Analysis of Trading Strategies

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Agenda

01 Introduction

02 Data Exploration

03 Methodology

04 Results & Discussion

05 Conclusion & Future Work

Introduction

Trading Bot Functionality:

- Trading Bot functionality is now complete.
- With this milestone achieved, we are ready to implement and test actual trading strategies.

MACD & Dynamic RSI Strategy Experiments:

- Initiated experiments focusing on a MACD & Dynamic RSI strategy.
- This detailed report covers the experiments, analysis, and insights derived from these strategies.

Introduction

Algorithmic Trading & Technical Indicators:

- Automated trade execution using quantitative models.
- **MACD:** Identifies trends by comparing moving averages.
- **RSI & Dynamic RSI:** Measures momentum and adjusts thresholds based on market volatility.

Motivation & Objectives:

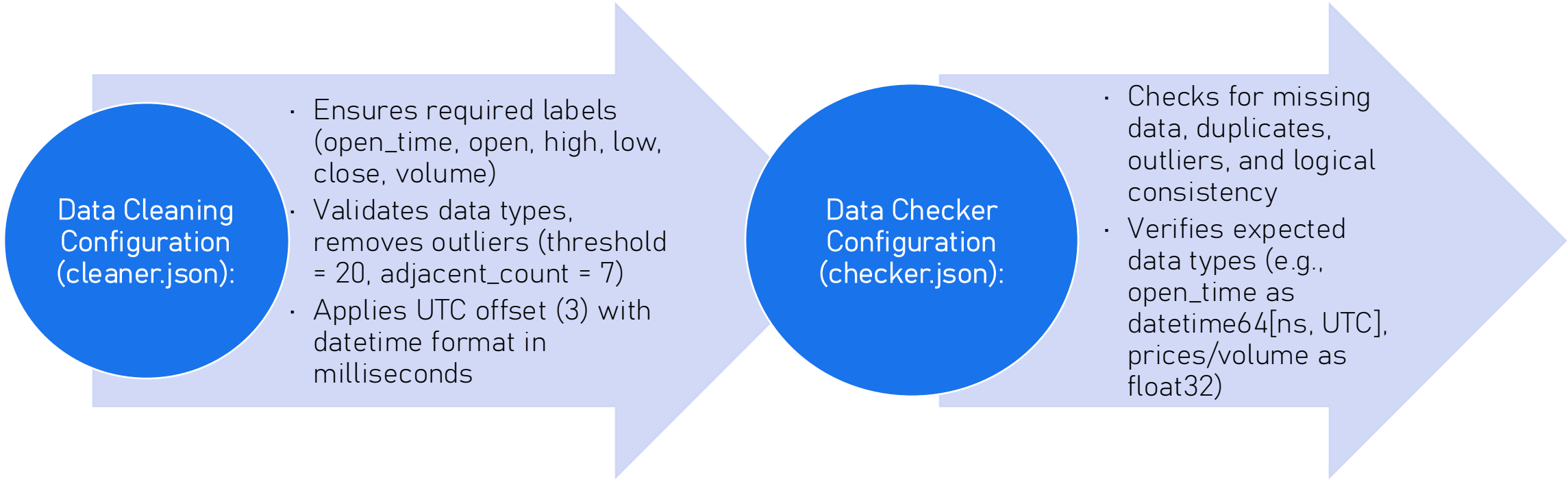
- Optimize parameters for improved performance.
- Validate strategy robustness through comprehensive backtesting.

Data Exploration

DATA CLEANING & CHECKING

FEATURE ENGINEERING

Data Cleaning & Checking Configurations



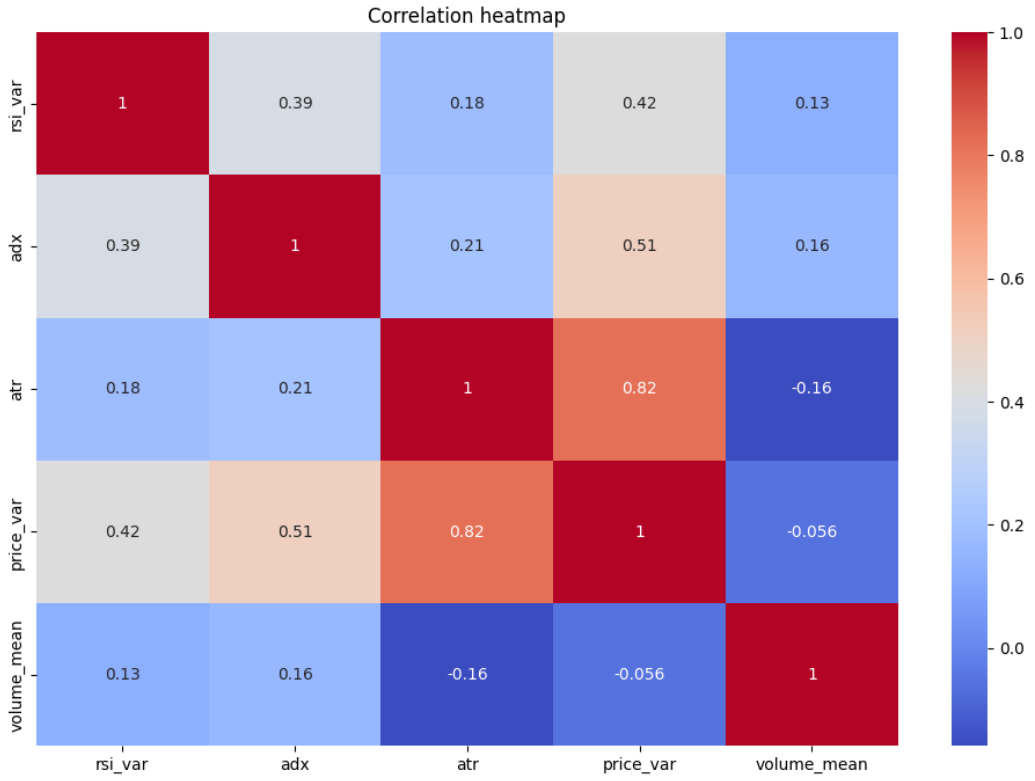
Data Exploration Overview

- Data Source & Timeframe:
  - BTCUSDT data from Jan 2023 to Sep 2024 (15-minute intervals)
- Feature Extraction:
  - Used SingleSymbolDataHandler & SingleSymbolFeatureExtractor
  - Key indicators: RSI, MACD (and its components), Stochastics, Bollinger Bands, ATR, VWAP, OBV, SMA, EMA, ADX, plus ‘close’ & ‘volume’

Derived Features & RSI Variance Analysis

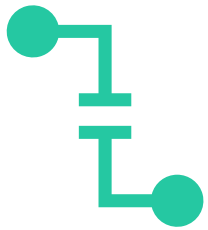
- RSI Variance & Range:
  - Calculated rolling RSI variance (window = 15)
  - Computed rolling RSI min & max (window = 30) to assess range
- Price Volatility:
  - Rolling standard deviation of close prices (window = 15)
- Insight:
  - Larger RSI variance (wider range) motivates the development of a dynamic RSI model to adapt thresholds in real-time

Correlation Heatmap with RSI variance



- **Correlation Analysis:**Scaled indicators using MinMaxScaler for uniformity
- Correlations observed among RSI-derived metrics (e.g., rsi_max, rsi_min, rsi_var)
  - Medium: price variance, adx
  - Small: ATR, Volume(rolling mean)

Implications & Dynamic RSI Model Development



Dynamic RSI Motivation:

Observed large variance in RSI supports dynamic adjustment of thresholds

Aims to adapt overbought/oversold levels based on current market volatility

Expected Benefits:

Improved signal responsiveness in sideways markets

Better risk management by reducing false signals and capturing market nuances

Methodology

OVERALL SETUP & DATA CONFIGURATION

STRATEGY OVERVIEWS

EXPERIMENTAL PROCESS & EVALUATION

OVERALL SETUP & DATA CONFIGURATION

- Tools & Environment:
  - Python libraries (pandas, NumPy, matplotlib, scikit-learn, etc.)
  - Custom modules for data handling and feature extraction
  - Automated data cleaning via the trading bot (detailed later)

OVERALL SETUP & DATA CONFIGURATION

Data & Timeframe:

- Symbol: BTCUSDT
- Interval: 15 minutes
- Example Date Ranges: 2023–2024 for initial tests; 2024–2025 for untouched data

Feature Set Parameters (from feature_set_15m.json):

- RSI period: 3
- MACD: short=15, long=30, signal=20
- Additional indicators: Stochastics, Bollinger Bands, ATR, VWAP, OBV, SMA, EMA, ADX, etc.

Strategy Overviews

- Strategy 1: MACD Histogram with Threshold
  - Compute MACD histogram (macd_diff)
  - **Buy:** When macd_diff > threshold
  - **Sell:** When macd_diff < –threshold
  - Full capital invested; performance metrics computed

Strategy Overviews

- Strategy 2: MACD with Trend Confirmation
  - Combine MACD signals with ADX for trend validation
  - **Buy**: When macd_diff > threshold **and** ADX **≥** 45
  - **Sell**: When macd_diff < –threshold while ADX confirms trend

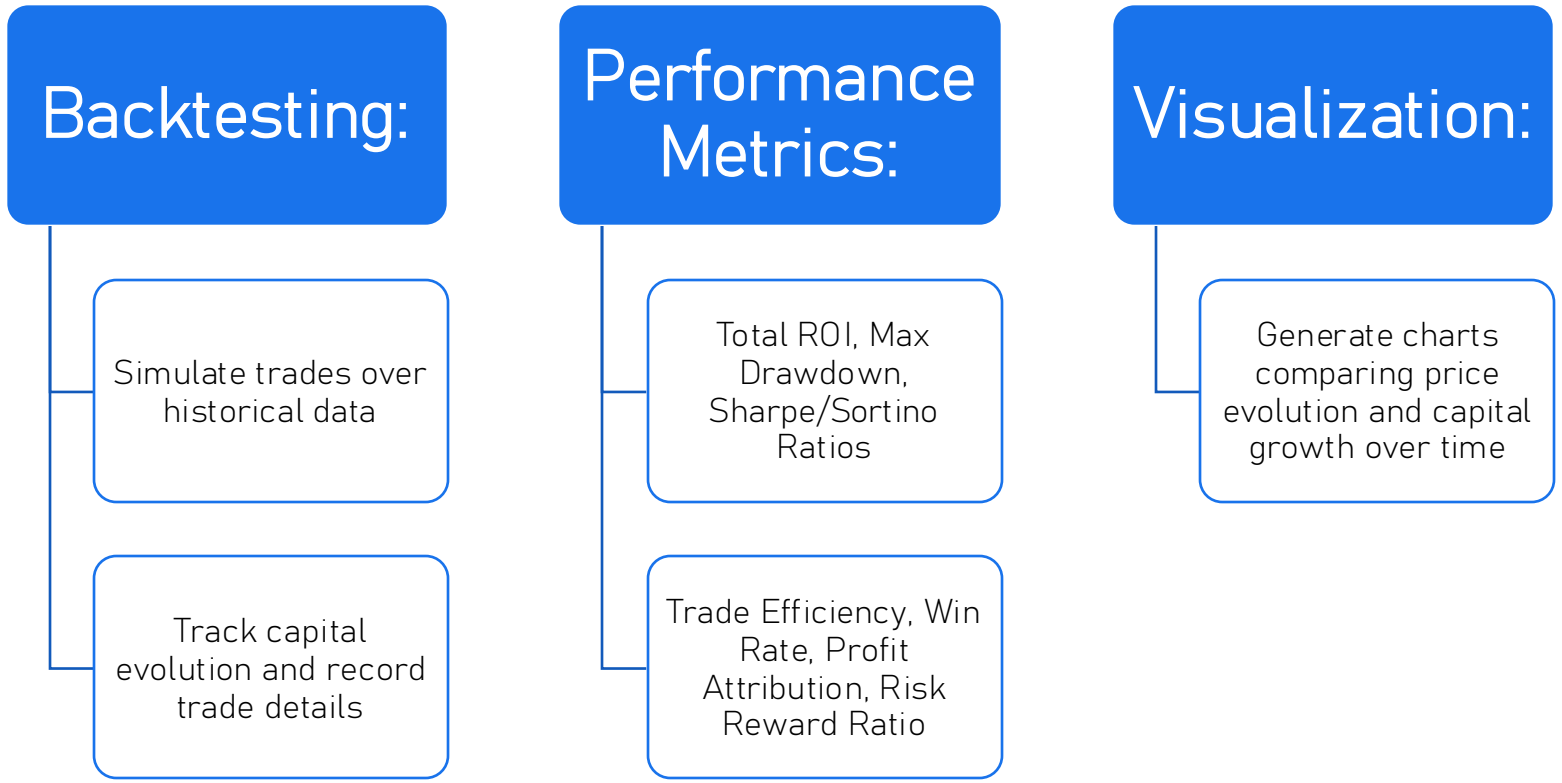
Strategy Overviews

- Strategy 3: Dynamic RSI on Sideways Markets
  - Active only when market is non-trending (ADX below threshold)
  - Calculate dynamic RSI thresholds using rolling mean and standard deviation
  - **Buy:** When RSI falls below the dynamic lower boundary
  - **Sell:** When RSI rises above the dynamic upper boundary

Strategy Overviews

- Strategy 4: Combined Strategy (Dynamic RSI + MACD)
  - Regime-based approach using ADX:
    - **Dynamic RSI Regime:** When ADX < rsi_trend_threshold (≈20–23)
    - **MACD Regime:** When ADX > adx_macd_threshold (≈45)
    - **Undefined Region:** Optionally use SSTI to trigger exits
  - Integrates benefits of both strategies while addressing conflicts and noise

Experimental Process & Evaluation

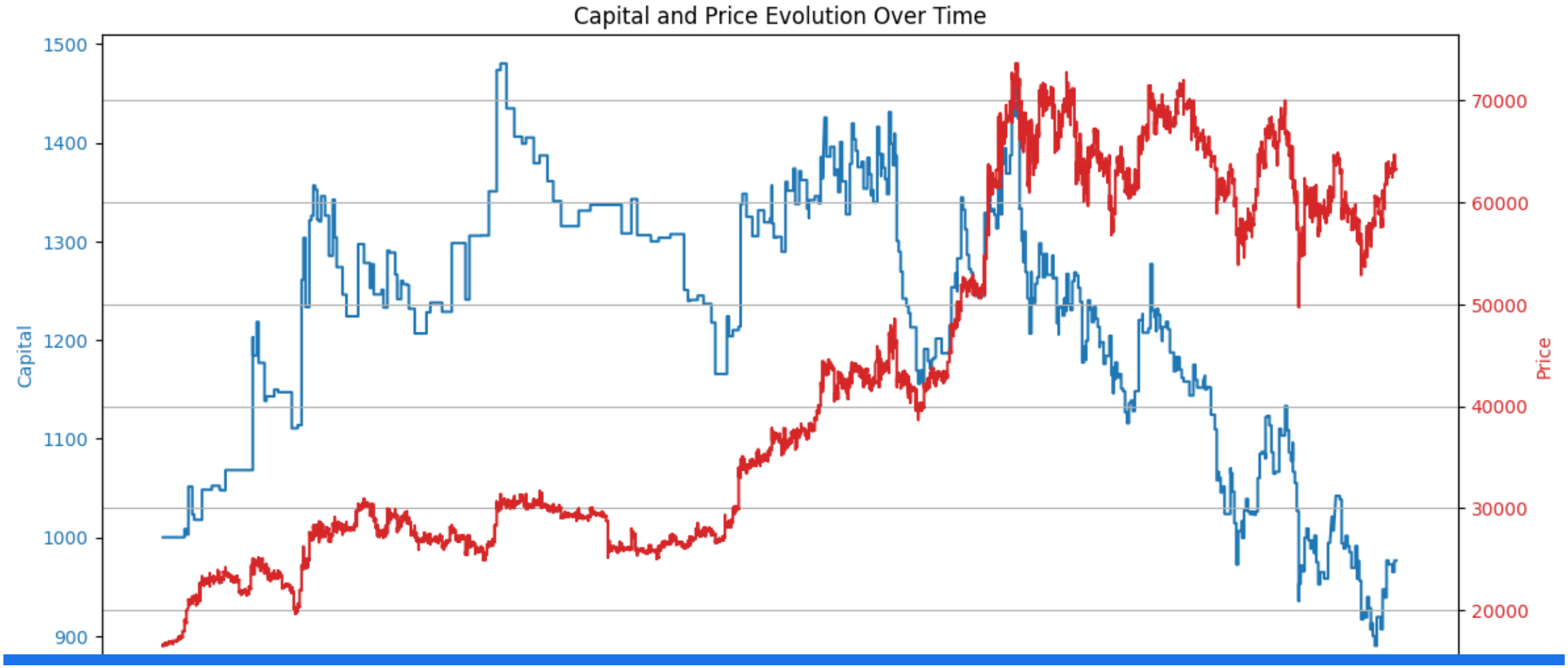


Strategy Performance Overview

OVERALL SETUP & DATA CONFIGURATION

STRATEGY OVERVIEWS

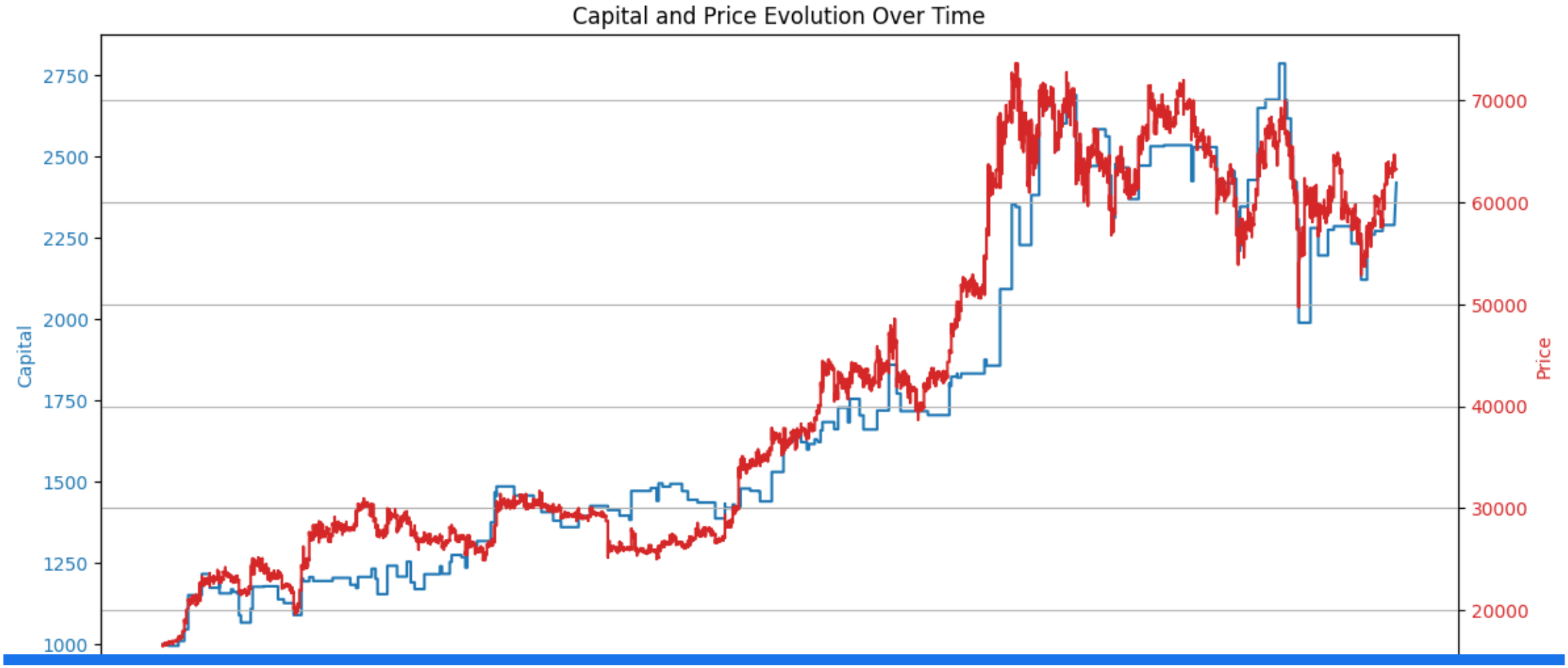
EXPERIMENTAL PROCESS & EVALUATION



Strategy Performance

Strategy 1: MACD Histogram with Threshold

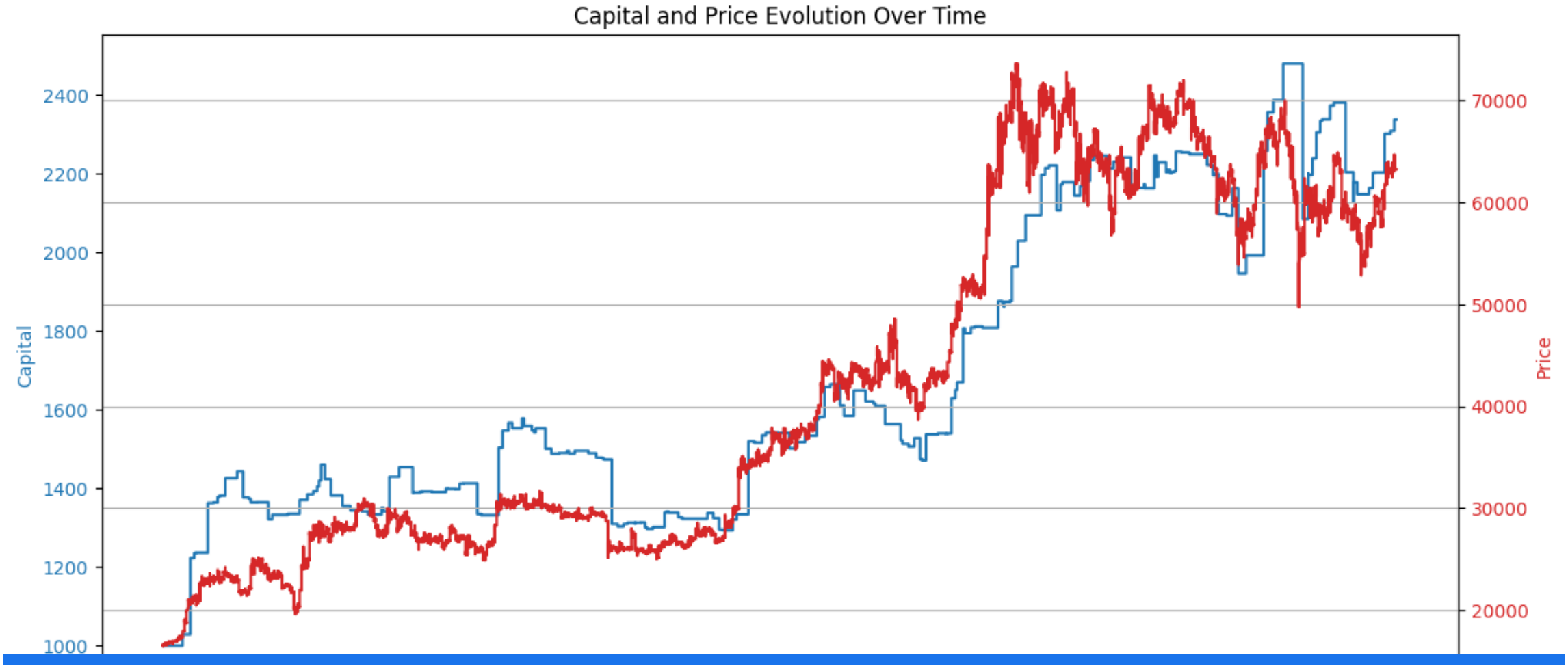
- ROI: ~ -2.36%
- Max Drawdown: ~39.87%
- Note: Despite a high underlying asset gain (Symbol ROI ~282.88%), frequent trades and noise lead to negative overall performance.



Strategy Performance

Strategy 2: MACD with Trend Confirmation

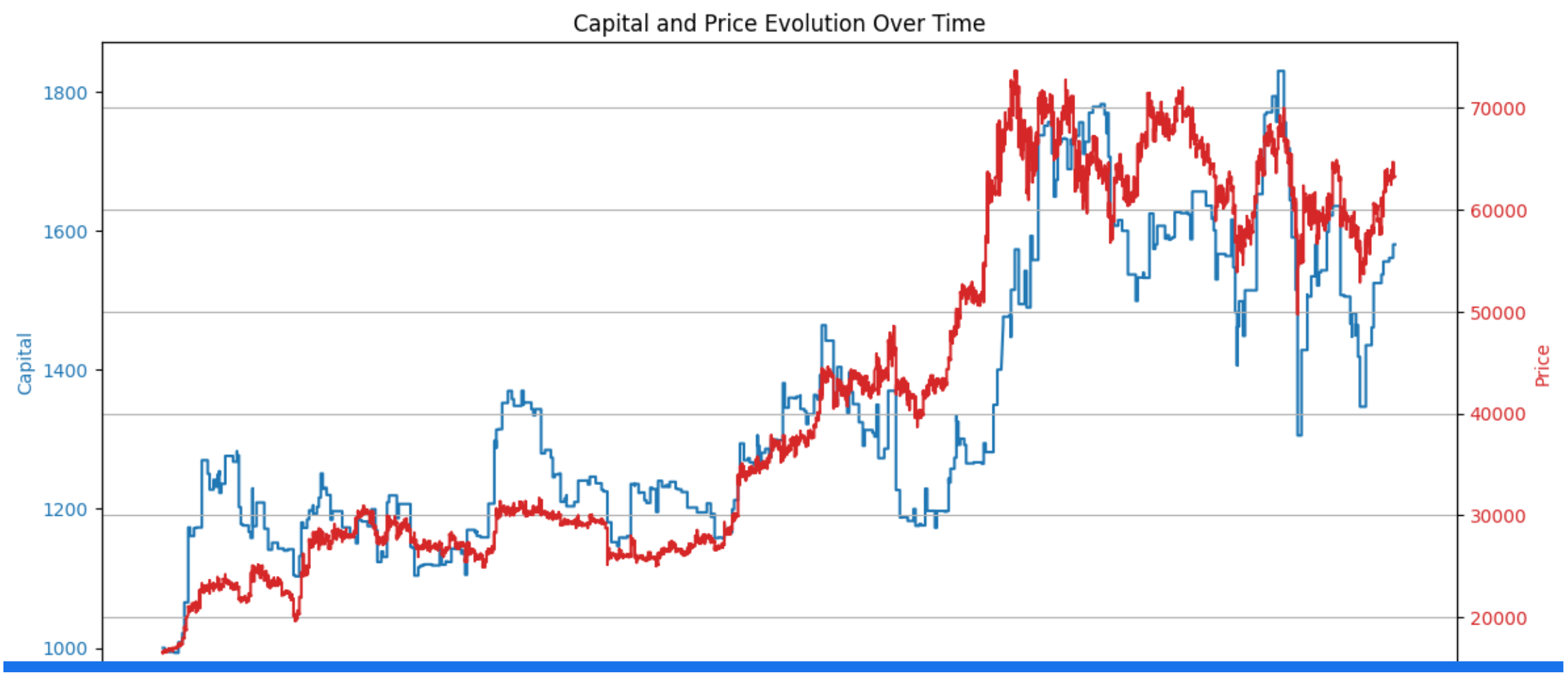
- ROI: ~142%
- Max Drawdown: ~28.64%
- ADX filter (threshold ≥45) improved performance by excluding trades in non-trending periods.



Strategy Performance

Strategy 3: Dynamic RSI on Sideways Markets

- ROI: ~133.73%
- Max Drawdown: ~18.04%
- Higher win rate (~57%) due to adaptive RSI thresholds that adjust to market volatility.

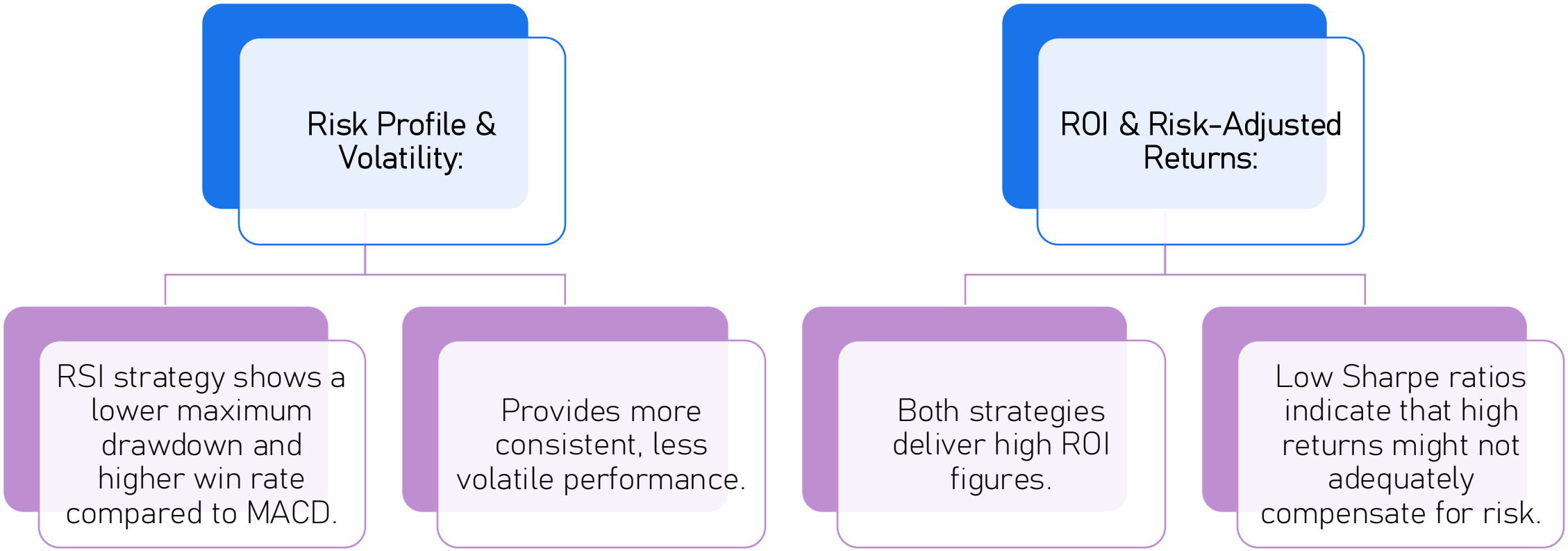


Strategy Performance

Strategy 4: Combined Strategy (Dynamic RSI + MACD)

- Mixed outcomes:
  - Variant 1: ROI ~58%
  - Variant 2 (with SSTI exit): ROI ~5.29%
- Complexity may cause signal conflicts and potential overfitting.

Comparative Analysis

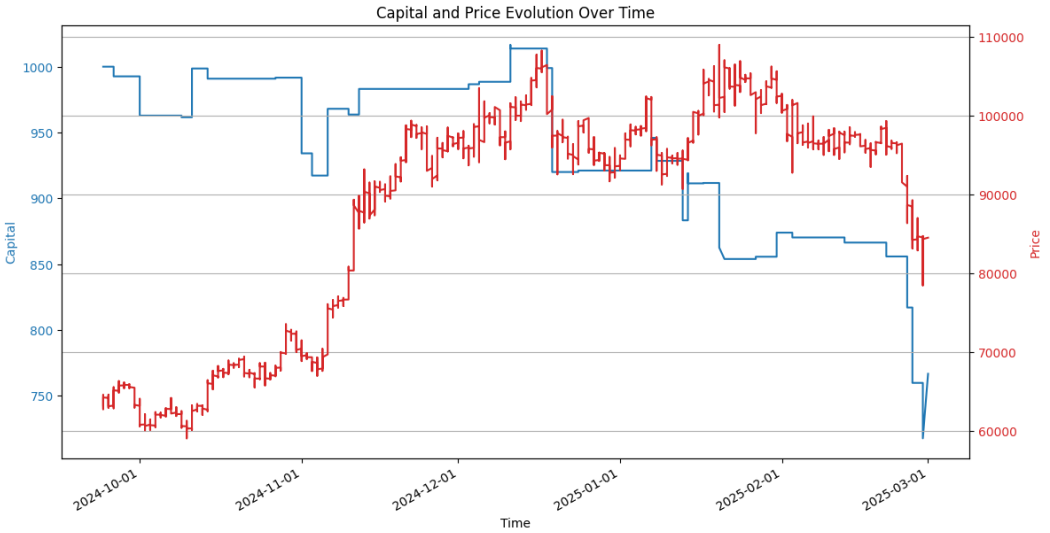


Comparative Analysis

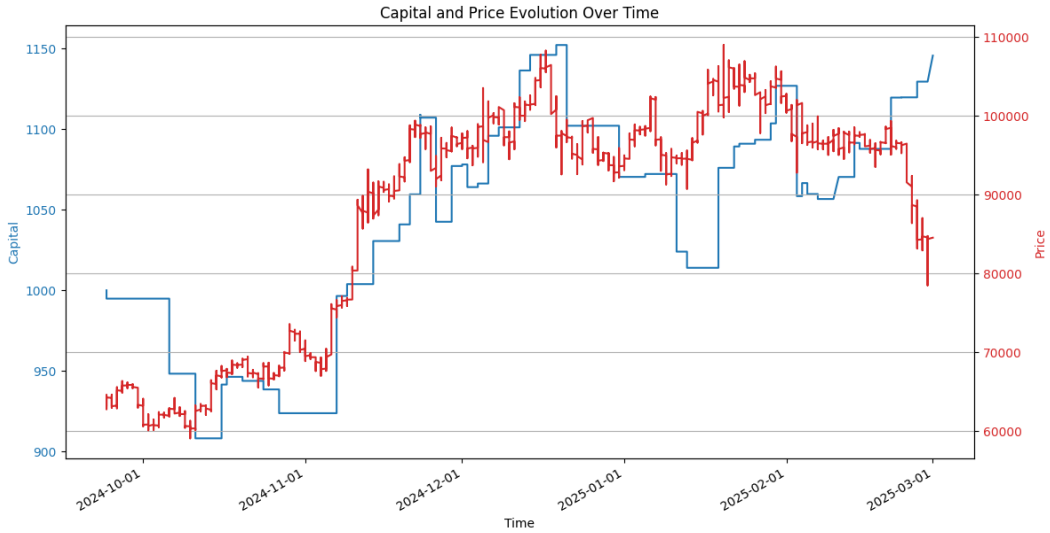
- Trade Efficiency & Robustness:
  - RSI strategy offers better trade efficiency.
  - RSI models are more robust under fine tuning, enhancing performance stability.
- Overall Effectiveness:
  - Despite slightly lower ROI, the improved drawdown profile, higher win rate, and robustness make the RSI strategy potentially more attractive for risk-conscious traders.
  - Balancing profit capture with loss control is key to long-term trading success.

Back test on Unseen Data – Robustness

MACD + ADX CONFIRMATION



RSI + ADX CONFIRMATION



More Attempts on Dynamical RSI

MOTIVATED BY THE DISCOVERY

MACHINE LEARNING ON RSI THRESHOLDS

ALTERNATIVE DYNAMICAL THRESHOLD MODEL

Random Forest Modeling for RSI Thresholds

Target: Predict dynamic RSI max and min using features explored (price variance, adx, atr, volume mean, etc.)

Validation: TimeSeriesSplit & GridSearchCV (R^2 ~0.78 with MSE around 2.72)

Observation: RF predictions are similar to simple rolling window values.

Alternative Dynamic Threshold Methods

Median-Based Adjustment:

Use historical median with margin (mae) adjustments.

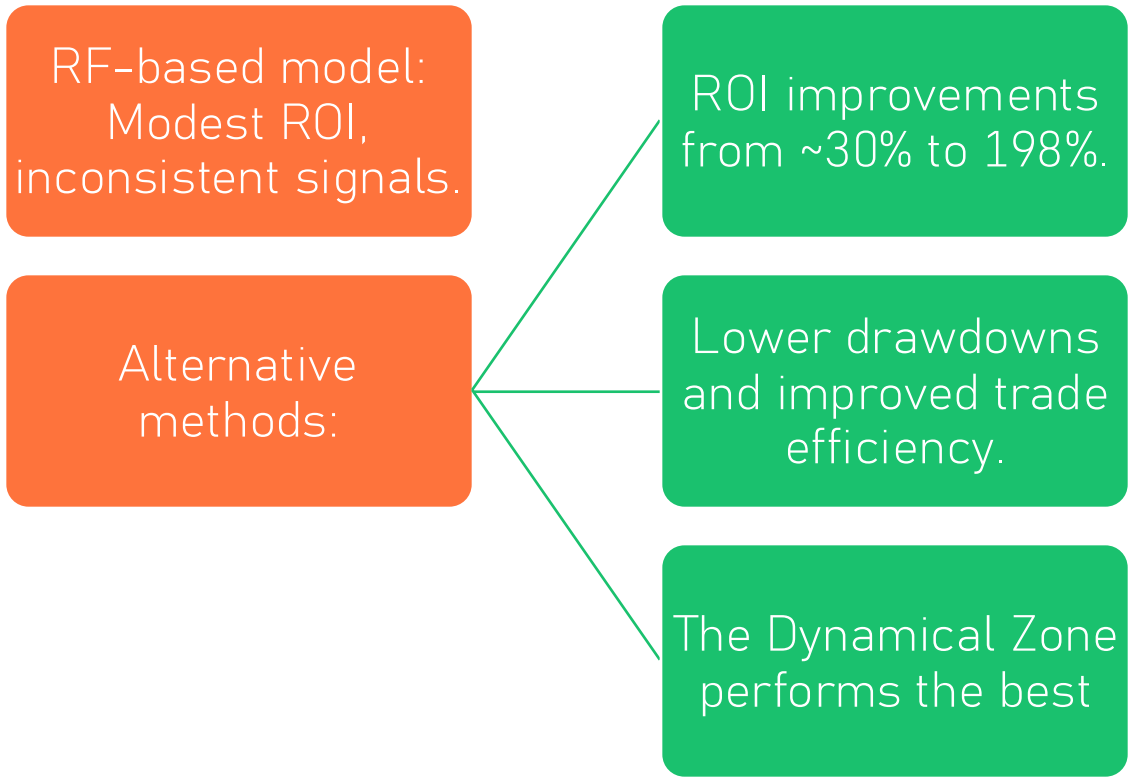
Dynamic Zone Approach:

Rolling RSI mean ± k * standard deviation (clipped within realistic RSI limits).

Volatility-Linked Model:

Adjust thresholds based on ATR and price variation.

Trading Strategy Performance



Using The Backtest Module

TO MIMIC THE REAL-TIME TRADING ENVIRONMENT

TESTING ROBUSTNESS OF STRATEGIES

Overview

To reflect real-world trading conditions more accurately than an idealized backtest:

- **Maximum Window Storage:** Limits on historical data storage.
- **Incremental Calculation:** Real-time updating of indicator values.
- **Rounding of Amounts:** Values are rounded to three digits (an empirically chosen setting for cryptocurrency volatility) to mitigate issues caused by lag-induced price fluctuations.

RSI+ADX Strategy Performance Comparison

REAL-TIME MIMIC RESULTS

- ROI: 154.40%
- Max Drawdown: 17.08%
- Sharpe Ratio: 0.00909
- Win Rate: 14.16%
- Profit Factor: 1.626
- Avg Trade Return: 8.99%

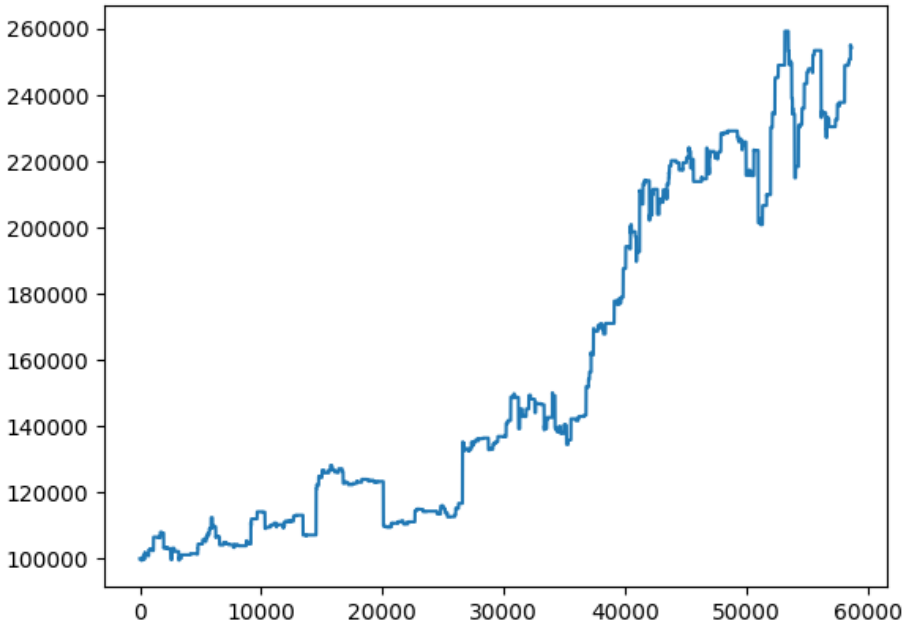
IDEAL NOTEBOOK RESULTS

- ROI: 133.73%
- Max Drawdown: 18.04%
- Sharpe Ratio: 0.00807
- Win Rate: 57.29%
- Trade Efficiency: 20.57%

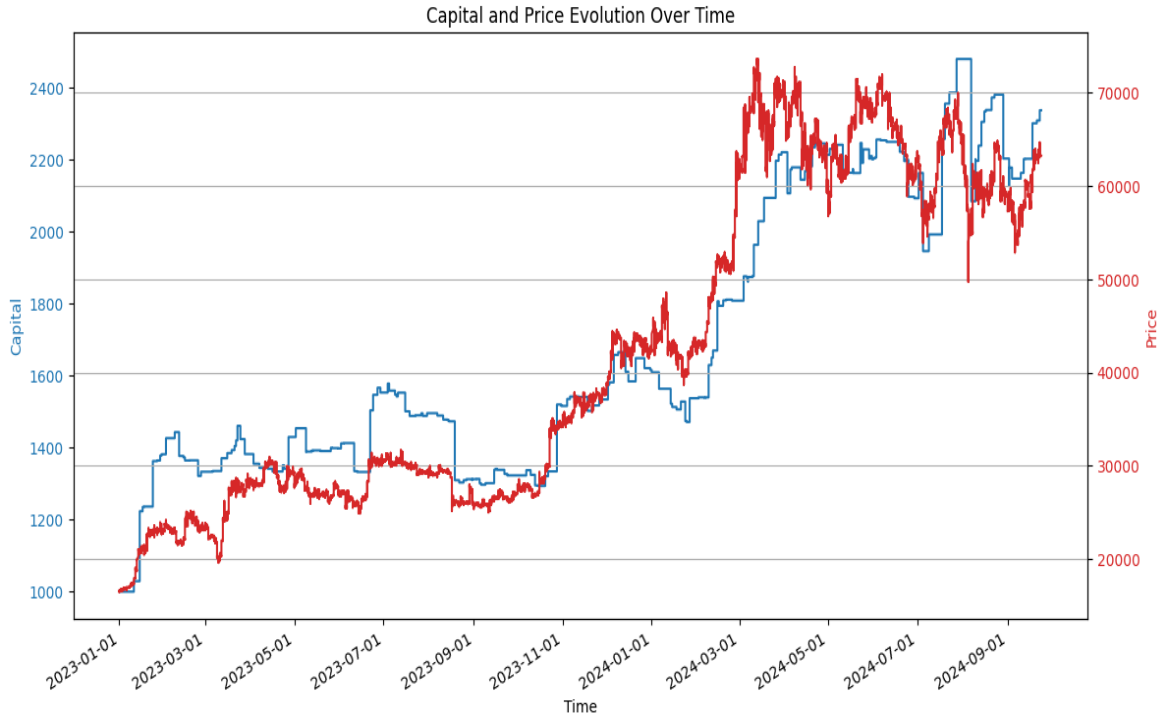
- Observations: Comparable ROI and drawdowns indicate **robustness.**
- The discrepancy in win rate may reflect execution differences (there are small trades opened due to the rounding).

RSI+ADX Strategy Performance Comparison

REAL-TIME MIMIC RESULTS



IDEAL NOTEBOOK RESULTS



MACD+ADX Strategy Performance Comparison

REAL-TIME MIMIC RESULTS

- ROI: 81.51%
- Max Drawdown: 26.20%
- Sharpe Ratio: 0.00564
- Win Rate: 17.26%
- Profit Factor: 1.391
- Avg Trade Return: 20.83%

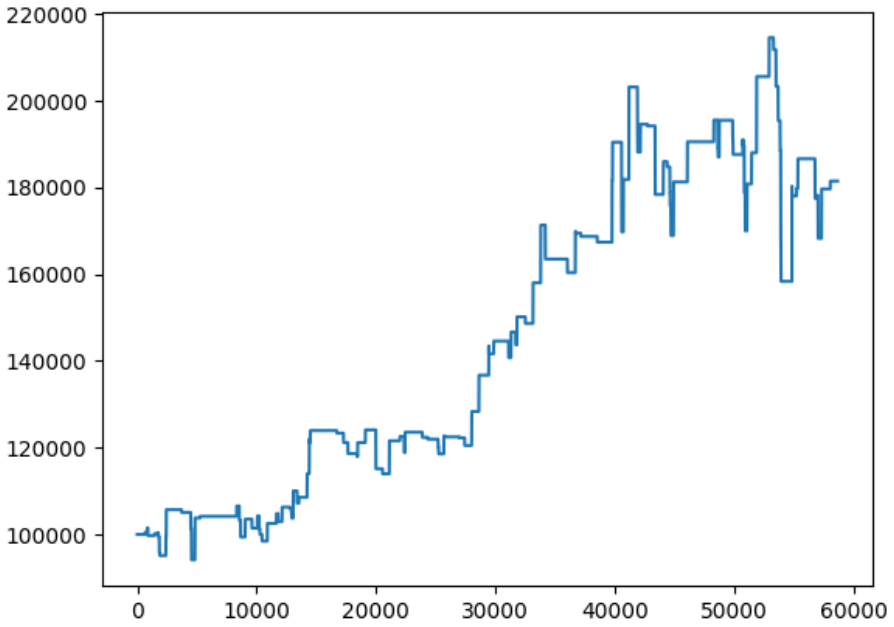
IDEAL NOTEBOOK RESULTS

- ROI: 142.00%
- Max Drawdown: 28.64%
- Sharpe Ratio: 0.00817
- Win Rate: 44.74%
- Trade Efficiency: 15.83%

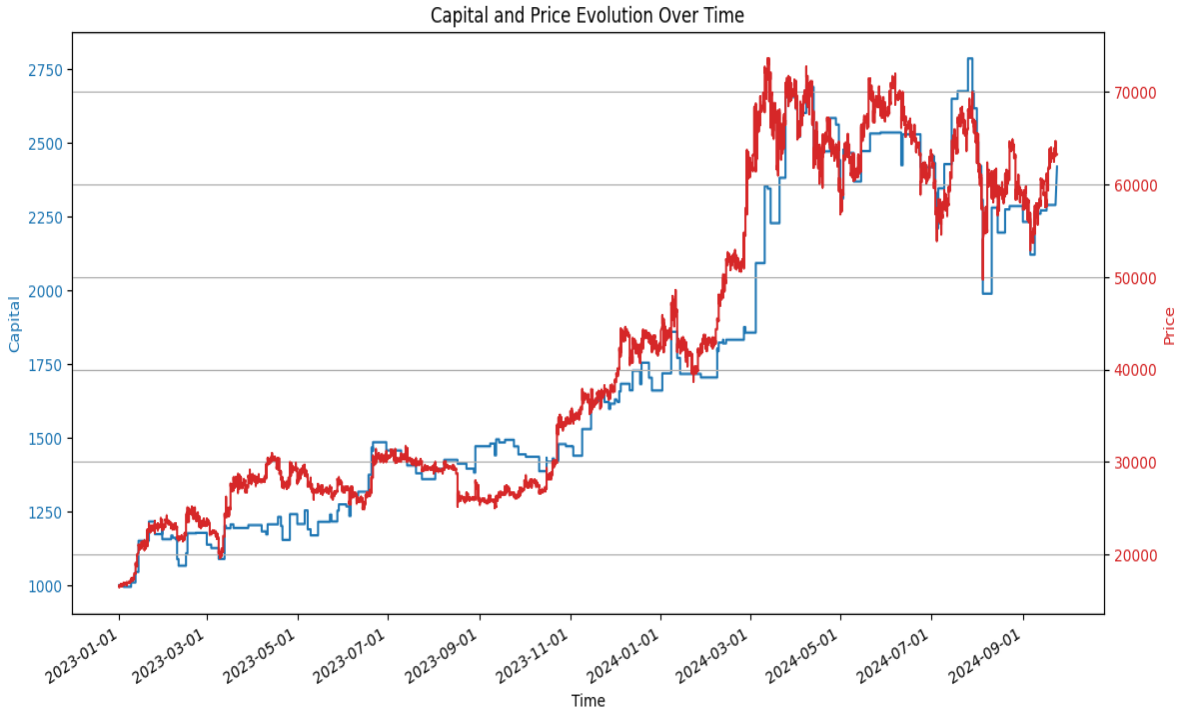
- Significant performance drop in real-time mimic.
- MACD+ADX appears more sensitive to incremental updates and rounding.

RSI+ADX Strategy Performance Comparison

REAL-TIME MIMIC RESULTS



IDEAL NOTEBOOK RESULTS



Comparative Analysis

RSI+ADX Strategy:

- Robust performance across environments.
- Slight differences in win rate; overall high ROI and low drawdown.

MACD+ADX Strategy:

- Strong in ideal tests, but affected by real-time constraints.
- Lower ROI and win rate in real-time simulation.

General Insights:

- Real-time mimic simulates practical constraints (window storage, incremental calculation, rounding).
- Highlights the need for strategy optimization under live conditions.

Conclusion & Future work

TO MIMIC THE REAL-TIME TRADING ENVIRONMENT

TESTING ROBUSTNESS OF STRATEGIES

Key Findings & Strategy Insights

RSI+ADX Strategy:

- Robust performance across both ideal and real-time environments.
- Consistent ROI with lower maximum drawdown.
- Better risk management and adaptability through dynamic thresholds.

MACD+ADX Strategy:

- Strong performance in ideal backtests.
- Sensitive to real-time constraints (incremental updates, rounding), leading to reduced ROI and win rate.

Dynamic RSI Models:

- Machine Learning (Random Forest) shows okay R^2 but does not work well on backtesting.
- Simpler statistical methods (median-based, dynamic zones, volatility-linked) often yield competitive or superior results.

Implications for Live Trading

Real-Time Adaptation:	Incremental calculation and limited window storage mimic live conditions. Rounding of trade amounts (3-digit precision) reduces execution noise.
Strategy Suitability:	RSI+ADX proves more robust and effective for live trading. MACD+ADX may need further optimization to overcome real-time execution challenges.

Limitations & Future Directions

Model Sensitivity:

- ML models are sensitive to small target scales; simpler methods may be more practical.
- MACD+ADX strategy's performance drops under real-time conditions.

Future Work:

- Refine hyperparameters and explore ensemble methods.
- Expand testing to multi-asset portfolios and varied market regimes.
- Integrate with live market data for further validation.

Final Conclusion

Dynamic RSI models that adapt to market volatility offer improved risk management.

RSI+ADX strategy emerges as a robust candidate for real-world trading.

Testing under realistic conditions is crucial to ensure strategies perform well live.

Future research will focus on optimizing strategies and mitigating real-time execution issues.

Future Works

Invent Customized Indicators:

- Develop bespoke indicators tailored to specific market regimes.
- Combine traditional technical indicators with novel measures (e.g., sentiment, liquidity, and order flow).

Enhance Machine Learning Models:

- Adapt ensemble methods (e.g., boosting, bagging) to predict dynamic RSI thresholds more robustly.
- Explore deep learning architectures (e.g., LSTM networks) for capturing temporal dependencies.

Future Works

Expand to Multi-Asset Portfolios:

- Extend dynamic RSI models to multi-asset or sector-based strategies.
- Incorporate cross-market correlations to optimize risk and diversification.

Integrate Alternative Data Sources:

- Include alternative data (news sentiment, social media signals, blockchain metrics) to refine indicator thresholds.
- Use real-time economic and financial data feeds to adapt strategies dynamically.

Future Works

Robust Risk Management

- Investigate adaptive stop-loss and take-profit mechanisms integrated with dynamic indicators.
- Develop risk-adjusted performance metrics that account for transaction costs and slippage.

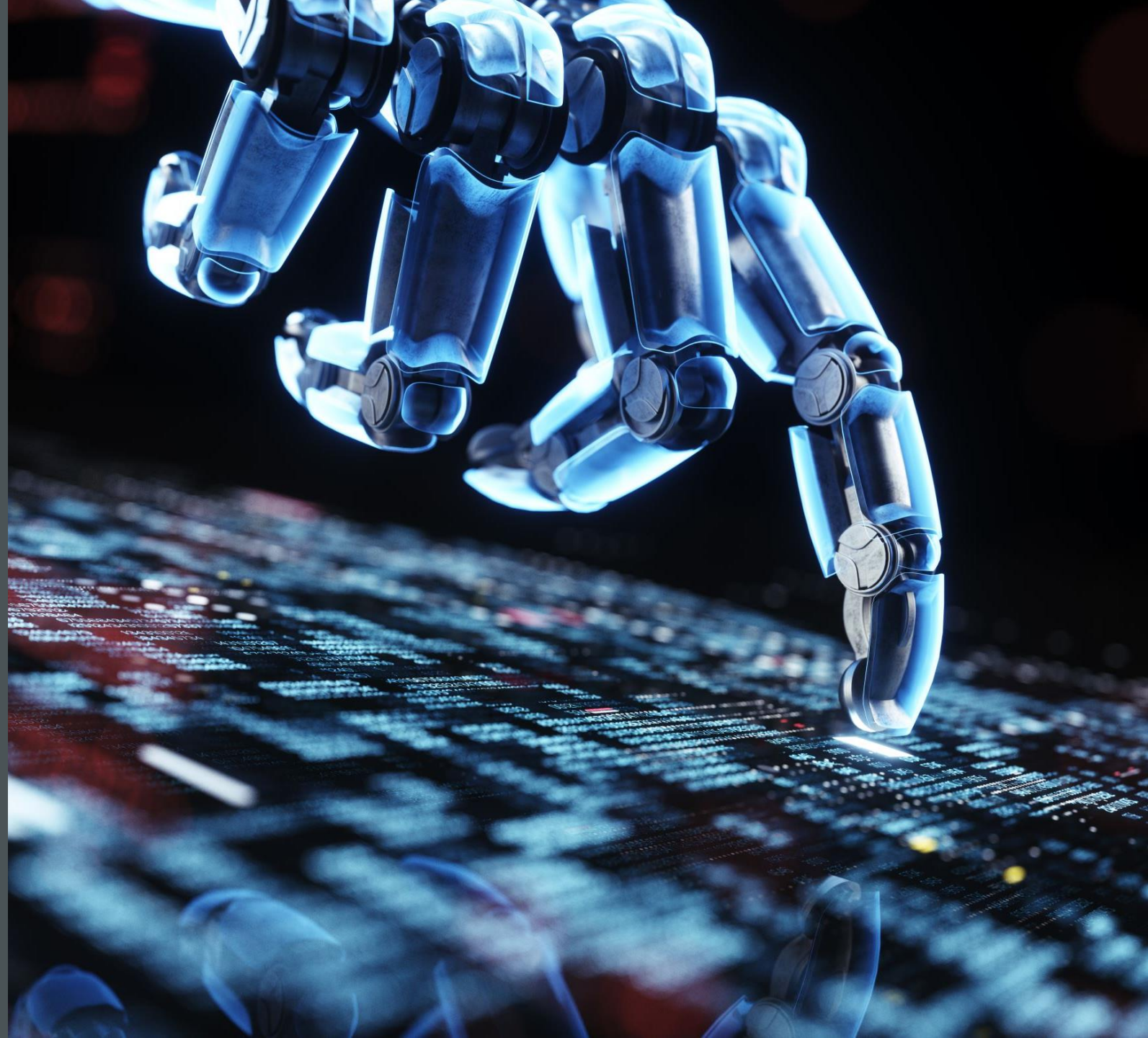
Backtesting & Simulation Enhancements

- Incorporate realistic transaction cost models and slippage.
- Implement simulation frameworks that allow for stress testing under extreme market conditions.

TRADE BOT REPORT

Zhaoyu Bai

2025 March



EXECTUTIVE SUMMARY

Introduction

- Addresses the opportunities and challenges of cryptocurrency trading, characterized by high volatility and rapid market changes.
- Highlights the limitations of manual trading, including the need for constant monitoring and high stress.
- Emphasizes the importance of a modular design for scalability and future upgrades.

Objective

- Develop a Python-based crypto trading bot that integrates with the Binance API.
- Incorporate key functionalities such as data handling, feature engineering, model development, signal processing, strategy and risk management, backtesting, and both live and mock trading.

EXECTUTIVE SUMMARY

Methodology & Implementation

- Leverages an event-driven architecture with real-time data flows for immediate market response.
- Uses a modular structure to simplify future expansions and allow easy modifications or replacements of individual components.
- Focuses on robust data processing, seamless integration of trading modules, and dynamic risk controls.

Results & Performance

- Demonstrated favorable performance metrics in backtesting, including ROI, drawdowns, and win rates.
- Validated the system's capability to manage risk effectively while executing trades in real time.

CONTENT

- Introduction
- Objectives
- Methodology & Implementation
- Results & Performance
- Future works

INTRODUCTION

- **Cryptocurrencies:** high volatility, rapid price movements, and continuous market development --- opportunities and challenges for short-term trading.
- **Manual Trading:** significant attention and constant market monitoring, workload and stress.
- **Scalability and Maintainability:** to handle future expansions, e.g. new trading strategies and upgrading existing components --- Modular design

OBJECTIVE

Develop a Python-based cryptocurrency trading bot integrating Binance API that does:

- ❑ **Data Handling**
- ❑ **Feature/Indicator Engineering**
- ❑ **Model Development**
- ❑ **Signal Processing**
- ❑ **Strategy Management**
- ❑ **Risk Management**
- ❑ **Backtesting**
- ❑ **Live and Mock Trading**
- ❑ **Logging and Reports**

The tradebot has been trough two major upgrade, the previous two does not integrate the Live and Mock trading functionality.

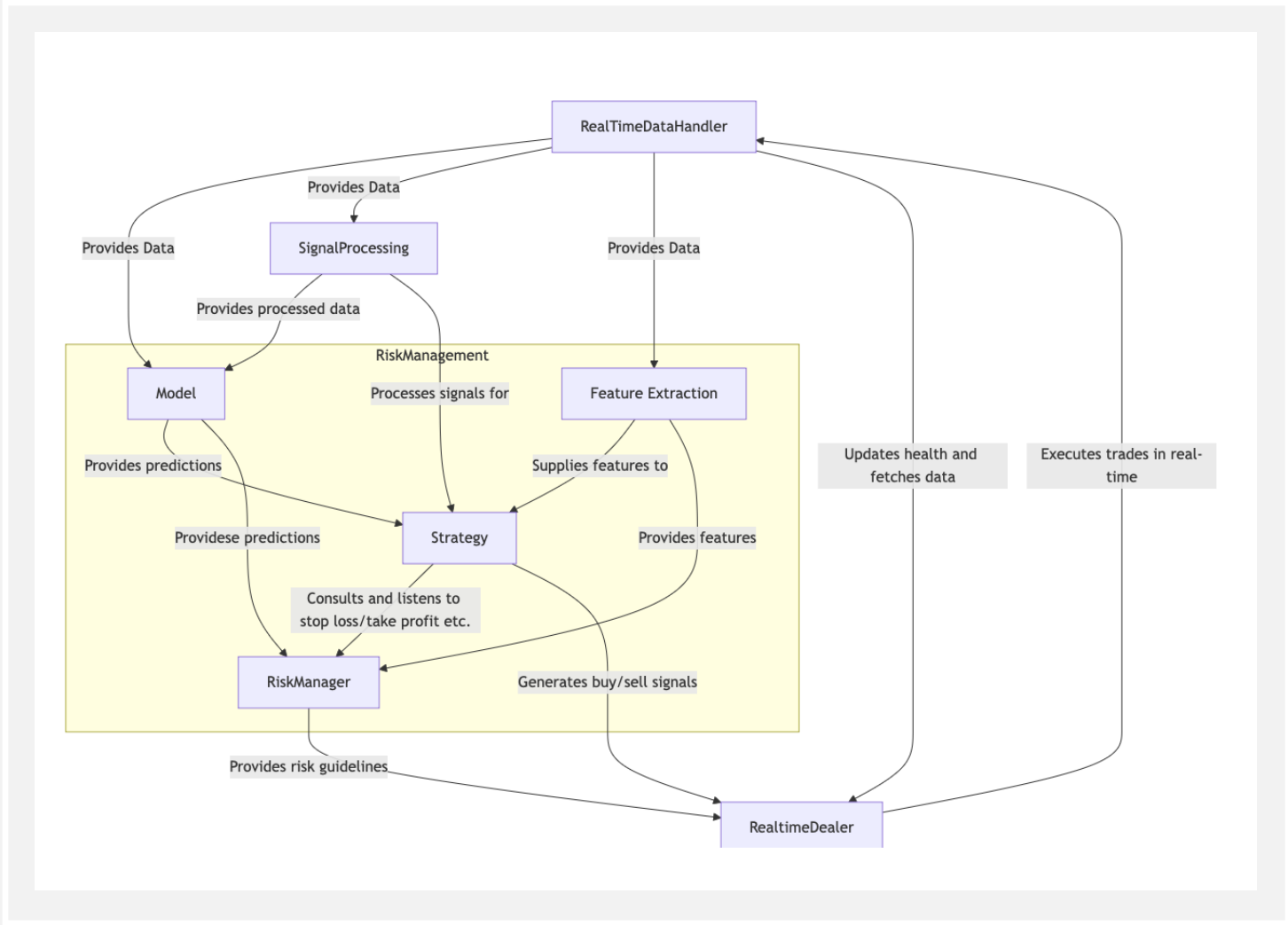
STRUCTURE OVERVIEW

Real-Time Data Flows

- Enables instant response to market changes
- Facilitates event-driven interactions across components

Modular Structure

- Increases scalability and flexibility
- Allows easy expansion, modification, or replacement of individual parts



METHODOLOGY & IMPLEMENTATION

DATA HANDLER

Data collection (historical/real-time), cleaning

METHODOLOGY: DATA HANDLER MODULE

- **Purpose & Objectives:**
  - Unified interface for managing, processing, and retrieving data (historical & real-time)
  - Designed for financial analysis and modeling
- **Core Principles:**
  - **Abstraction:**
    - Base class with common functionalities (e.g., configuration loading, URL construction, parameter management)
  - **Modularity:**
    - Separates core functionalities from specialized tasks in derived classes (HistoricalDataHandler, RealTimeDataHandler)
  - **Scalability & Flexibility:**
    - Adapts to various data sources and formats using dynamic configuration (JSON files)

METHODOLOGY: DATA HANDLER MODULE

- **Workflow Integration:**
  - **Configuration Management:**
    - Loads source URLs, endpoints, and parameters consistently
  - **Data Processing Pipeline:**
    - Standardized methods for data retrieval, error handling, and transformation
  - **Extensibility:**
    - Derived modules extend the base functionality for specific data types and operations

IMPLEMENTATION: DATA HANDLER MODULE

- **Core Components**
  - **Configuration Loader:**
    - Methods to load JSON configuration files for data sources, cleaning, and validation parameters
  - **URL Builder & Data Fetching:**
    - Constructs API endpoints and fetches data accordingly
  - **Utility Methods:**
    - Standardizes date formatting and file path generation for consistent data storage
- **Error Handling & Robustness**
  - Implements retry loops with delays for API request failures
  - Uses progress monitoring (via tqdm) for long-running data downloads

IMPLEMENTATION: DATA HANDLER MODULE

- **Extensions via Derived Classes**
  - **HistoricalDataHandler**
    - Loads pre-processed data from local files
    - Fetches data in chunks to manage API limits and memory usage
    - Integrates cleaning and rescaling routines (via DataCleaner and DataChecker)
  - **RealTimeDataHandler**
    - Streams live data feeds
    - Processes data in real time with rapid error handling and dynamic updates

FEATURE ENGINEERING

Technical/Customize Indicator calculation and selection

METHODOLOGY: FEATURE MODULE – EXTRACTION

- **Data Transformation:**
  - Convert raw input into a standardized format (e.g., Pandas DataFrame)
  - Clean, normalize, and structure data for uniform downstream processing
- **Modularity:**
  - Modular design allows extension with new extraction techniques
  - Encourages reusability and customization based on data type/requirements
- **Integration:**
  - Final output is a well-structured dataset for seamless integration with feature selection and modeling

METHODOLOGY: FEATURE MODULE – EXTRACTION

- **Technical Indicators:** Utilized the TA library for traditional indicators (e.g., moving averages, RSI, MACD)
- **Incremental Updates:** Developed an incremental update mechanism for technical indicators to efficiently process streaming or updated data
- **Custom Metrics:** Domain-specific features capturing unique patterns

METHODOLOGY: FEATURE MODULE – SELECTION

- **Evaluations:**
  - Assess relevance via statistical correlations
  - Use machine learning techniques
- **Dimensionality Reduction:**
  - Apply PCA or similar methods to reduce redundancy and feature space
- **Selection Criteria:**
  - Use variance thresholds and mutual information to decide which features to retain
- **Optimization:**
  - Produce a refined dataset focused on features with the highest predictive value
  - Reduce overfitting, lower computational cost, and enhance interpretability

IMPLEMENTATION: FEATURE MODULE

- **Modularity & Extensibility:**
  - Clear separation of extraction methods allows for easy extension
  - Users can add new feature computations without disrupting the existing pipeline
- **Pipeline Integration:**
  - Extracted features are formatted to integrate smoothly with subsequent modules

IMPLEMENTATION: FEATURE MODULE – EXTRACTOR

- **Pre-processing:**
  - Cleaning and normalization methods
- **Computation Routines:**
  - Functions for calculating statistical measures, technical indicators (leveraging the TA library), and custom metrics
- **Incremental Update:**
  - Implements incremental updates for traditional technical indicators to handle data updates efficiently
- **Structured Output:**
  - Organize computed features into a DataFrame for further use

IMPLEMENTATION (FUTURE FOCUS): FEATURE MODULE – SELECTION

- **Evaluation Methods:**
  - Compute statistical metrics and apply machine learning techniques for feature importance
- **Dimensionality Reduction Tools:**
  - Implement algorithms (e.g., PCA) to retain essential information (ongoing)
- **Selection Algorithms:**
  - Filter out less relevant features using dynamic or predefined thresholds
- **Output Optimization:**
  - Produces a dataset containing only the most informative features for improved modeling performance

MODEL DEVELOPMENT

Forcasting Model design and training

METHODOLOGY: MODEL MODULE

- **Unified Modeling Framework:**
  - Base Model provides common methods (train, predict, evaluate)
  - Specialized models to be developed for:
    - **Machine Learning:** Neural networks, decision trees, ensembles
    - **Physics:** Simulation-based, analytical models from physics inspiration
    - **Statistical:** Regression, time series, hypothesis testing
- **Model Trainer:**
  - Centralized module for model training, evaluation, and integration

IMPLEMENTATION (FUTURE FOCUS): MODEL MODULE

- **Current State:**
  - Machine learning/physics/statistical Modules are empty and serve as scaffolding
- **Planned Features:**
  - Define common interfaces and shared methods in base_model.py
  - Extend specialized models from the base model
  - Implement model trainer to manage training loops and evaluation metrics
  - Parameter management, scalability, and extensibility as key design principles

SIGNAL PROCESSING

Applications in time-series analysis, noise reduction

METHODOLOGY: SIGNAL PROCESSING MODULE

- **Design Principles:**
  - **Modularity:**
    - Separate modules for filtering, processing, and transformation
  - **Scalability & Flexibility:**
    - Designed to handle a wide range of signals and data formats
  - **Integration:**
    - Seamless pipeline from filtering through to feature extraction, and predictive models

METHODOLOGY: SIGNAL PROCESSING MODULE

Core Components:

- **Signal Processor (signal_processor.py):**
  - Coordinates the application of filters and transformations
  - Manages tasks like segmentation, normalization, and sequential processing
- **Filters (filters.py):**
  - Remove noise and unwanted frequency components
  - Implements various filtering techniques (low-pass, high-pass, band-pass)
- **Transformation (transform.py):**
  - Converts signals from the time domain to the frequency domain
  - Implements techniques such as Fourier and Wavelet Transforms for frequency analysis

IMPLEMENTATION: SIGNAL PROCESSING MODULE

- **Signal Processor Module (signal_processor.py):**
  - Supports processing of both batch and streaming data
- **Filters Module (filters.py):**
  - Designs filters with configurable parameters (e.g., cutoff frequencies, order)
  - Dynamic configurability allows easy tuning for different signal types
- **Transformation Module (transform.py):**
  - Provides functions for converting signals from time to frequency domain (e.g., FFT, Wavelet)
  - Enables feature extraction from transformed signals

RISK MANAGEMENT

To Mitigate risk and protect capital at both single asset and portfolio levels

METHODOLOGY: RISK MANAGEMENT MODULE

- **Single Asset Risk Management (single_risk.py):**
  - Sets stop-loss and take-profit levels based on volatility and risk/reward ratios.
  - Adjusts position sizes to limit risk per trade.
  - Supports incremental risk updates with evolving market data.
- **Central Risk Manager (risk_manager.py):**
  - Aggregates risk metrics across different strategies.
  - Provides a unified interface for monitoring and adjusting risk parameters.

METHODOLOGY: RISK MANAGEMENT MODULE

- **Portfolio Risk Management (portfolio_manager.py):**
  - Manages risk across multiple assets using diversification and rebalancing.
  - Monitors overall portfolio exposure and correlations.
- **Capital Allocation (capital_allocator.py):**
  - Allocates capital based on risk-adjusted returns.
  - Dynamically adjusts allocations in response to market conditions.
- **Design Considerations:**
  - Systematic and quantitative risk controls (e.g., using ATR for thresholds).
  - Customization via JSON configuration files for risk parameters.
  - Seamless integration with trading strategies and real-time data updates.

IMPLEMENTATION: RISK MANAGEMENT MODULE

- **Single Asset Risk Management:**
  - Implements functions for calculating stop-loss/take-profit levels.
  - Adjusts position sizes using predefined risk metrics.
  - Updates risk measures incrementally as new data arrives.
- **Central Risk Manager:**
  - Consolidates individual risk metrics.
  - Provides utilities for enforcing risk limits and making adjustments.
  - Incorporates logging and error-handling for robust risk monitoring.

IMPLEMENTATION (FUTURE FOCUS): RISK MANAGEMENT MODULE

- **Portfolio Risk Management:**
  - Evaluates asset correlations and implements diversification strategies.
  - Monitors overall portfolio exposure and triggers rebalancing when needed.
- **Capital Allocation:**
  - Uses risk-adjusted metrics to distribute capital among assets.
  - Dynamically modifies allocations based on real-time risk and market changes.
  - Integrates with central and portfolio risk managers for comprehensive control.

STRATEGY MODULE

Realization of trading strategy

METHODOLOGY: STRATEGY MODULE

- **Single Asset Strategy:**
  - Focus on one asset using technical analysis and tailored risk management
  - Use chosen model to forecast and make buy and sell signals.
- **Multi Asset Strategy:**
  - Aggregates signals from multiple assets for portfolio-level trading
  - Uses portfolio optimization, diversification, and dynamic rebalancing

METHODOLOGY: STRATEGY MODULE

Customization via JSON Files:

- Strategies can be customized using JSON configuration files (e.g., strategy.json)
- Example configuration includes parameters for:
  - **Model:** e.g., Base_RSIwADX_type0 with custom indicator thresholds and parameters
  - **Risk Manager:** Stop-loss, take-profit, and position sizing parameters
  - **Decision Maker:** Decision rules such as threshold levels
- Enables flexible, user-defined strategy adjustments for different assets

IMPLEMENTATION: STRATEGY MODULE

- **Single Asset Strategy (single_asset_strategy.py):**
  - Implements technical indicators and signal generation for one asset
  - Integrates risk management (stop-loss, take-profit) specific to single asset dynamics
  - Applies incremental updates to process evolving market data efficiently
- **Multi Asset Strategy (multi_asset_strategy.py):**
  - Aggregates signals from individual asset strategies
  - Performs portfolio-level analysis for optimal capital allocation
  - Dynamically rebalances the portfolio based on market conditions

IMPLEMENTATION: STRATEGY MODULE

- **Customization & Integration:**
  - Loads and applies strategy configurations from JSON files
  - Allows user-defined customization for models, risk management, and decision-making parameters
  - Seamlessly integrates with data handling and execution systems for live trading
- **Additional Considerations:**
  - Systematic signal generation through predefined rules and algorithms
  - Emphasis on modularity, enabling rapid iteration and testing of strategy rules

BACKTESTING MODULE

To Simulate historical trading performance to evaluate strategies/models

METHODOLOGY: BACKTESTING MODULE

- **Backtester (backtester.py):**
  - Simulates trade execution and virtual order management
  - Tracks performance metrics like cumulative returns and drawdowns
- **Model Evaluation (model_evaluation.py):**
  - Computes performance metrics (accuracy, ROI, Sharpe ratio)
  - Compares predictive power of different models
- **Strategy Evaluation (strategy_evaluation.py):**
  - Aggregates trade and model performance to assess overall strategy effectiveness
  - Supports optimization and parameter tuning

METHODOLOGY: BACKTESTING MODULE

- **Design Principles:**
  - Systematic simulation to mirror live market conditions
  - Modularity for independent development and testing of components
- **Customization via JSON Files:**
  - *strategy.json* for multi-asset strategies: Configures model methods, risk manager parameters, and decision rules (e.g., Base_MACD_type0)
  - *single_strategy.json* for single-asset strategies: Defines specific parameters like start date, interval, and indicator thresholds (e.g., Base_RSIwADX_type0)
- **Data Handling Customization:**
  - *data_h.json* sets data ingestion parameters such as file type, symbols, retry count, memory and log settings, and required data labels

IMPLEMENTATION: BACKTESTING MODULE

- **Workflow Integration:**
  - Use python notebook for quick analysis
  - Sequential processing: Data ingestion → Trade simulation → Model & Strategy evaluation
  - Customization via JSON files allows flexible configuration of models, risk management, and data parameters
- **Backtester:**
  - Loads and processes historical market data
  - Executes simulated trades based on generated signals
  - Records detailed performance statistics

IMPLEMENTATION: BACKTESTING MODULE

- **Model Evaluation:**
  - Calculates performance metrics to compare various predictive models
  - Provides statistical analysis for model validation
- **Strategy Evaluation:**
  - Aggregates trade-level and model-level results to gauge overall strategy effectiveness
  - Supports tuning of strategy parameters based on backtest outcomes

LIVE/MOCK TRADING MODULE

Execution of orders, tracking of accounts in real time

METHODOLOGY: REAL/MOCK TRADING MODULE

- **Key Concepts:**
  - **Unified Trading Engine:**
    - Shared core for order generation, risk controls, and connectivity
  - **Real-Time Trading:**
    - Executes live trades via Binance API
  - **Mock Trading:**
    - Simulates orders, account balance, and order status
    - Mimics Binance behavior for realistic testing
- **Customization:**
  - Configurable via JSON files (e.g., API keys, account settings, order parameters)

IMPLEMENTATION: REAL/MOCK TRADING MODULE

- **Real-Time Dealer:**
  - Connects directly to Binance for live market data and order execution
  - Implements order submission, modification, and cancellation
- **Mock Trading Modules:**
  - **Mock Real-Time Dealer:**
    - Simulates live trading by generating mock order responses
  - **Mock Order Manager:**
    - Manages simulated orders and virtual account details

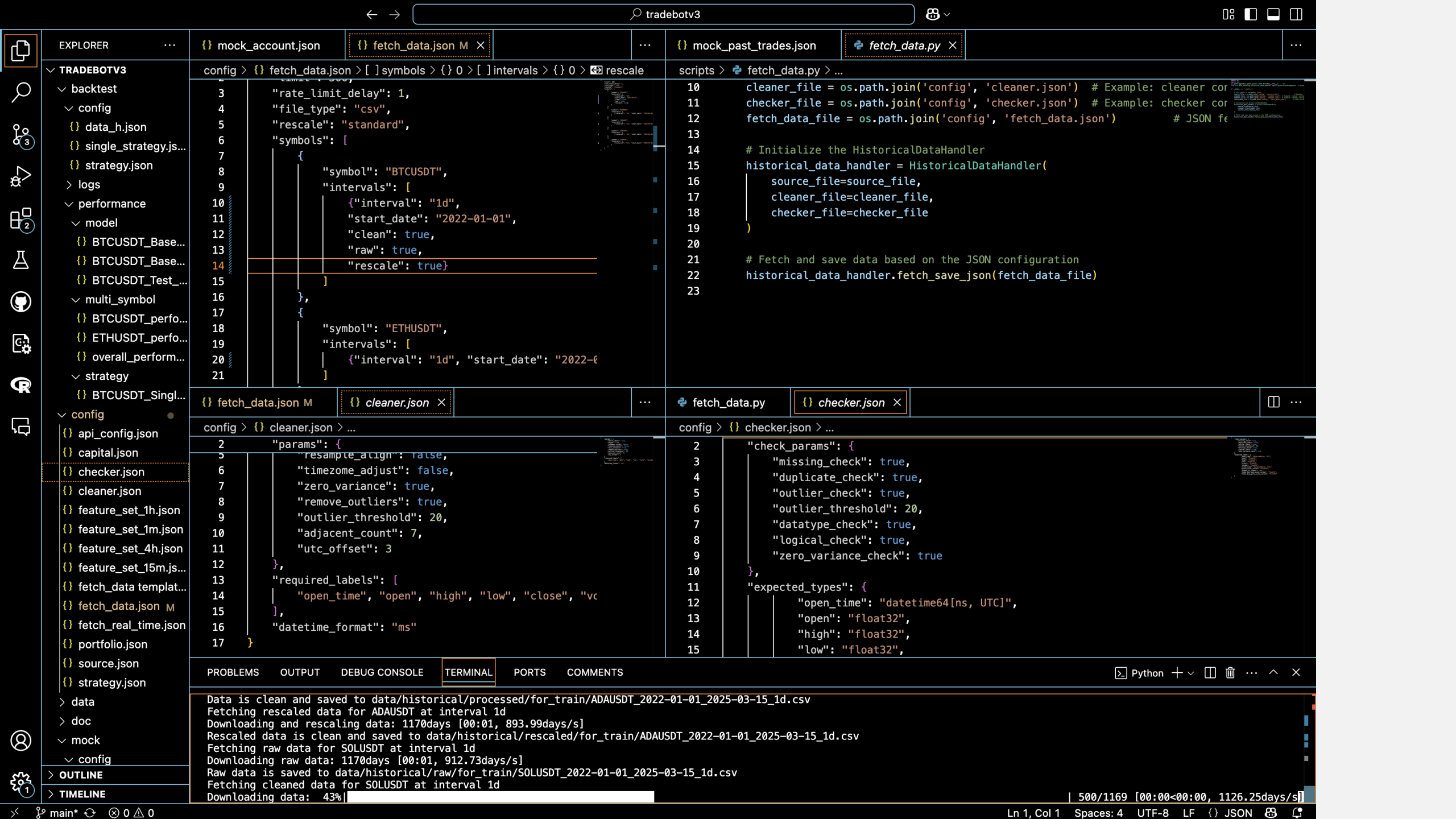
IMPLEMENTATION: REAL/MOCK TRADING MODULE

- **Common Features:**
  - Integrated risk management (stop-loss, take-profit, position sizing)
  - Logging, error-handling, and consistent API compatibility with Binance
- **Configuration & Flexibility:**
  - JSON-based settings allow easy switching and parameter tuning between real and mock environments

RESULTS & PERFORMANCE

Code Snippets and performance demonstration

DATA RETRIVAL & CLEANING


tradebotv3
EXPLORER
TRADEBOTV3
backtest
config
data_h.json
single_strategy.js...
strategy.json
logs
performance
model
BTCUSDT_Base...
BTCUSDT_Base...
BTCUSDT_Test_...
multi_symbol
BTCUSDT_perfo...
ETHUSDT_perfo...
overall_perform...
strategy
BTCUSDT_Singl...
config
api_config.json
capital.json
checker.json
cleaner.json
feature_set_1h.json
feature_set_1m.json
feature_set_4h.json
feature_set_15m.js...
fetch_data templat...
fetch_data.json M
fetch_real_time.json
portfolio.json
source.json
strategy.json
data
doc
mock
config
OUTLINE
TIMELINE
mock_account.json
fetch_data.json M
config > {} fetch_data.json > [ ] symbols > {} 0 > [ ] intervals > {} 0 > rescale
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"file_type": "csv",
"rescale": "standard",
"symbols": [
"symbol": "BTCUSDT",
"intervals": [
{"interval": "1d",
"start_date": "2022-01-01",
"clean": true,
"raw": true,
"rescale": true}
"symbol": "ETHUSDT",
"intervals": [
{"interval": "1d", "start_date": "2022-
mock_past_trades.json
fetch_data.py
scripts > fetch_data.py > ...
cleaner_file = os.path.join('config', 'cleaner.json') # Example: cleaner cor
checker_file = os.path.join('config', 'checker.json') # Example: checker cor
fetch_data_file = os.path.join('config', 'fetch_data.json') # JSON fe
# Initialize the HistoricalDataHandler
historical_data_handler = HistoricalDataHandler(
source_file=source_file,
cleaner_file=cleaner_file,
checker_file=checker_file
)
# Fetch and save data based on the JSON configuration
historical_data_handler.fetch_save_json(fetch_data_file)
fetch_data.json M
cleaner.json
config > {} cleaner.json > ...
"params": {
"timezome_adjust": false,
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"remove_outliers": true,
"outlier_threshold": 20,
"adjacent_count": 7,
"utc_offset": 3
"required_labels": [
"open_time", "open", "high", "low", "close", "vc
"datetime_format": "ms"
fetch_data.py
checker.json
config > {} checker.json > ...
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"duplicate_check": true,
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"logical_check": true,
"zero_variance_check": true
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"open": "float32",
"high": "float32",
"low": "float32",
PROBLEMS
OUTPUT
DEBUG CONSOLE
TERMINAL
PORTS
COMMENTS
Python
Data is clean and saved to data/historical/processed/for_train/ADAUSDT_2022-01-01_2025-03-15_1d.csv
Fetching rescaled data for ADAUSDT at interval 1d
Downloading and rescaling data: 1170days [00:01, 893.99days/s]
Rescaled data is clean and saved to data/historical/rescaled/for_train/ADAUSDT_2022-01-01_2025-03-15_1d.csv
Fetching raw data for SOLUSDT at interval 1d
Downloading raw data: 1170days [00:01, 912.73days/s]
Raw data is saved to data/historical/raw/for_train/SOLUSDT_2022-01-01_2025-03-15_1d.csv
Fetching cleaned data for SOLUSDT at interval 1d
Downloading data: 43%| | 500/1169 [00:00<00:00, 1126.25days/s]
main*
0 0
Ln 1, Col 1
Spaces: 4
UTF-8
LF
JSON


tradebotv3
EXPLORER
_account.json
{} fetch_data.json M
BTCUSDT_2022-01-01_2025-03-04_4h.csv
SOLUSDT_2022-01-01_2025-03-15_1d.csv
data > historical > processed > for_train > BTCUSDT_2022-01-01_2025-03-04_4h.csv > data
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17 2022-01-03 12:00:00+00:00,47378.0,47570.0,46575.25,46693.45,5463.72
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data > historical > processed > for_train > SOLUSDT_2022-01-01_2025-03-15_1d.csv > data
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{} fetch_data.json M
ETHUSDT_2022-01-01_2025-03-15_1d.csv
data > historical > raw > for_train > ETHUSDT_2022-01-01_2025-03-15_1d.csv > data
1 open_time,open,high,low,close,volume,close_time,quote_asset_volume,number_of_trades,taker_buy_base_asset_volume,taker_buy_quote_asset_volume,ignore
2 2022-01-01 00:00:00+00:00,3676.22000000,3776.45000000,3673.46000000,3765.54000000,154143.89680000,2022-01-01 23:59:59.999000+00:00,574718328.45274400,
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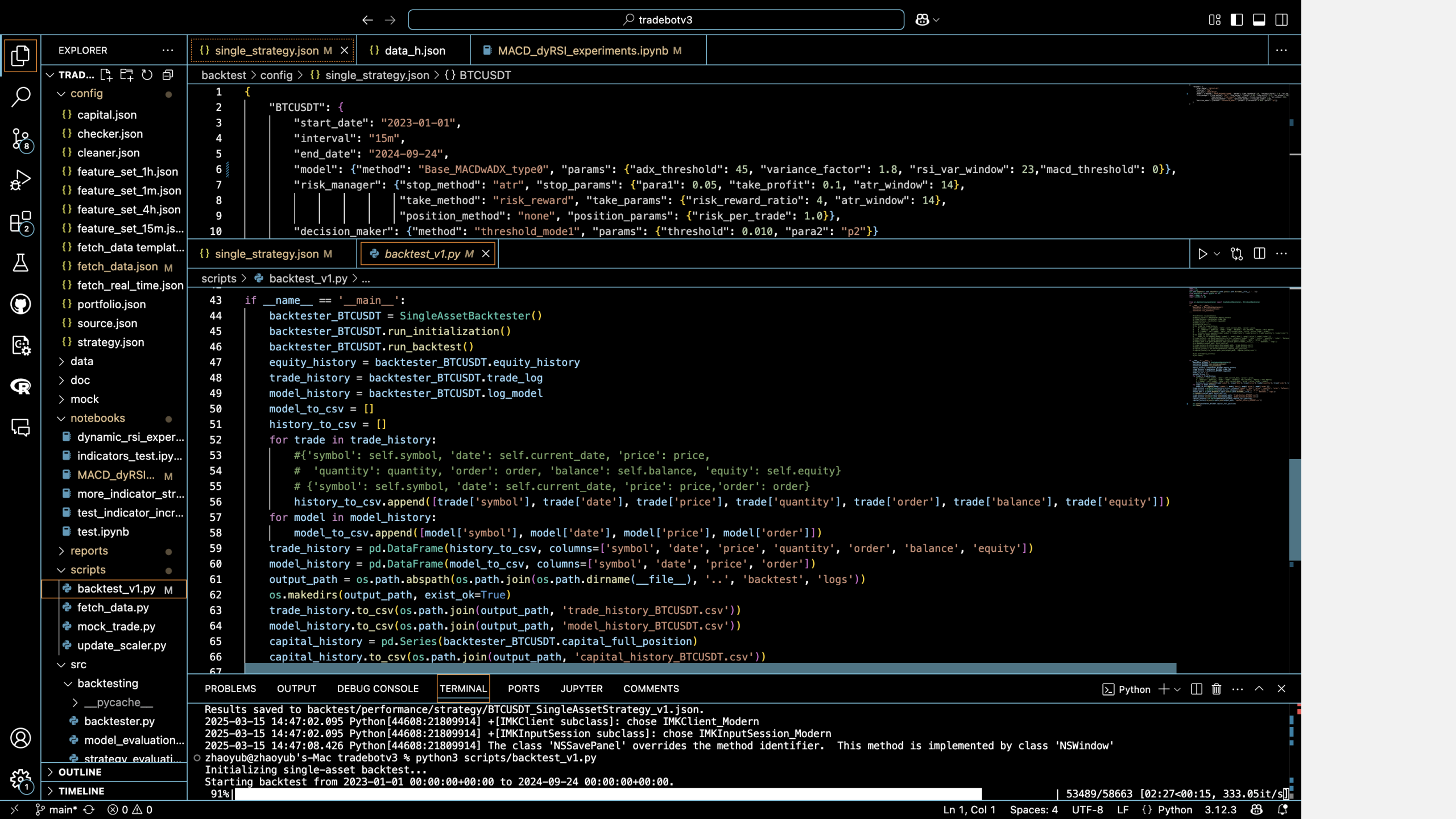
EXPLORER
TRAD...
data
historical
processed
for_train
SOLUSDT_202...
XTZUSDT_202...
from_real
raw
for_train
ADAUSDT_202...
BTCUSDT_202...
ETHUSDT_202...
SOLUSDT_202...
OUTLINE
TIMELINE
PROBLEMS
OUTPUT
DEBUG CONSOLE
TERMINAL
PORTS
COMMENTS
zsh
Fetching rescaled data for XTZUSDT at interval 1d
Downloading and rescaling data: 1170days [00:01, 901.50days/s]
Rescaled data is clean and saved to data/historical/rescaled/for_train/XTZUSDT_2022-01-01_2025-03-15_1d.csv
zhaoyub@zhaoyub's-Mac tradebotv3 %
main*
CSVLint
Query
Align
Col 1: open_time
Ln 1, Col 1
Spaces: 4
UTF-8
LF
CSV

BACKTESTING


tradebotv3
EXPLORER
single_strategy.json M
data_h.json
MACD_dyRSI_experiments.ipynb M
backtest > config > single_strategy.json > BTCUSDT
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"model": {"method": "Base_MACDwADX_type0", "params": {"adx_threshold": 45, "variance_factor": 1.8, "rsi_var_window": 23,"macd_threshold": 0}},
"risk_manager": {"stop_method": "atr", "stop_params": {"para1": 0.05, "take_profit": 0.1, "atr_window": 14},
"take_method": "risk_reward", "take_params": {"risk_reward_ratio": 4, "atr_window": 14},
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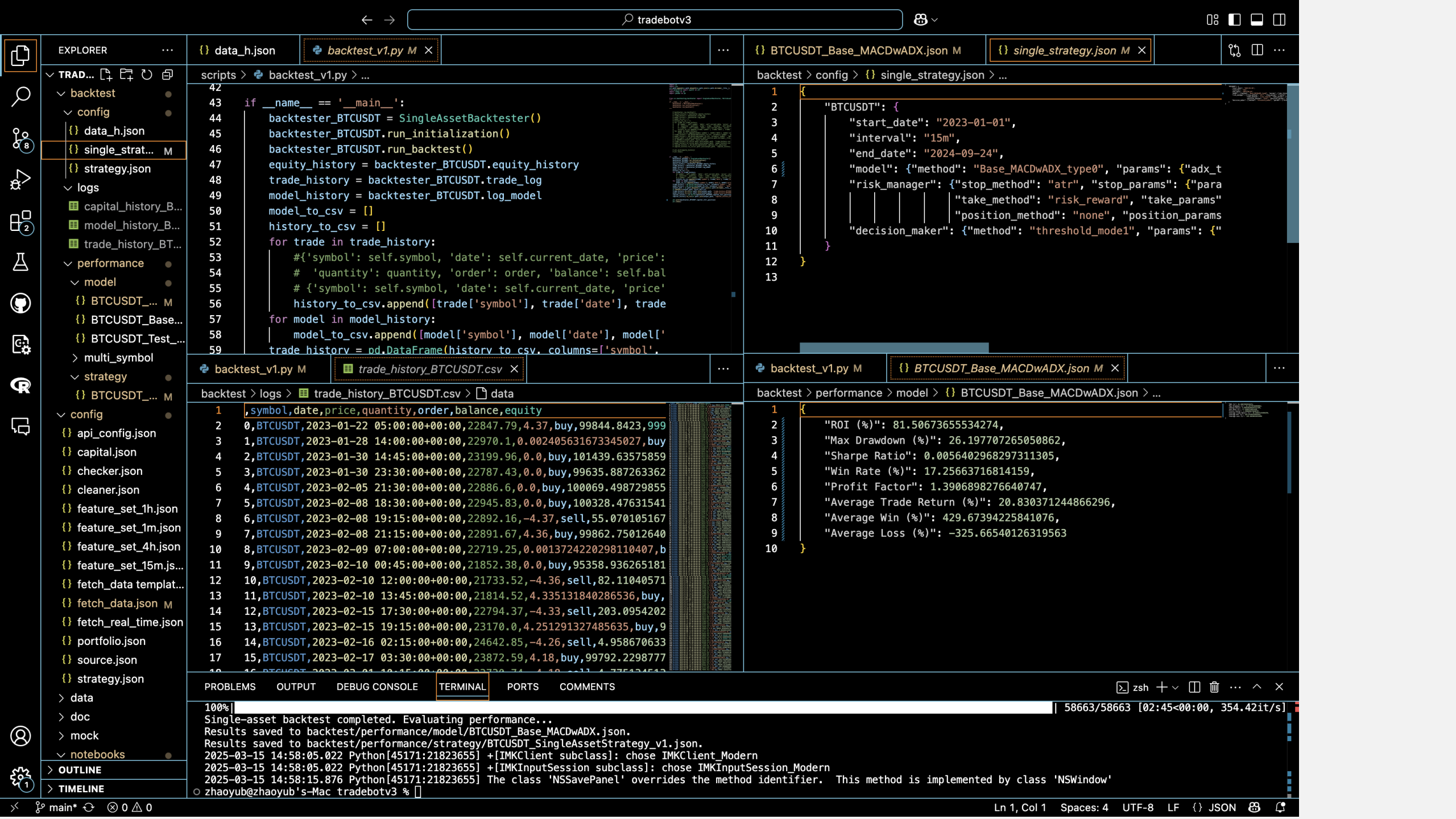
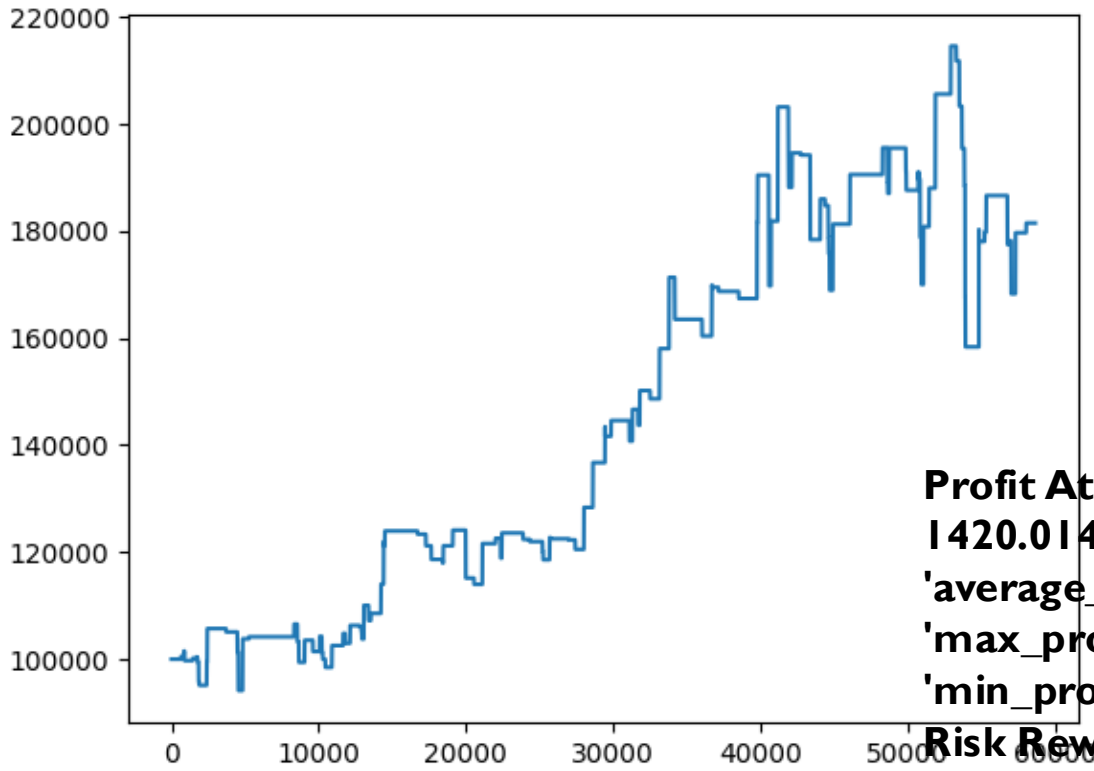
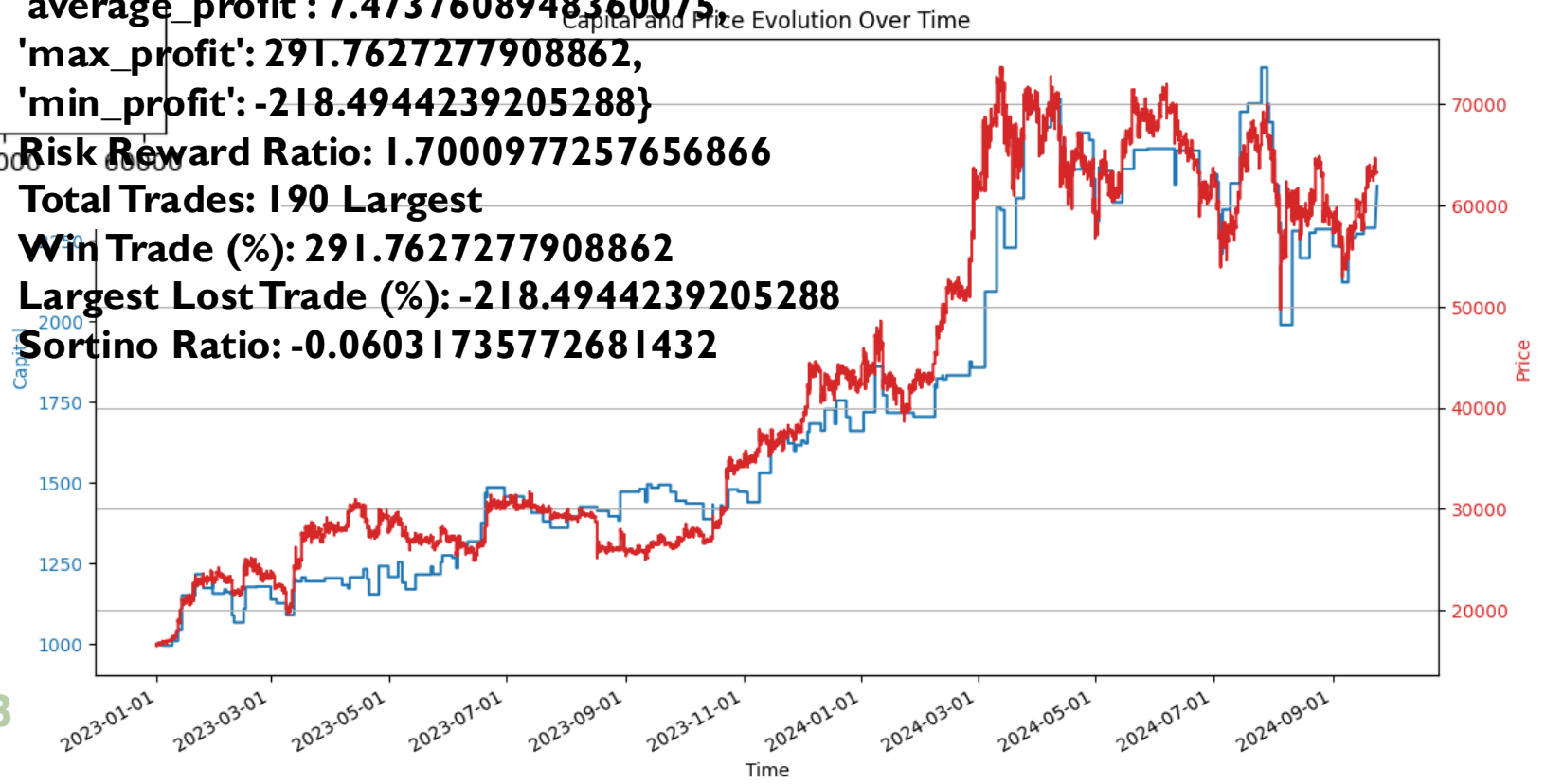
"decision_maker": {"method": "threshold_mode1", "params": {"threshold": 0.010, "para2": "p2"}}
single_strategy.json M
backtest_v1.py M
scripts > backtest_v1.py > ...
if __name__ == '__main__':
backtester_BTCUSDT = SingleAssetBacktester()
backtester_BTCUSDT.run_initialization()
backtester_BTCUSDT.run_backtest()
equity_history = backtester_BTCUSDT.equity_history
trade_history = backtester_BTCUSDT.trade_log
model_history = backtester_BTCUSDT.log_model
model_to_csv = []
history_to_csv = []
for trade in trade_history:
#{'symbol': self.symbol, 'date': self.current_date, 'price': price,
# 'quantity': quantity, 'order': order, 'balance': self.balance, 'equity': self.equity}
# {'symbol': self.symbol, 'date': self.current_date, 'price': price,'order': order}
history_to_csv.append([trade['symbol'], trade['date'], trade['price'], trade['quantity'], trade['order'], trade['balance'], trade['equity']])
for model in model_history:
model_to_csv.append([model['symbol'], model['date'], model['price'], model['order']])
trade_history = pd.DataFrame(history_to_csv, columns=['symbol', 'date', 'price', 'quantity', 'order', 'balance', 'equity'])
model_history = pd.DataFrame(model_to_csv, columns=['symbol', 'date', 'price', 'order'])
output_path = os.path.abspath(os.path.join(os.path.dirname(__file__), '..', 'backtest', 'logs'))
os.makedirs(output_path, exist_ok=True)
trade_history.to_csv(os.path.join(output_path, 'trade_history_BTCUSDT.csv'))
model_history.to_csv(os.path.join(output_path, 'model_history_BTCUSDT.csv'))
capital_history = pd.Series(backtester_BTCUSDT.capital_full_position)
capital_history.to_csv(os.path.join(output_path, 'capital_history_BTCUSDT.csv'))
PROBLEMS
OUTPUT
DEBUG CONSOLE
TERMINAL
PORTS
JUPYTER
COMMENTS
Python
Results saved to backtest/performance/strategy/BTCUSDT_SingleAssetStrategy_v1.json.
2025-03-15 14:47:02.095 Python[44608:21809914] +[IMKClient subclass]: chose IMKClient_Modern
2025-03-15 14:47:02.095 Python[44608:21809914] +[IMKInputSession subclass]: chose IMKInputSession_Modern
2025-03-15 14:47:08.426 Python[44608:21809914] The class 'NSSavePanel' overrides the method identifier. This method is implemented by class 'NSWindow'
zhaoyub@zhaoyub's-Mac tradebotv3 % python3 scripts/backtest_v1.py
Initializing single-asset backtest...
Starting backtest from 2023-01-01 00:00:00+00:00 to 2024-09-24 00:00:00+00:00.
91%| | 53489/58663 [02:27<00:15, 333.05it/s]
main*
Ln 1, Col 1
Spaces: 4
UTF-8
LF
Python
3.12.3


tradebotv3
EXPLORER
data_h.json
backtest_v1.py M
BTCUSDT_Base_MACDwADX.json M
single_strategy.json M
scripts > backtest_v1.py > ...
backtest > config > single_strategy.json > ...
backtest_v1.py M
trade_history_BTCUSDT.csv
backtest > logs > trade_history_BTCUSDT.csv > data
backtest_v1.py M
BTCUSDT_Base_MACDwADX.json M
backtest > performance > model > BTCUSDT_Base_MACDwADX.json > ...
PROBLEMS
OUTPUT
DEBUG CONSOLE
TERMINAL
PORTS
COMMENTS
zsh
100%| | 58663/58663 [02:45<00:00, 354.42it/s]
Single-asset backtest completed. Evaluating performance...
Results saved to backtest/performance/model/BTCUSDT_Base_MACDwADX.json.
Results saved to backtest/performance/strategy/BTCUSDT_SingleAssetStrategy_v1.json.
2025-03-15 14:58:05.022 Python[45171:21823655] +[IMKClient subclass]: chose IMKClient_Modern
2025-03-15 14:58:05.022 Python[45171:21823655] +[IMKInputSession subclass]: chose IMKInputSession_Modern
2025-03-15 14:58:15.876 Python[45171:21823655] The class 'NSSavePanel' overrides the method identifier. This method is implemented by class 'NSWindow'
zhaoyub@zhaoyub's-Mac tradebotv3 %
main*
Ln 1, Col 1
Spaces: 4
UTF-8
LF
JSON



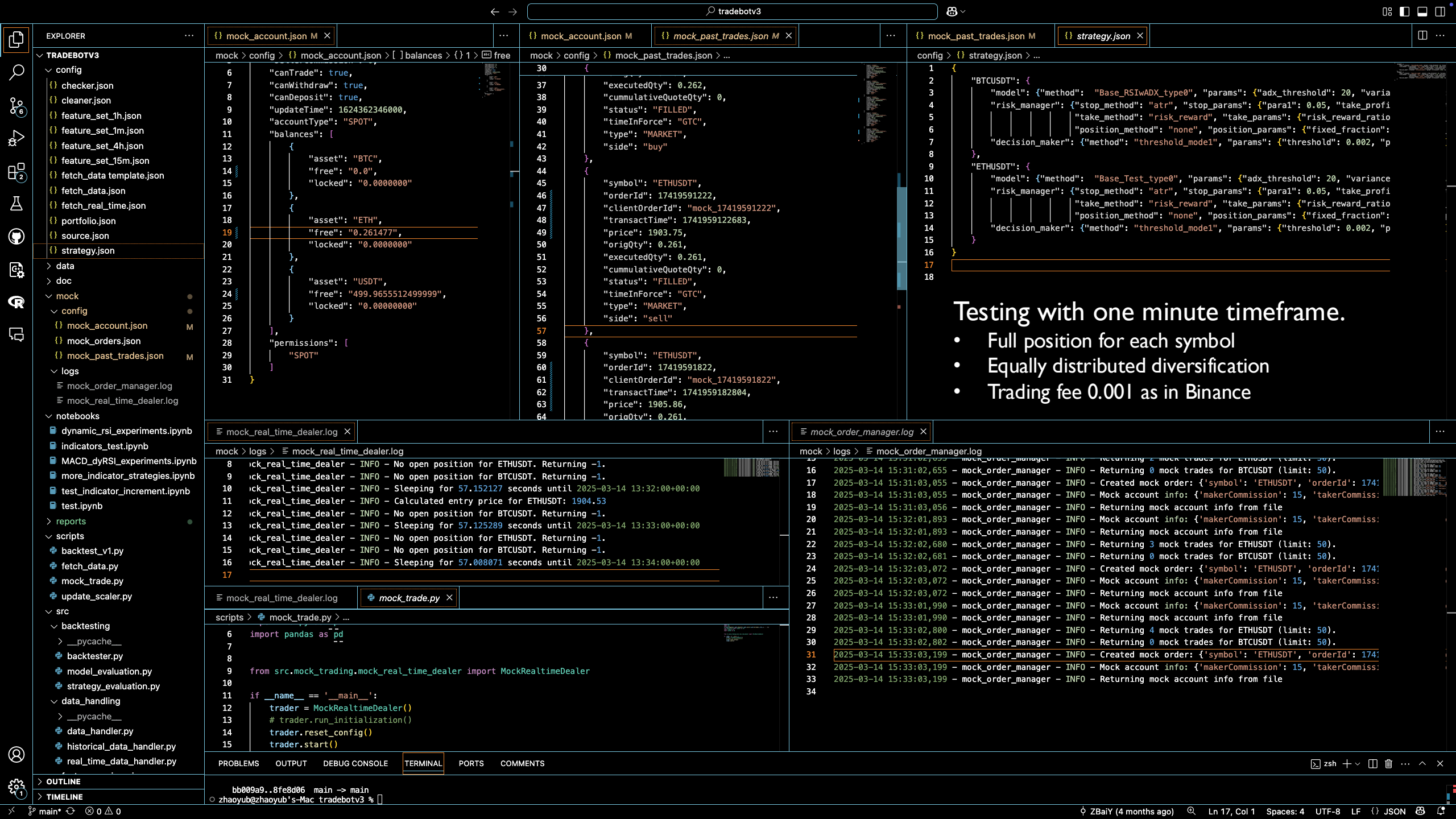
Performance Metrics:
Total ROI (%): 142.00145700188415
Max Drawdown (%): 28.636068837554156
Sharpe Ratio: 0.008170404219610626
Symbol ROI (%): 282.882555147515
Trade Efficiency (%): 15.8344654790018 58
Trade Distribution: {
'winning_trades': 85,
'losing_trades': 105,
'win_rate (%)': 44.73684210526316}

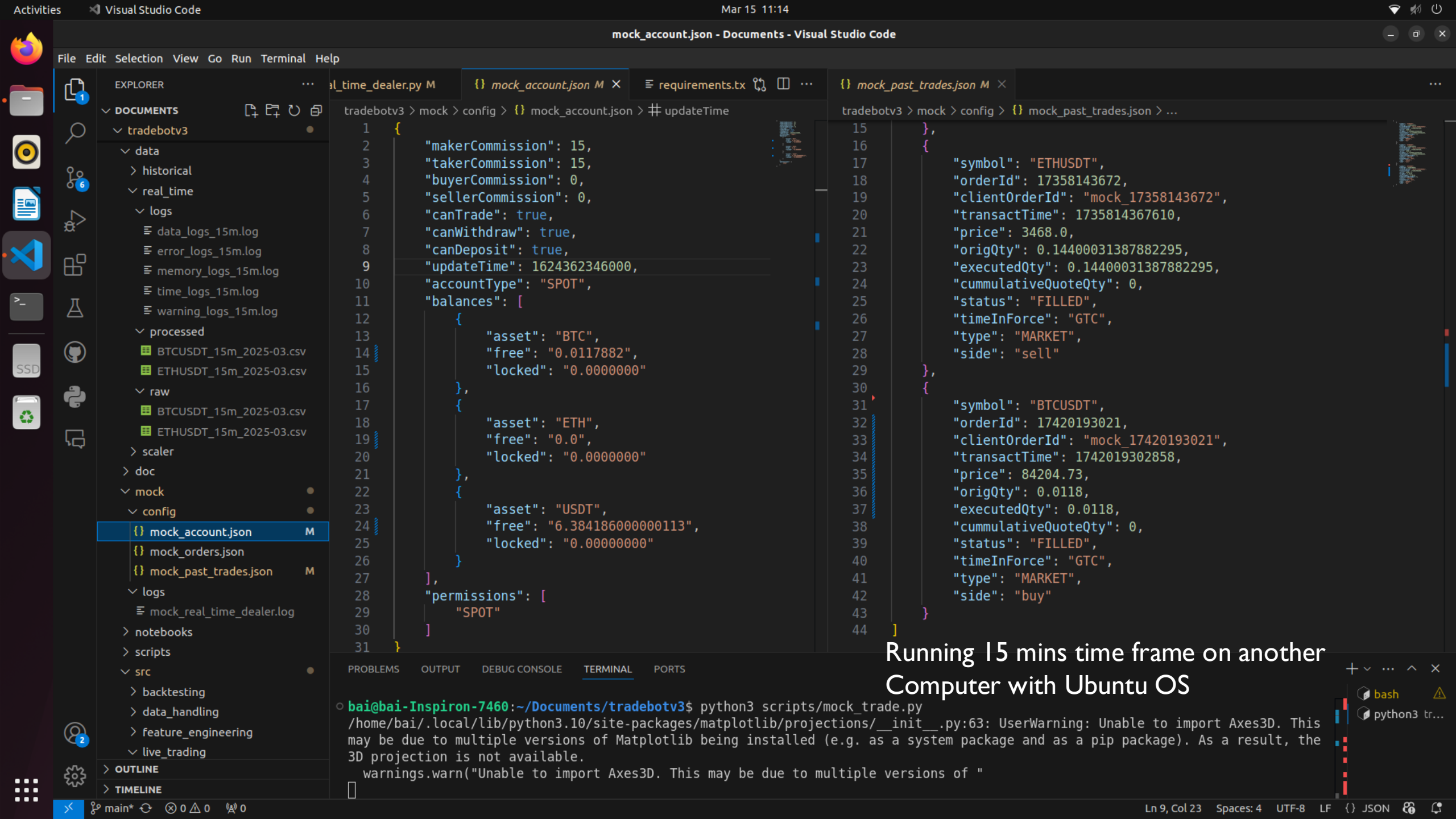
Profit Attribution: {'total_profit': 1420.0145700188414,
'average_profit': 7.473760894836007 5,
'max_profit': 291.7627277908862,
'min_profit': -218.4944239205288}
Risk Reward Ratio: 1.7000977257656866
Total Trades: 190 Largest
Win Trade (%): 291.7627277908862
Largest Lost Trade (%): -218.4944239205288
Sortino Ratio: -0.060317357726814 32



"ROI (%)": 81.50673655534274,
"Max Drawdown (%)": 26.197707265050862,
"Sharpe Ratio": 0.005640296829731 1305,
"Win Rate (%)": 17.256637168141 59,
"Profit Factor": 1.3906898276640747,
"Average Trade Return (%)": 20.830371244866296,
"Average Win (%)": 429.67394225841076,
"Average Loss (%)": -325.665401263 19563

MOCK TRADING


tradebotv3
EXPLORER
TRADEBOTV3
config
checker.json
cleaner.json
feature_set_1h.json
feature_set_1m.json
feature_set_4h.json
feature_set_15m.json
fetch_data template.json
fetch_data.json
fetch_real_time.json
portfolio.json
source.json
strategy.json
data
doc
mock
config
mock_account.json M
mock_orders.json
mock_past_trades.json M
logs
mock_order_manager.log
mock_real_time_dealer.log
notebooks
dynamic_rsi_experiments.ipynb
indicators_test.ipynb
MACD_dyRSI_experiments.ipynb
more_indicator_strategies.ipynb
test_indicator_increment.ipynb
test.ipynb
reports
scripts
backtest_v1.py
fetch_data.py
mock_trade.py
update_scaler.py
src
backtesting
__pycache__
backtester.py
model_evaluation.py
strategy_evaluation.py
data_handling
__pycache__
data_handler.py
historical_data_handler.py
real_time_data_handler.py
OUTLINE
TIMELINE
mock_account.json M
mock > config > mock_account.json > [ ]balances > {}1 > free
"canTrade": true,
"canWithdraw": true,
"canDeposit": true,
"updateTime": 1624362346000,
"accountType": "SPOT",
"balances": [
{
"asset": "BTC",
"free": "0.0",
"locked": "0.0000000"
},
{
"asset": "ETH",
"free": "0.261477",
"locked": "0.0000000"
},
{
"asset": "USDT",
"free": "499.96555124999999",
"locked": "0.00000000"
}
],
"permissions": [
"SPOT"
]
}
mock_account.json M
mock_past_trades.json M
mock > config > mock_past_trades.json > ...
{
"executedQty": 0.262,
"cummulativeQuoteQty": 0,
"status": "FILLED",
"timeInForce": "GTC",
"type": "MARKET",
"side": "buy"
},
{
"symbol": "ETHUSDT",
"orderId": 17419591222,
"clientOrderId": "mock_17419591222",
"transactTime": 1741959122683,
"price": 1903.75,
"origQty": 0.261,
"executedQty": 0.261,
"cummulativeQuoteQty": 0,
"status": "FILLED",
"timeInForce": "GTC",
"type": "MARKET",
"side": "sell"
},
{
"symbol": "ETHUSDT",
"orderId": 17419591822,
"clientOrderId": "mock_17419591822",
"transactTime": 1741959182804,
"price": 1905.86,
"origQty": 0.261,
mock_past_trades.json M
strategy.json
config > strategy.json > ...
{
"BTCUSDT": {
"model": {"method": "Base_RSIwADX_type0", "params": {"adx_threshold": 20, "varia
"risk_manager": {"stop_method": "atr", "stop_params": {"para1": 0.05, "take_profi
"take_method": "risk_reward", "take_params": {"risk_reward_ratio
"position_method": "none", "position_params": {"fixed_fraction":
"decision_maker": {"method": "threshold_mode1", "params": {"threshold": 0.002, "p
},
"ETHUSDT": {
"model": {"method": "Base_Test_type0", "params": {"adx_threshold": 20, "variance
"risk_manager": {"stop_method": "atr", "stop_params": {"para1": 0.05, "take_profi
"take_method": "risk_reward", "take_params": {"risk_reward_ratio
"position_method": "none", "position_params": {"fixed_fraction":
"decision_maker": {"method": "threshold_mode1", "params": {"threshold": 0.002, "p
}
}
Testing with one minute timeframe.
• Full position for each symbol
• Equally distributed diversification
• Trading fee 0.001 as in Binance
mock_real_time_dealer.log
mock > logs > mock_real_time_dealer.log
ock_real_time_dealer - INFO - No open position for ETHUSDT. Returning -1.
ock_real_time_dealer - INFO - No open position for BTCUSDT. Returning -1.
ock_real_time_dealer - INFO - Sleeping for 57.152127 seconds until 2025-03-14 13:32:00+00:00
ock_real_time_dealer - INFO - Calculated entry price for ETHUSDT: 1904.53
ock_real_time_dealer - INFO - No open position for BTCUSDT. Returning -1.
ock_real_time_dealer - INFO - Sleeping for 57.125289 seconds until 2025-03-14 13:33:00+00:00
ock_real_time_dealer - INFO - No open position for ETHUSDT. Returning -1.
ock_real_time_dealer - INFO - No open position for BTCUSDT. Returning -1.
ock_real_time_dealer - INFO - Sleeping for 57.008071 seconds until 2025-03-14 13:34:00+00:00
mock_order_manager.log
mock > logs > mock_order_manager.log
2025-03-14 15:31:02,655 - mock_order_manager - INFO - Returning 0 mock trades for BTCUSDT (limit: 50).
2025-03-14 15:31:03,055 - mock_order_manager - INFO - Created mock order: {'symbol': 'ETHUSDT', 'orderId': 1741
2025-03-14 15:31:03,055 - mock_order_manager - INFO - Mock account info: {'makerCommission': 15, 'takerCommiss
2025-03-14 15:31:03,056 - mock_order_manager - INFO - Returning mock account info from file
2025-03-14 15:32:01,893 - mock_order_manager - INFO - Mock account info: {'makerCommission': 15, 'takerCommiss
2025-03-14 15:32:01,893 - mock_order_manager - INFO - Returning mock account info from file
2025-03-14 15:32:02,680 - mock_order_manager - INFO - Returning 3 mock trades for ETHUSDT (limit: 50).
2025-03-14 15:32:02,681 - mock_order_manager - INFO - Returning 0 mock trades for BTCUSDT (limit: 50).
2025-03-14 15:32:03,072 - mock_order_manager - INFO - Created mock order: {'symbol': 'ETHUSDT', 'orderId': 1741
2025-03-14 15:32:03,072 - mock_order_manager - INFO - Mock account info: {'makerCommission': 15, 'takerCommiss
2025-03-14 15:32:03,072 - mock_order_manager - INFO - Returning mock account info from file
2025-03-14 15:33:01,990 - mock_order_manager - INFO - Mock account info: {'makerCommission': 15, 'takerCommiss
2025-03-14 15:33:01,990 - mock_order_manager - INFO - Returning mock account info from file
2025-03-14 15:33:02,800 - mock_order_manager - INFO - Returning 4 mock trades for ETHUSDT (limit: 50).
2025-03-14 15:33:02,802 - mock_order_manager - INFO - Returning 0 mock trades for BTCUSDT (limit: 50).
2025-03-14 15:33:03,199 - mock_order_manager - INFO - Created mock order: {'symbol': 'ETHUSDT', 'orderId': 1741
2025-03-14 15:33:03,199 - mock_order_manager - INFO - Mock account info: {'makerCommission': 15, 'takerCommiss
2025-03-14 15:33:03,199 - mock_order_manager - INFO - Returning mock account info from file
mock_real_time_dealer.log
mock_trade.py
scripts > mock_trade.py > ...
import pandas as pd
from src.mock_trading.mock_real_time_dealer import MockRealtimeDealer
if __name__ == '__main__':
trader = MockRealtimeDealer()
# trader.run_initialization()
trader.reset_config()
trader.start()
PROBLEMS
OUTPUT
DEBUG CONSOLE
TERMINAL
PORTS
COMMENTS
zsh
bb009a9..8fe8d06 main -> main
zhaoyub@zhaoyub's-Mac tradebotv3 %
main*
0 0
ZBaiY (4 months ago)
Ln 17, Col 1
Spaces: 4
UTF-8
LF
JSON


Activities
Visual Studio Code
Mar 15 11:14
mock_account.json - Documents - Visual Studio Code
File Edit Selection View Go Run Terminal Help
EXPLORER
DOCUMENTS
tradebotv3
data
historical
real_time
logs
data_logs_15m.log
error_logs_15m.log
memory_logs_15m.log
time_logs_15m.log
warning_logs_15m.log
processed
BTCUSDT_15m_2025-03.csv
ETHUSDT_15m_2025-03.csv
raw
BTCUSDT_15m_2025-03.csv
ETHUSDT_15m_2025-03.csv
scaler
doc
mock
config
mock_account.json M
mock_orders.json
mock_past_trades.json M
logs
mock_real_time_dealer.log
notebooks
scripts
src
backtesting
data_handling
feature_engineering
live_trading
OUTLINE
TIMELINE
l_time_dealer.py M
mock_account.json M
requirements.tx
mock_past_trades.json M
tradebotv3 > mock > config > mock_account.json > updateTime
{
"makerCommission": 15,
"takerCommission": 15,
"buyerCommission": 0,
"sellerCommission": 0,
"canTrade": true,
"canWithdraw": true,
"canDeposit": true,
"updateTime": 1624362346000,
"accountType": "SPOT",
"balances": [
{
"asset": "BTC",
"free": "0.0117882",
"locked": "0.0000000"
},
{
"asset": "ETH",
"free": "0.0",
"locked": "0.0000000"
},
{
"asset": "USDT",
"free": "6.384186000000113",
"locked": "0.00000000"
}
],
"permissions": [
"SPOT"
]
}
tradebotv3 > mock > config > mock_past_trades.json > ...
},
{
"symbol": "ETHUSDT",
"orderId": 17358143672,
"clientOrderId": "mock_17358143672",
"transactTime": 1735814367610,
"price": 3468.0,
"origQty": 0.14400031387882295,
"executedQty": 0.14400031387882295,
"cummulativeQuoteQty": 0,
"status": "FILLED",
"timeInForce": "GTC",
"type": "MARKET",
"side": "sell"
},
{
"symbol": "BTCUSDT",
"orderId": 17420193021,
"clientOrderId": "mock_17420193021",
"transactTime": 1742019302858,
"price": 84204.73,
"origQty": 0.0118,
"executedQty": 0.0118,
"cummulativeQuoteQty": 0,
"status": "FILLED",
"timeInForce": "GTC",
"type": "MARKET",
"side": "buy"
}
]
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS
bai@bai-Inspiron-7460:~/Documents/tradebotv3$ python3 scripts/mock_trade.py
/home/bai/.local/lib/python3.10/site-packages/matplotlib/projections/__init__.py:63: UserWarning: Unable to import Axes3D. This may be due to multiple versions of Matplotlib being installed (e.g. as a system package and as a pip package). As a result, the 3D projection is not available.
warnings.warn("Unable to import Axes3D. This may be due to multiple versions of "
bash
python3 tr...
Running 15 mins time frame on another Computer with Ubuntu OS
main*
Ln 9, Col 23
Spaces: 4
UTF-8
LF
JSON

FUTURE WORKS

FUTURE WORKS

- Optimization of data storage
- Shorting Capabilities
- Expansion of strategy/indicator portfolio

Trade Bot version 4:

- Cleaner modular design
- Enhancement of Configuration File designs