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Project 002 - Introduction to Trading

ITESO, Universidad Jesuita de Guadalajara

Presented by:
Ana Luisa Espinoza López

Professor:
Luis Felipe Gómez Estrada

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Introduction

This project aims to use technical analysis indicators in a Python-based backtesting framework to create, optimize, and assess systematic trading strategies for BTCUSDT hourly data. In order to find configurations that maximizes the Calmar Ratio, the system uses Optuna for hyperparameter optimization. It adjusts important parameters such as RSI, MACD, Stochastic Oscillator, stop-loss, take-profit, and position sizing.

For metrics, Calmar Ratio, Sharpe Ratio, Sortino Ratio, Win Rate, and CAGR (Compound Annual Growth Rate) are among the industry-standard financial indicators used to evaluate performance at monthly, quarterly, and annual intervals. The initiative offers a thorough, data-driven basis for comprehending how parameter selections affect risk and profitability, allowing for more resilient and flexible trading systems appropriate for changing market circumstances in highly volatile assets.

Methodology

The methodology of this project follows a structured workflow designed to ensure robustness, reproducibility, and realistic performance assessment of systematic trading strategies in a time-series context. The structure of the trading system follows the following flow:

1. **Data Splitting**

   The dataset was divided in three subsets: 60% train, 20% test and 20% validation. Since the data is a time series, the chronological order was preserved to avoid look-ahead bias and for each block to reflect their respective market conditions.

   - *Training set:* Used exclusively for model calibration and parameter optimization.
   - *Test and Validation sets:* Used simultaneously to evaluate the generalization performance and robustness of the optimized strategy under unseen market conditions.

The dataset provides multiple columns of data, where the information used was extracted from the columns: date, open, low, high and close price.

2. **Feature Engineering – Technical Indicators**
A set of robust technical indicators was constructed using the ta (Technical Analysis) library to serve as the primary features for generating trading signals. The indicator used for this strategy are Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD) and Stochastic Oscillator.

    - RSI: indicator that measures the magnitude of recent price changes to evaluate overbought or oversold conditions on a scale of 0 to 100 (Investopedia, 2025).
    - MACD: trend-following momentum indicator that shows the relationship between two exponential moving averages (EMAs) (OANDA, 2025).
    - Stochastic Oscillator: this indicator compares a closing price to its price range over a period. It helps to identify overbought/oversold levels and potential reversal points.

3. **Buy and Sell Signals**
To generate the Boolean trading signals for buy and sell, a rule was established requiring that two out of the three indicators agree in order to issue the signal. The parameter ranges were designed for a highly volatile environment, that's crypto and their fast swings. The following table lists the parameters used for creating signals, their ranges and interpretation.

Table 1. Signal creation parameters description.

Parameter	Range	Description
rsi_window	10-21	Lookback period for RSI; shorter windows produce more reactive signals in hourly data
rsi_buy	15-25	Oversold threshold range (entry)
rsi_sell	75-85	Overbought threshold range (exit)
macd_fast	8-15	Fast EMA period for MACD
macd_slow	20-30	Slow EMA period for MACD
macd_signal	3-12	Signal line (smoothing) period for MACD
stoch_window	10-21	Lookback window for %K in Stochastic oscillator
smooth_window	3-7	Smoothing period for stochastic (or %D)

The chosen ranges for the parameters were chosen for hourly BTCUSDT hourly data, with this it is aimed to balance responsiveness and signal reliability in highly volatile markets. According to Hamed (2019), a (9-10) RSI with 75/25 overbought/oversold is better suited for short term charts; the standard is 14 but it's often considered to slow for short term data.

Given that eplanet mentions five-minute charts and the data is hourly the range was chosen to try values suited for short term data to a more standard approach in order to find a proper parameter to capture momentum changes. On the other hand, for MACD, according to OANDA (2025), the standard default settings are (12, 26, 9) but also causing late exit or entry to trades, according to many professional traders. OANDA (2025), suggests three alternative settings (8, 21, 5), (3, 17, 5), (3,10,16). With these in consideration the parameters were established in a range that covers the standard settings with the alternative settings. Finally, for the stochastic oscillator according to GOODCRYPTO (2025), the default settings for %K and %D are usually (5, 3) or other alternatives such as (14, 3) or (21, 5).

4. Optimization and Backtesting

Optimization

The optimization of strategy parameters was conducted using Optuna, a modern and efficient hyperparameter optimization framework that employs Bayesian optimization by default. A total of 11 parameters were optimized, covering technical indicators (RSI, MACD, and Stochastic Oscillator) and the parameters required for the backtesting portion (stop-loss, take-profit, and position sizing). The code is structured to create only one dictionary with all the parameters set for optimizing. Each function is designed to unpack the dictionary and take only the required parameters. The goal of the optimization process is to *maximize* the Calmar Ratio. This ratio measures the return potential adjusted to risk where a higher ratio means less risk to significant losses.

$$Calmar\ ratio = \frac{CAGR}{Maximum\ drawdown}$$

The optimization was performed with the train data set, which was also divided in 5 k-folds to try to mitigate overfitting. Each trial tested a certain set of parameters and calculated the Calmar ratio for each subset, the optimal parameters were determined with the highest average of Calmar ratios. Once this set of parameters was determined, it was tested in the train, test and validation sets. An additional test of the optimal parameters was made using the full set of data.

Backtesting

A custom backtesting environment was developed to simulate the execution of the trading strategy. The simulation starts with a hypothetical capital of $1,000,000 and processes the data hour-by-hour, mirroring how a live trading system would operate. The main assumptions of the backtesting includes no leverage, only short/long positions and cost of transaction of 0.125%.

The engine performs three core functions for each time interval:

- Opens positions: When a buy or sell signal is generated, it calculates the cost of the trade, deducts it from the available cash, and creates a new position with its associated stop-loss and take-profit levels.
- Closes positions: It goes through all open positions which are automatically closed if the market price touches its pre-defined stop-loss or take-profit level. The resulting profit or loss is then added back to the cash balance.
- Tracks Portfolio Value: At every step, the total portfolio value is calculated by summing the remaining cash and the current market value of all open positions.

The backtesting environment returns a portfolio historic DataFrame with a portfolio value associated to a date. With this historical the metrics and returns are to be calculated. In addition to the parameters previously mentioned, the dictionary contains the three following necessary for the backtest.

Table 2. Backtest parameters description

Parameter	Range	Description
stop_loss	0.02 – 0.08	Stop loss 2-8% to minimize drawdown
take_profit	0.03 – 0.12	Take profit 3-12%
n_shares	0.01– 1.5	Shorter position to protect from high volatility

5. Performance Evaluation

To evaluate the trading strategy performance a metric framework was implemented. The metrics included in the framework asses three key dimensions: risk-adjustment returns, downside risk protection and consistency. For the metric calculations, the code performs a backtest on the data samples and take as input the historical portfolios.

The Calmar Ratio is the main key performance indicator for optimization and general evaluation since it evaluates the annualized return (CAGR) against the maximum amount ever lost (Maximum Drawdown). The ratio is suitable for volatile assets such as Bitcoin. In addition, the following metrics were also calculated:

- Sharpe Ratio: Evaluates returns per unit of total risk (volatility), annualized.

$$Sharpe = \frac{R_p - R_f}{\sigma_p} \times \sqrt{periods\ per\ year}$$

Where:

- R_p = Portfolio return
- R_f= Risk-free rate
- σ_p = Standard deviation of portfolio returns

- Sortino Ratio: Measures returns per downside risk, punishing only negative volatility that is harmful to investors.

$$Sortino = \frac{R_p - R_f}{\sigma_d} \times \sqrt{periods\ per\ year}$$

Where σ_d = standard deviation of returns below a target (0 in this case).

- Maximum Drawdown: Measures historic worst-case peak-to-trough loss, providing the view of the strategy's maximum drawdown risk potential.

$$MDD = \min_{\tau \in (0,t)} \left(\frac{V_t}{peak_\tau} \right) - 1$$

- Win Rate: Measures the percentage of profitable periods (monthly/quarterly/yearly), providing insight into a strategy's probability of providing positive returns consistently.

$$Win\ rate = \frac{\text{Number of Positive Periods}}{Total\ number\ of\ periods}$$

As for the modular python-based code structure, the architecture and dependencies are as shown below in Figure 1.

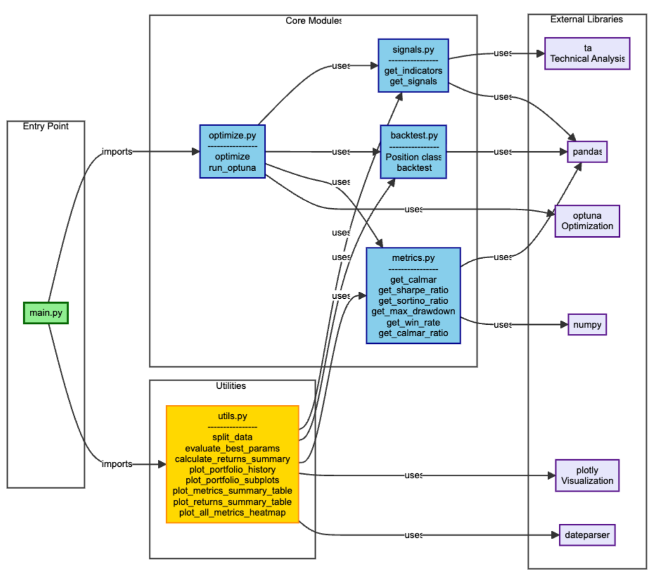

Figure 1. Code Architecture & Dependencies. Source: Self made

Results and Discussions

To test the performance of the trading strategy, the best parameters, obtained from the optimize function are tested for de train, test and validation datasets. This in order to verify that the strategy can also generate reliable signals under unseen market conditions. Additional to these datasets, the backtest was also performed on the full dataset.

The optuna study maintained its default setting to use Bayesian Optimization with a default number of 50 trials. The optimal parameters for the train data set (BTCUSDT august/2017 to June/2022) where the following with a Calmar average of 2.5627:

Table 3. Best study parameters

Parameter	Value
rsi_window	20
rsi_buy	18
rsi_sell	79
macd_fast	11
macd_slow	22
macd_signal	11
stoch_window	12
smooth_window	5
stop_loss	0.0466
take_profit	0.1135
n_shares	0.7846

With the optimal parameters it the following historic portfolios were obtained:

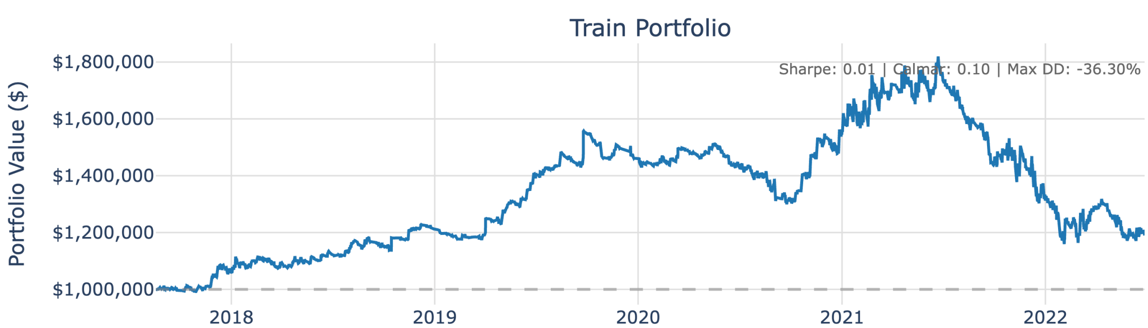

Figure 2. Historic Portfolio Train dataset

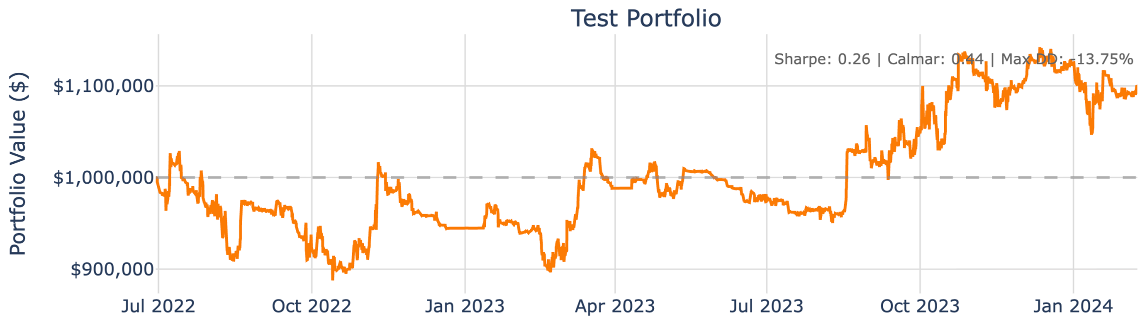

Figure 3. Historic Portfolio Test dataset

Figure 4. Historic Portfolio Validation dataset

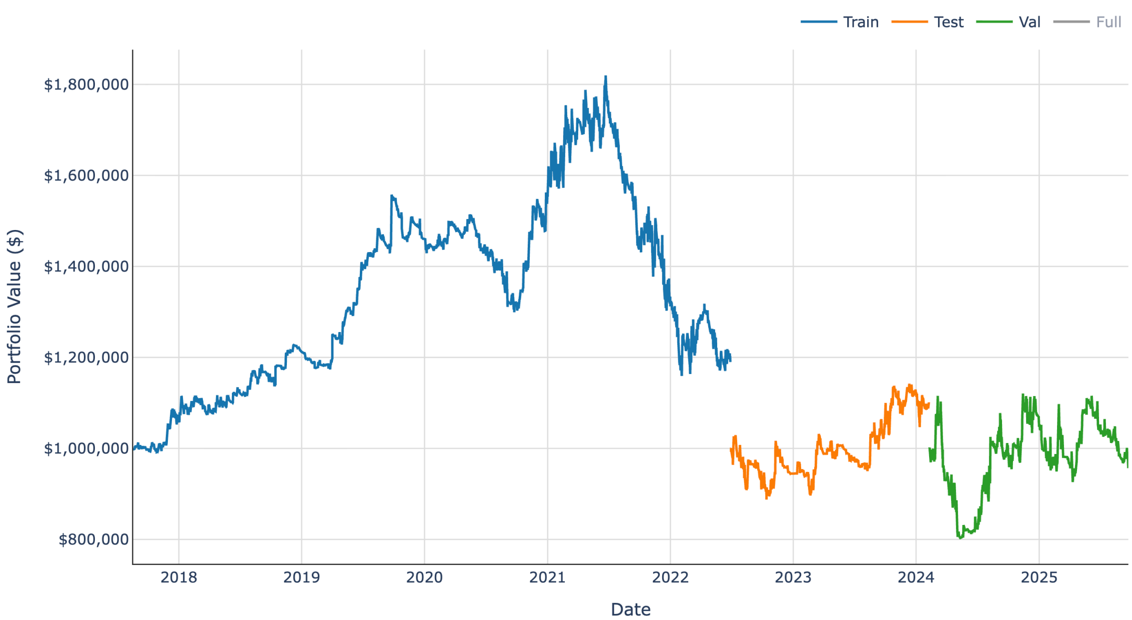

Figure 5. Historic Portfolio Comparison

Figure 6. Historic Portfolio Full dataset

For the historical portfolios, the current metrics were calculated:

Table 4. Annualized returns per period. Calculated with CAGR

Dataset	Monthly %	Quarterly %	Yearly %
Train	3.49%	3.77%	3.64%
Test	6.61%	6.28%	6.09%
Val	-6.40%	2.32%	-2.44%
Full	2.88%	3.04%	2.98%

Observing table 4, the train and test validation show positive returns. The key difference between the historic portfolios is that the train set shows a downward trend while the test shows a bullish trend. However, the validation data set shows a bigger drawdown and appears to behave in a lateral tendency looking more bearish. Finally, when testing the strategy on the full dataset it appears to have positive returns but loses money in the long run. This suggests that the strategy shows a good result on lower volatility scenarios given that after 2022, BTCUSDT shows high volatility periods. This is also a sign that the strategy loses effectiveness in more up to date data. Note that all returns are expressed annually for comparison purposes.

Table 5. Metrics summary – Monthly

Metric	Train	Test	Val	Full
Calmar Ratio	0.100	0.442	-0.087	0.068
Sharpe Ratio	0.015	0.259	-0.324	-0.014
Sortino Ratio	0.014	0.374	-0.351	-0.014
Max Drawdown	-36.30%	-13.75%	-28.02%	-43.48%
Win Rate	56.90%	45.00%	42.11%	52.58%

Table 6. Metrics summary – Quarterly

Metric	Train	Test	Val	Full
Calmar Ratio	0.100	0.442	-0.087	0.068
Sharpe Ratio	0.064	0.255	0.025	0.014
Sortino Ratio	0.067	0.298	0.030	0.016
Max Drawdown	-36.30%	-13.75%	-28.02%	-43.48%
Win Rate	57.89%	57.14%	50.00%	53.12%

Table 7. Metrics summary – Yearly

Metric	Train	Test	Val	Full
Calmar Ratio	0.100	0.442	-0.087	0.068
Sharpe Ratio	-0.075	0.403	-0.324	-0.067
Sortino Ratio	-0.080	1.923	-0.351	-0.064
Max Drawdown	-36.30%	-13.75%	-28.02%	-43.48%
Win Rate	60.00%	50.00%	0.00%	62.50%

The Calmar Ratio, the main optimization metric, provides insights into the risk-return profile of the strategy. The test period produced a strong Calmar Ratio of 0.442, suggesting returns were adequate to the maximum drawdown of -13.75%. In contrast, the validation period produced a negative Calmar Ratio (-0.087) due to poor returns and a maximum drawdown period (-28.02%) and displayed clear signs of significant underperformance and risk.

Observing the Sharpe and Sortino ratios, the insights back up the signs of underperformance and risk to loses. In the testing period, both ratios were positive, representing that the strategy produced return over risk, with a higher Sortino ratio (1.923 yearly) indicating successful downside volatility management. In contrast, the validation period returns were negative for both ratios, showing that the strategy doesn't compensate risk. The full-period statistics were also slightly negative Sharpe and Sortino ratios, suggesting that the strategy has not compensated for the volatility and downside of the returns over its history. In addition to this, all ratios for monthly and quarterly periods were under 1, meaning that even though they are positive, the return is not appealing enough given the risk.

The Maximum Drawdown shows that the strategy incurred its maximum peak-to-trough loss of -43.48% across the entire dataset, and there were also sizeable drawdowns in the training (-36.30%) and validation (-28.02%) periods, confirming the strategy is exposed to loses under the highly volatile crypto market conditions.

Finally, the win rate which is the measurement of consistent profitability shows its highest value on the training data, which is not the purpose of the model or the current market conditions. The yearly win rate for the validation subset is 0% which is consistent with made points with the other metrics: the strategy declines overtime and the training conditions don't match or represent current market conditions.

Discussions

Looking at the obtained results, it is clear that the optimal parameters do not adjust well for unseen scenarios. The train data set which contains data until June 2022 does not capture the rising current tendency and the increasing volatility that the asset has had for the following years (Figure 7). With this in consideration, it is quite clear that in these kinds of volatile environments, parameters for trading signals should be adjusted with more periodicity to adjust to current market conditions, especially with unregulated assets.

Figure 7. BTCUSDT price overview. Source: Trading View, (October 6, 2025)

Looking at the parameters and comparing them to the settings mentioned in the Methodology section, some of the parameters such as all macd parameters or rsi_sell produce slow signals for this crypto currency.

Model Limitations

The model has 3 key limitations, the first one and most important is that for this type of volatile assets, the use of old data is not optimal for training models to capture current tendencies a momentum changes due to the radical behavior change in the price dynamics. On the other hand, according to Hayes (2024), the Stochastic Oscillator is known to produce false signals leading to losing trades, especially in volatile market conditions like the test or validation dataset. Hayes (2024) mentions that this can be controlled conditioning the signal true only if it follows the current asset trend. Finally, another important limitation is that the position size in the backtest environment is constant. In real life trading the amount of shares to buy and sell depend not only on cost and cash availability but also in opportunity. To buy and sell always the same amount of BTCUSDT is not necessarily realistic. Small positions limit losses but also limit potential profit.

Conclusions

The backtesting and analysis show that the purposed optimal strategy for trading the cryptocurrency BTCUSDT is not optimal for current market conditions. The strategy showed its best performance on the Test subset but failed to generate returns adjusted to risk overtime, backed up by the negative Calmar Ratio and a 0% yearly win rate on the validation set and the deep maximum drawdowns exceeding -28%. The strategy also showed its best performance on the test set with a Sortino of 1.9 and a maximum drawdown of 13.75%.

This shows that the strategy shows signs of overfitting in spite of the k-fold splits and that the train subset doesn’t capture the current behavior of the asset for the model to create reliable trading signals in conditions of higher volatility. The model has mayor opportunity areas including training the model with more up to date data, reducing the ranges for the parameters to have a bigger control on the strategy’s approach and sensibility and to condition the position size given the strength of the signals.

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