Summary Document Zelta Labs

Indicator-Based Strategies

BTC STRATEGIES

Btc_main_1:

The algorithm generates reliable trading signals for ETH and BTC by combining advanced tools and indicators. It uses the Hawkes Process to detect market events, Heikin-Ashi Transformation to smooth price trends, and indicators like ATR, ADX, MACD, and Bollinger Bands to evaluate volatility, trend strength, and overbought/oversold conditions. Fibonacci retracements set dynamic exit points. Trades are triggered when Hawkes spikes align with strong ADX and Bollinger Band levels, while exits follow Fibonacci levels.

Risk management includes Fibonacci retracement, ADX-based exits, drawdown monitoring, avoiding conflicting signals, and factoring transaction costs for realistic profit estimates.

Key lessons included balancing multiple indicators for reliable signals, leveraging adaptive Fibonacci-based exits, optimizing calculations for large datasets, and managing the trade-off between profit maximization and risk minimization.

Btc_main_2:

The algorithm uses RSI, EMAs, VWAP, Bollinger Bands, and Heikin Ashi candles to detect trade signals, combining trend-following and mean-reversion strategies. RSI measures momentum, EMAs confirm trends, and VWAP, Bollinger Bands, and Heikin Ashi help identify overbought or oversold zones while reducing noise. Entries and exits dynamically adjust to market conditions, ensuring adaptability to both trending and volatile markets.

Risk management employs support-level stop-losses that adapt to volatility, with wider margins for longs and tighter ones for shorts. Exits are triggered by price thresholds, weakening RSI, and reduced volatility.

Key lessons included integrating indicators for reliability, using filters like RSI and ADX to reduce false signals, and systematic backtesting to balance profitability with controlled drawdowns. Adaptability to market shifts ensures the strategy's robustness.

ETH STRATEGIES

Eth_main_1:

The algorithm combines Heikin-Ashi candles, the Hawkes process, and technical indicators like ATR, ADX, Bollinger Bands, MACD, RSI, and Parabolic SAR to generate optimized trading signals for ETH and BTC. Heikin-Ashi smooths price data to clarify trends, while the Hawkes process identifies significant market events like price spikes. Fibonacci retracements and Parabolic SAR dynamically manage exits and confirm trend reversals, adapting to changing market conditions.

Risk management is central, utilizing ATR-based stop-losses to adjust to volatility, monitoring drawdowns to ensure robustness, and filtering signals to prevent conflicting trades. Transaction costs and market volatility are factored in for realistic profitability. Key takeaways include balancing signal reliability with computational efficiency, using adaptive Fibonacci exits for flexibility, and optimizing large-scale processes like Kalman filters and Hawkes modeling for robust, scalable trading performance.

Eth_main_2: The trade logic for this Ethereum 30-minute strategy combines trend, momentum, and volatility indicators to balance precision and risk management. Trend validation relies on EMA_50 and EMA_200 relationships and Heikin Ashi close to filter noise, while MACD refines entries by capturing strong directional momentum. Standard deviation checks against rolling averages further reduce false signals in choppy markets. RSI identifies overbought and oversold conditions for timely exits, and ATR adjusts stop-loss levels dynamically, adapting to market volatility. This approach not only captures significant price movements but also minimizes drawdowns, offering insights into combining multi-layered confirmation and adaptive risk management for robust trading strategies.Risk management in this strategy is achieved through dynamic and adaptive mechanisms. ATR-based stop-loss levels adjust to market volatility, ensuring trades have room to develop while controlling potential losses. Standard deviation filters reduce exposure to erratic price movements in choppy markets. Combining these measures with RSI-guided exits and multi-layered trend validation minimizes drawdowns and enhances overall capital preservation.

ML APPROACHES

Patch-TST (Patch Time Series Transformer)

This script predicts close prices, SMA (Simple Moving Average), and EMA (Exponential Moving Average) for BTC/ETH using a PatchTST model based on transformers. It processes the data by normalizing it and creating sequences to train and test the model. The model splits the data into smaller patches, helping it learn patterns in time series more effectively.

The training process includes advanced techniques like:

- Gradient accumulation to manage memory and improve learning.

- Gradient clipping to avoid large updates that can destabilize the training.
- Weight decay and learning rate scheduling to prevent overfitting and ensure smooth learning.

The script evaluates the model using metrics such as MSE, RMSE, MAPE, and MPE to measure the accuracy of predictions for close prices, SMA, and EMA. It showcases how the model can adapt to different forecasting tasks with stable and reliable performance.

ARIMA LSTM

This trading strategy combines LSTM and Auto ARIMA models to predict BTC price movements. LSTM captures complex temporal patterns, while ARIMA models linear trends. Predictions from both models are compared with actual prices and a 20-period EMA to identify trade opportunities.

A long entry signal is generated when both models predict a higher price and the actual price is above the EMA. Conversely, a short entry signal occurs when both predict a lower price and the actual price is below the EMA. Exit signals are based on predefined thresholds to align trades with market momentum. This hybrid approach integrates machine learning, statistical analysis, and technical indicators for a robust trading framework.

XGBOOST

The algorithm for ETH and BTC relies on XGBoost to predict trade signals based on oscillator-based technical indicators, ensuring minimal autocorrelation. These predictions are refined with a moving average crossover (9/26 periods) to confirm entry signals and an ATR-based trailing stop-loss to manage exits systematically.

Risk management practices include robust validation through K-fold cross-validation, monitoring train-test errors to detect overfitting, and using RandomizedSearchCV for effective hyperparameter tuning. The moving average crossover further reduces noise and enhances signal reliability.

The most crucial learning point was understanding how integrating machine learning with traditional technical indicators and strong validation techniques can improve both predictive accuracy and practical applicability in trading strategies.