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 futures data (with roughly 7 years held out for testing), the framework achieves **AUCs between 0.58 and 0.62**, yet enables confidence-filtered strategies with **CAGRs above 1400%** and **Sharpe Ratios exceeding 5** under idealized conditions—demonstrating strong local signal quality despite modest global classification performance.

Illustrative Figures and Tables

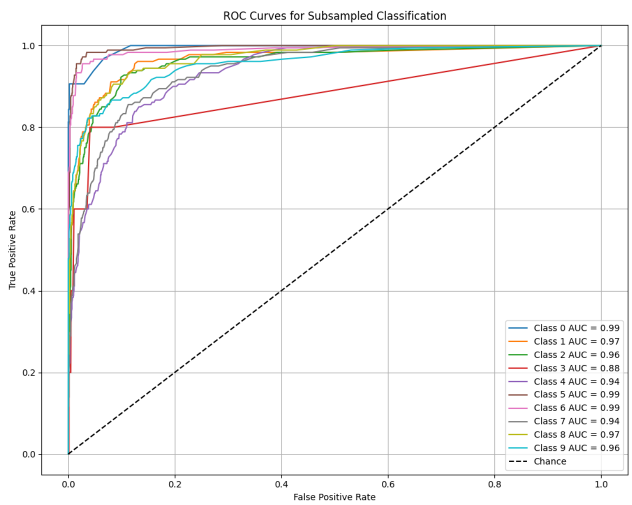

Figure 1: ROC Curves for Arrhythmia Classification Across 10 Classes.

Metric	**Value**
CAGR	1523.89%
Sharpe Ratio	5.73
Sortino Ratio	37.92
Max Drawdown	-23.21%

Table 1: Backtested performance on crude oil using latent-based XGBoost signals with threshold filtering and capped returns (no costs/slippage).