Imitation Learning for Skill Transfer in Human-Robot Teleoperation

- **Group 11**

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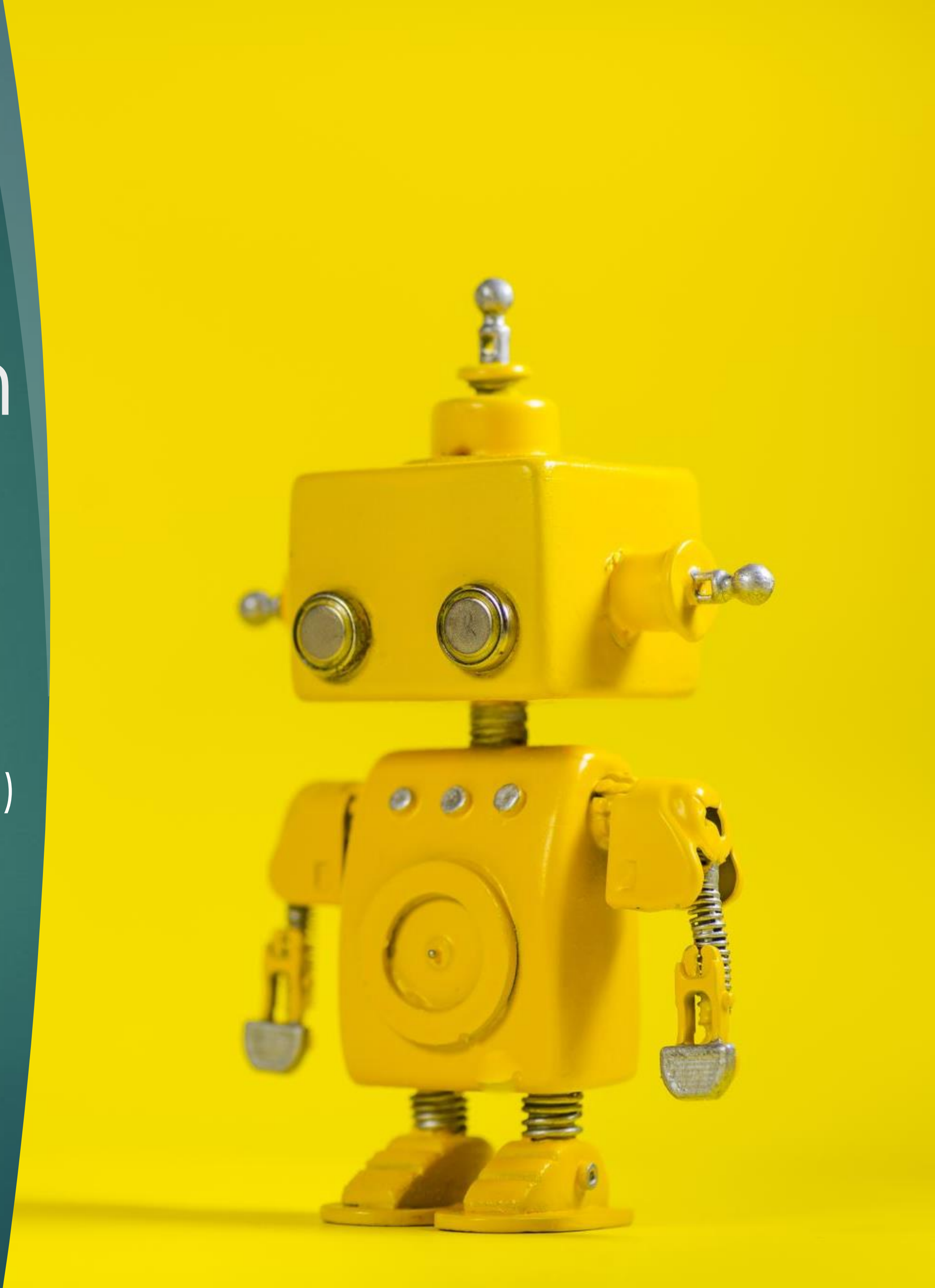
TUDelft



Project Background

- ❑Robotic intelligence for specific skills
  → **Imitation Learning**

- ❑Rapid development of 5G technology
  → **Teleoperation**

Fig 1. the Surgery Performed by Da Vinci Robot

Applications:
Service Robot; Biped Robot; Surgery Robot;

Motivation

Main Problem:
Transmission time delay
Transmission data size

Control interval: 1 ms = 0.001 s
Number of control input: 6

Reproduce the trajectory in the past 1 s:
6000 float number data
\+ force data & torque data

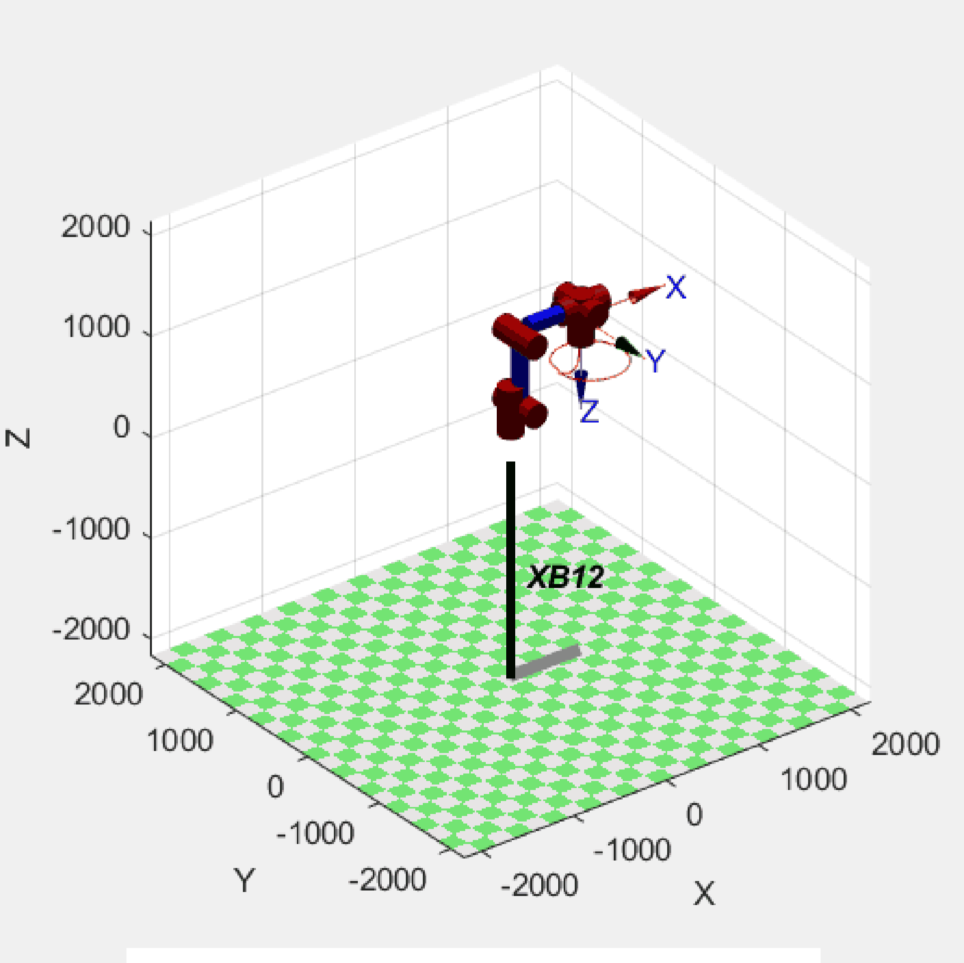


Fig 3. example for 6-axis Industrial Robot

Setup

Project Requirements

Learn the trajectories

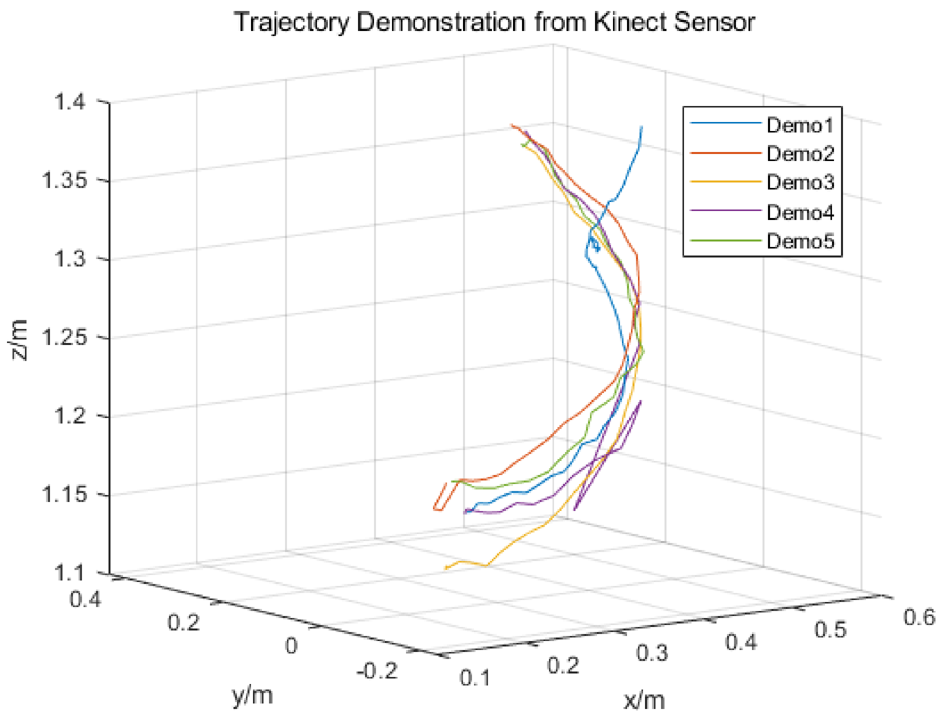
Minimal inputs

Ethical and societal implications

Normative Ethics

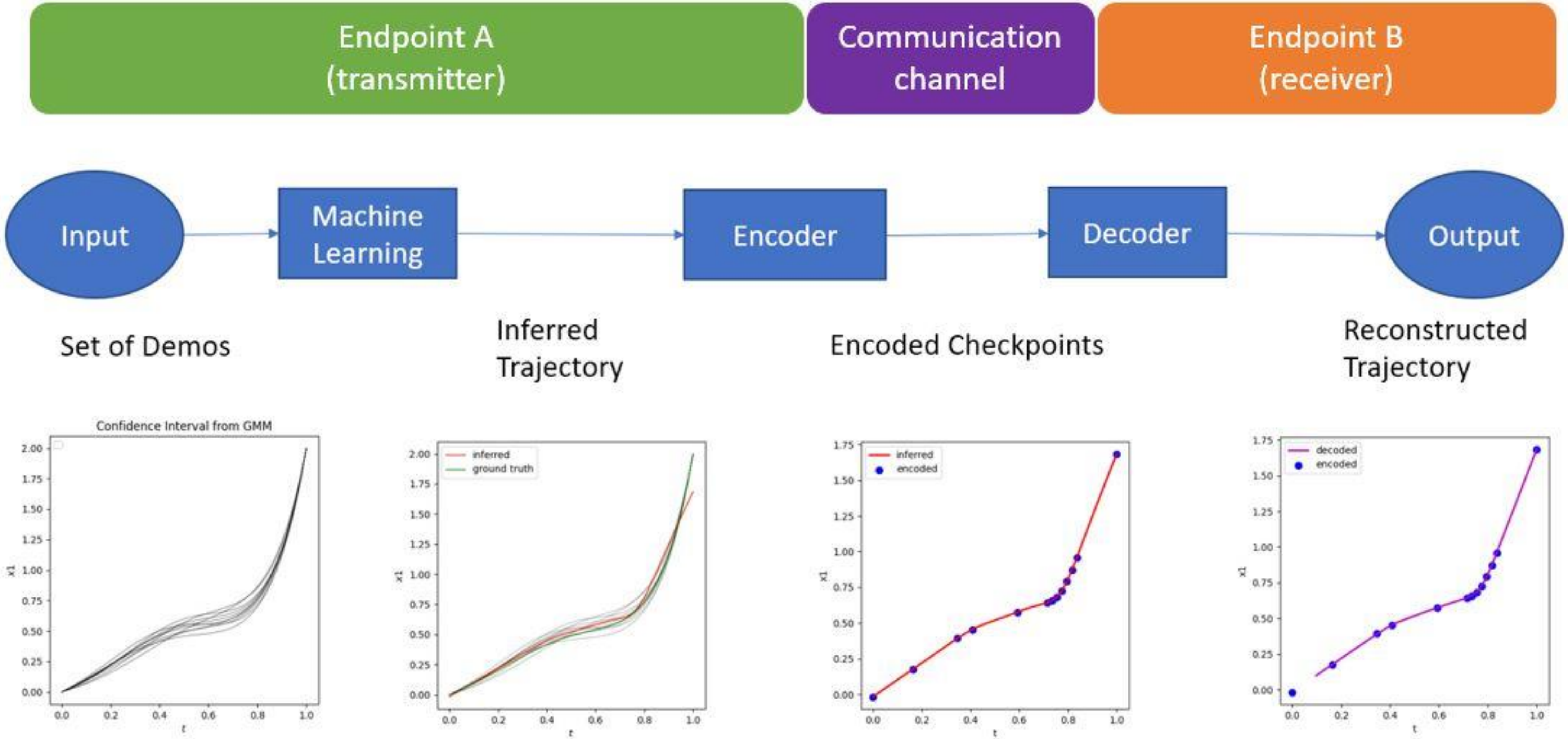
- Consequentialism
- Deontology
- Virtue Ethics

Design



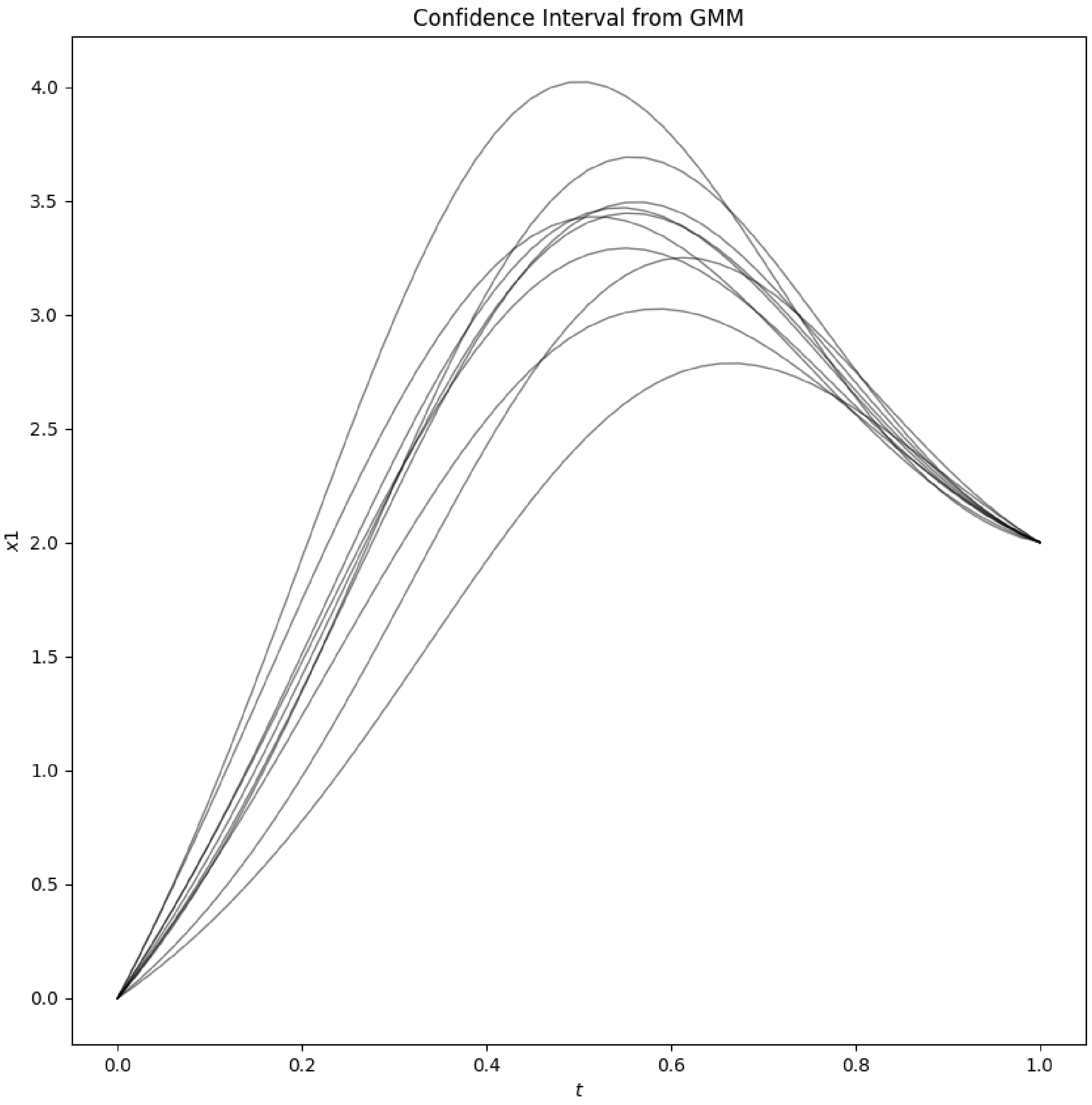
Trajectory Demonstration from Kinect Sensor
Demo1
Demo2
Demo3
Demo4
Demo5
z/m
1.4
1.35
1.3
1.25
1.2
1.15
1.1
0.4
0.2
0
-0.2
y/m
0.1
0.2
0.3
0.4
0.5
0.6
x/m

Design



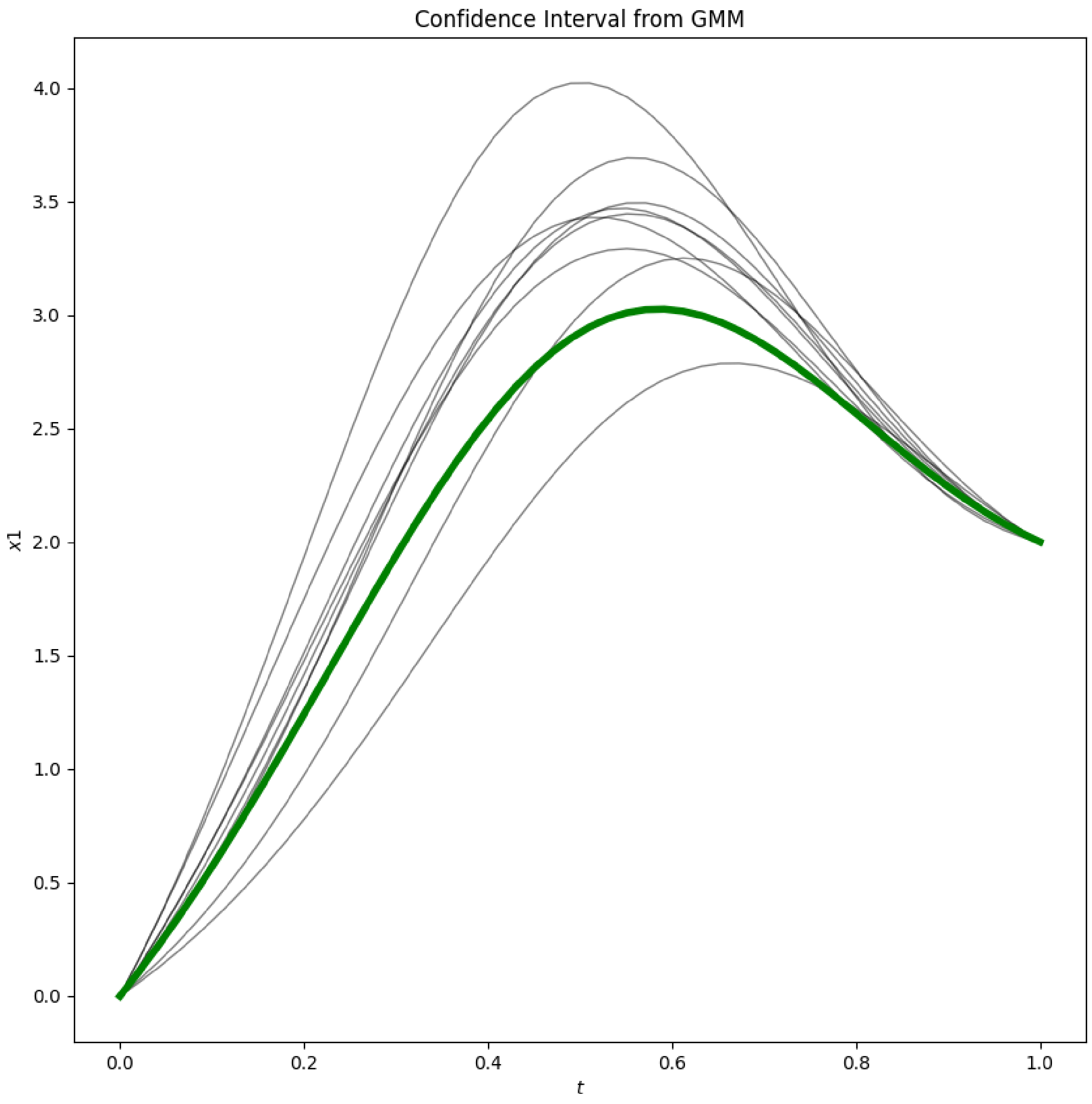
Endpoint A
(transmitter)
Communication
channel
Endpoint B
(receiver)
Input
Machine
Learning
Encoder
Decoder
Output
Set of Demos
Inferred
Trajectory
Encoded Checkpoints
Reconstructed
Trajectory
Confidence Interval from GMM
inferred
ground truth
inferred
encoded
decoded
encoded
x1
t

Demos

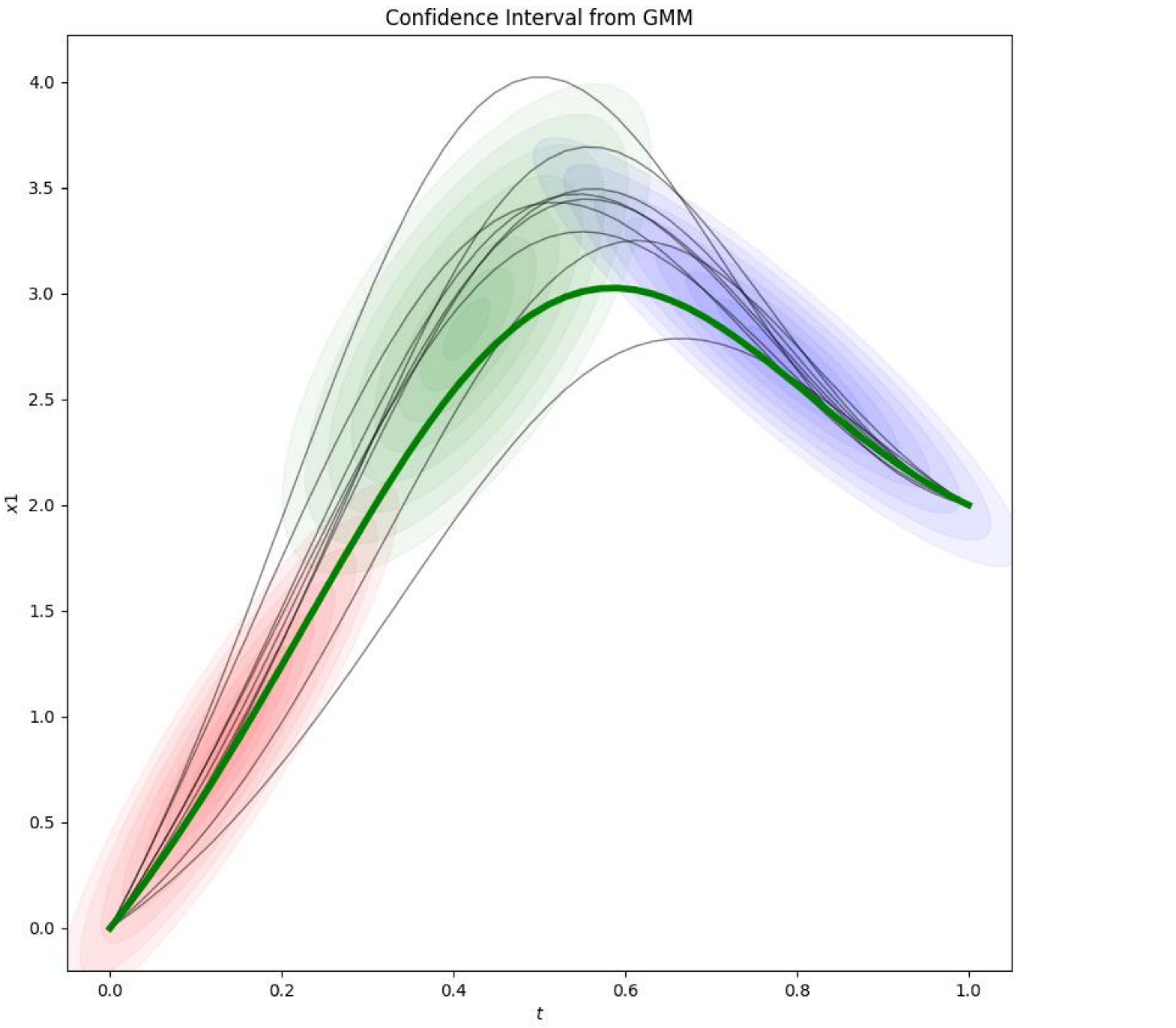


Confidence Interval from GMM
x1
t
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
0.0
0.2
0.4
0.6
0.8
1.0

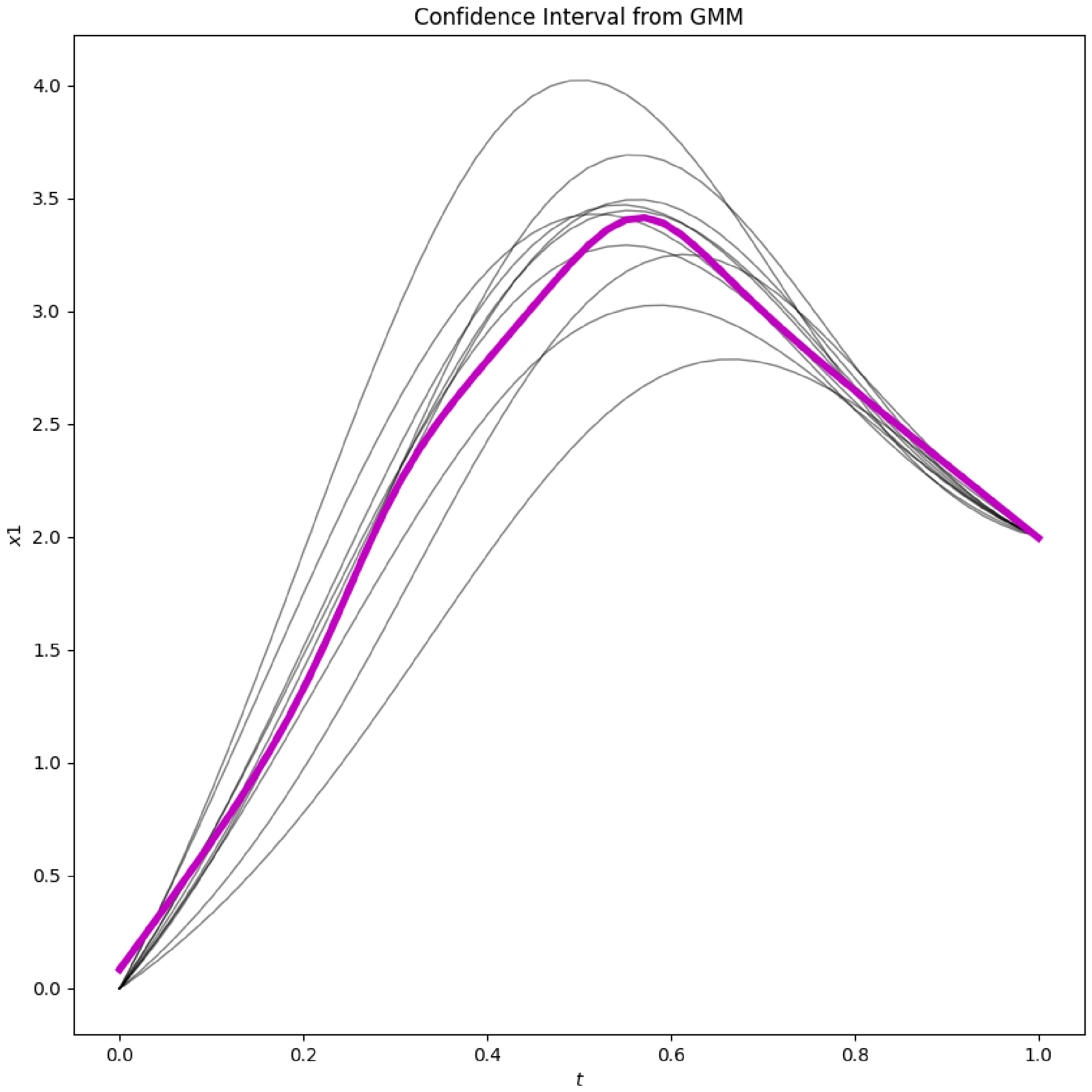
Ground Truth



Gaussians Components

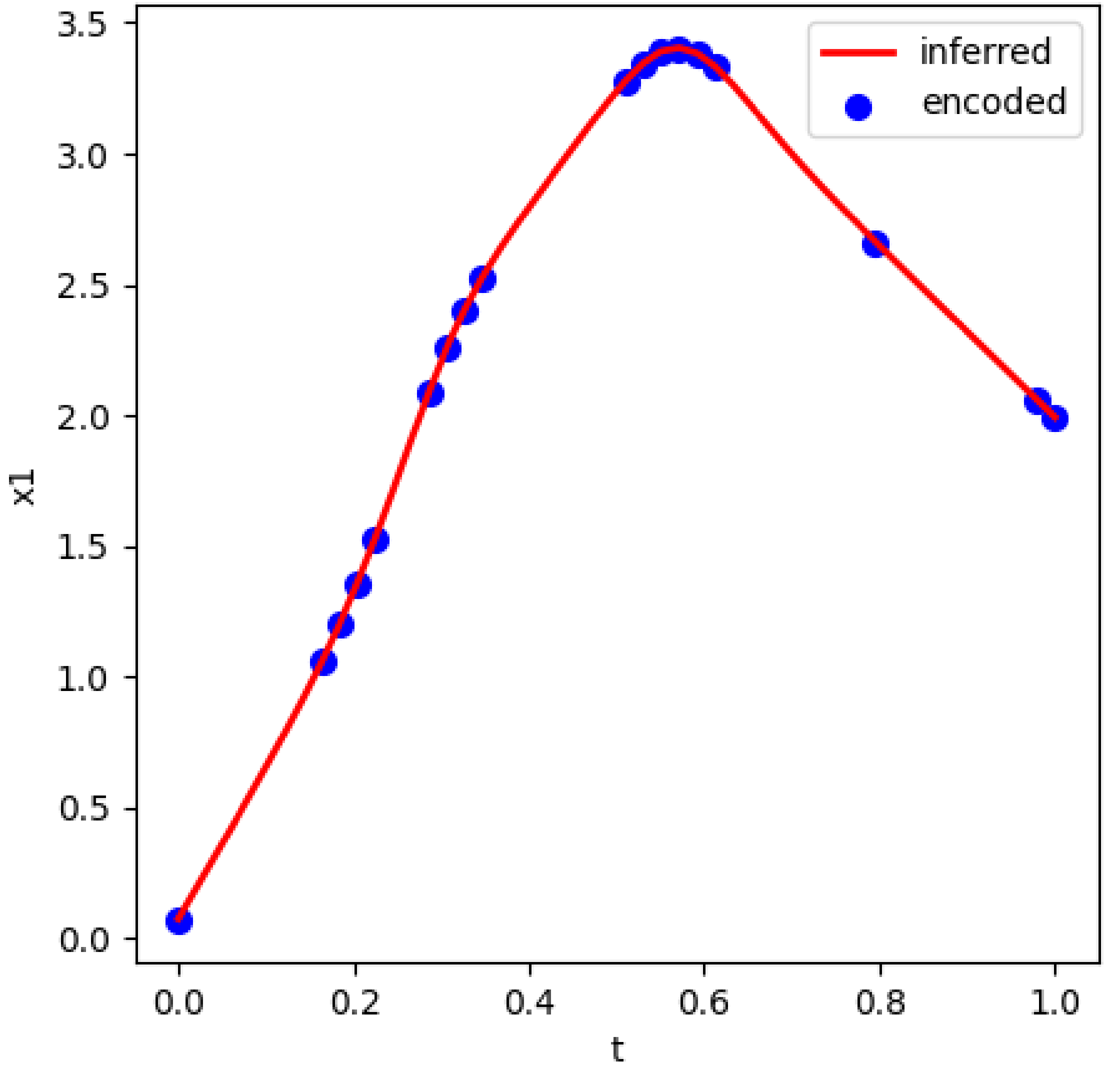


Inference

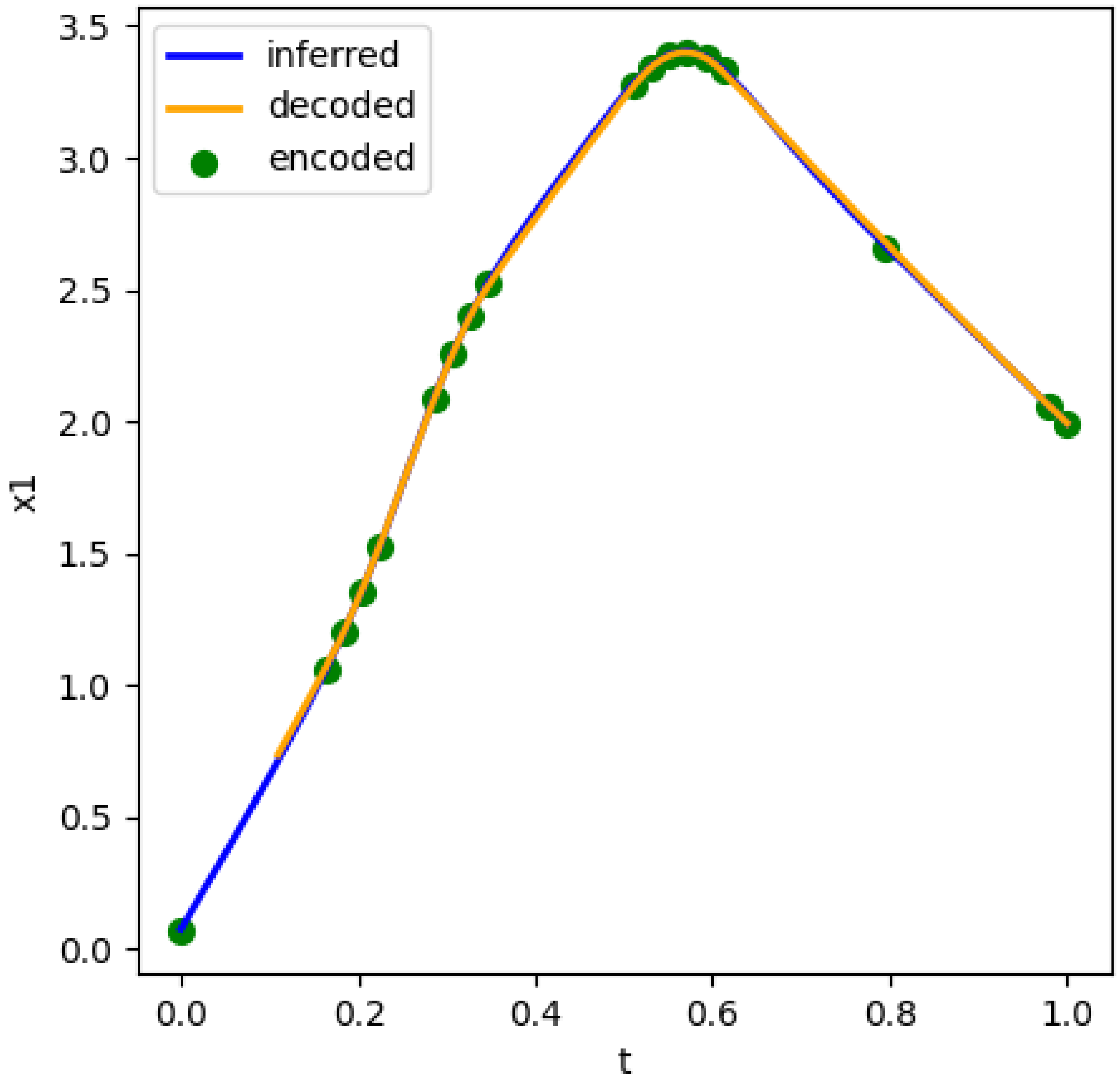

Confidence Interval from GMM
x1
t
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0.0
0.2
0.4
0.6
0.8
1.0

Encoder

Reduced datapoints by 64%

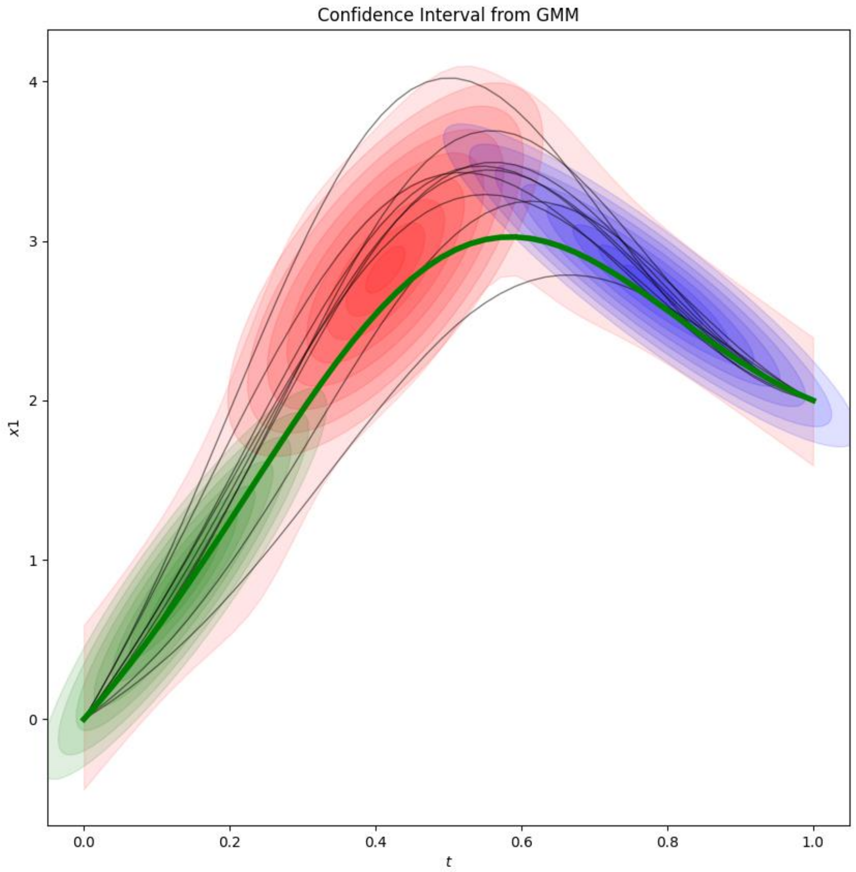


Decoder

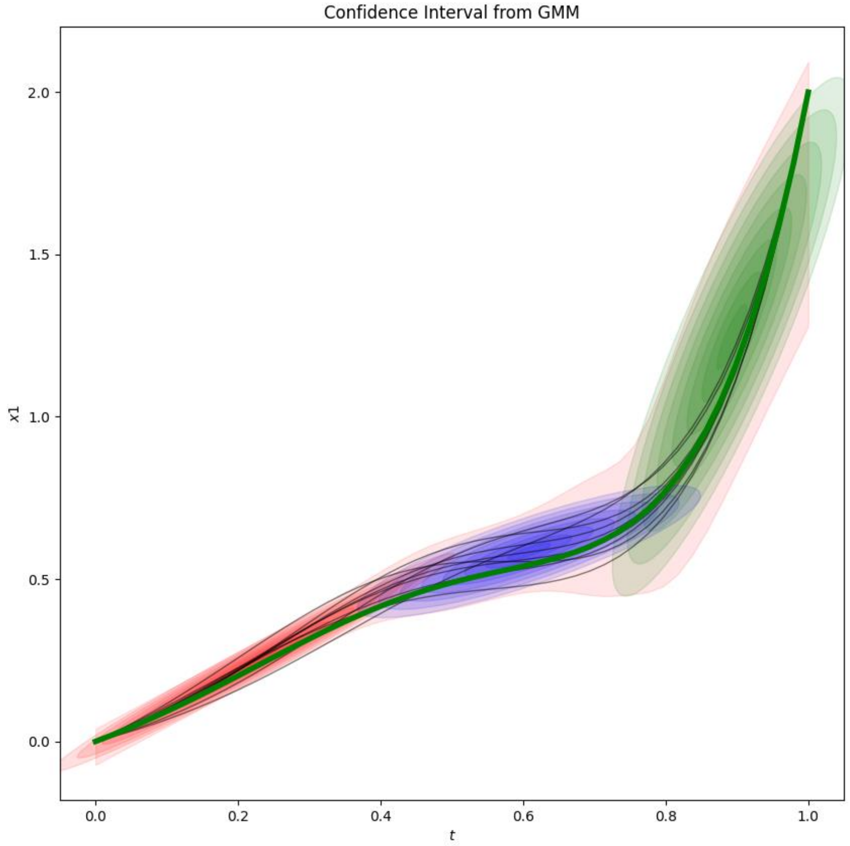


inferred
decoded
encoded
x1
t
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
0.0
0.2
0.4
0.6
0.8
1.0

Tasks Dictionary



Task A



Task B

EM Algorithm

Algorithm 2.1 Expectation Maximization for GMM

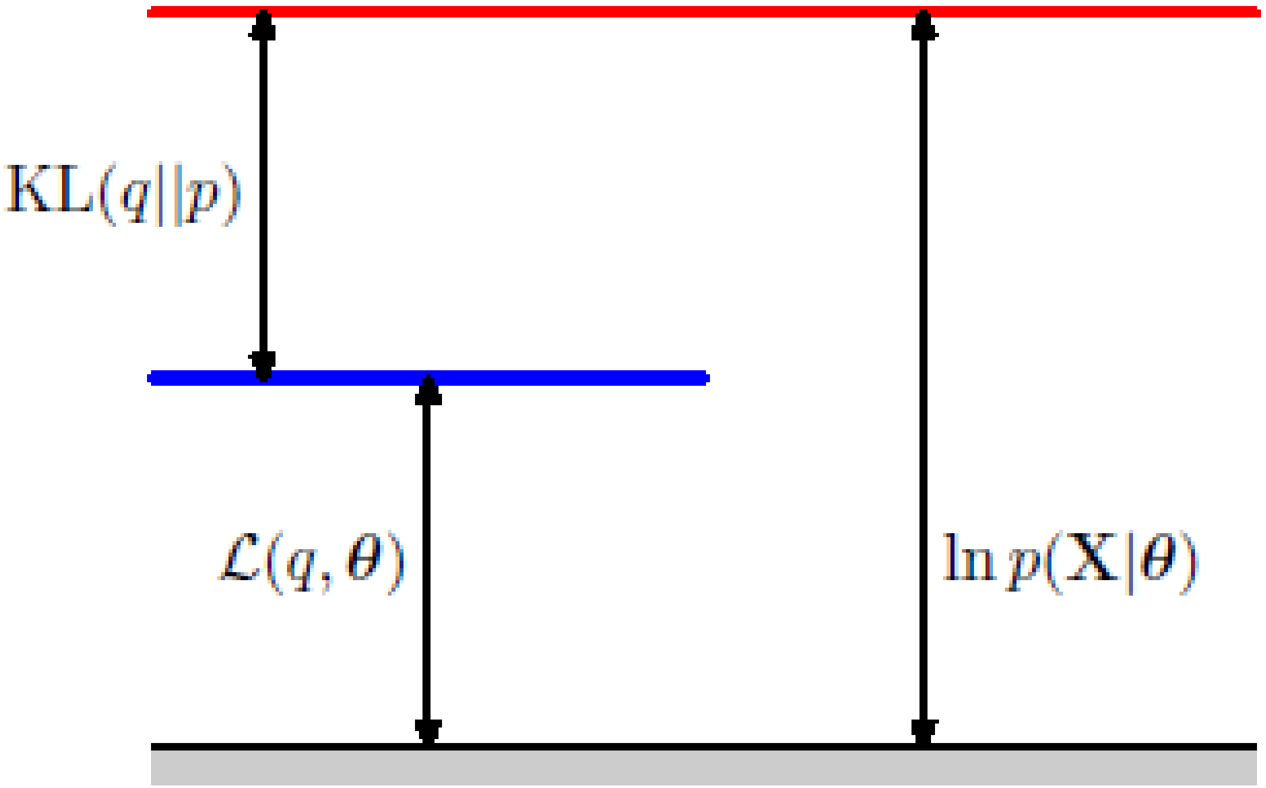
function EM_GMM($\boldsymbol{x}_{1:N}$, $\{\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k, \pi_k\}_{k=1}^{K}$)
  while $\delta ll > \epsilon_{conv}$ **do** ▷ Check change of likelihood, δll, between iterations
    `# E-Step:`
    for $k \in \{1, \cdots, K\}$ **do**
      for $n \in \{1, \cdots, N\}$ **do**
        $\gamma_{n,k} = \frac{\pi_k \mathcal{N}(\boldsymbol{x}_n | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_{l=1}^{K} \pi_l \mathcal{N}(\boldsymbol{x}_n | \boldsymbol{\mu}_l, \boldsymbol{\Sigma}_l)}$
      $N_k = \sum_n^N \gamma_{n,k}$

    `# M-Step:`
    for $k \in \{1, \cdots, K\}$ **do**
      $\boldsymbol{\mu}_k \leftarrow \arg\max_{\boldsymbol{\mu}_k} \left(\mathrm{L}\left(\boldsymbol{x}_{1:N}, \boldsymbol{\mu}_k, \gamma_{1:N,k}\right)\right)$
      $\boldsymbol{\Sigma}_k \leftarrow \frac{1}{N_k} \sum_n^N \gamma_{n,k} \operatorname{Log}_{\boldsymbol{\mu}}(\boldsymbol{x}_n) \operatorname{Log}_{\boldsymbol{\mu}}(\boldsymbol{x}_n)^{\top}$
      $\pi_k \leftarrow \frac{N_k}{N}$

    `# Compute log-likelihood:`
    $ll = \sum_{n=1}^{N} \ln\left(\sum_{k=1}^{K} \pi_k \mathcal{N}(\boldsymbol{x}_n | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)\right)$
  return $\{\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k, \pi_k\}_{k=1}^{K}$

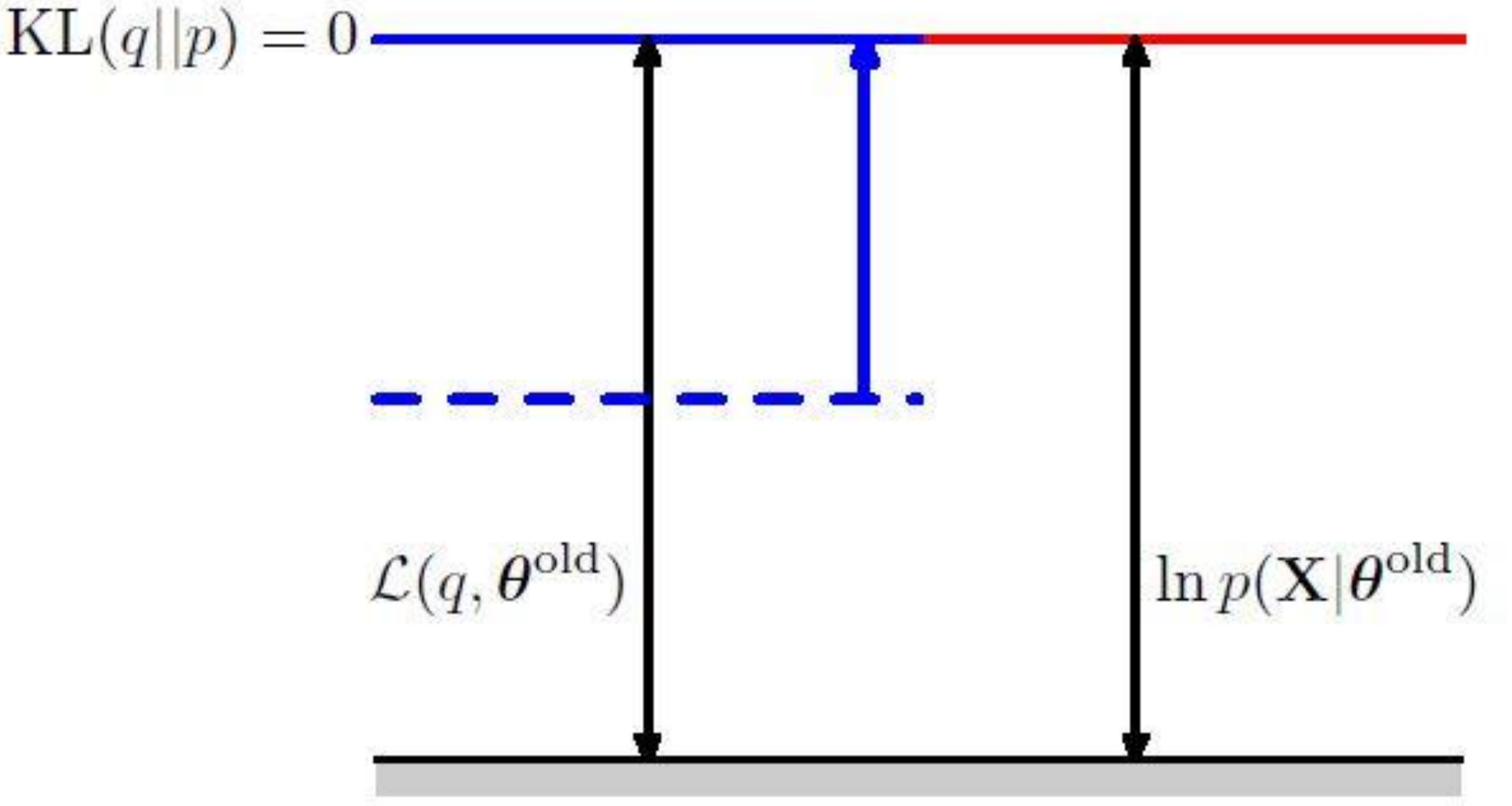
EM decomposition

Illustration of the decomposition given by (9.70), which holds for any choice of distribution $q(\mathbf{Z})$. Because the Kullback-Leibler divergence satisfies $\mathrm{KL}(q\|p) \geqslant 0$, we see that the quantity $\mathcal{L}(q, \boldsymbol{\theta})$ is a lower bound on the log likelihood function $\ln p(\mathbf{X}|\boldsymbol{\theta})$.



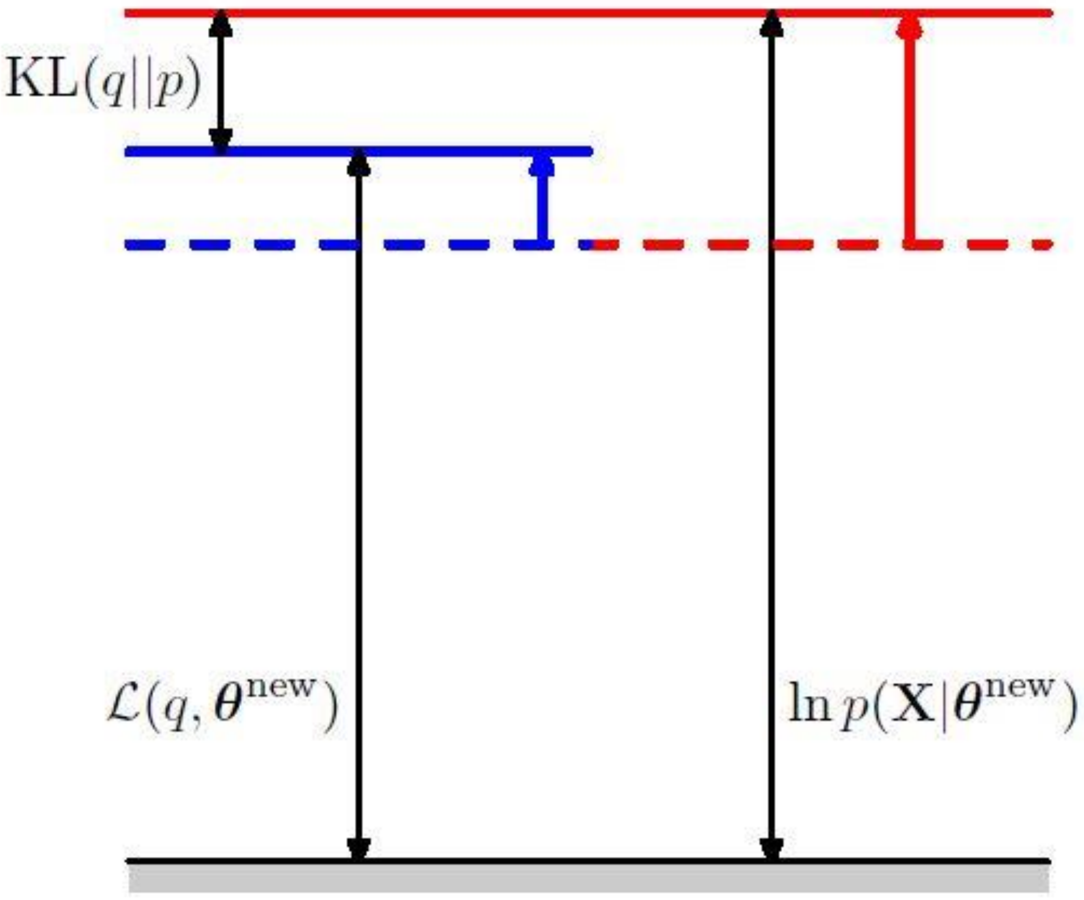
E step

Illustration of the E step of the EM algorithm. The q distribution is set equal to the posterior distribution for the current parameter values θ^{old}, causing the lower bound to move up to the same value as the log likelihood function, with the KL divergence vanishing.



M Step

Illustration of the M step of the EM algorithm. The distribution $q(\mathbf{Z})$ is held fixed and the lower bound $\mathcal{L}(q, \theta)$ is maximized with respect to the parameter vector θ to give a revised value θ^{new}. Because the KL divergence is nonnegative, this causes the log likelihood $\ln p(\mathbf{X}|\theta)$ to increase by at least as much as the lower bound does.



Evaluation

- r2
- Mean Square Error
- Mean Absolute Error

Results

	x1	x2
mae	3.69664244e-06	3.86535089e-02
mse	2.37086698e-11	3.72760437e-03
r2	1.	0.98059981]

TABLE I
MACHINE LEARNING BLOCK.
GROUND TRUTH TRAJECTORY—— INFERRED TRAJECTORY

	x1	x2
mae	0.15835882	0.18605222
mse	0.03214314	0.04579591
r2	0.62513977	0.73572401

TABLE II
ENCODER BLOCK
INFERRED TRAJECTORY —— RECONSTRUCTED TRAJECTORY

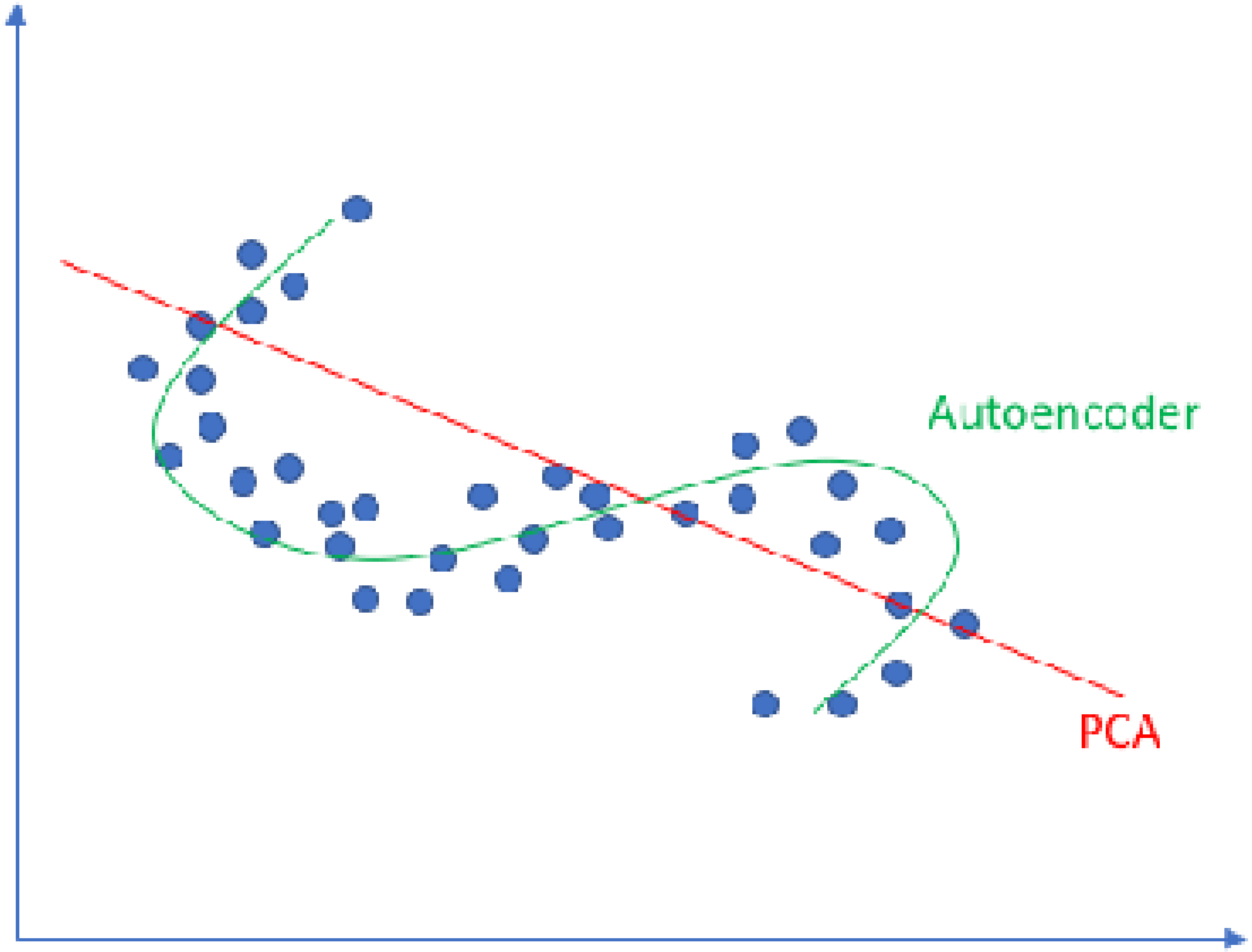
	x1	x2
mae	0.15835999	0.2043527
mse	0.03214367	0.05349581
r2	0.62514137	0.72158294]

TABLE III
OVERALL SYSTEM PERFORMANCE
GROUND TRUTH TRAJECTORY—— RECONSTRUCTED TRAJECTORY

Limitations

Does not Include

- force
- Acceleration
- Orientation

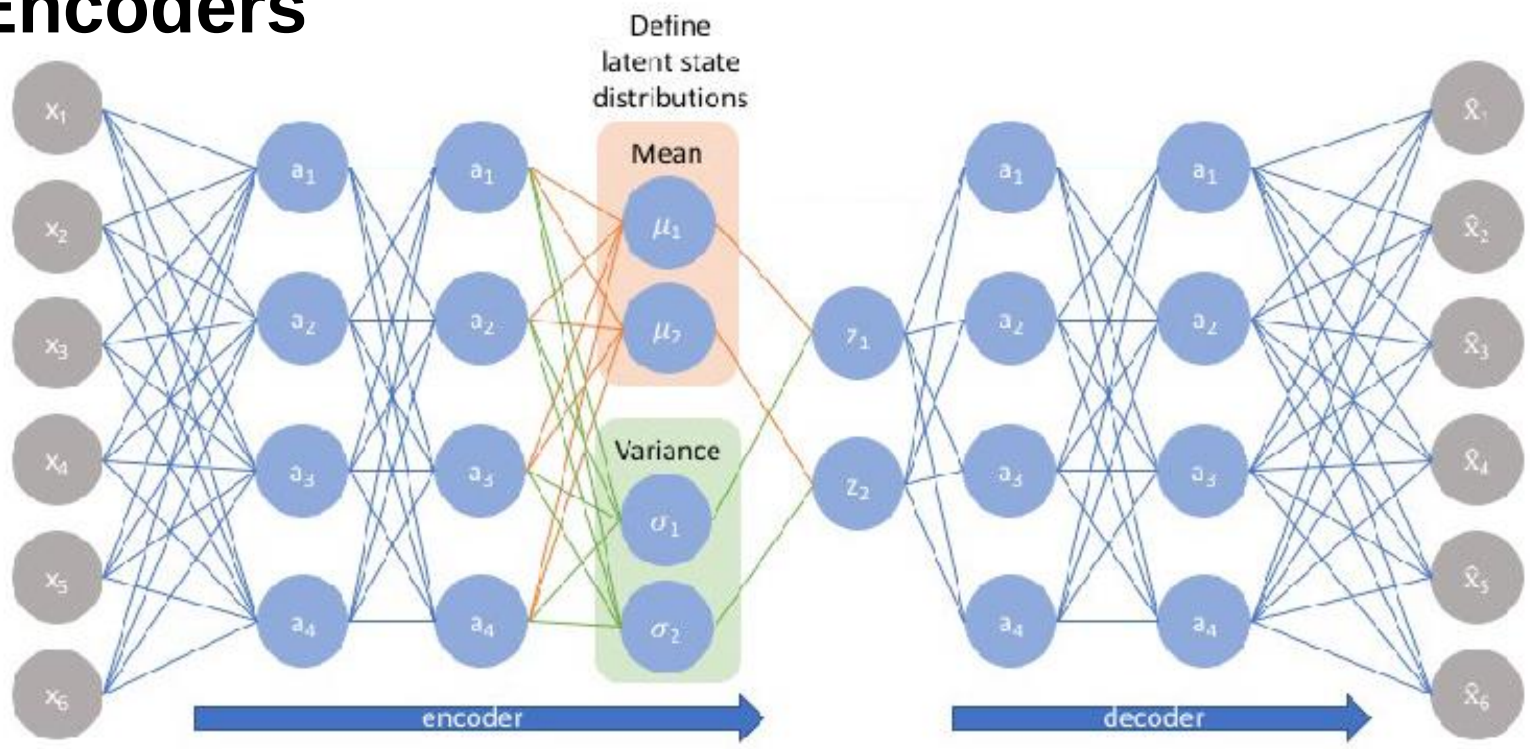


Limitations

- Simple dim reduction algorithm do not work
- Space is highly nonlinear

Limitations

Variational Auto Encoders

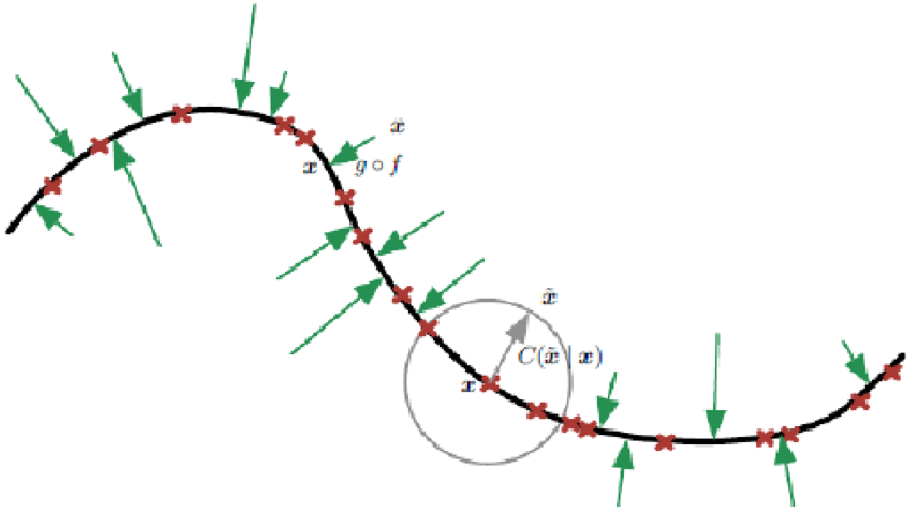


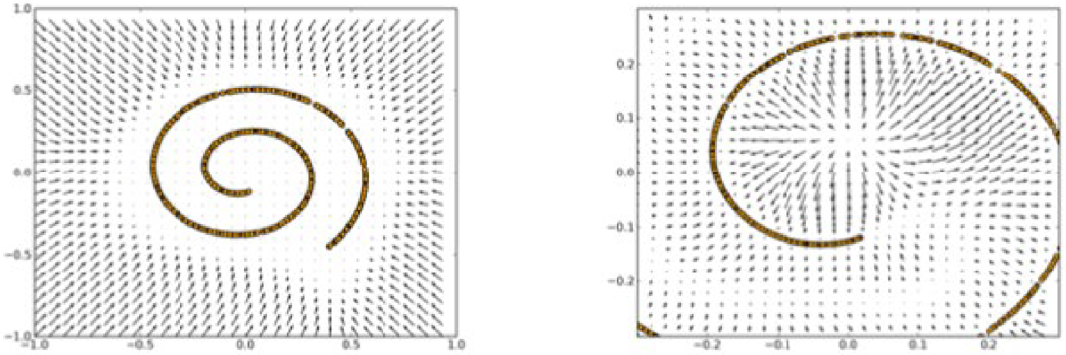
VAE replaces *deterministic* hidden layer (latent) $\boldsymbol{z}$ with *stochastic* sampling:

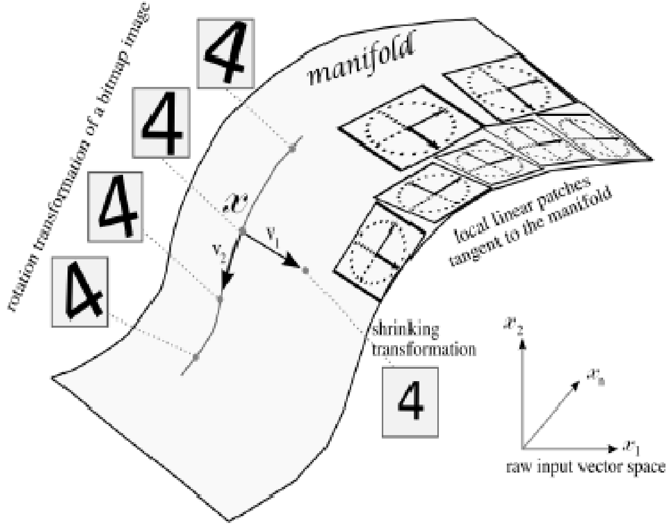
$$\text{input } x \;\rightarrow\; \text{latent space } p(\boldsymbol{z} \mid \boldsymbol{x}) \;\rightarrow\; \text{sampling } z \sim p(\boldsymbol{z} \mid \boldsymbol{x}) \;\rightarrow\; \text{input reconstr. } \tilde{\boldsymbol{x}} = d(\boldsymbol{z})$$

Limitations

Learning a *vector field* around a *low-dimensional manifold* . . .







Goodfellow et al.

Future Work

Variational Auto Encoder (deep generative models)

Bayesian Modelling for Prior for Task trajectory

Non-Euclidean Spaces

Wider Implications

ASSISTED SURGERY

CONSTRUCTIONS IN EXTREME ENVIRONMENTS

Thank you for your attention