

Generative Adversarial Networks for Time-Based Data

In collaboration with Dow Chemical

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What can a GAN model do for its users?

USE CASE 1

Using GAN model to generate augmented data

User input: Time series data (ex: experimentally derived data-points)

User receives: Generated time series data set (based on patterns from experimentally derived data-point)

Purpose: Generate data for processes that are very costly to collect experimentally. Generate artificial data for cross-company collaboration.

USE CASE 2

Using GAN model with new multi-featured data

User input: Time series dataset with multiple features (ex: data from various chemical processes, pressures, temperatures)

User receives: Generated multi-feature time series data set via a model learning each feature trend and their correlations

Purpose: Expanding the model to encompass data with multiple features

USE CASE 3

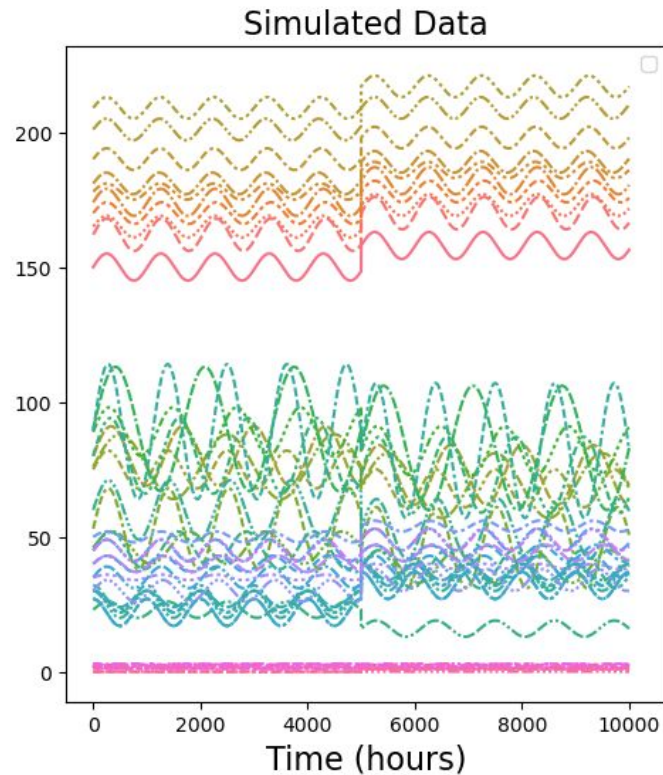
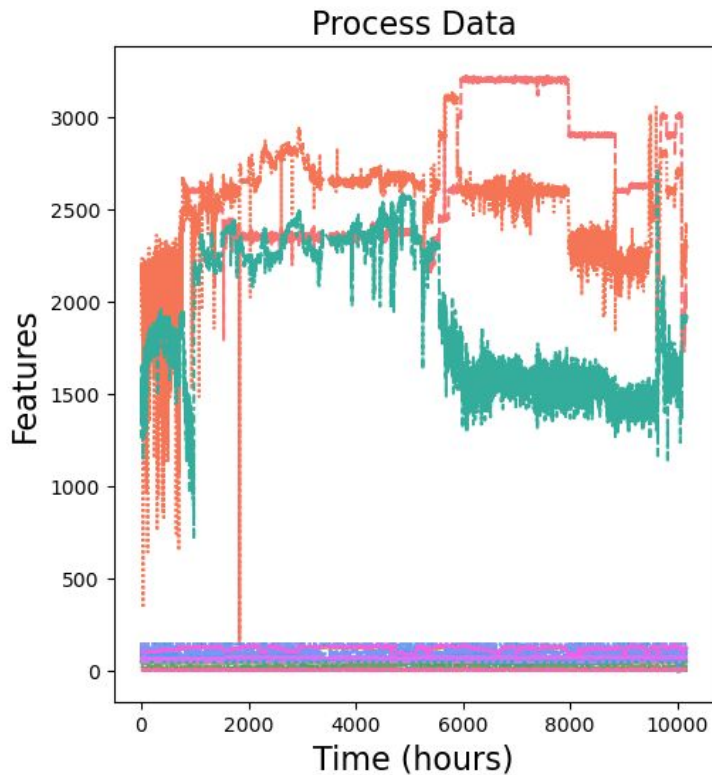
Using GAN model to extrapolate data beyond given time range

User input: Time series data until $t = x$ seconds

User receives: Time series data past the point of experimentally derived data

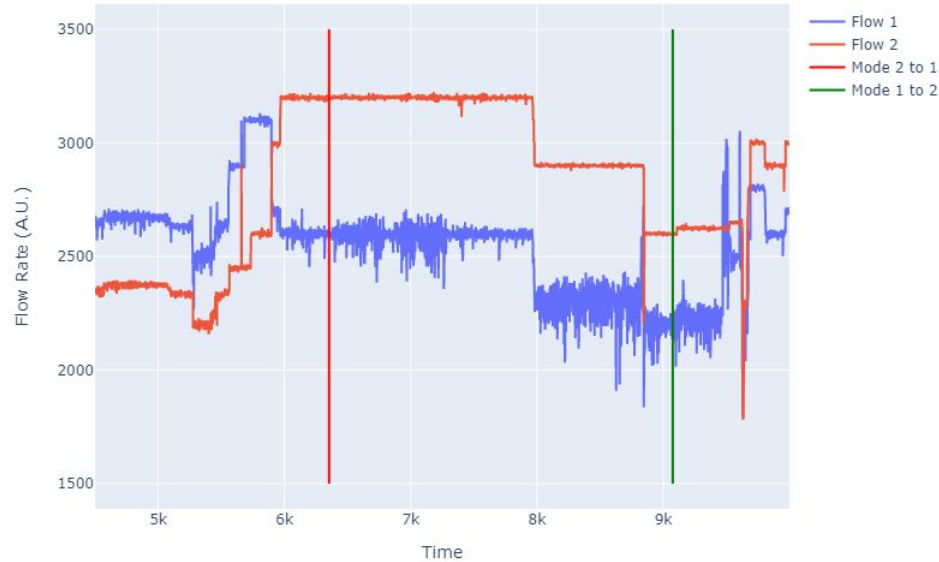
Purpose: Generate time series data for costly or time intensive experiments to leverage in decision making.

Data we are currently working with: testing & training



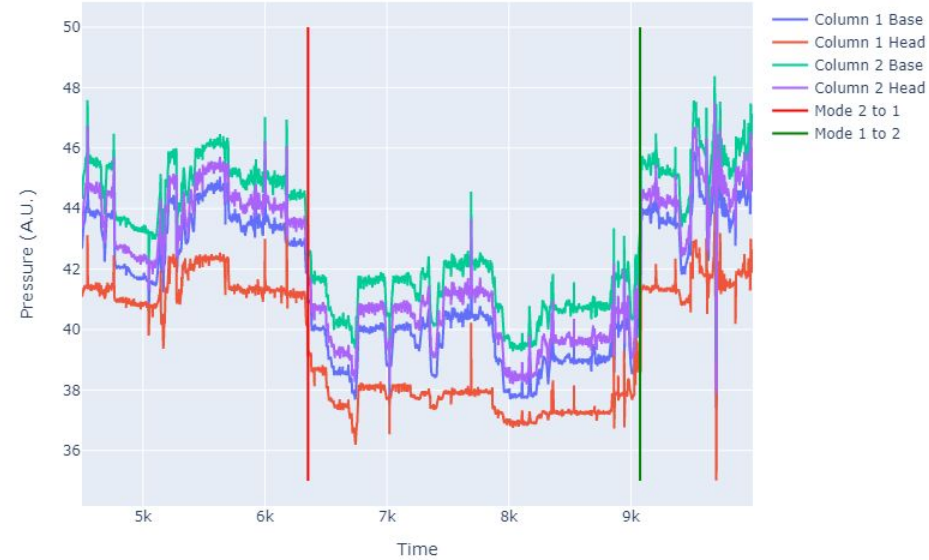
Data has two operating conditions

Flow



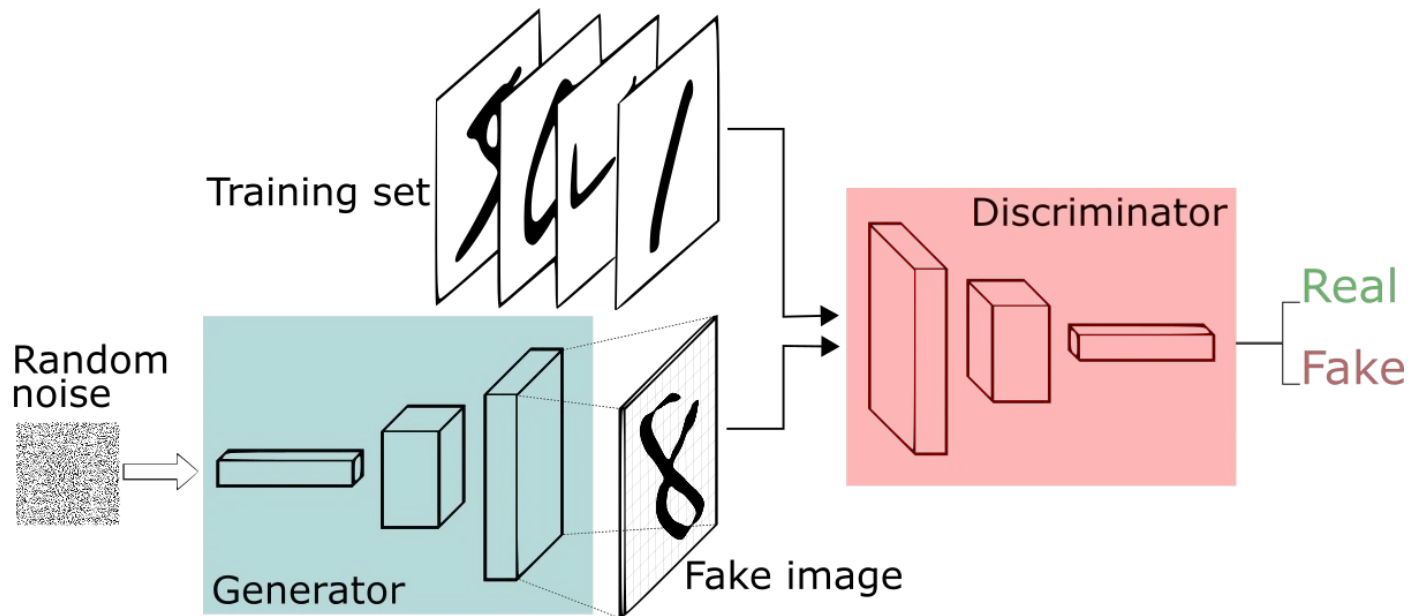
Manual operating conditions for some features

Pressure



Condition is based on column pressure

How do GANs work?



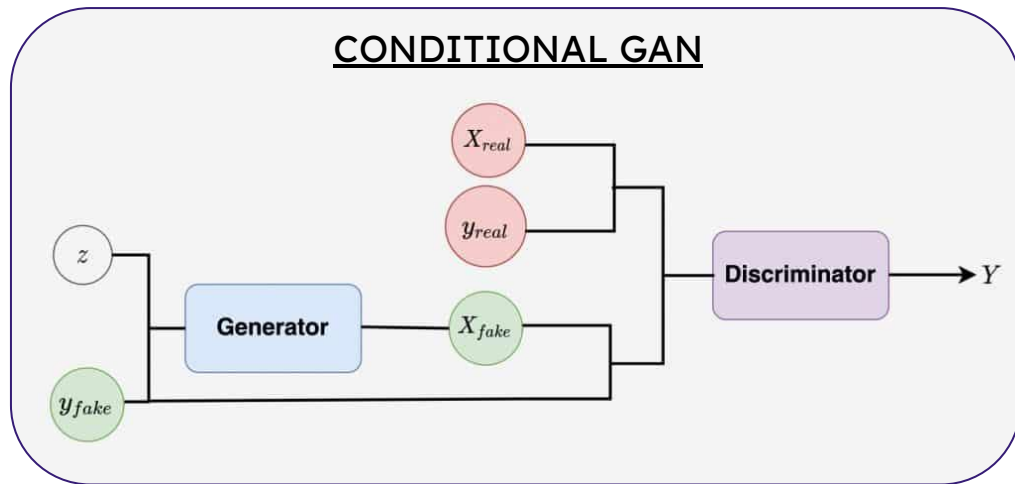
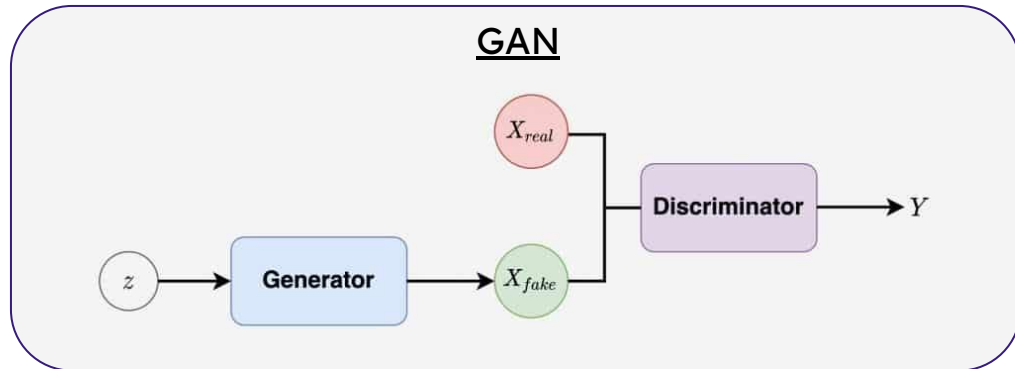
Conditional GANs vs. GANs

Typical GANs — “unsupervised”

- No control on modes of the data being generated

Conditional GAN (CGAN) —
“semi-supervised”

- Generator learns to generate a fake sample **with a specific condition or characteristics** (such as a label associated with an image or more detailed tag)



Initial CGAN model architecture: basic convolutions

Number of datapoints:
10,000

Number of samples: 59

**Number of features per
sample:** 45

**Number of datapoints
per sample:** 168

Process Condition: 1 or 2

DATA PRE-PROCESSING

- Target = samples of time-series data, condition/label = process condition
- Min-max scaling of the target
- Batching the targets and conditions for input

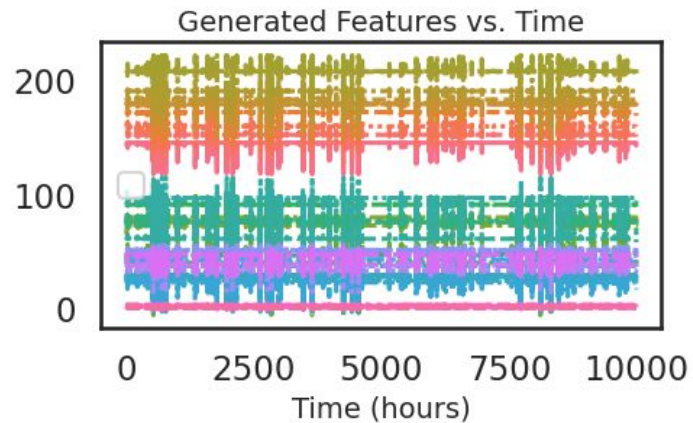
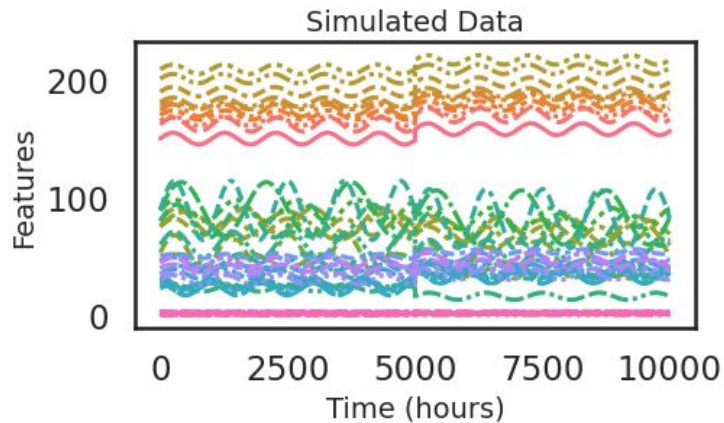
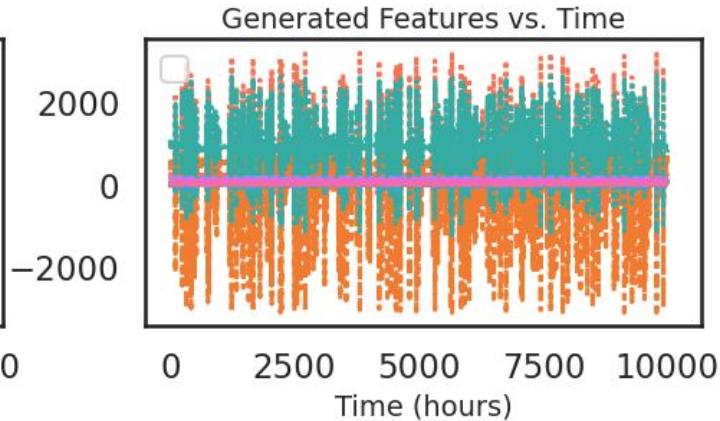
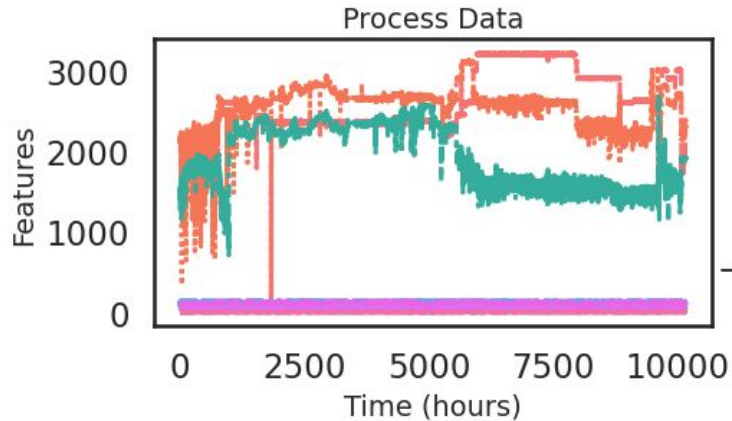
DISCRIMINATOR

- Concatenate time-series matrix + conditions for each time-series point
- Passes through a series of convolutional/max pool layers
- Activation function: Sigmoid
- Output size: [10, 1]

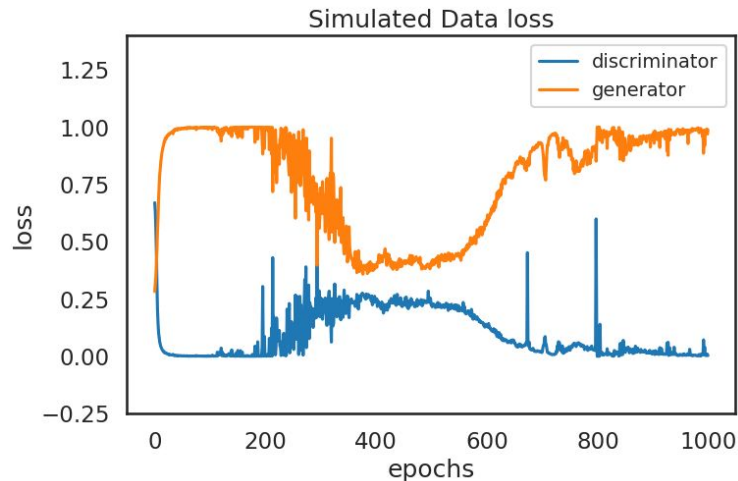
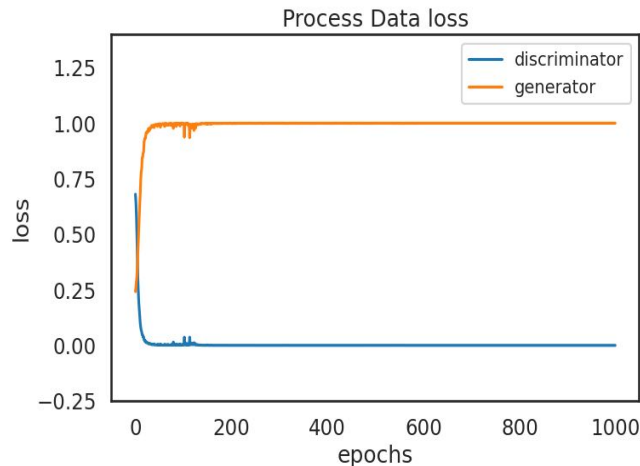
GENERATOR

- Concatenate time-series matrix + conditions for each time-series point
- Pass through convolutional/batch norm layers
- Activation function: Tanh
- Output size: [10, 168, 45]

Results



Models are not learning



Data preprocessing:
Dropping NaN values
MinMaxScaler (0,1)

D. parameters / G. parameters:
Epochs: 1000
Activation function: Sigmoid()
Learning rate: 0.0005
Optimizer: Adam
G. Loss function: MSE Loss
D. Loss function: BCE Loss

Vanishing gradient problem - discriminator is not providing enough information for generator to make progress, weights are not updated

Example Optimization

D. parameters / G. parameters:

Epochs: 200

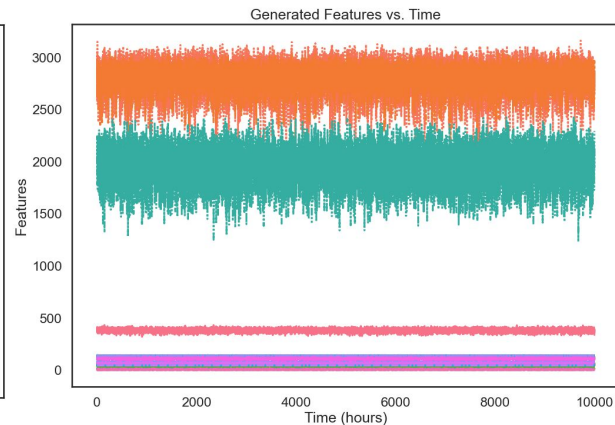
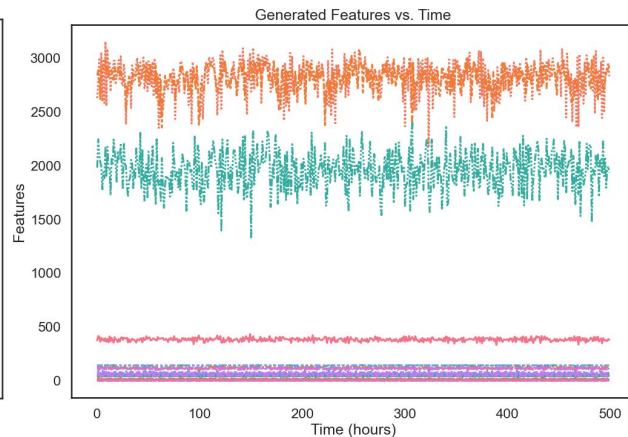
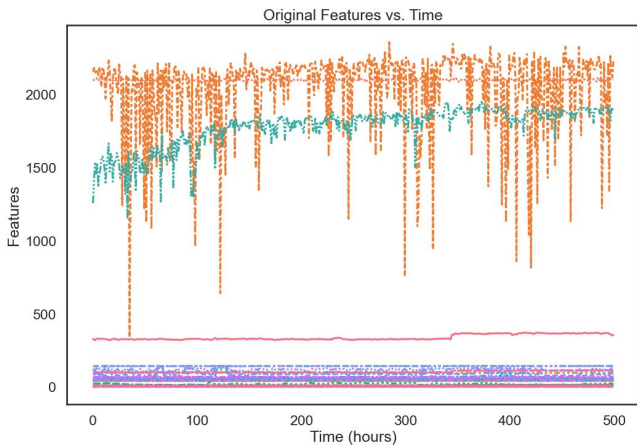
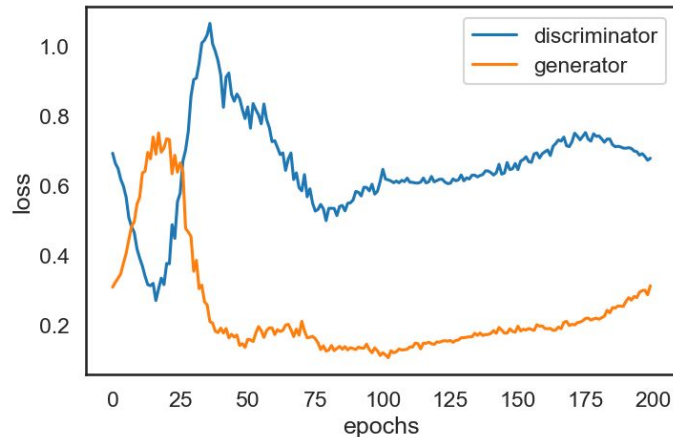
Activation function: Sigmoid()

Learning rate: 0.0002

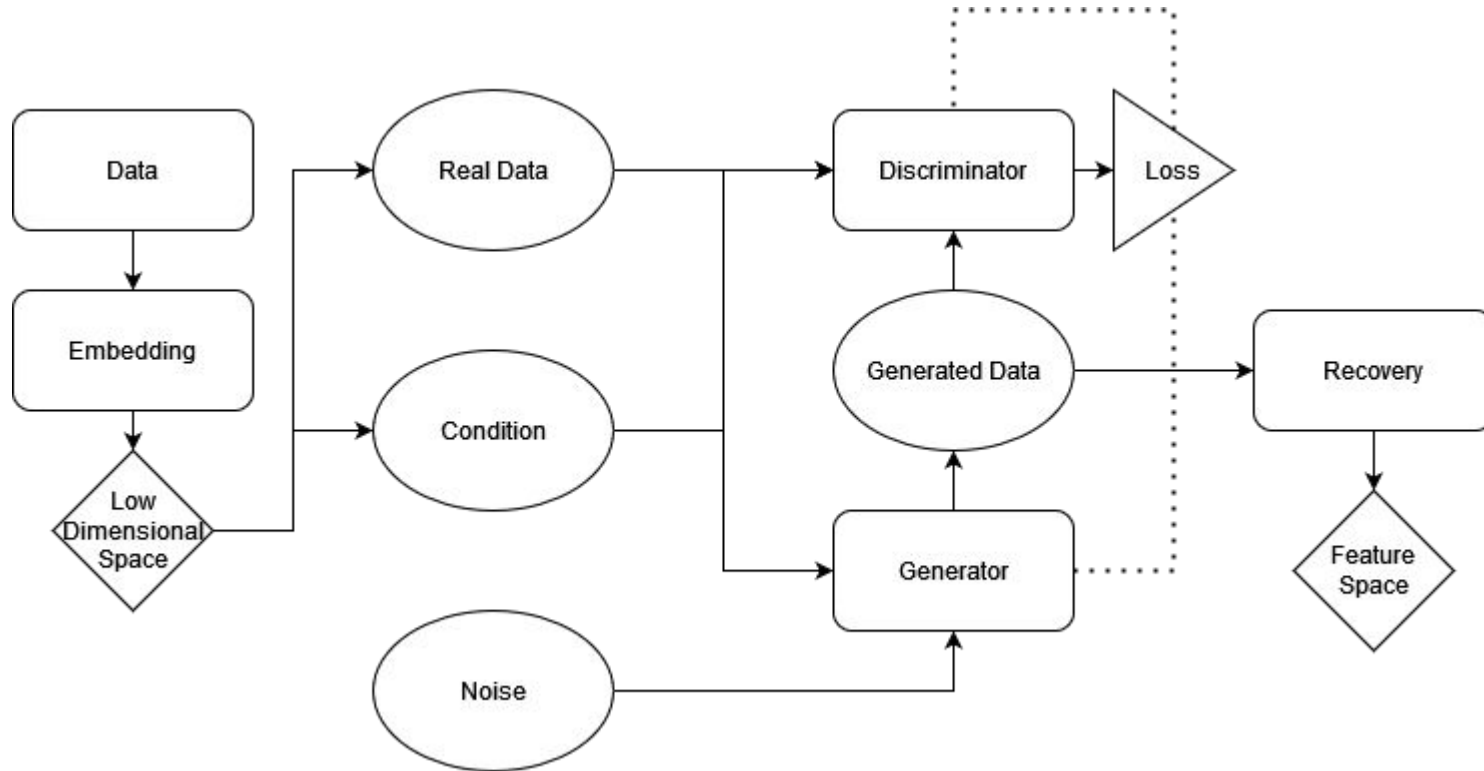
Optimizer: Adam

G. Loss function: MSE Loss

D. Loss function: BCE Loss



Encoder CGAN Model



Embedding and Recovery Model Architecture

Layer (type)	Output Shape	Param #
GRU-1	[[-1, 10, 50], [-1, 2, 50]]	0
Linear-2	[-1, 10, 15]	765
Sigmoid-3	[-1, 10, 15]	0

Total params: 765

Trainable params: 765

Non-trainable params: 0



Embedder

Layer (type)	Output Shape	Param #
GRU-1	[[-1, 10, 50], [-1, 2, 50]]	0
Linear-2	[-1, 10, 45]	2,295

Total params: 2,295

Trainable params: 2,295

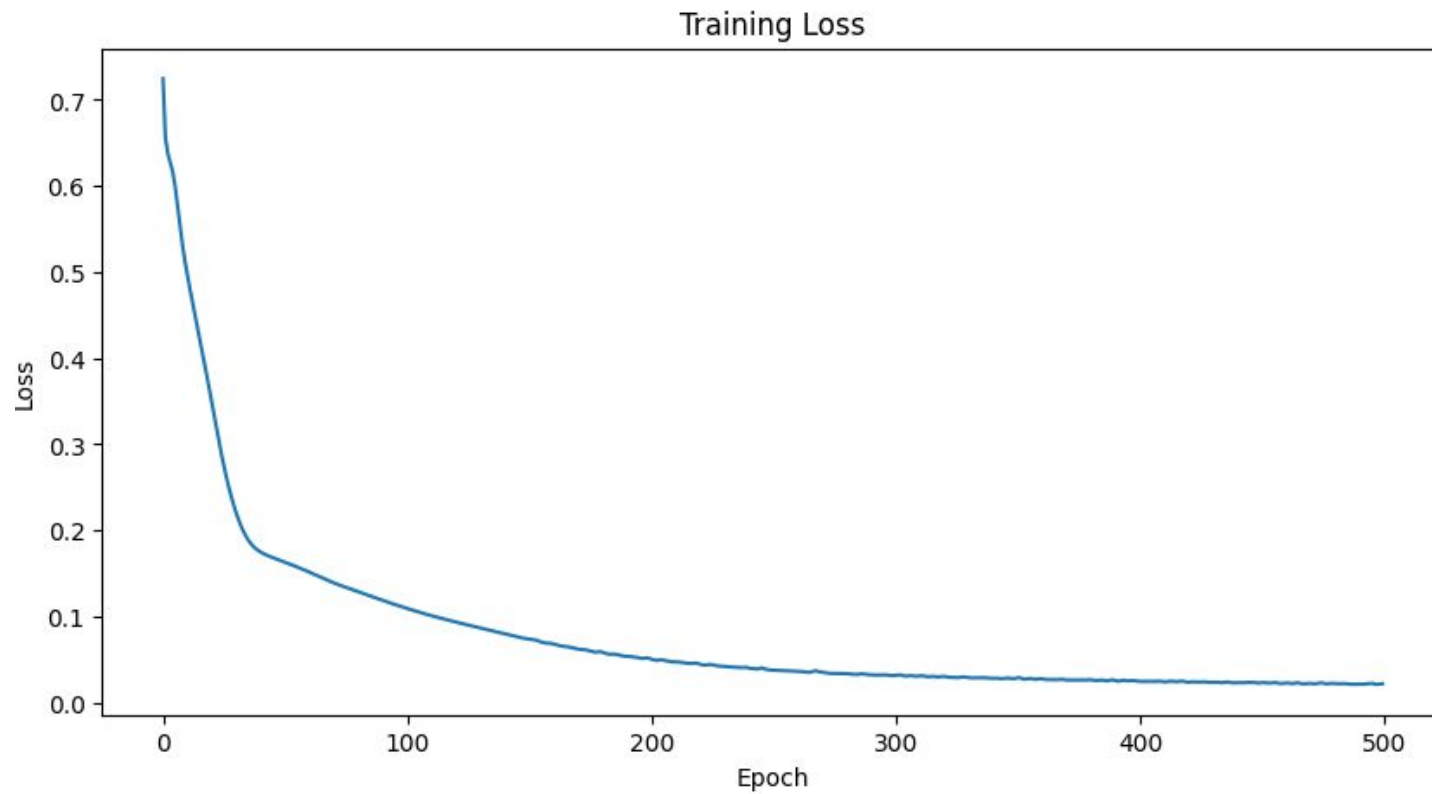
Non-trainable params: 0



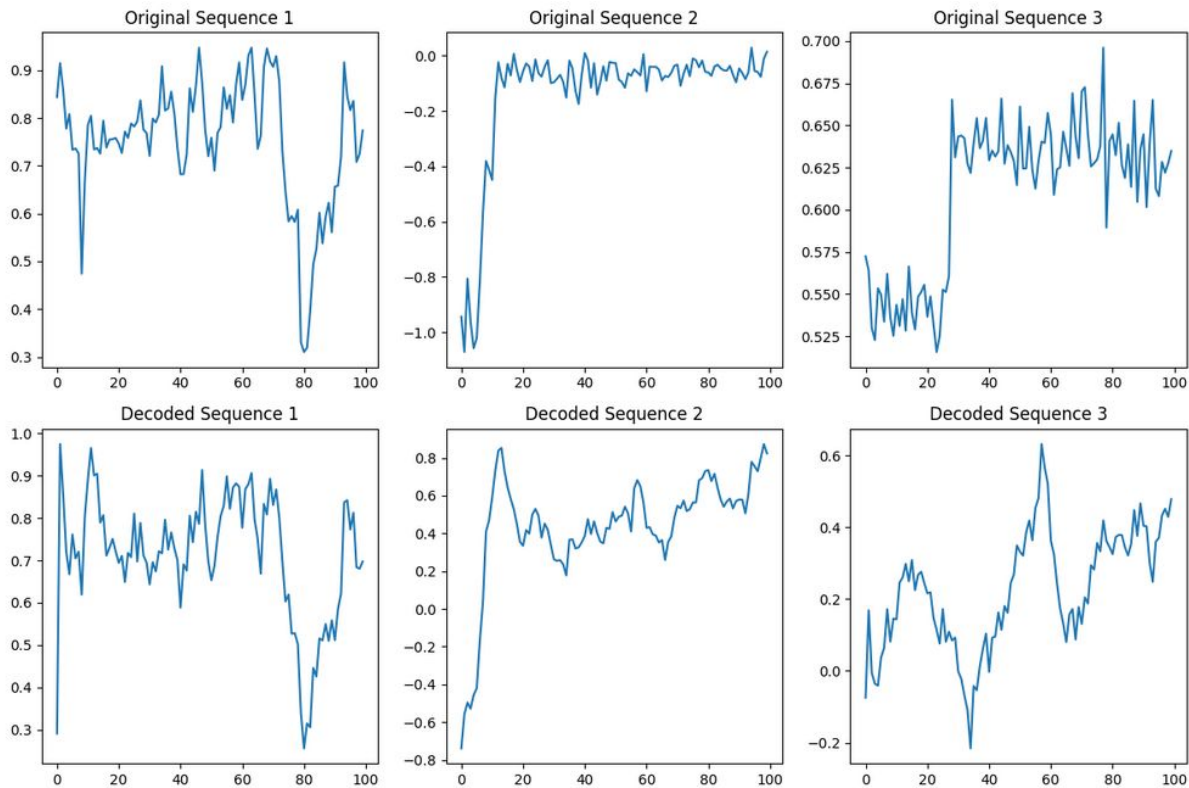
Recovery

Summary by torchsummary
Visual by Netron.app

Embedder Recovery Loss



Recovery of Process Data



CGAN Architecture

Generator:

- Generates synthetic data by combining noise and condition using a GRU unit and linear layers.

Discriminator:

- Rates the "realness" of data based on condition using convolutional and linear layers.



Generator

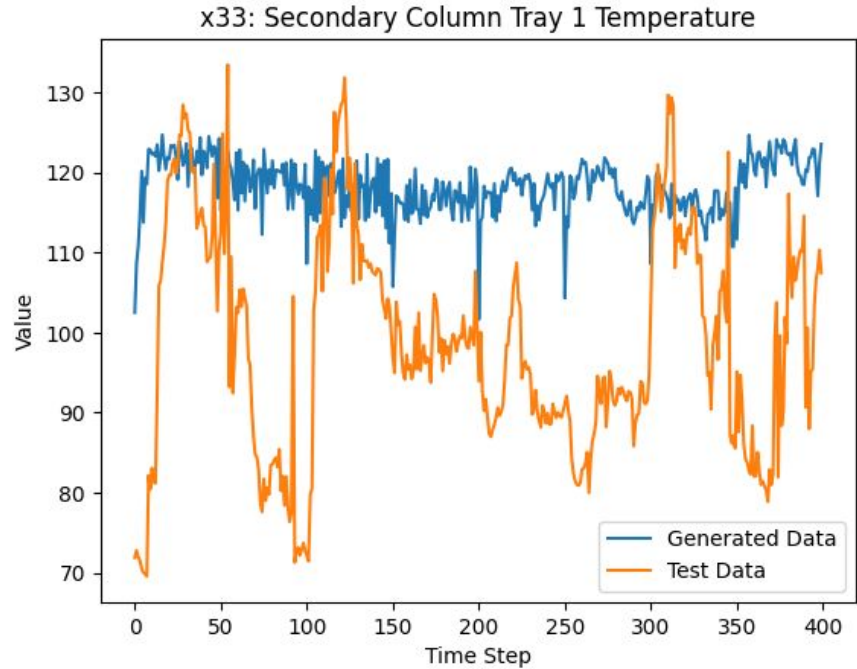
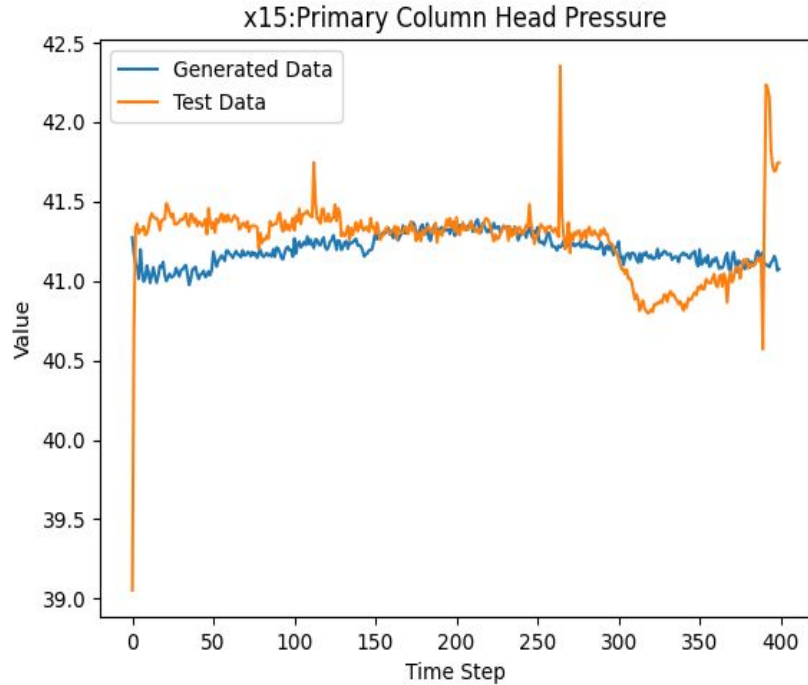


Discriminator

CGAN Loss

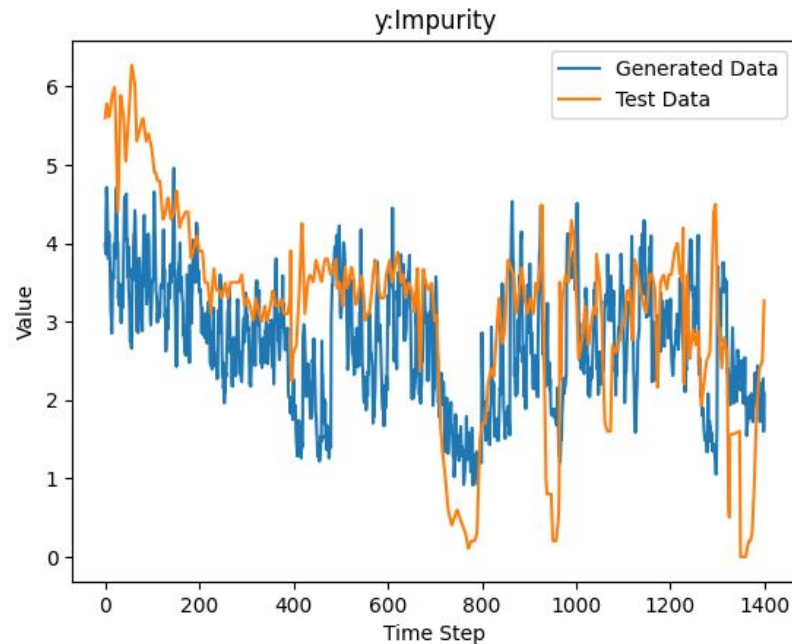
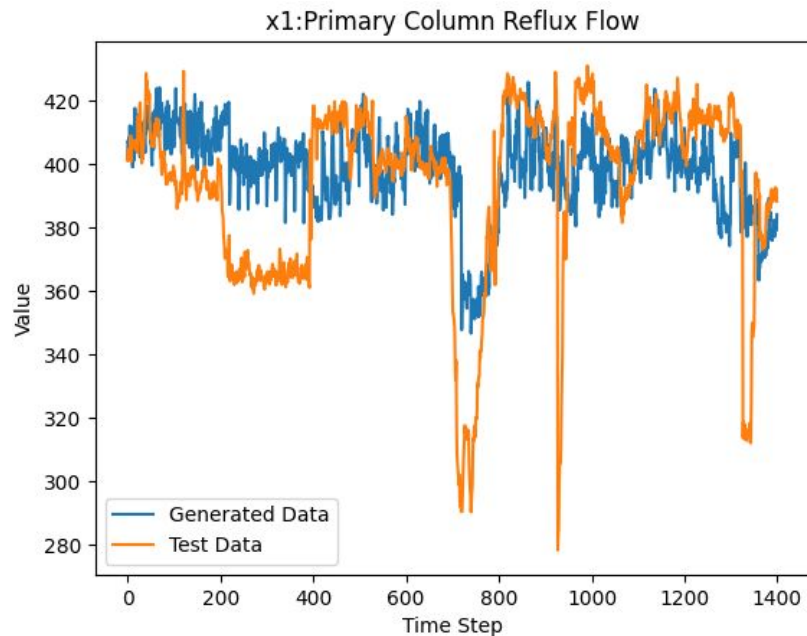


Data Generation Visualization



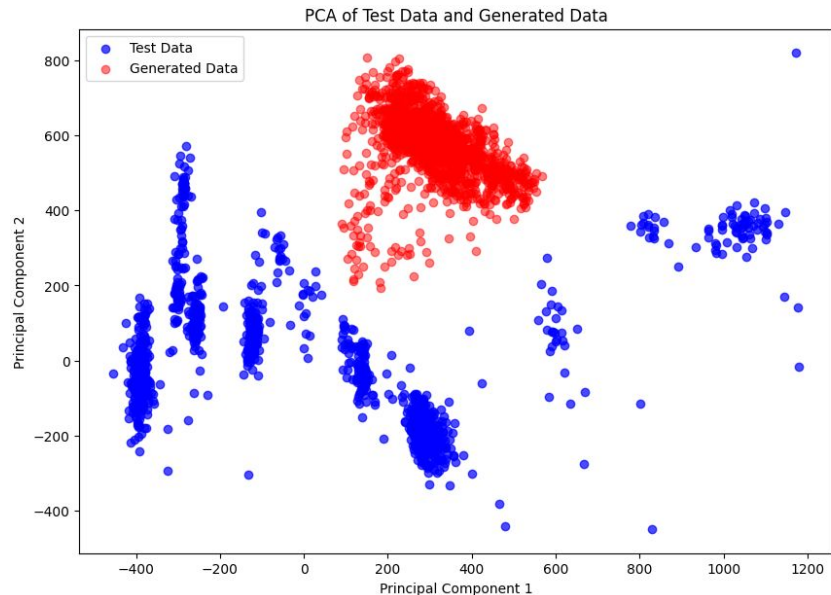
Sequence Length 50

Data Augmentation Visualization

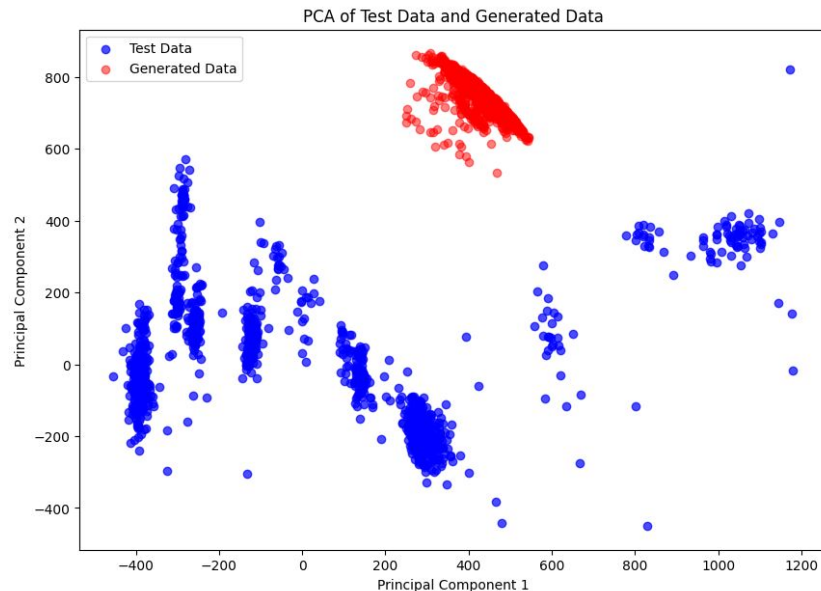


Sequence Length 20

Primary Component Analysis

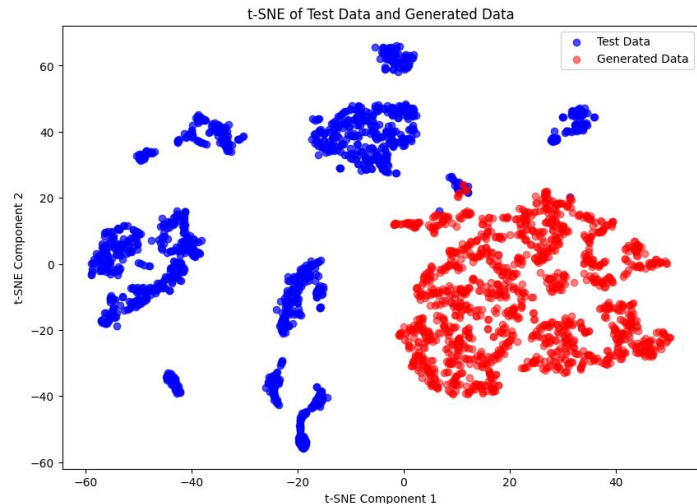


Generated with recurrent condition feed

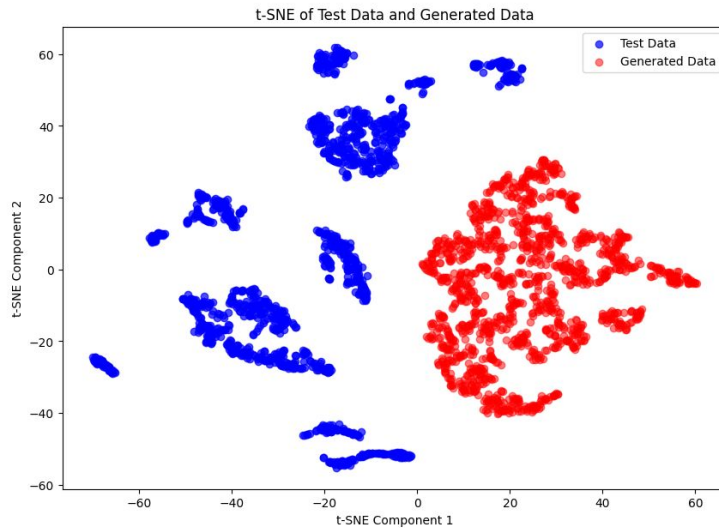


Generated with single condition feed

t-Distributed Stochastic Neighbor Embedding



Generated with recurrent condition feed



Generated with single condition feed

Future Efforts

- Incorporate reconstruction loss into Embedder/ Recovery Model training
- Increase Model Complexity with more layers
- Data preprocessing for steady state condition