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4. Go through the signal optimization and backtest process

a. What is your signal parametrization:

Binary: If the predicted volatility exceeds a predefined threshold (e.g., the top 70th percentile), it is classified as "High-Volatility Signal = 1"; otherwise, it is set to 0.

Continuous signal: Instead of thresholding, keep the predicted volatility as a continuous variable, which retains magnitude and gradation; richer for regression or portfolio sizing, but also might make it harder to set explicit trading rules (needs mapping to exposure).

Multi-regime categorical: Define several regimes (e.g., Low / Medium / High / Extreme): it contains interpretable regime switching; keeps ordering, but also make it still discretized, but less information loss than binary.

b. Which parameters you would like to optimize.

GARCH(1,1): α, β → fit to data to determine best GARCH model as the basis

XGBoost: learning_rate, max_depth, n_estimators, etc

Window size: 15min, 30min, 60min

LSTM: input_window_size, hidden_size, num_layers, dropout, learning_rate, batch_size, num_epochs, optimizer, bidirectional

c. What is the metric you would use to optimize

Primary metrics: RMSE (Root Mean Squared Error) , R^2 (Coefficient of Determination)

Secondary metrics: MAE (Mean Absolute Error) , Precision / Recall (High-Volatility Detection Accuracy) , Sharpe Ratio (when embedded in trading simulation)

d. What is the optimization/backtest procedure?

Validation: Walk-forward validation to replicate real trading conditions and avoid lookahead bias. Each cycle trains for 3 months and tests in the following month.

Hyperparameter Tuning: Cross-time optimization using grid search and Bayesian methods.

LSTM / Transformer: hidden_size, dropout, learning_rate, sequence_length

Evaluation Metrics: RMSE, R^2, and MAE

Benchmark: Compare all ML models against a standalone GARCH(1,1) baseline to measure relative performance improvement.

e. What is your out-of-sample testing? How do you reduce overfit?

To assess true generalization, the final model is tested on a hold-out set representing the most recent market period that was never used during training or validation.

Overfitting is mitigated through multiple mechanisms: Strict chronological data splitting to eliminate leakage, Early stopping based on validation loss, Regularization (L1/L2, dropout, or shrinkage depending on model type), Cross-validation across time folds to ensure stability under different regimes, Feature evaluation will also determine best features to include without overfitting

Additionally, we evaluate model robustness across market volatility regimes (high vs. low) to ensure consistent predictive performance under varying market conditions.

5. How do you plan to deploy your signal?

a. Which real time data will you need for deployment

Input Data: Real-time Level 1 quote data (bid, ask, spread, volume, etc.)
Real-time funding rate and open interest (optional, for cross-asset analysis)
Data Frequency: 1-minute intervals, with continuously updating rolling windows (15–60 minutes).

b. How do you plan to incorporate your signal into trading strategy?

Risk Management Filter: When predicted volatility is high → reduce position size or widen stop-loss levels to control risk.
Regime-Based Strategy Switch: Low-volatility regime: activate mean-reversion strategies., High-volatility regime: activate momentum or trend-following strategies.
Execution Optimization: Execute large orders during periods of predicted low volatility to minimize market impact and slippage.