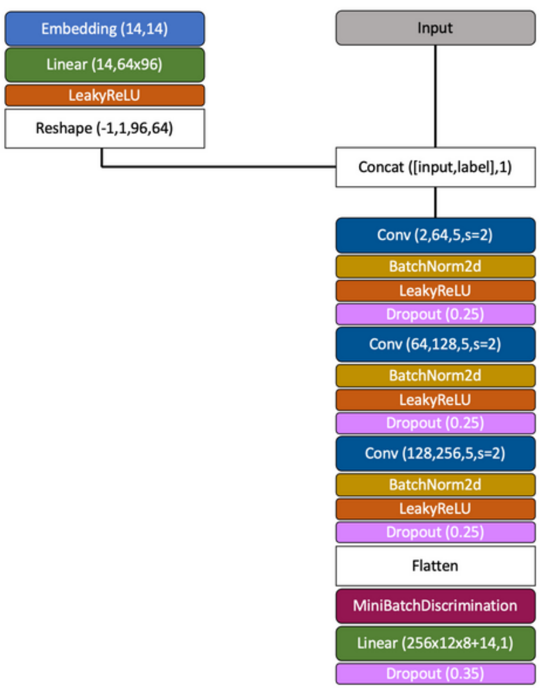


The Architecures
cGAN Minibatch

Generator

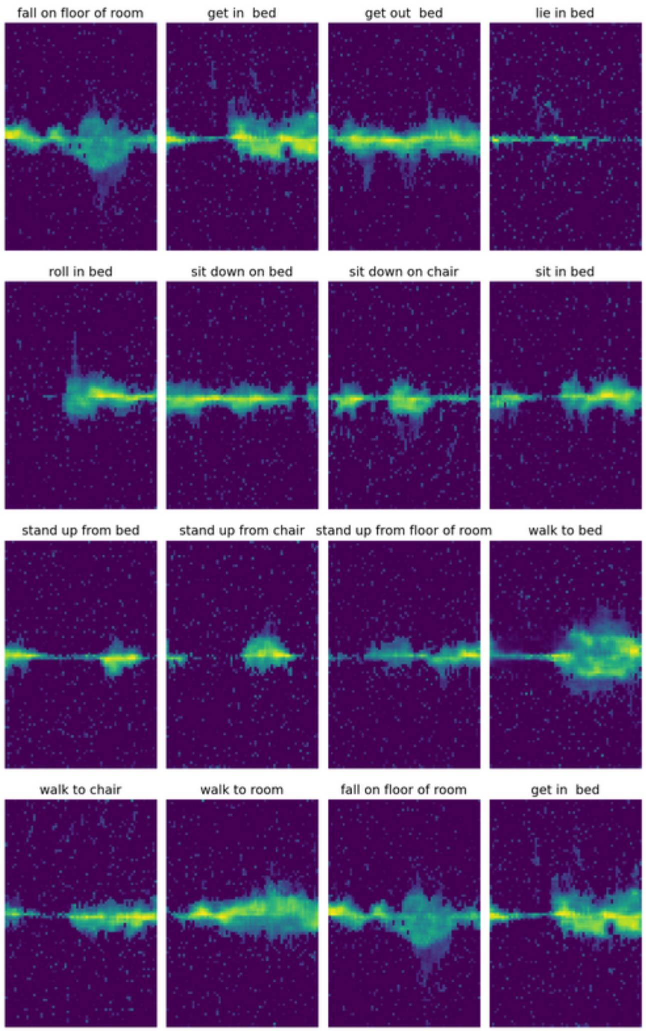


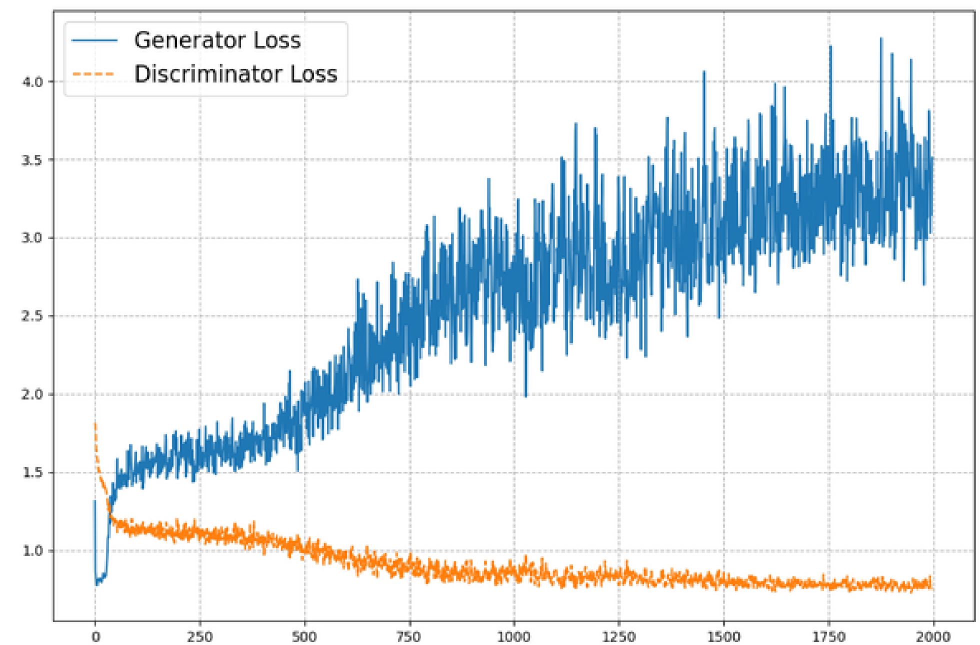
Discriminator

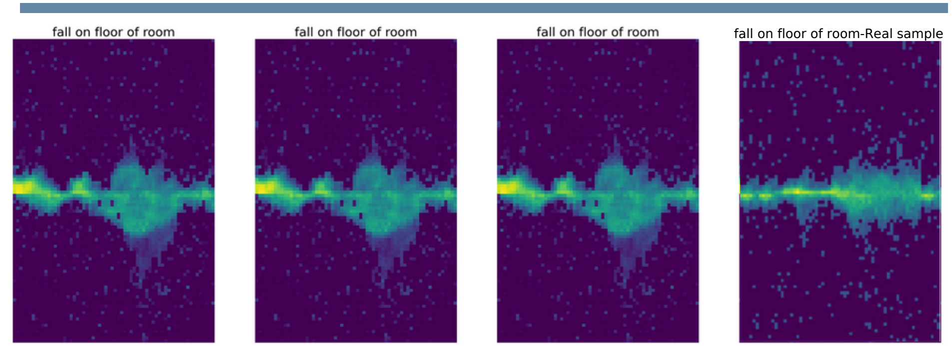


The Architecures

cGAN Minibatch - Results







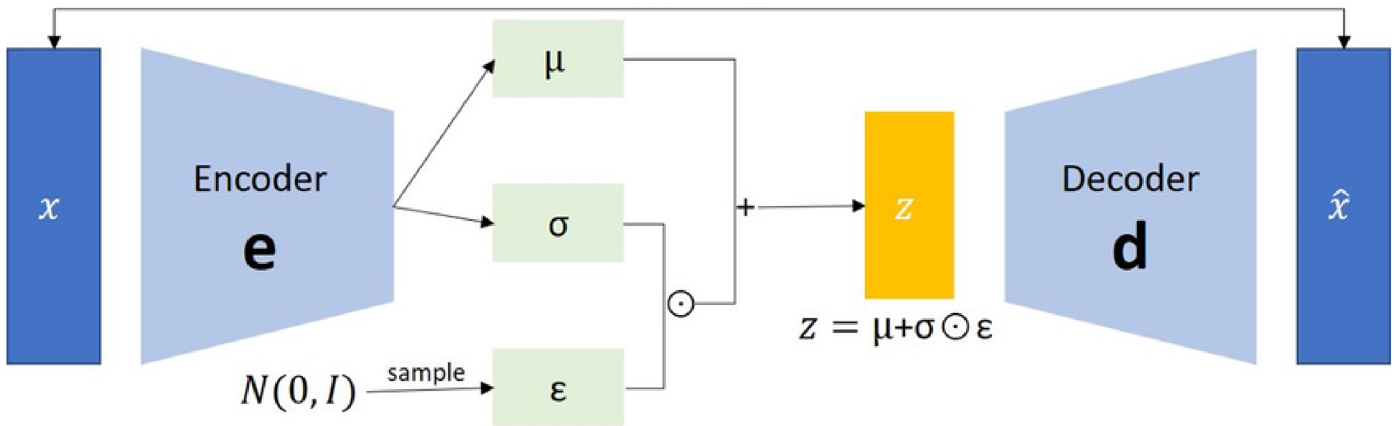
2nd approach: cVAE

VAE

Intro

Reconstruction

Minimize 1: $(x - \hat{x})^2$



Minimize 2: $\frac{1}{2}\sum_{i=1}^{N}(\exp(\sigma_i) - (1+\sigma_i) + \mu_i^{\,2})$

KL-divergence

+ clustering

+ regularization

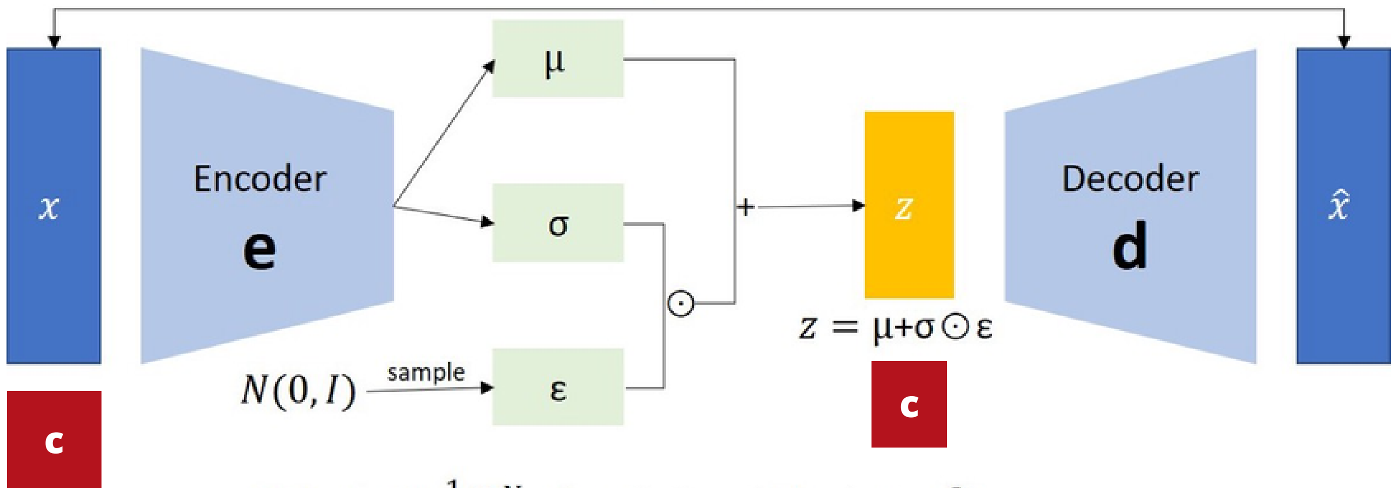
+ continuity

- smoothing

cVAE
Intro

Reconstruction

Minimize 1: $(x - \hat{x})^2$

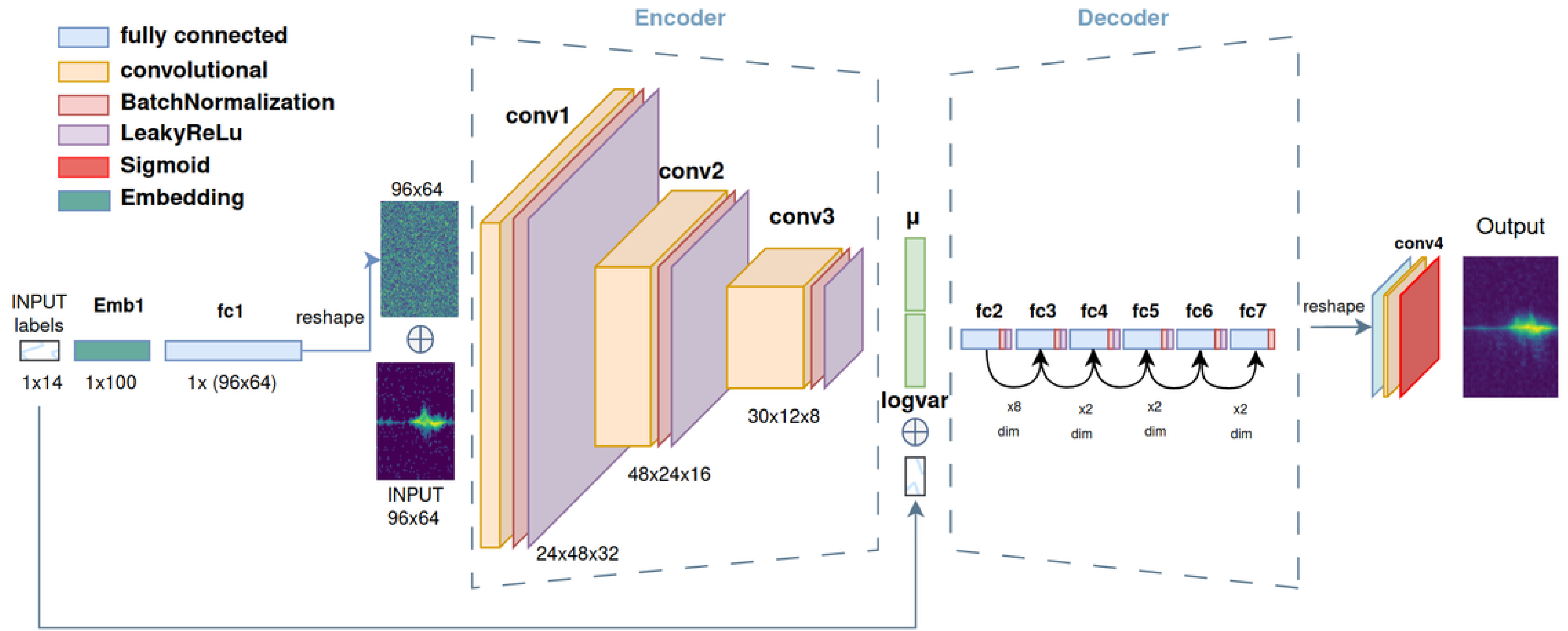


Minimize 2: $\frac{1}{2}\sum_{i=1}^{N}(\exp(\sigma_i) - (1+\sigma_i) + \mu_i{}^2)$

KL-divergence

+ conditional
- clustering
+ regularization
+ continuity
- smoothing

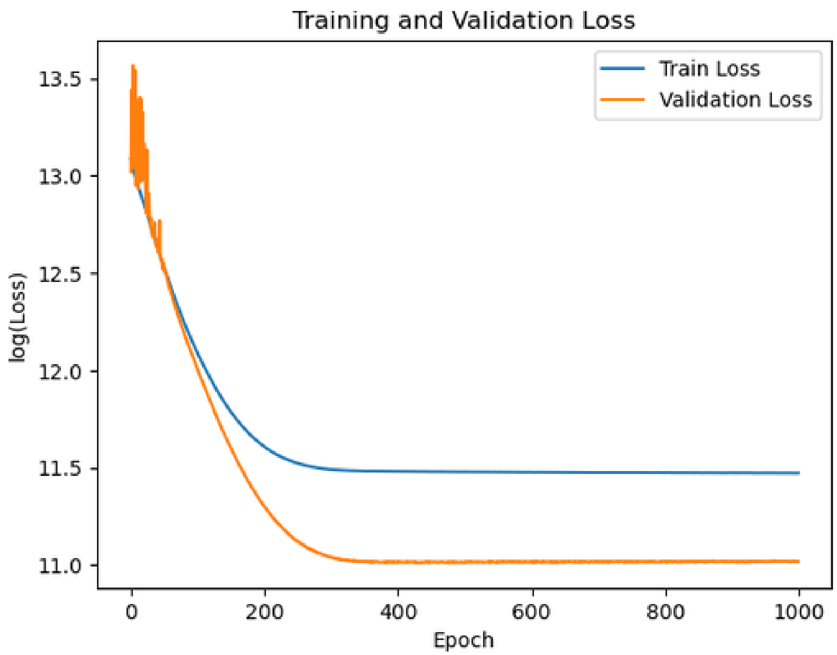
Our approach

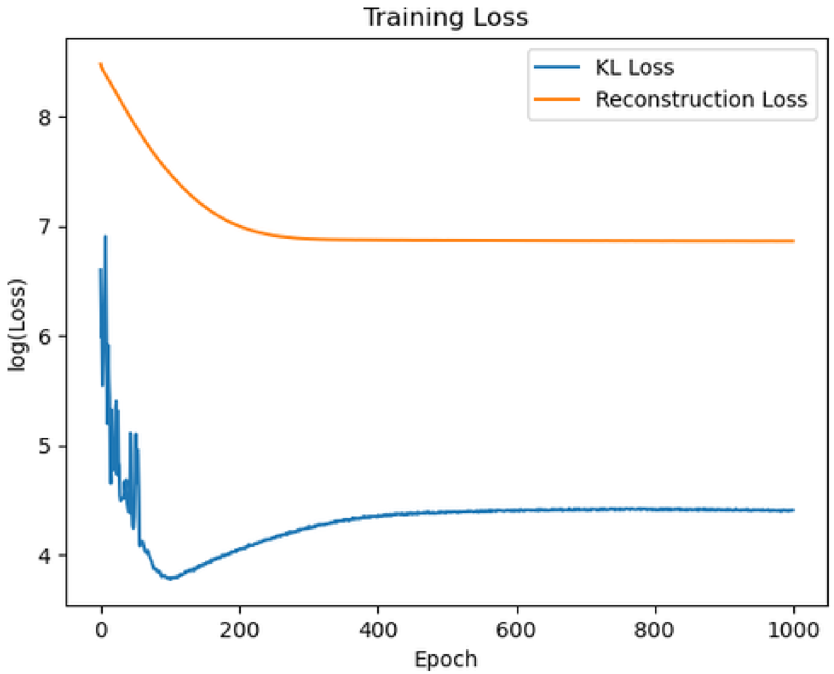


- z dim = 32
- batch size = 32
- Adam, lr 0.0001

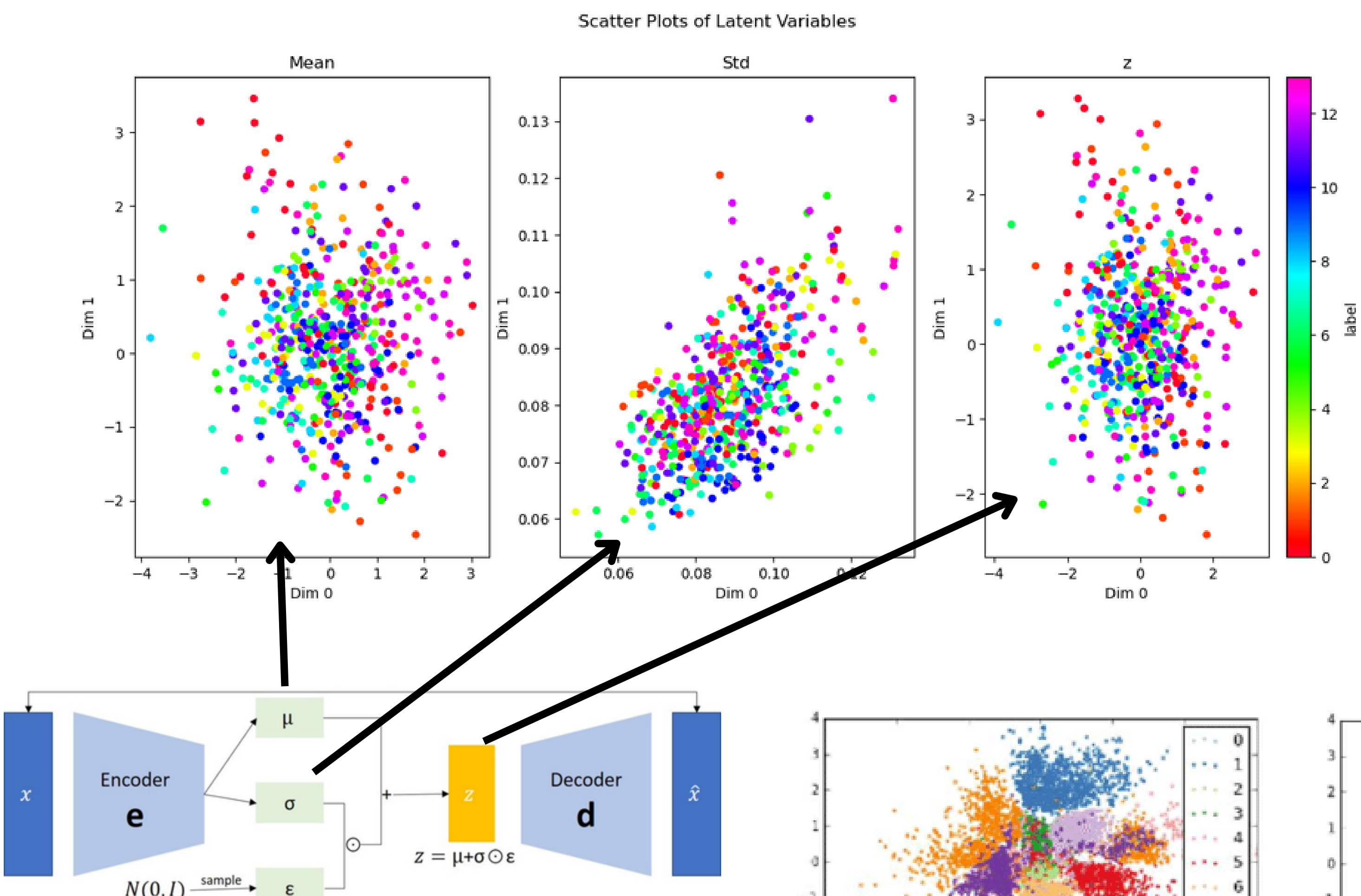
- Conv enc, Lin dec
- 1000 epochs
- L = KL + 100*recon

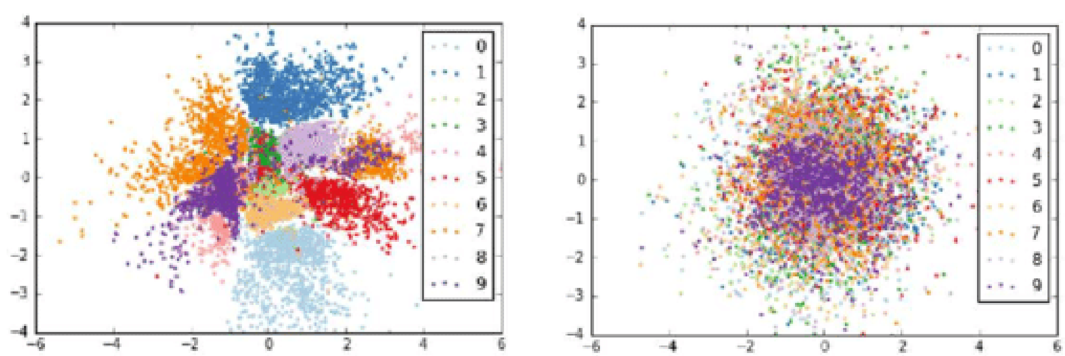
Learning process





Clustering in latent space?



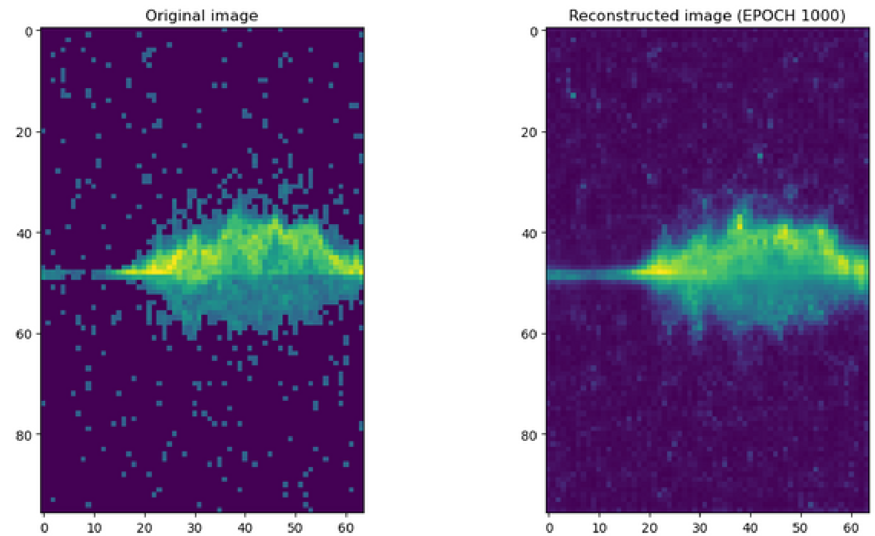


(a) VAE (b) CVAE

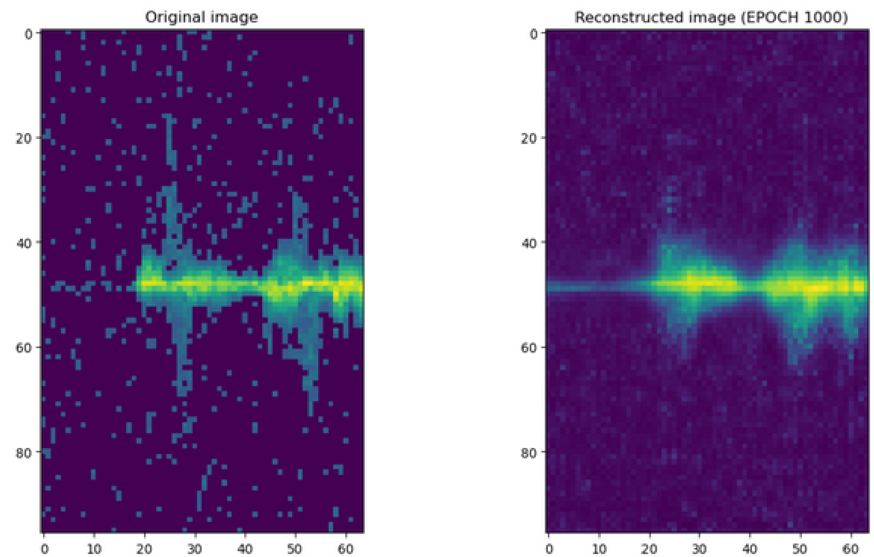
Joint Multimodal Learning with Deep Generative Models (Suzuki et al., 2016)

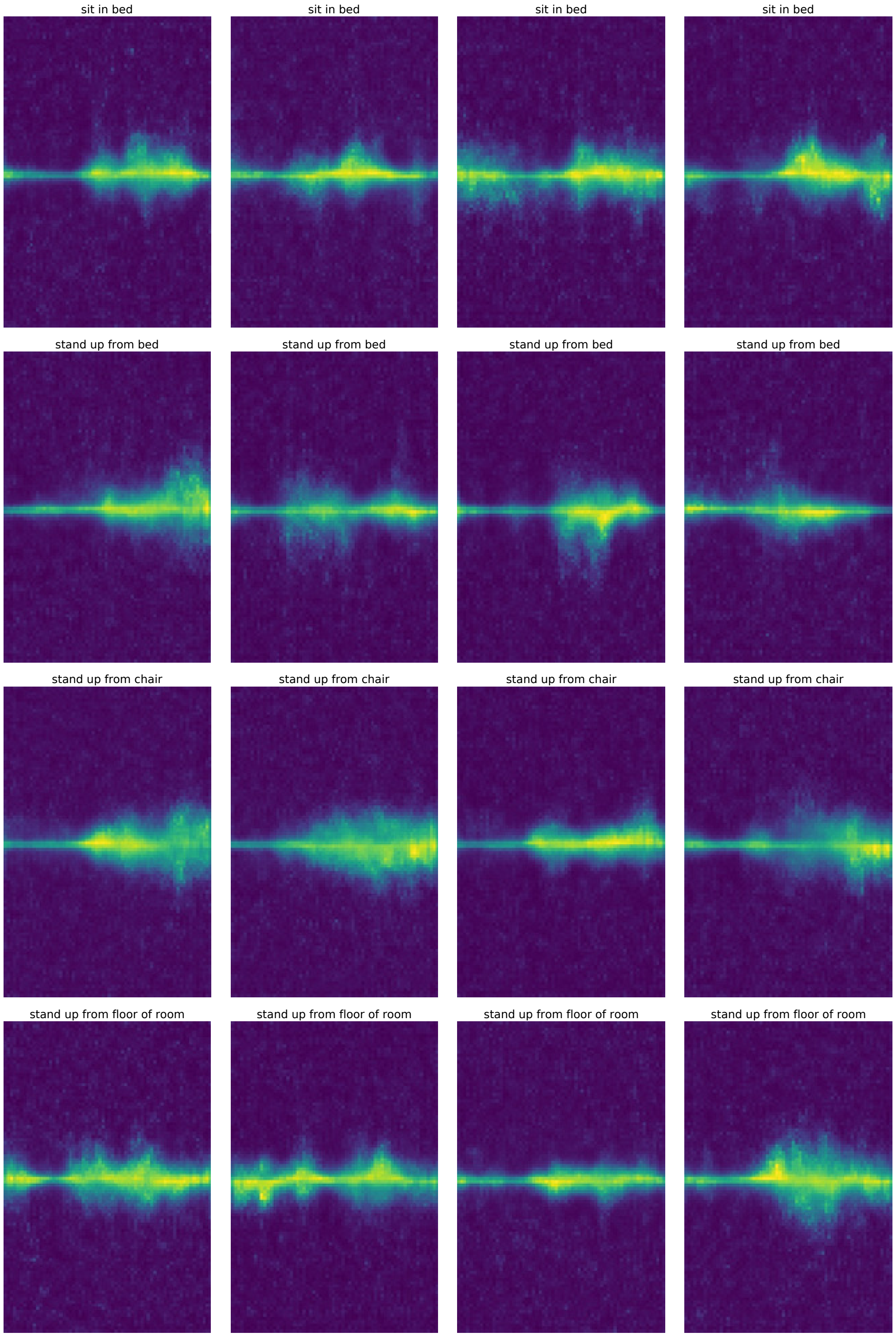
Results

Training



Test





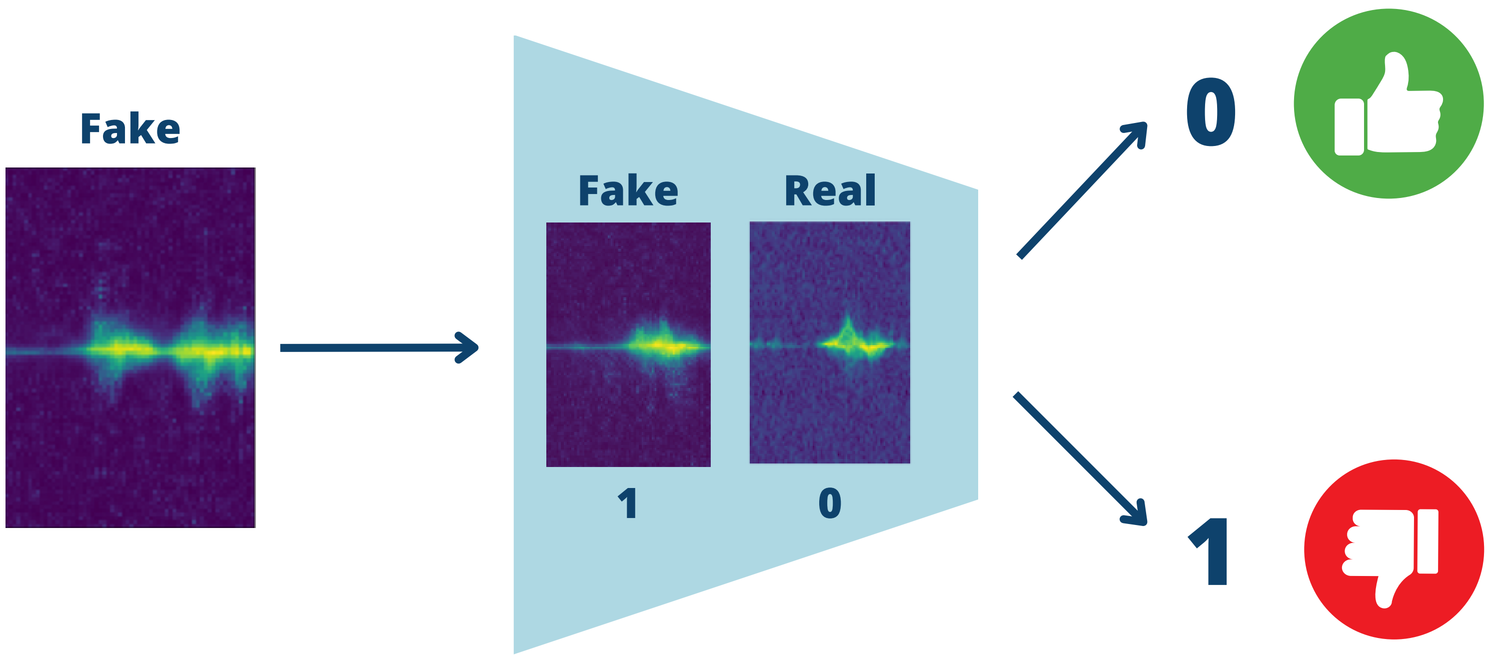
Generated data

10000 samples from Latent Space

Two-Samples Test

The goal is to trick a simple classifier:

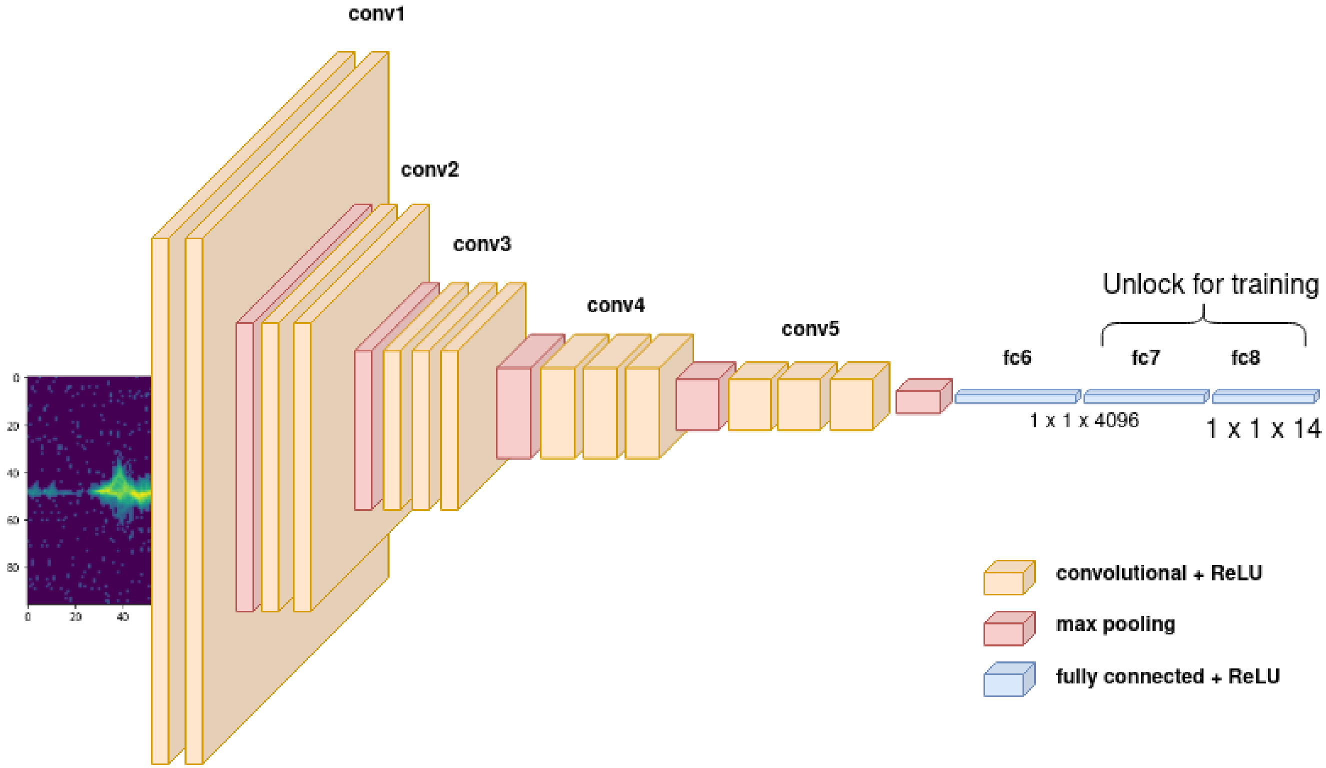
- 20 units hidden layer + ReLu + Sigmoid
- 100 epochs train + Adam 0.001 learning rate



Classificator guess correctly 99% of time

VGG16 classifier

- Fine-tuned on both Fake and Real, tested on Real



	Real Data	Generated Data
Accuracy	**0.49**	**0.09**

Future work

CGAN

- working on the divergence of the loss
- understand the mode collapse

CVAE

- solving the loss of label information

Backup
Number of parameters

- **cGAN Simple**
  - Generator: 9559722
  - Discriminator: 113429
- **cGAN Refresh**
  - Generator: 9652078
  - Discriminator: 16628515
- **cGAN Minibatch**
  - Generator: 11244628
  - Discriminator: 34175635
- **cVAE**
  - total parameters: 25972900

Backup
Class Balance