GOLDEN PRICE PREDICTION: CLASSICAL & DEEP LEARNING APPROACHES

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AAI-501 Final Project

Group - 4

PROJECT MOTIVATION

Gold is a safe-haven asset

Volatility from macro cycles

Compare classical vs deep learning models

Does complexity improve accuracy?

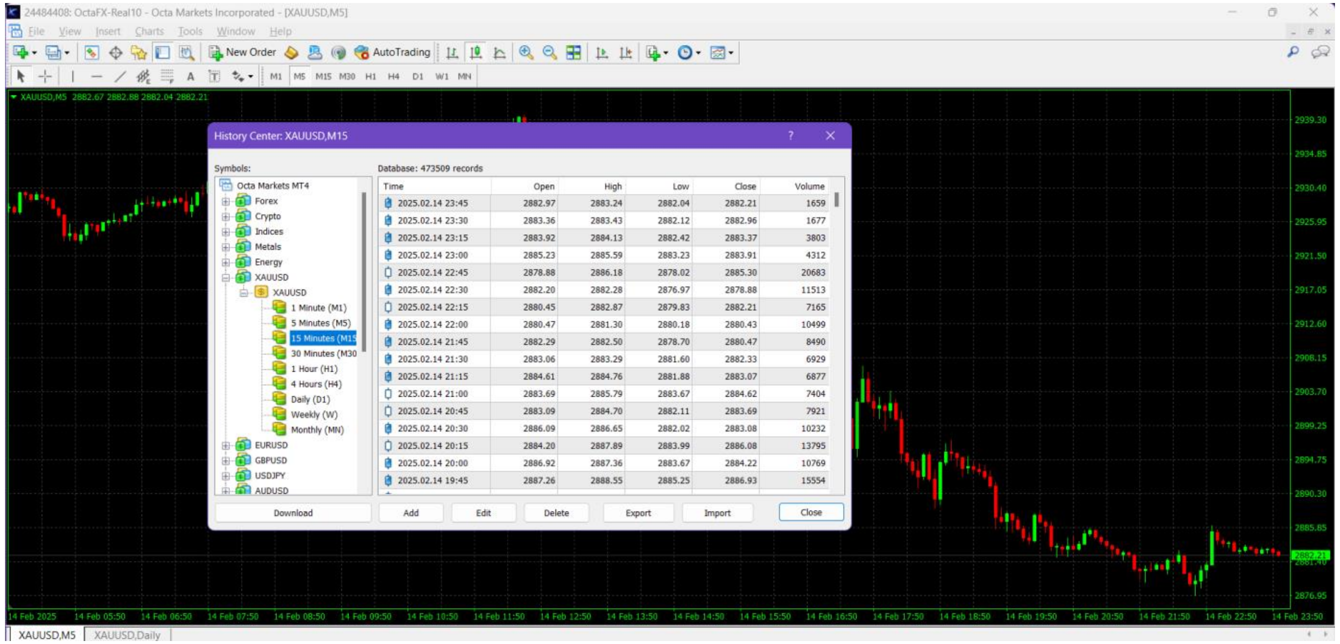
DATASET OVERVIEW

Daily & monthly gold prices

Cleaned, indexed, numeric-coerced

Monthly df_m for long-term

Daily captures micro-volatility



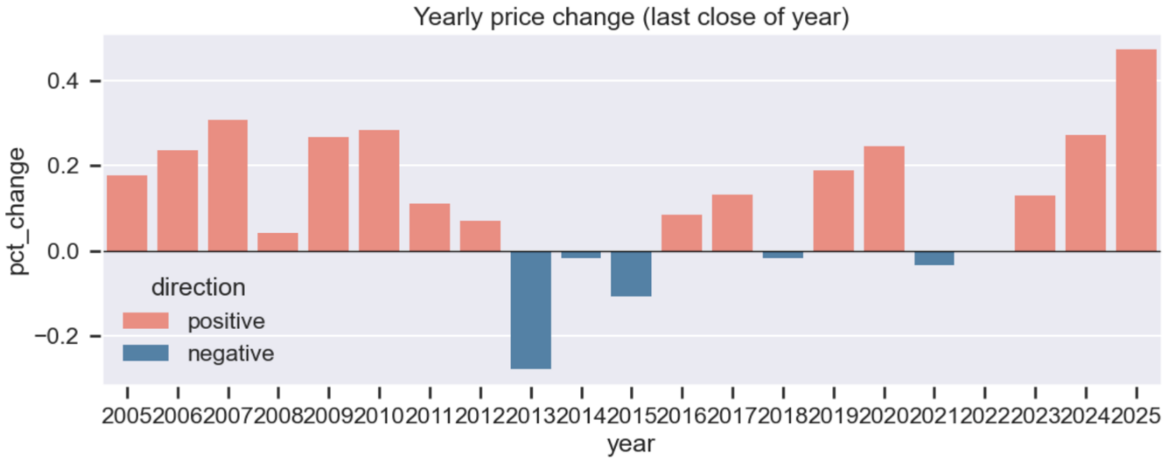
EDA: KEY PATTERNS

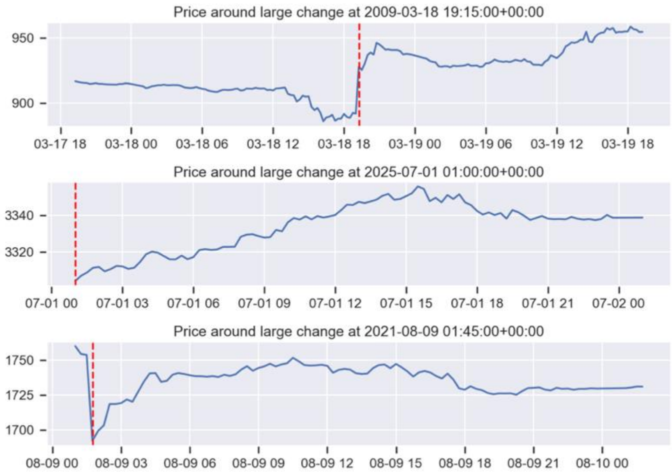
UPWARD LONG-TERM TREND

MODERATE ANNUAL SEASONALITY

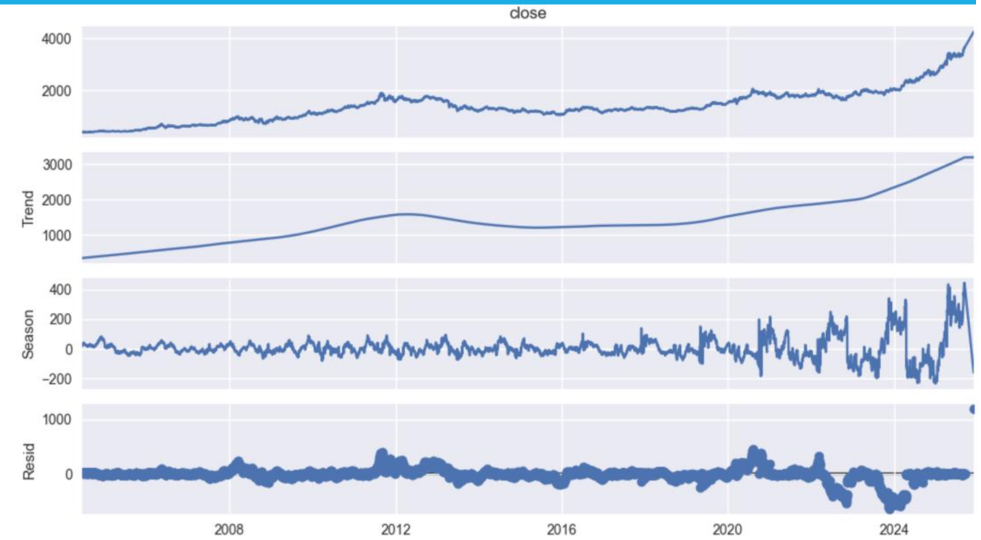
FAT-TAILED RETURNS

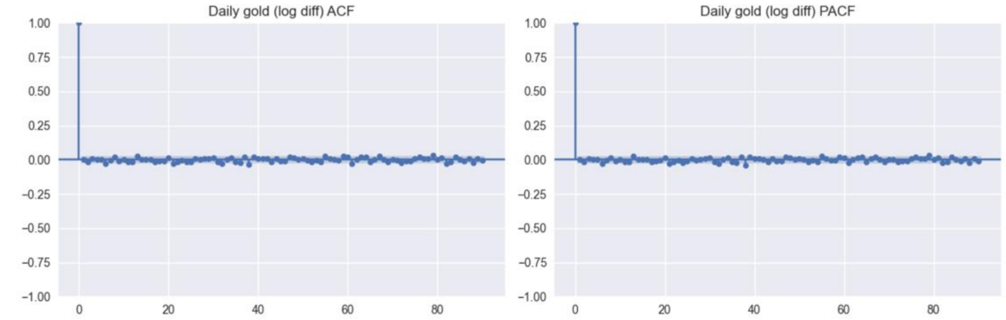
VOLATILITY CLUSTERING





STL DECOMPOSITION





Trend shows multi-year growth

Seasonality mild

Residuals capture shocks

STATIONARITY & ACF/PACF

LOG TRANSFORM + DIFFERENCING

ACF: MULTI-MONTH CORRELATION

PACF: AR STRUCTURE

SEASONAL LAG AT 12 MONTHS

VOLATILITY & REGIME ANALYSIS

Rolling means
-> bull/bear cycles

Rolling SD
-> volatility clusters

Z-score regimes
-> crisis detection

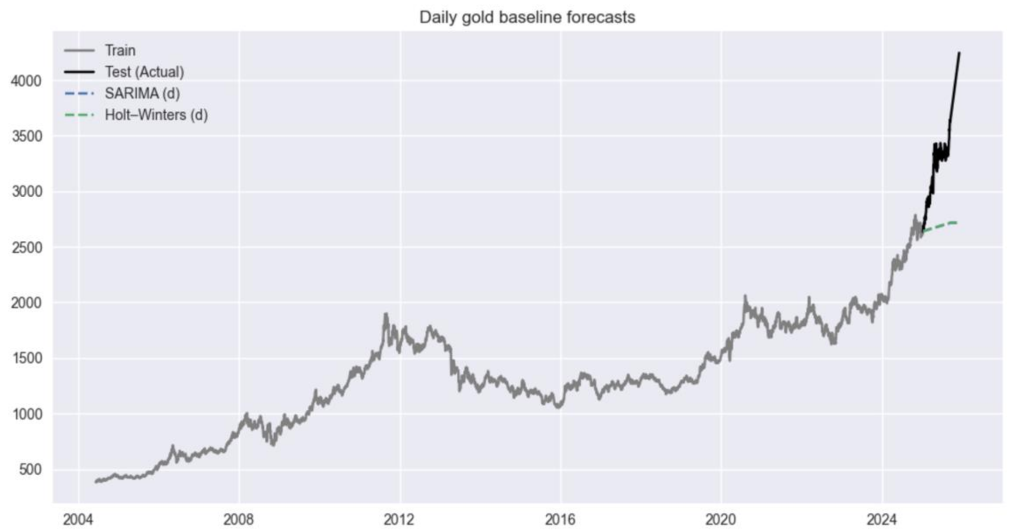
SARIMA (monthly & daily)

Holt–Winters

Metrics: MAE, RMSE, MAPE

HW: flexible cycles • SARIMA: stable structure

CLASSICAL MODEL BASELINES



DEEP LEARNING MODELS EVALUATED

- Simple RNN, LSTM, GRU
- Bidirectional LSTM
- LSTM with Attention
- CNN & CNN-LSTM
- Unified training pipeline (Adam, MSE, EarlyStopping)

Model	MAE	RMSE	MAPE	R^2	Training Time (s)
Simple RNN	97.807	159.049	3.41	0.913	2293.865
LSTM with Attention	179.489	194.711	7.48	0.869	8075.827
GRU	135.293	236.200	4.58	0.808	10273.686
Bidirectional LSTM	192.257	267.678	7.13	0.753	5375.605
CNN-LSTM	336.742	385.666	13.61	0.487	2628.596
LSTM	299.934	394.256	11.40	0.464	9712.762

PERFORMANCE SUMMARY

SIMPLE RNN BEST PERFORMER

DEEP MODELS OVERFIT

COMPLEX ≠ BETTER

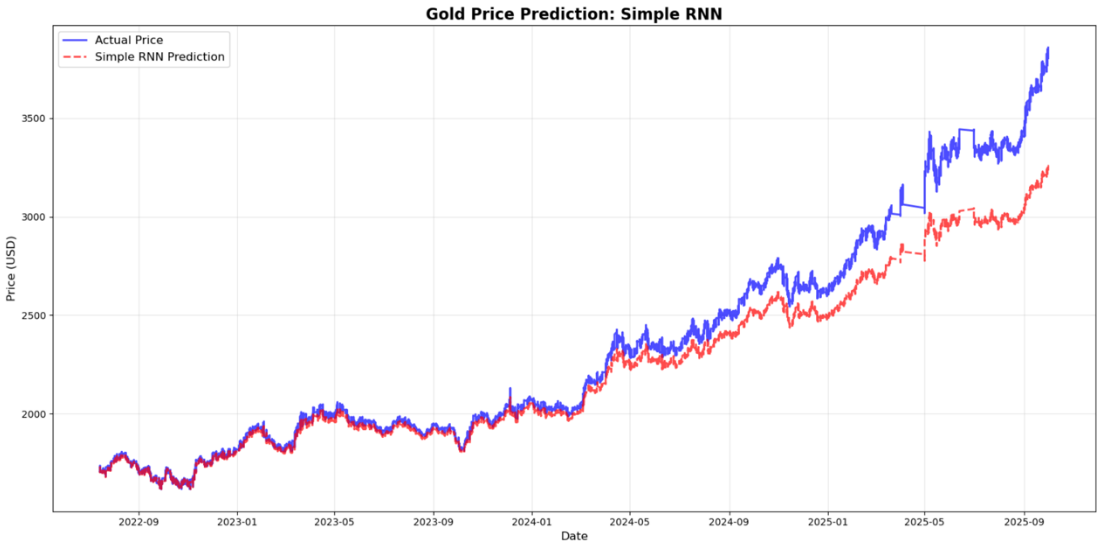
WHY SIMPLE RNN WON

Moderate smoothness in data

Complex models amplify noise

Just-enough structure

Faster training



LSTM-ATTENTION & GRU INSIGHTS

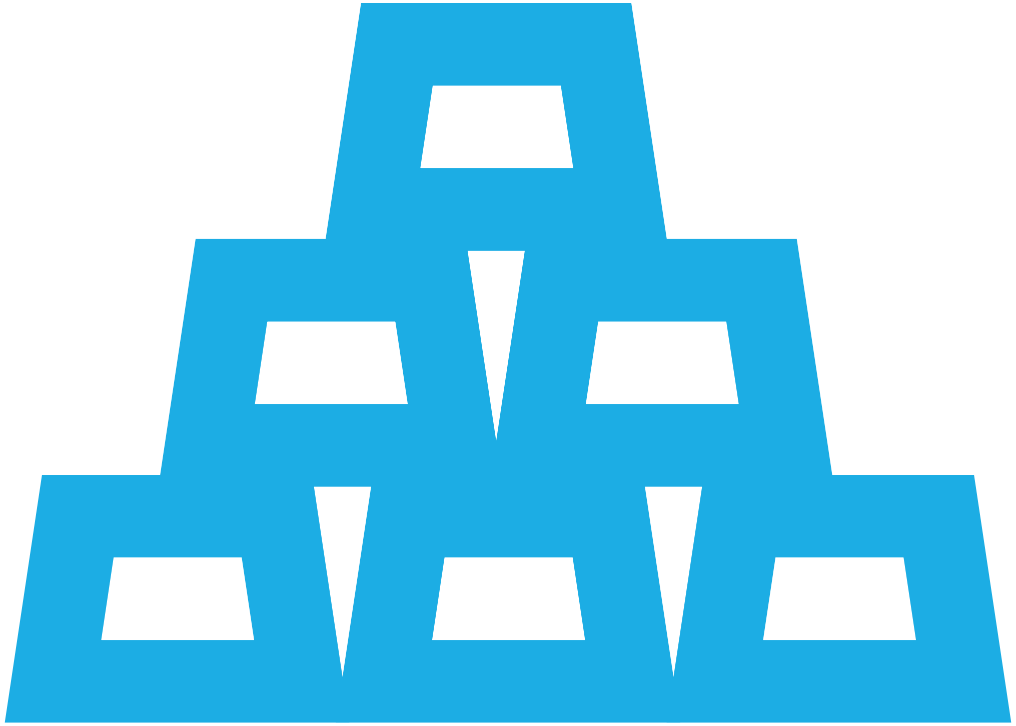
- Attention highlights noise
- GRU underutilised
- Bi-LSTM not causal
- LSTM over-parameterised

CNN-LSTM Architecture Summary

- Conv1D: local patterns
- LSTM: long-term
- LOOKBACK too small
- Filters amplify volatility

CNNS FOR TIME-SERIES

- Capture micro-patterns
- Useful in high-frequency data
- Gold trend dominates -> less effective



IMPROVING CNN MODELS

- Multi-kernel, dilated convs
- Residual blocks
- Light attention
- Bayesian tuning

SYNTHESIS & TAKEAWAYS

- Classical models = solid baseline
- Simple RNN aligns with data
- Complexity reduced robustness
- Match architecture to signal complexity

THANK YOU