



Summer Workshop 25' London

Malleable Latent Space for Reliable Time Series Generation and OOD Detection

Project n° 4



Time series Generation



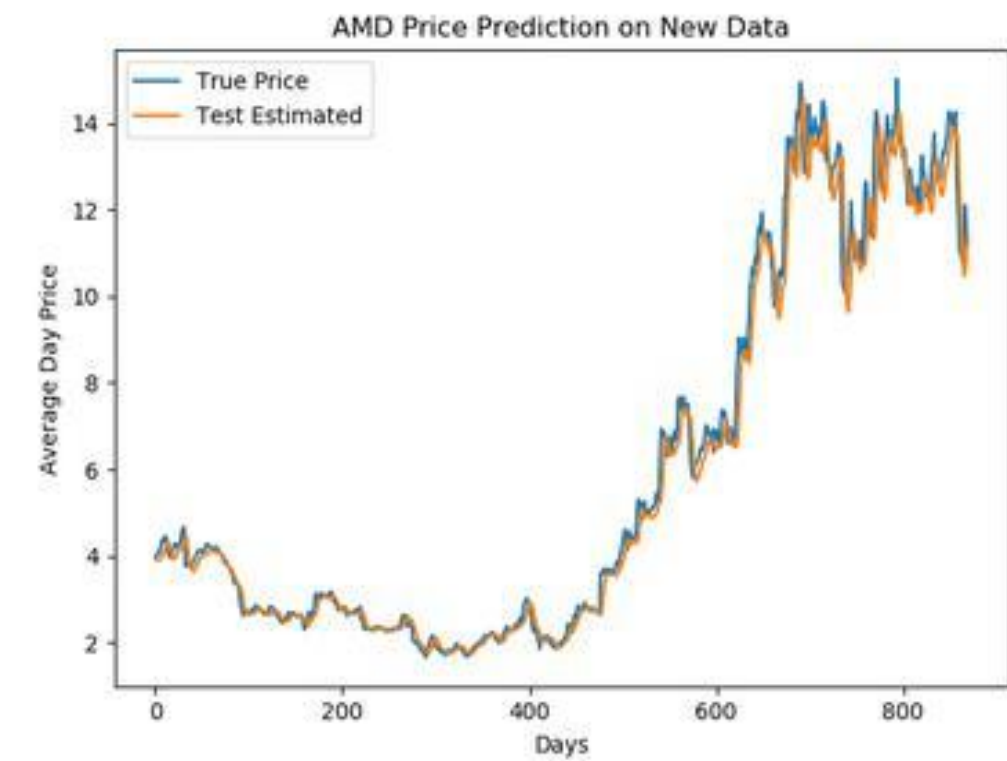
Ubiquitous



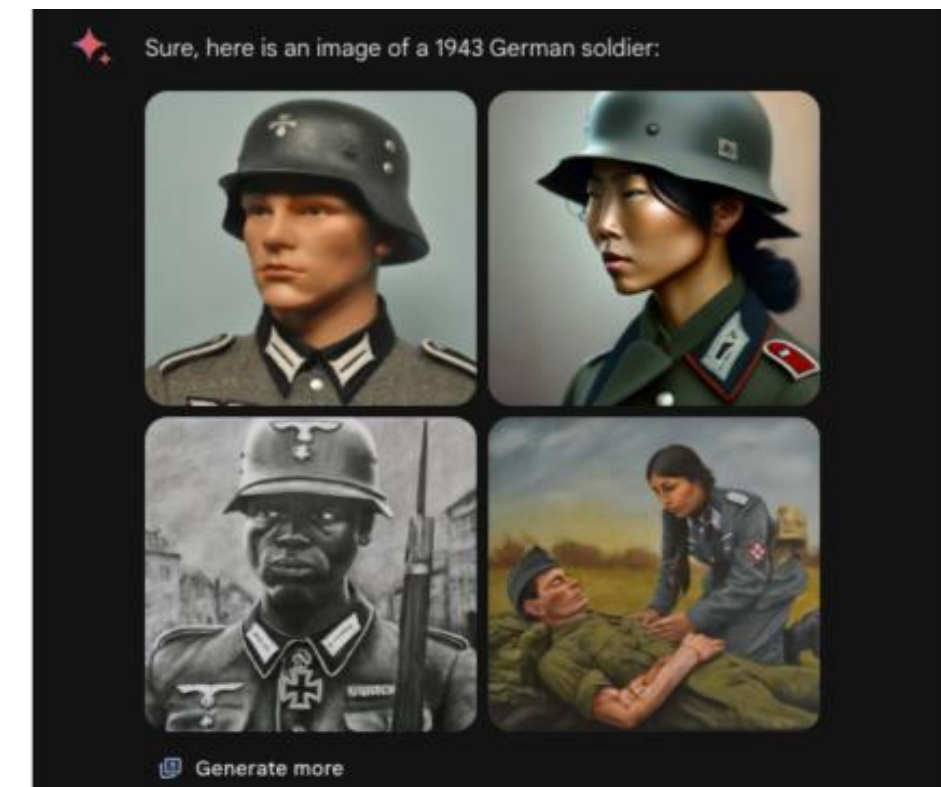
Time series Generation



Ubiquitous



Non-intuitive



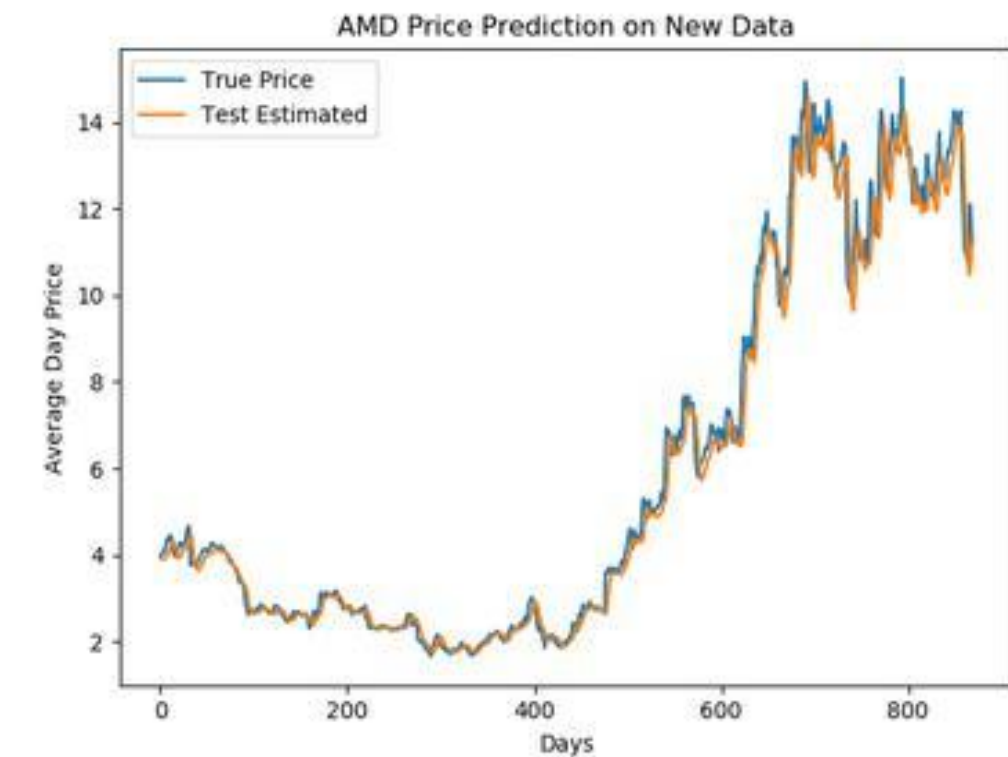
Time series Generation



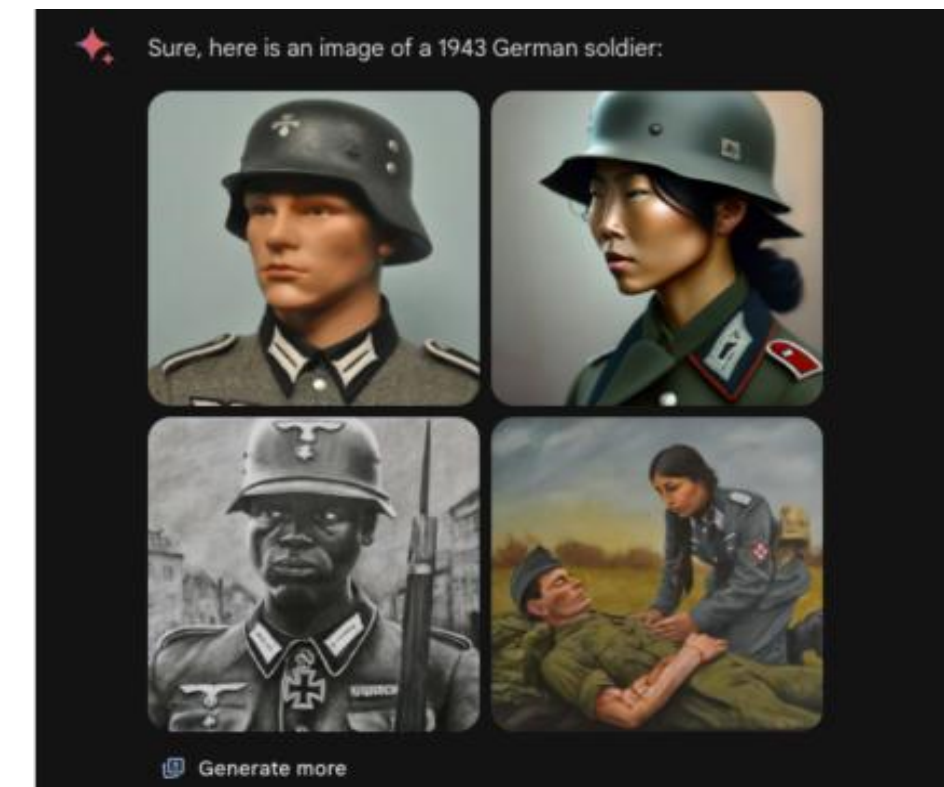
Ubiquitous



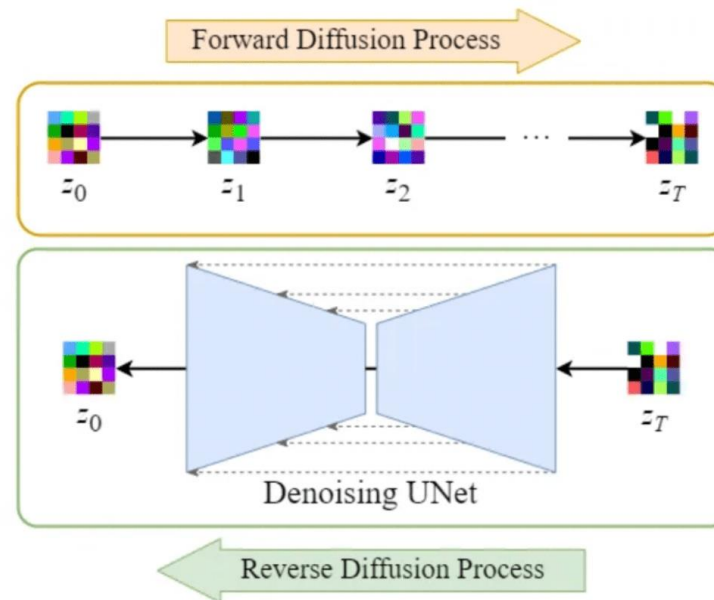
- Current QM for Gen AI in TS:
- Are not deep learning aware
 - Are not temporality aware



Non-intuitive

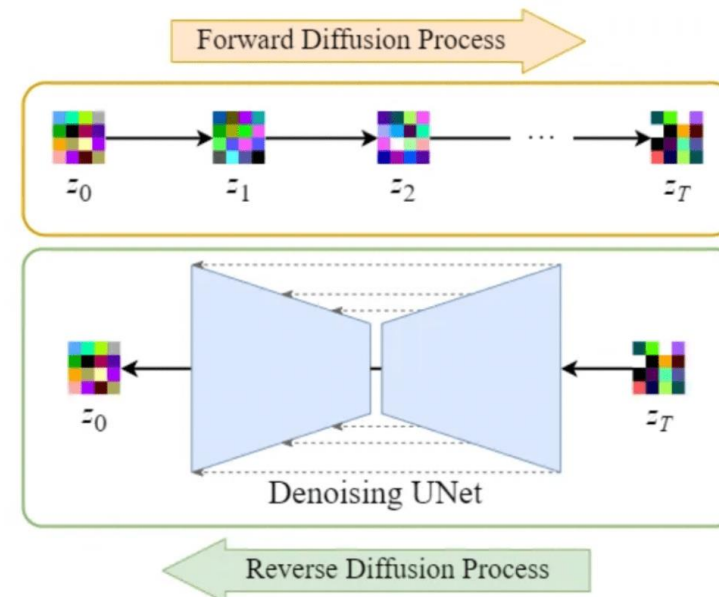


Diffusion Models

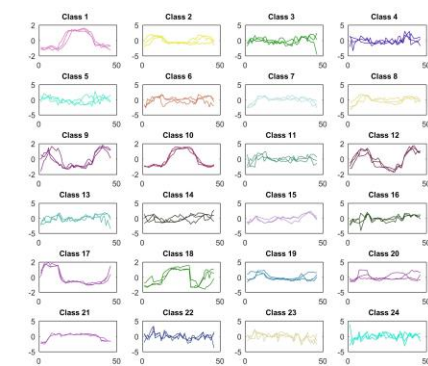


- Modality agnostic
- Highly modifiable and tunable training process
- High quality samples
- Robust against common generative models' drawbacks

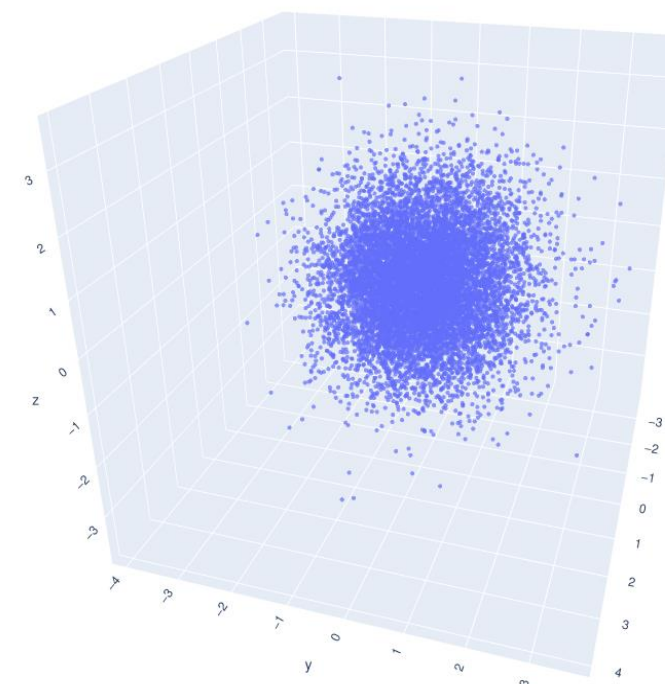
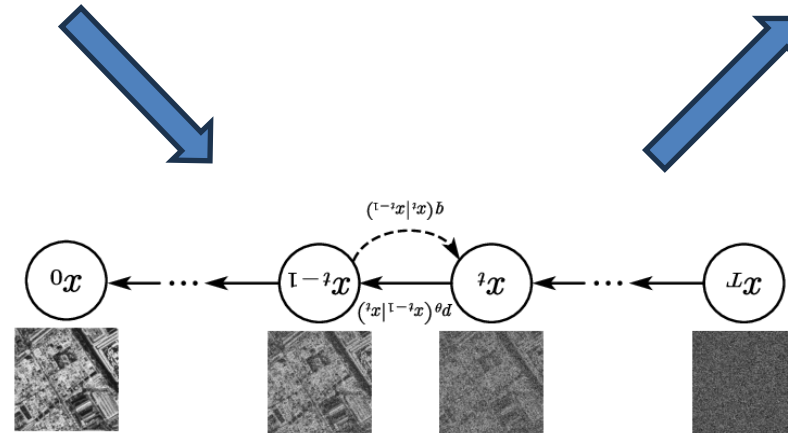
Diffusion Models



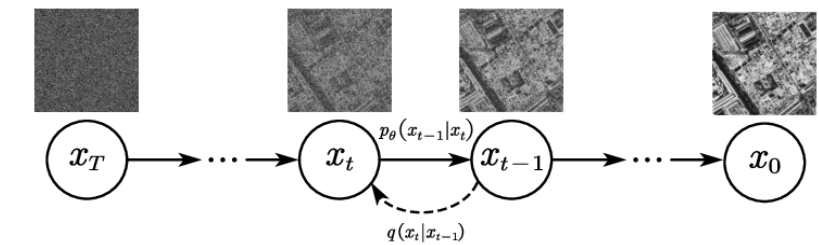
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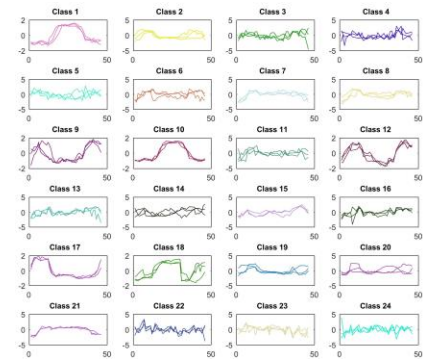
Diffuse



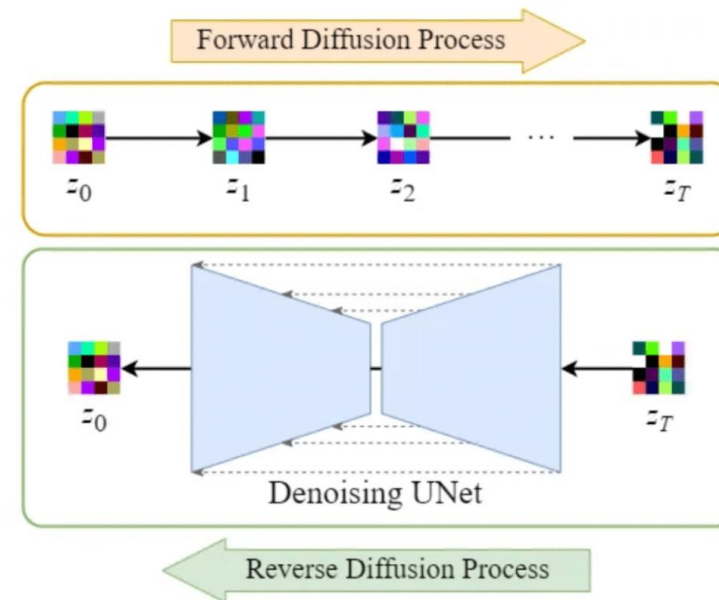
Sample



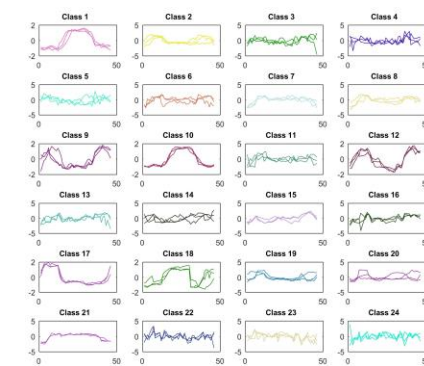
Denoise



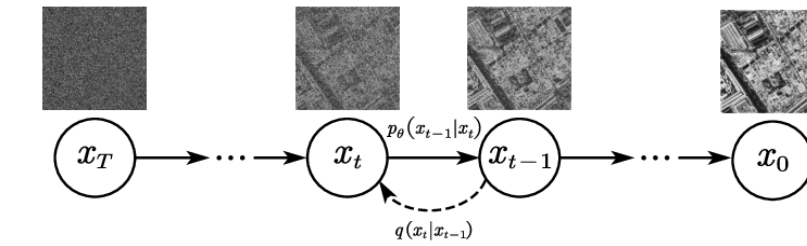
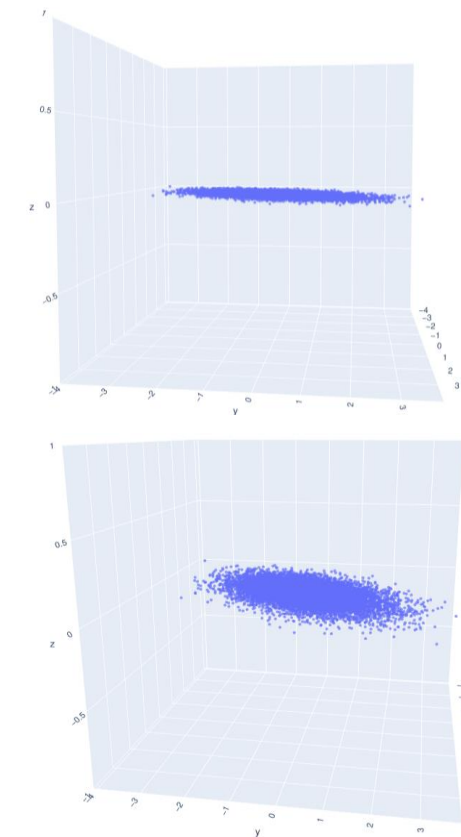
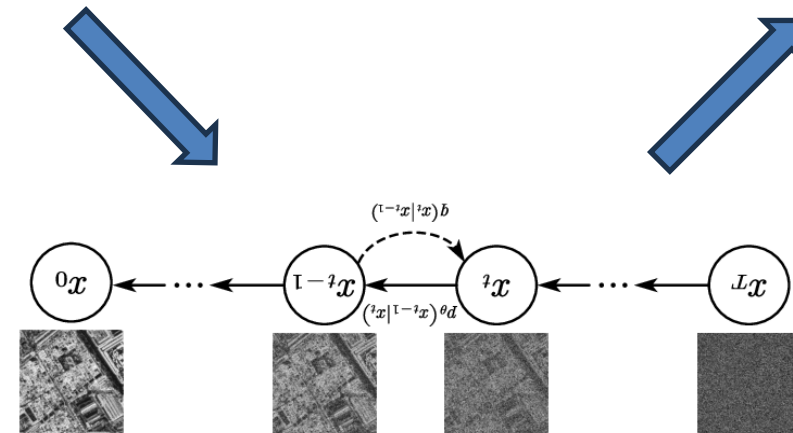
Diffusion Models



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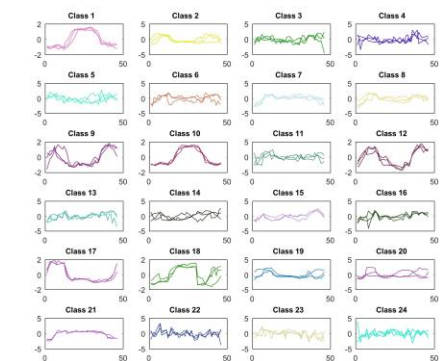


Diffuse "smartly"

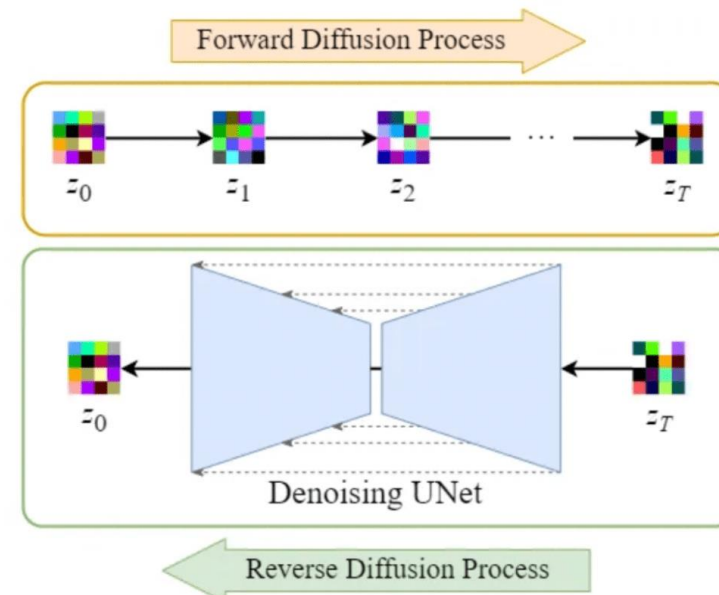


"Smart" Sampling

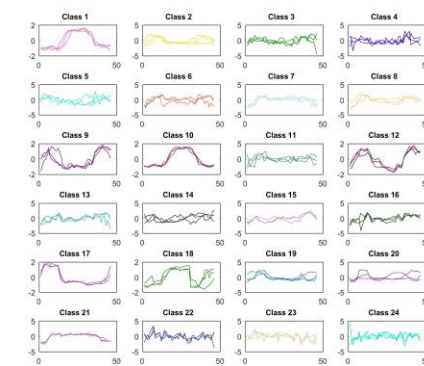
Denoise



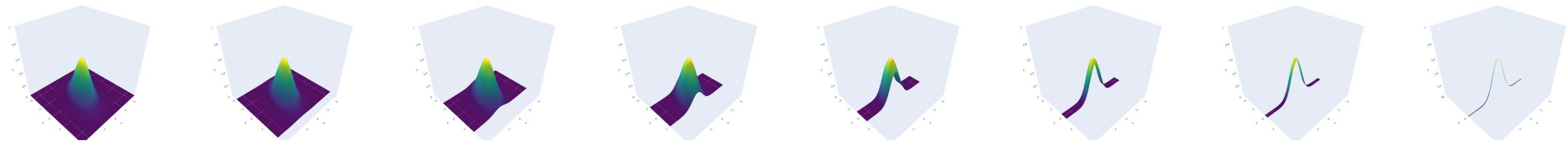
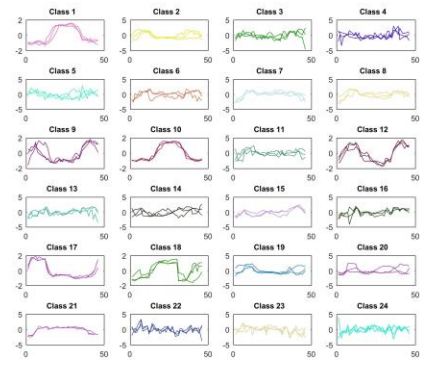
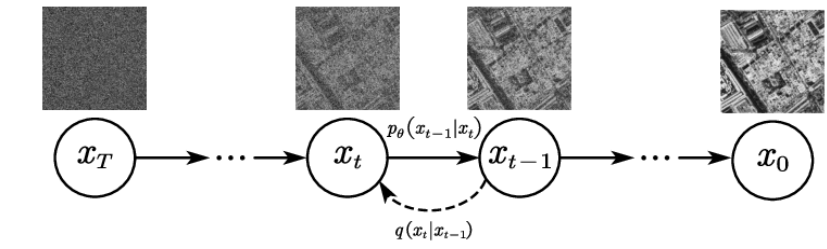
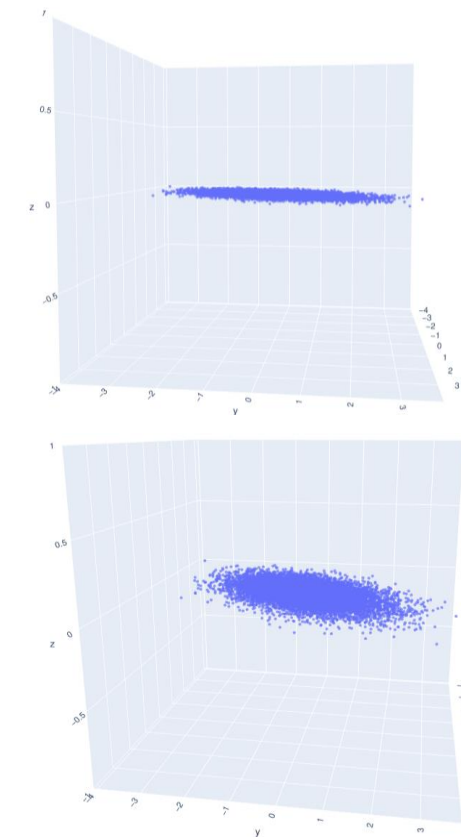
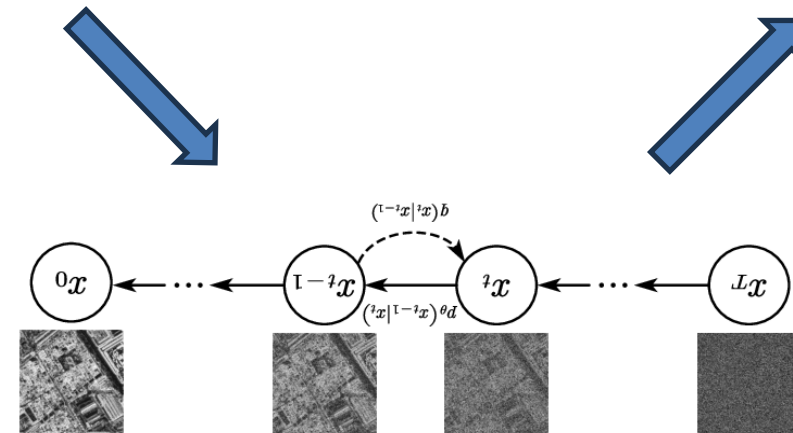
Diffusion Models



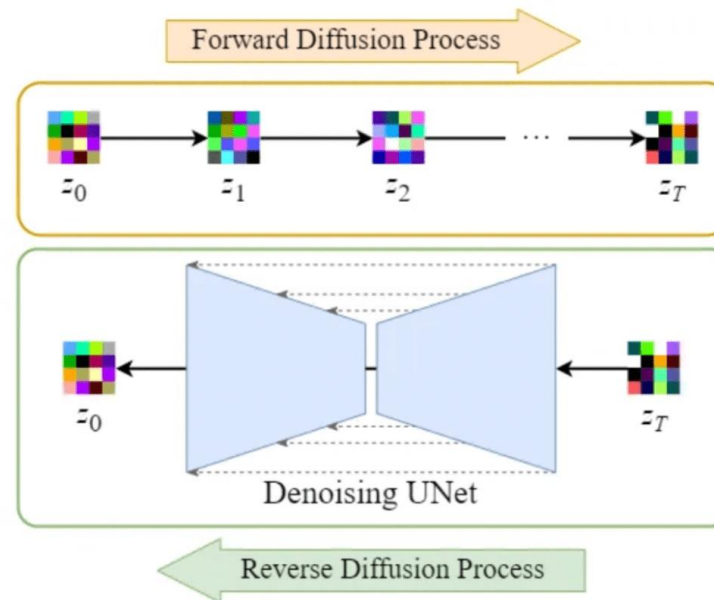
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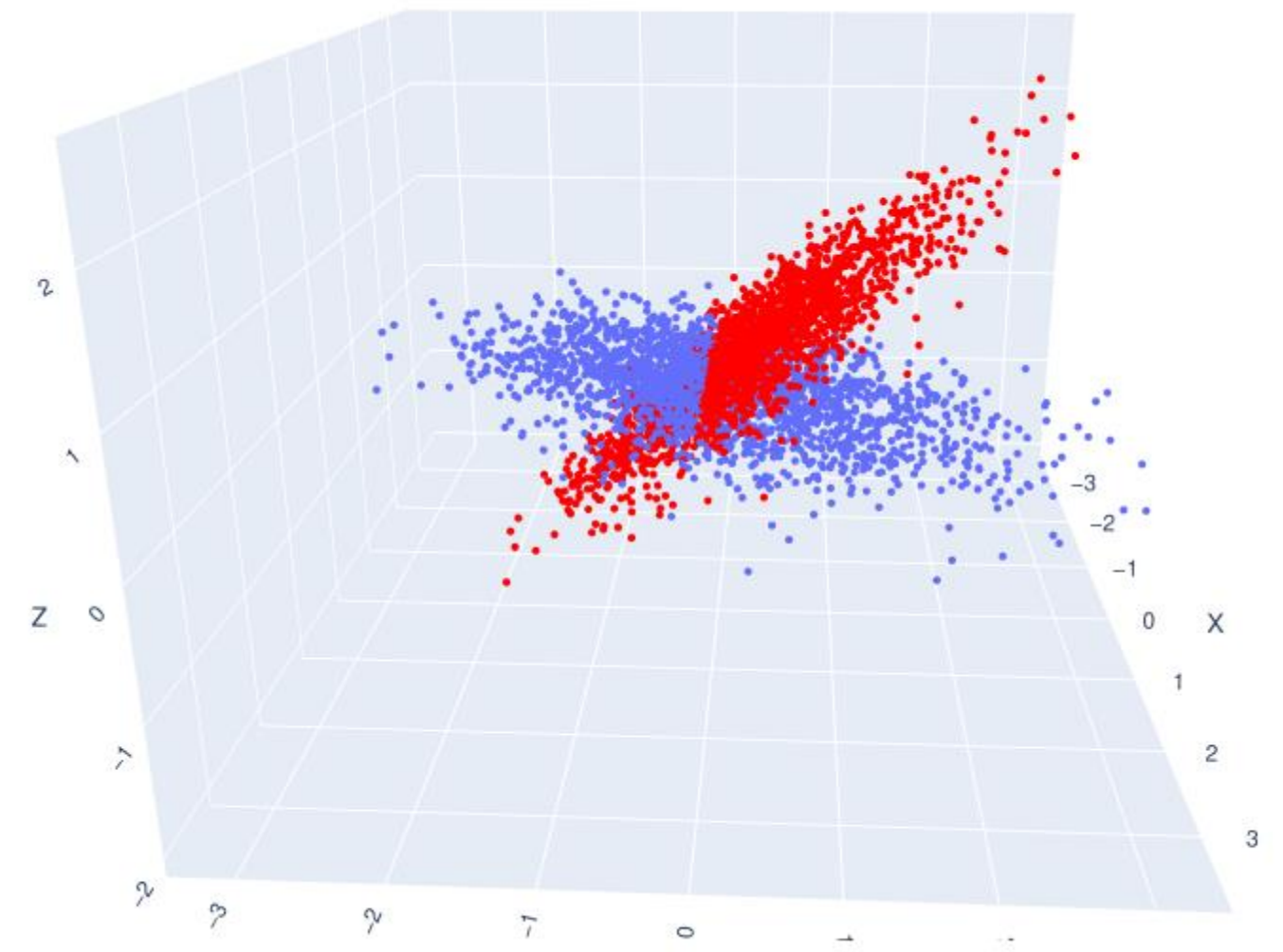
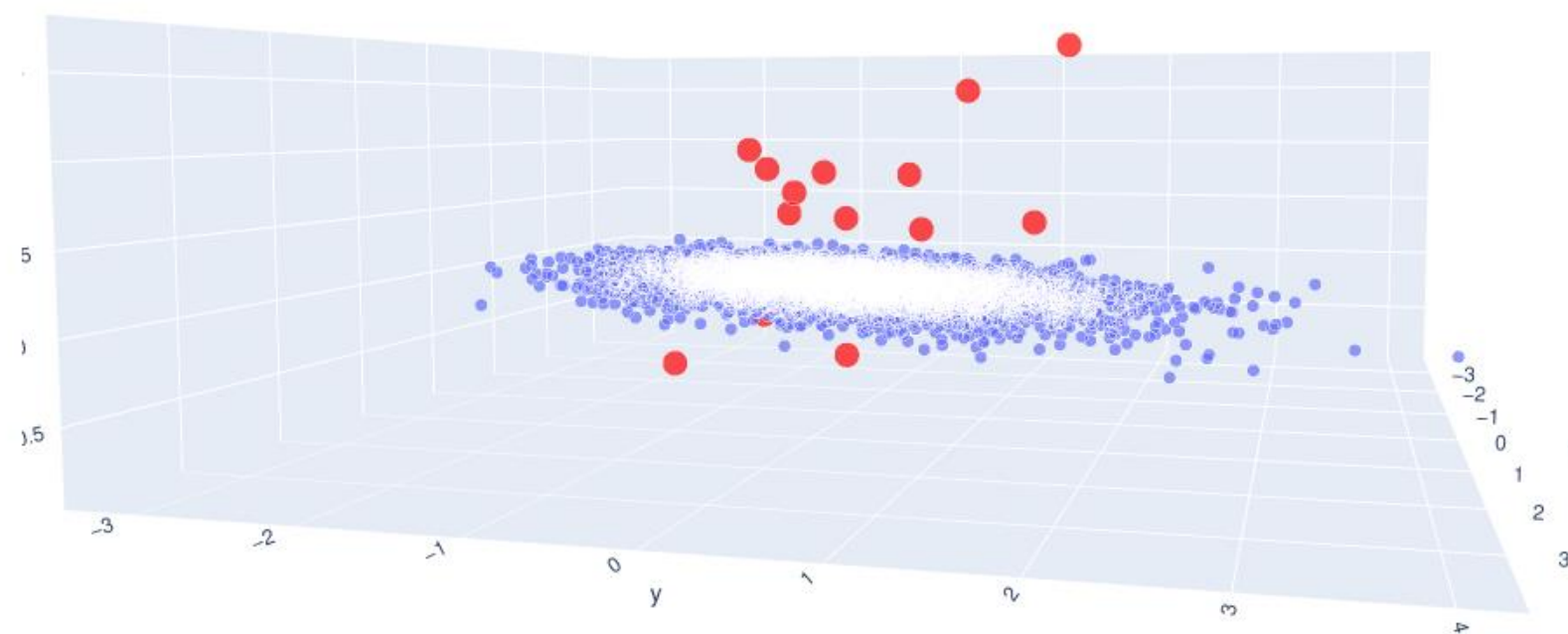
QM Gen AI and OOD



- Modality agnostic
- Highly modifiable and tunable training process
- High quality samples
- Robust against common generative models' drawbacks
- **High reliability and guarantees during generation**

Noise attenuated in selected dimensions \rightarrow Low-dimensional subspace

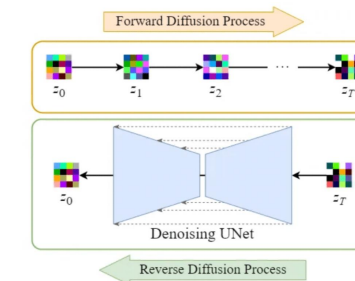
Mahalanobis distance, KDE, Laplacian eigenmaps, AUROC, F1, FID, IS, KID, MSE, MAE, CRPS



Work Plan

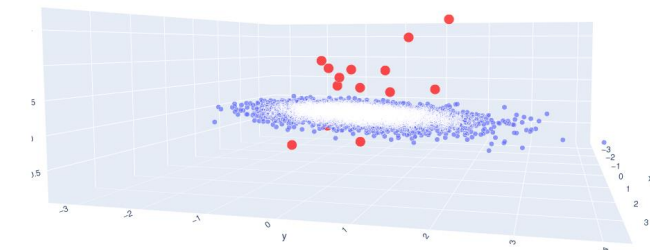
WP1 – Mapping Time:

- Prepare the data (“NASA Anomaly Detection Dataset SMAP & MSL”)
- Prepare the noise sampling recipe
- Train the model



WP2 - Experimentation Time:

- Test and select metrics (both outliers aware metrics and distribution metrics)
- Prove that the methodology works



WP3 – Paper time:

- Publish and gain eternal glory (only if it works)



Expertise Sought

Research Axis 1:

- Data cruncher
- Python
- Docker + git

Research Axis 2:

- Time series and temporal data
- Diffusion Models
- Math background

TRAIL Summer Workshop 25' London

TRUSTED AI LABS

Thank you for your attention !

Contact: tellez@multitel.be

PS: part of GD5

Full Proposal

