# Latent Space Models for Signals

*One-Page Summary*

## Key Questions Addressed

| Theme | Question |
|---|---|
| Arrhythmia Classification | Can variational autoencoders (VAEs), augmented with physics-inspired reasoning, be used to classify arrhythmias? |
| Cross-Domain Adaptation | Can these techniques be adapted to other domains such as commodities pricing and trading? |
| Trading Strategy Development | Can trading strategies be developed based on these latent-space modeling ideas? |

## Conceptual Ideas Proposed

- Inspired by physics, the latent space is decomposed into **z_offset** (capturing non-periodic sudden changes) and **z_rhythm** (capturing periodic behaviors).
- A custom loss function penalizes reliance on **z_offset** unless necessary, alongside standard reconstruction and KL divergence terms.
- The same latent decomposition framework is applied to commodity time series, interpreting **z_offset** as shocks and **z_rhythm** as underlying cycles.
- This structure provides interpretable latent dimensions, supporting explainable classification in healthcare and trading strategy design in finance.

## Key Results

- On a dataset of 15M+ datapoints across 40 patient records, the model classifies most arrhythmias with **AUC** $>$ **0.9**, except for 1–2 under-sampled categories.
- Applied to 24 years of crude oil and wheat data, the framework achieves ≈**0.6 AUC** yet supports trading strategies delivering **200%+ CAGR** and **Sharpe Ratio** $>$ **2.5** with further optimization potential.

## Illustrative Figures and Tables

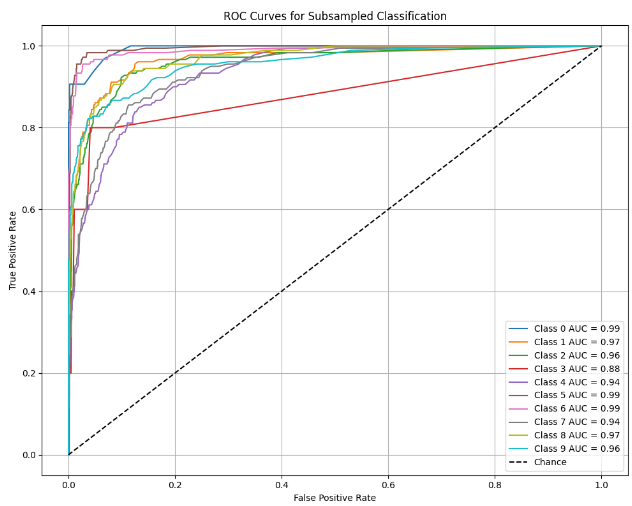


Figure 1: ROC Curves for Arrhythmia Classification Across 10 Classes.

| Metric | Value |
|---|---|
| CAGR | 246.83% |
| Sharpe Ratio | 3.15 |
| Sortino Ratio | 4.77 |
| Max Drawdown | -55.24% |

Table 1: Out-of-Sample Trading Performance Using Latent Decomposition (Crude Oil).