A Data Science Pipeline for Algorithmic Trading:

A Comparative Study in Applications to Finance and Cryptoeconomics

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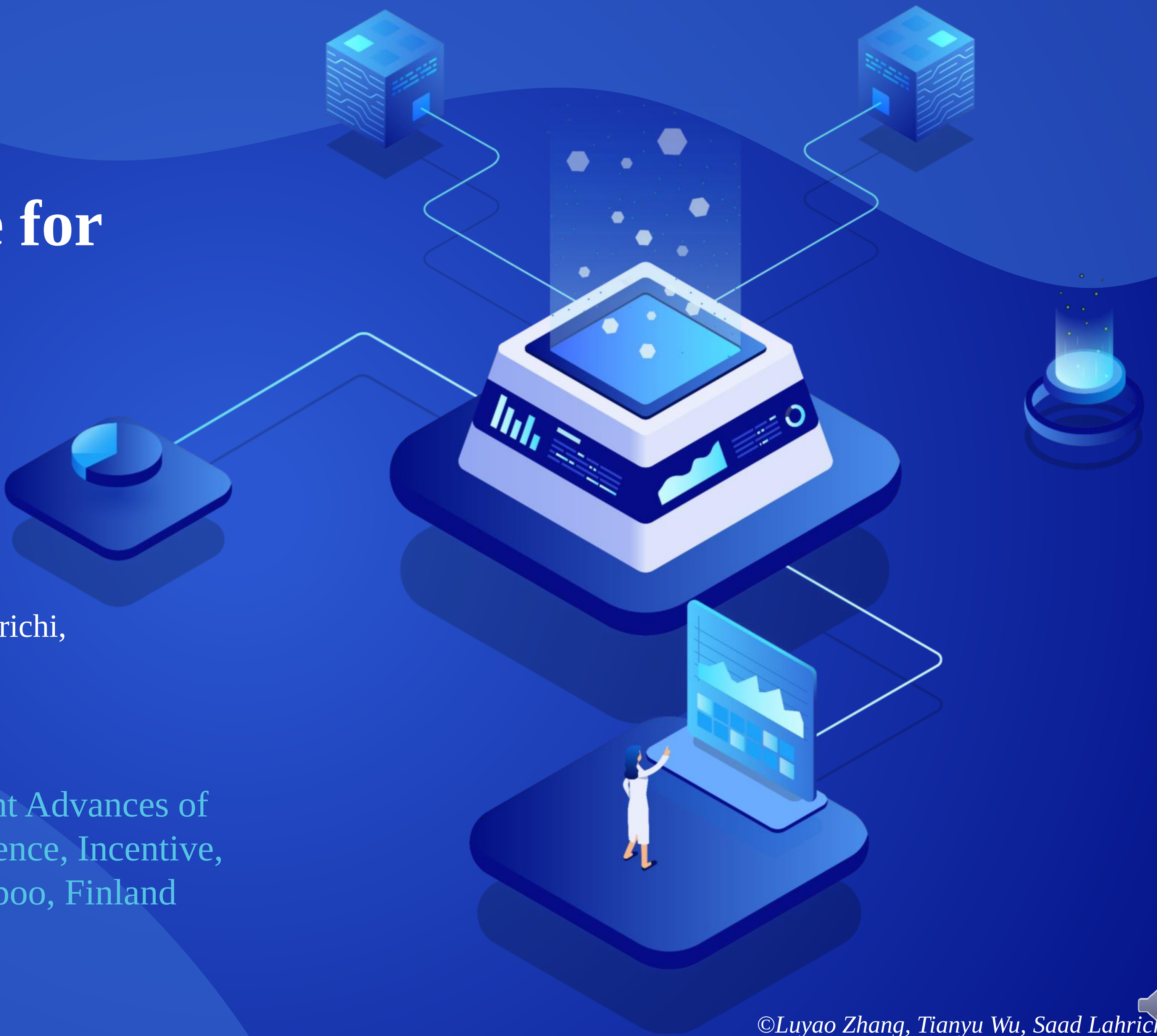
Carlos-Gustavo Salas-Flores, and Jiayi Li



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At a Glance

The Team

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✓ Data Science, Finance, Cryptocurrencies
✓ Cultivate undergraduate research
✓ Across different time zones

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Luyao, Tianyu, and Saad are joint 1st authors, and Jiayi and Carlos-Gustavo are 2nd authors.

Background and Research Questions

The Big Picture

1. Artificial Intelligence – **an important technique** of algorithmic trading in finance and cryptoeconomics.

2. Lack of **established pipeline** leads to process inconsistency and makes ceteris-paribus comparison difficult.

3. No **open-source coding algorithms** to evaluate and compare different trading strategies.

Our Questions

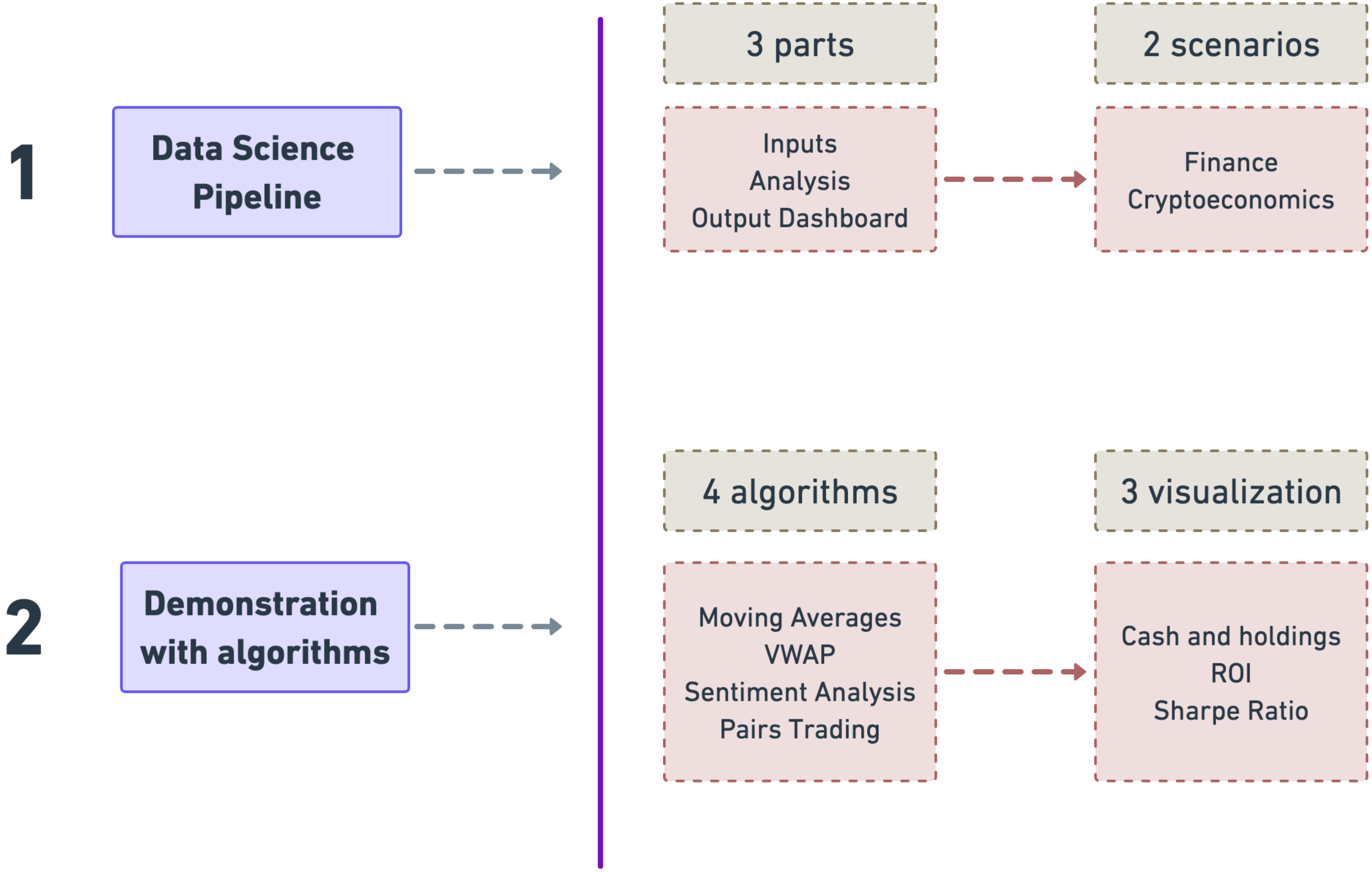
1. **A generally applicable data science pipeline:**

   What are the inputs, analysis, and output dashboard in this workflow?

2. **A comparative study in Applications to Finance and Cryptoeconomics:**

   How can this data science pipeline be generally applicable to design, program, and evaluate algorithmic trading of stock and crypto assets with conventional algorithms?

Main Results



https://whimsical.com/fig1-GkT91dQfNvYLfY1pTJ5T6g

Data Source and Methodology

Moving Averages (MA) Crossover

Data Sources

API Documentation | Alpha Vantage

Assets

Tesla (TSLA)
Apple (AAPL)
Bitcoin (BTC)
Ether (ETH)

Calculate Index

Short-window Moving Average (SWMA)
Commonly 50-Days

Long-window Moving Average (LWMA)
Commonly 200-Days

Buy Signal

SWMA crosses above LWMA

Input Variable

Historical Close Price
Frequency: Daily
Start date: 2020/01/01
End date: 2022/02/04

Trading Condition

Initial capital: 10,000

max_buy: 10,000,000
max_sell: 10,000,000
gas fee: 0.1%

Sell Signal

SWMA crosses below LWMA

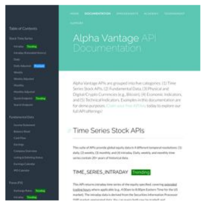
Evaluations

ROI
Sharpe Ratio

$$\mathrm{SMA}_t^n = \frac{1}{n} \sum_{i=t-n+1}^{t} p_i$$

Volume-Weighted Average Price (VWAP)

Data Sources



API Documentation | Alpha Vantage

Input Variables

Historical Price
Frequency: intraday
Start date: 2022-02-08
End date: 2022-02-11

Assets

Ethereum (ETH)
Bitcoin (BTC)

Calculate index

VWAP

Trading Condition

Initial Capital: 100,000 USD
Max_buy: 1,000,000
Max_sell: 1,000,000
Gas fee: 0.1%

Buy Signals

Price cross above VWAP

Sell Signals

Price cross below VWAP

Evaluations

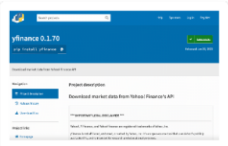
ROI
Sharpe Ratio

$$VWAP = \frac{\sum P_t \cdot Q_t}{\sum Q_t}$$

Data Source and Methodology

Sentiment Analysis

Data Sources 1



yfinance PyPI

Input Variable 1

Historical Prices

Frequency: Daily
Start date: 2021-01-01
End date: 2021-06-01

Calculate Index

EMA

Buy Signal

Price-EMA< -std(Price-EMA) &
Positive Sentiment

Data Sources 2

Github: snscrape: A social networking service scraper in Python

Input Variable 2

Tweets

Frequency: 1 tweet
Start date: 2021-01-01
End date: 2021-06-01

NLP

VADER

Sentiment Category

(Positive, Negative)

Sell Signal

Price-EMA > std(Price-EMA) &
Negative Sentiment

Evaluation

ROI
Sharpe Ratio

Assets

Apple (AAPL)
Bitcoin (BTC)
Ether (ETH)

Trading Condition

Initial capital: 100000
max_buy: 10000000
max_sell: 10000000
gas fee: 0.1%

Pairs Trading

Data Sources

API Documentation | Alpha Vantage

Input Variables

Historical Close Prices
Frequency Daily
Start date: 4/22/2021
End date: 10/22/2021

Trading Condition

initial_capital: 10,000 USD
max_number_of_pairs: 20
transaction_fee: 0.01
gas_fee: 0.001
borrow_fee: 0.01
max_buy: 1000000
max_sell: 1000000
max_short: 1000000

Assets

Dataset 1: S&P500
Dataset 2: Digital Currencies

Pairs Selection using Machine Learning

Compute ROI → Dimensionality Reduction (PCA) → Unsupervised Machine Learning (OPTICS) → Mean Reversion & Cointegration Tests

Pairs Selection using Brute Force

Sum of Standard Deviations (SDD) → Select top k pairs with the smallest SDD

Calculate Simple Spread

Spread_simple = PriceA - PriceB

Calculate Normalized Spread

Spread_normal = PriceA/PriceA_0 - PriceB/PriceB_0

Define Thresholds

Define:
mu = mean(Spread)
sigma = standard deviation (Spread)

buy threshold = mu - 2 sigma
short threshold = mu + 2 sigma
exit = mu

Define:
sigma = standard deviation (Spread)

buy threshold = - 2 sigma
short threshold = 2 sigma
exit = 0

Buy A and Short B Signal

Spread < buy threshold

Short A and Buy B Signal

Spread > short threshold

Sell and Payback Signals

Spread = exit

Evaluations

ROI
Sharpe Ratio

1

Introduction to Data Science Pipeline

Introduction to Data Science Pipeline

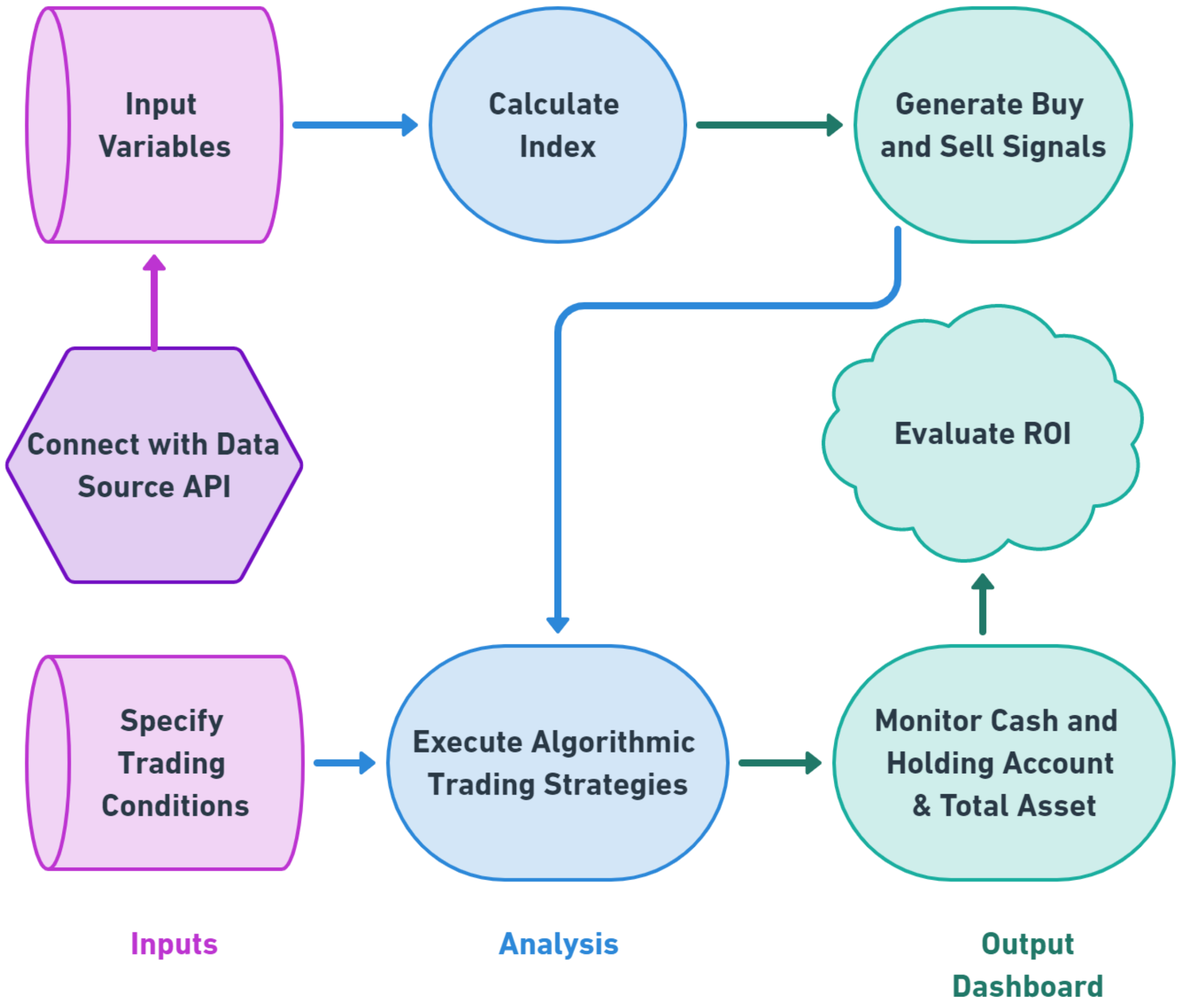


Figure 1: Our proposed data science pipeline for algorithmic trading

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Demonstration with Four Conventional Algorithms

Moving Averages Crossover
Volume-Weighted Average Price
Sentiment Analysis
Pairs Trading

Moving Averages Crossover

Variable	Frequency	Unit	Description
Date	daily	YYYY-MM-DD	Date and time for which the data were recorded
Close	daily	USD	Price at which the stock ended trading in a given time period
Short MA	daily	USD	Average price of a security within a certain period, typically 50 days
Long MA	daily	USD	Average price of a security within a certain period, typically 200 days
Signal	-	-	Buy-and-sell signal (e.g., TSLA, AAPL for stock, BTC, ETH for crypto)

Table 1: Moving Average Crossover: Data
Data Source: Alpha Vantage API

Moving Averages Crossover

Take Ether (ETH) for example:

Figure 2: Buy-and-Sell Signal: ETH moving averages crossover

Figure 3: Portfolio time series: ETH moving averages crossover

Moving Averages Crossover

Take Ether (ETH) for example:

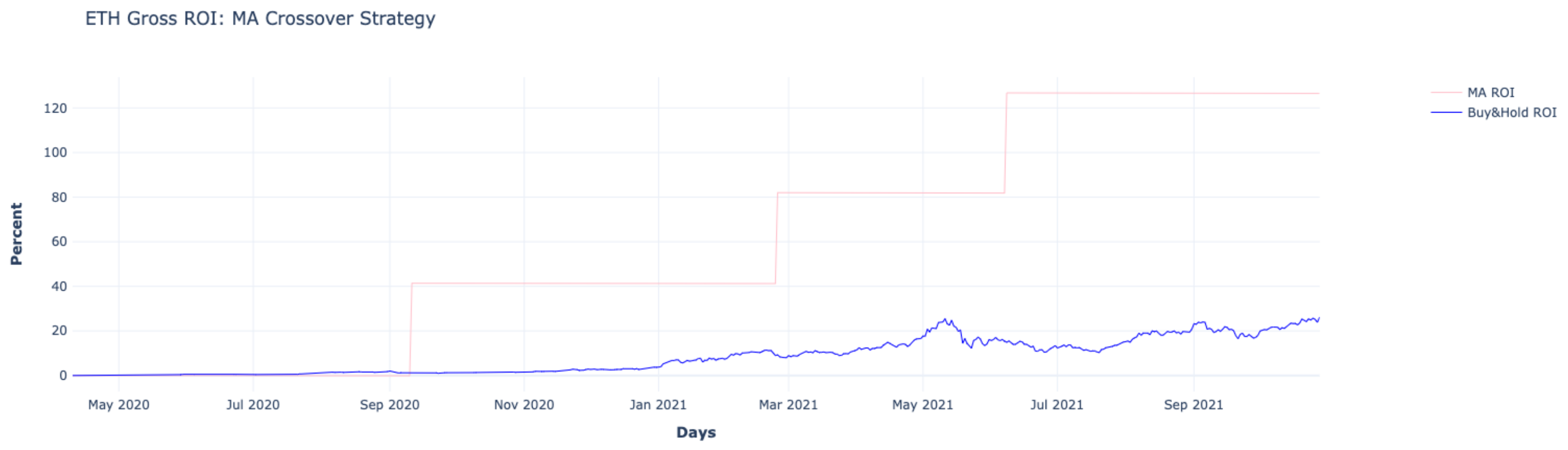

Figure 4: Gross ROI: ETH moving average crossover vs. buy-and-hold

Moving average crossover strategy ROI: 849.84%
Buy & hold strategy ROI: 11.97%

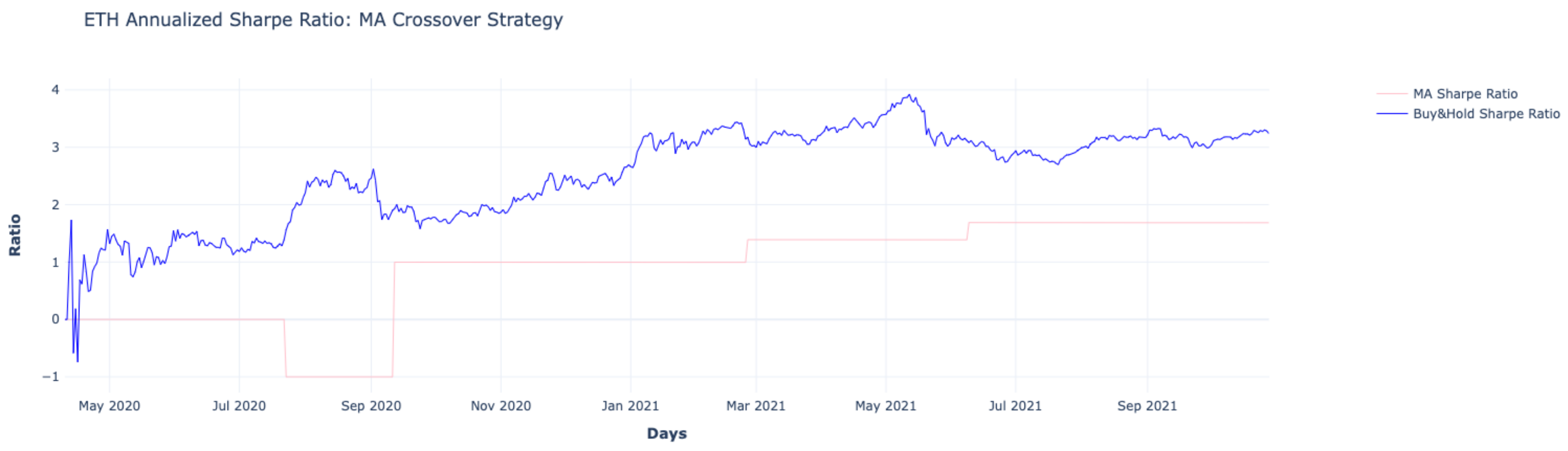

Figure 5: Sharpe Ratio: ETH moving average crossover vs. buy-and-hold

Moving average crossover strategy Sharpe ratio: 0.98
Buy-and-hold strategy Sharpe ratio: 2.60

Volume-Weighted Moving Average

Variable	Frequency	Unit	Description
Date	5 min	YYYY-MM-DD HH:MM:SS	Date and time for which the data were recorded
Close	5 min	USD	Price at which the stock ended trading in a given time period
VWAP	5 min	USD	Average price of a security within a day, adjusted for its volume. Available for an API call only for traditional stocks; manually calculated using the formula for crypto
Ticker	-	-	Stock symbol (e.g., TSLA, AAPL for traditional, BTC, ETH for crypto)
Interval	5 min	min/hr/day	Time difference between two data points

Table 2: Volume-Weighted Moving Average: Data
Data Source: Alpha Vantage API

Volume-Weighted Moving Average

Take Ether (ETH) for example:

Figure 6: Buy-and-Sell Signal:
ETH volume-weighted moving average

Figure 7: Portfolio time series:
ETH volume-weighted moving average

Volume-Weighted Moving Average

Take Ether (ETH) for example:

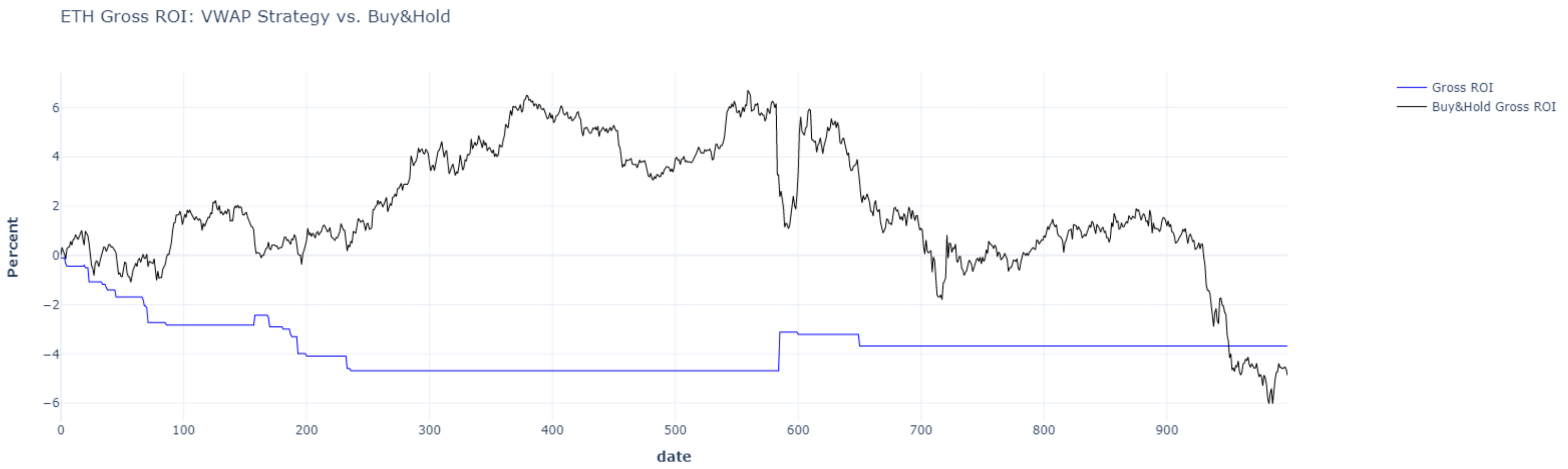

Figure 8: Gross ROI: ETH volume-weighted moving average vs. buy-and-hold

Moving average crossover strategy ROI: -3.93%
Buy & hold strategy ROI: -4.26%

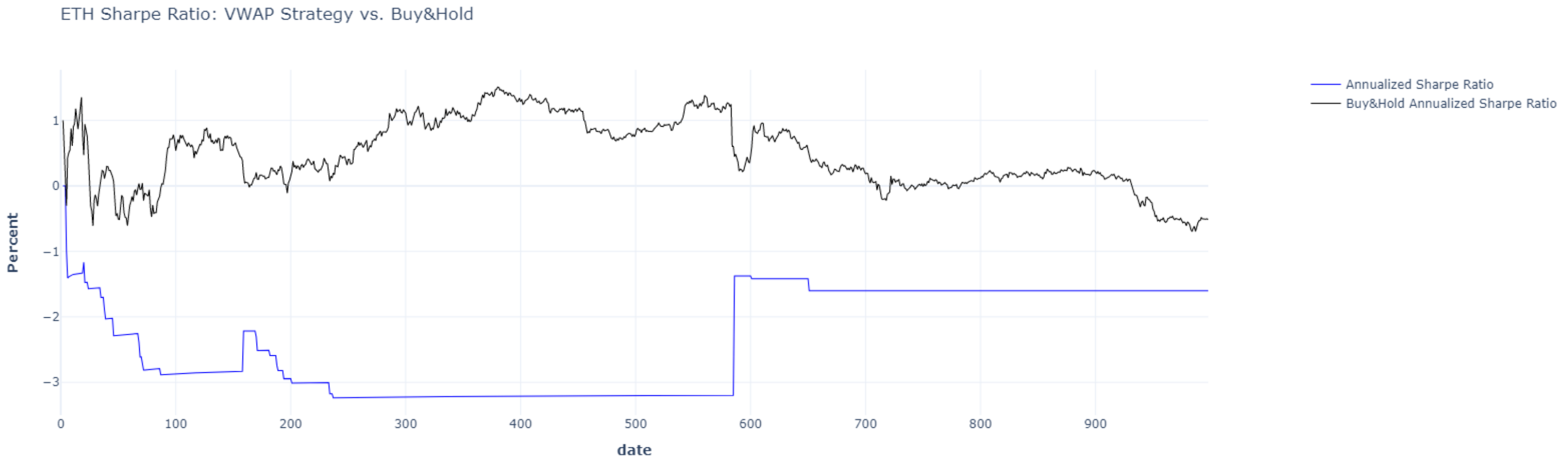

Figure 9: Sharpe Ratio: ETH volume-weighted moving average vs. buy-and-hold

Moving average crossover strategy Sharpe ratio: -1.62
Buy-and-hold strategy Sharpe ratio: -0.52

Sentiment Analysis

Variable Name	Frequency	Unit
Date	daily	YYYY-MM-DD
Tweets	-	-
Stock Price	daily	USD
Crypto Price	daily	USD

Table 3: Sentiment Analysis: Raw Variables
Data Sources: Snscrape API, Yahoo Finance API, Alpha Vantage API

ID	Frequency	Unit	Description
P_{comp}	per tweet	-	A normalized compound score that sums every lexicon rating and takes values from -1 to 1
EMA_t (10-day)	daily	USD	Exponential moving average of adjusted closing price, where $EMA_0 = P_0$ and $EMA_t = (1-\alpha)EMA_{t-1} + P_t, \alpha = 2/(s+1)$. For span $s \geq 1, s$: decay in terms of span P_t : day t closing price
Raw Trading Position	daily	USD	$P_t - EMA_t$
Sentiment Category	daily	Negative, Positive, Neutral	Negative: $P_{comp} < \bar{P}_{comp} - 0.2\sigma_{P_{comp}}$ Positive: $P_{comp} > \bar{P}_{comp} + 0.2\sigma_{P_{comp}}$ Neutral: $P_{comp} \geq \bar{P}_{comp} - 0.2\sigma_{P_{comp}}$ or $P_{comp} \leq \bar{P}_{comp} + 0.2\sigma_{P_{comp}}$
Trading Positions	daily	-	1 represents buy, and -1 represents sell

Table 4: Sentiment Analysis: Calculated Variables

Sentiment Analysis

Take Bitcoin (BTC) for example:

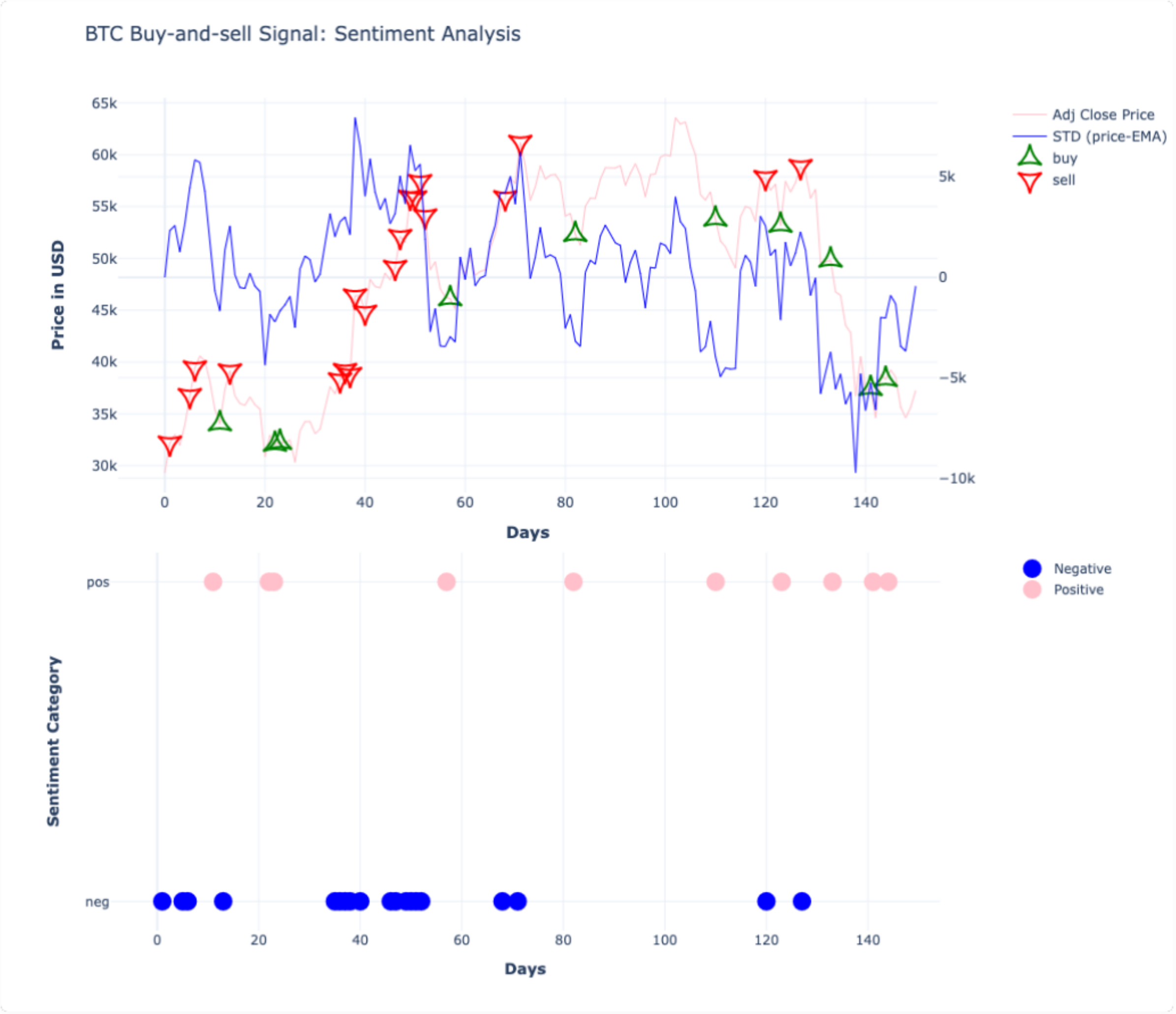

Figure 10: Buy-and-Sell Signal: BTC Sentiment Analysis

Sentiment Analysis

Take Bitcoin (BTC) for example:

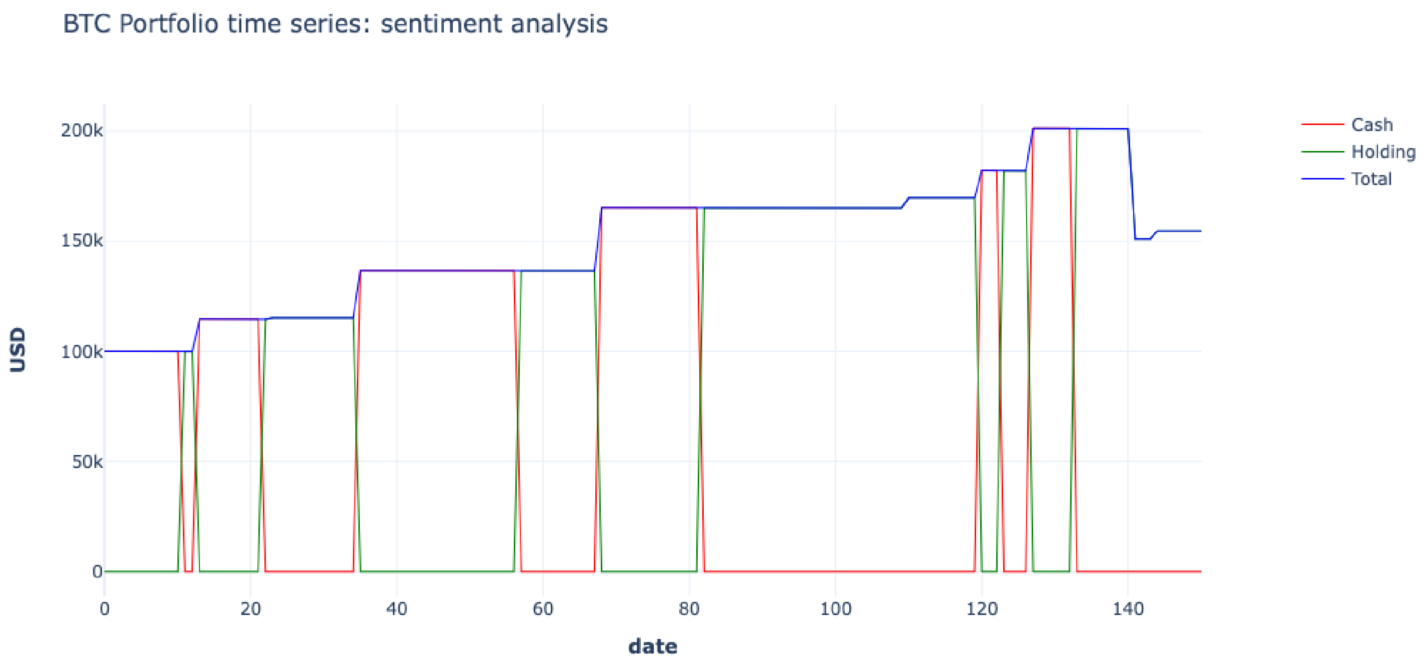

Figure 11: Portfolio time series: BTC Sentiment Analysis

Sentiment Analysis

Take Bitcoin (BTC) for example:

Figure 12: Gross ROI: BTC Sentiment Analysis vs Buy-And-Hold

Sentiment strategy ROI: 54.57%
Buy & hold strategy ROI: 27.00%

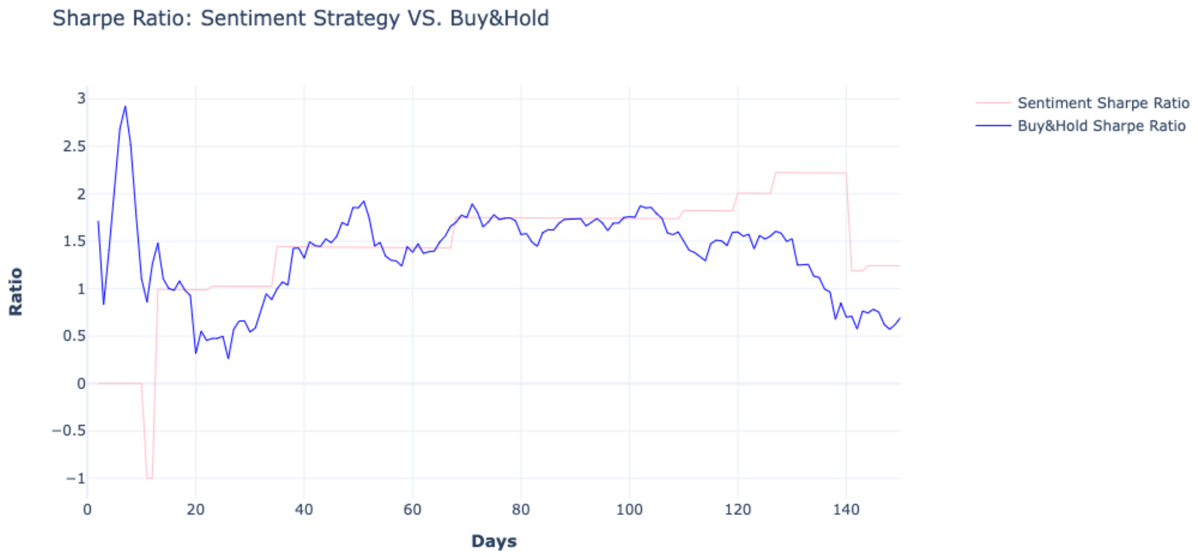

Figure 13: Sharpe Ratio: BTC Sentiment Analysis vs Buy-And-Hold

Sentiment strategy Sharpe Ratio: 1.24
Buy & hold strategy Sharpe Ratio: 0.69

Pairs Trading

Variable name	Frequency	Unit
Date	daily	YYYY-MM-DD
Close	daily	USD
Asset Name	-	-

Table 5: Pairs Trading: Data
Data Source: Alpha Vantage API

Variable name	Description
P-value	P-value from Engle and Granger's cointegration test
Hurst Exponent	The Hurst exponent is a value between 0 and 1 that serves to evaluate the mean-reversion property of a time-series
Half-life	A value λ that tells how long it takes for a time series to mean-revert
Times Crossing the Mean	Times the spread goes across the mean during the formation period

Table 6: Pairs Trading: Calculated Variables

Threshold	Value Using $\mathrm{S}_{\mathrm{simple}}$	Value Using $\mathrm{S}_{\mathrm{normal}}$
Short	2σ	$\mu + 2\sigma$
Buy	-2σ	$\mu - 2\sigma$
Exit	0	μ

Table 7: Pairs Trading: Trading Signals

Pairs Trading

Take Binance USD Token (BUSD) & EOS.IO Token (EOS) pair for example:

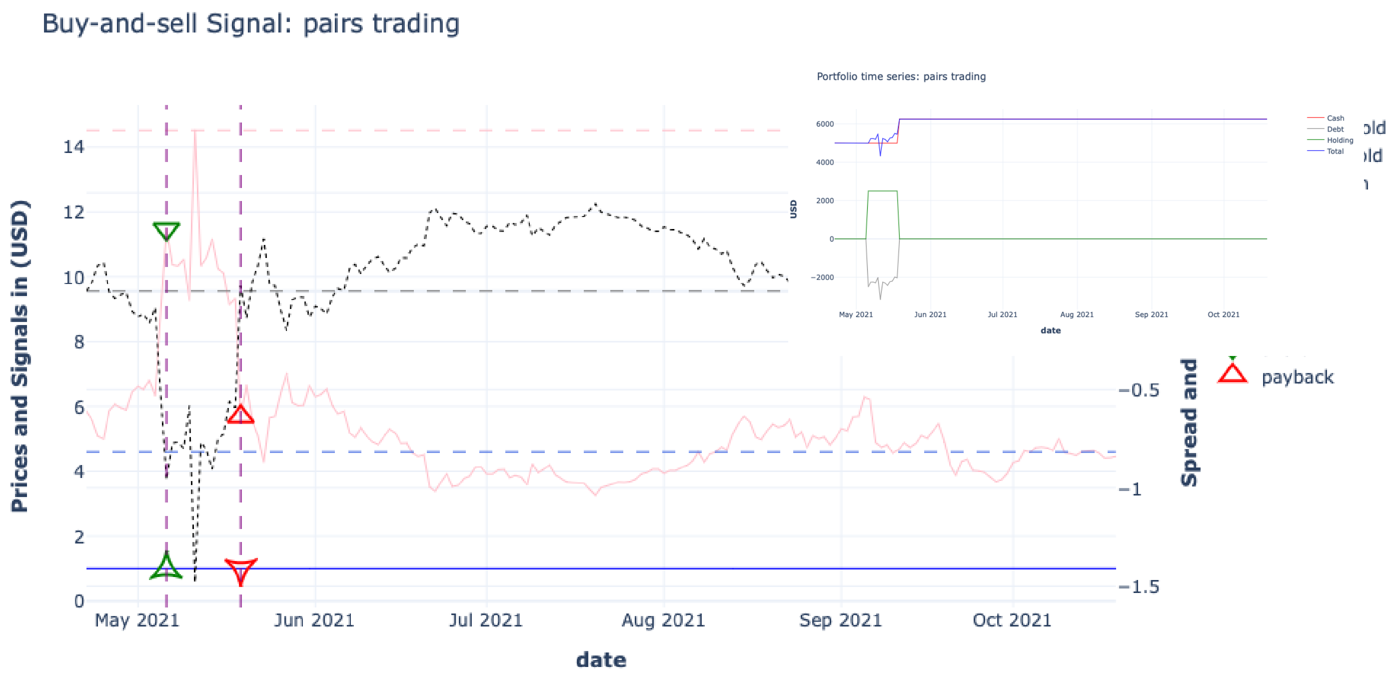

Figure 14: Buy-and-Sell Signal: BUSD & EOS Pair Trading

Pairs Trading

Take Binance USD Token (BUSD) & EOS.IO Token (EOS) pair for example:

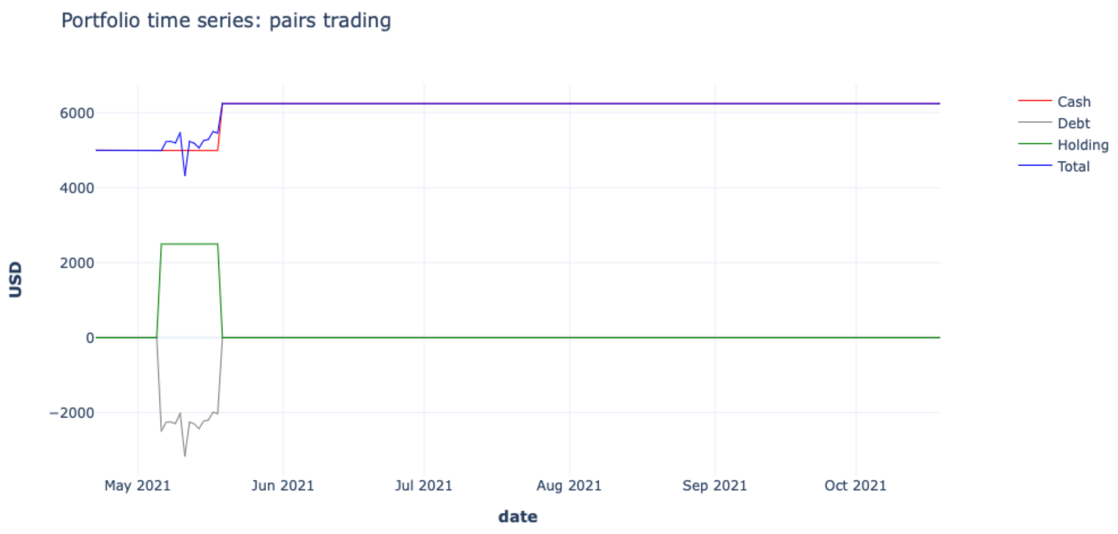

Figure 15: BUSD & EOS Portfolio time series: Pairs Trading

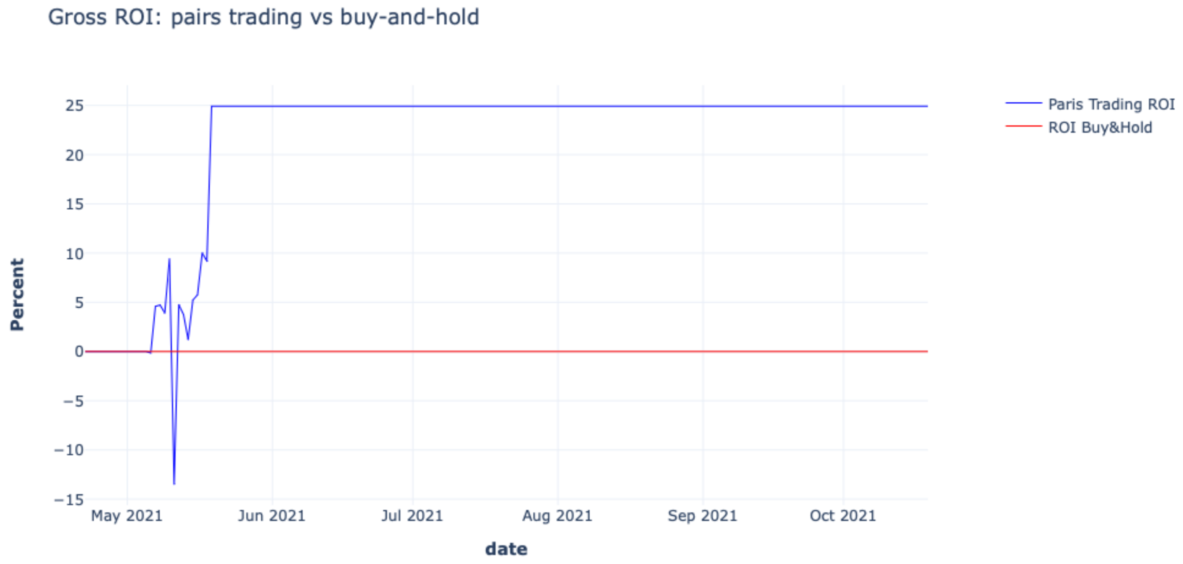

Figure 16: BUSD & EOS Gross ROI: Pairs Trading vs buy-and-hold

Pairs Trading strategy ROI: 24.92%
Buy & hold strategy ROI: 0.00%

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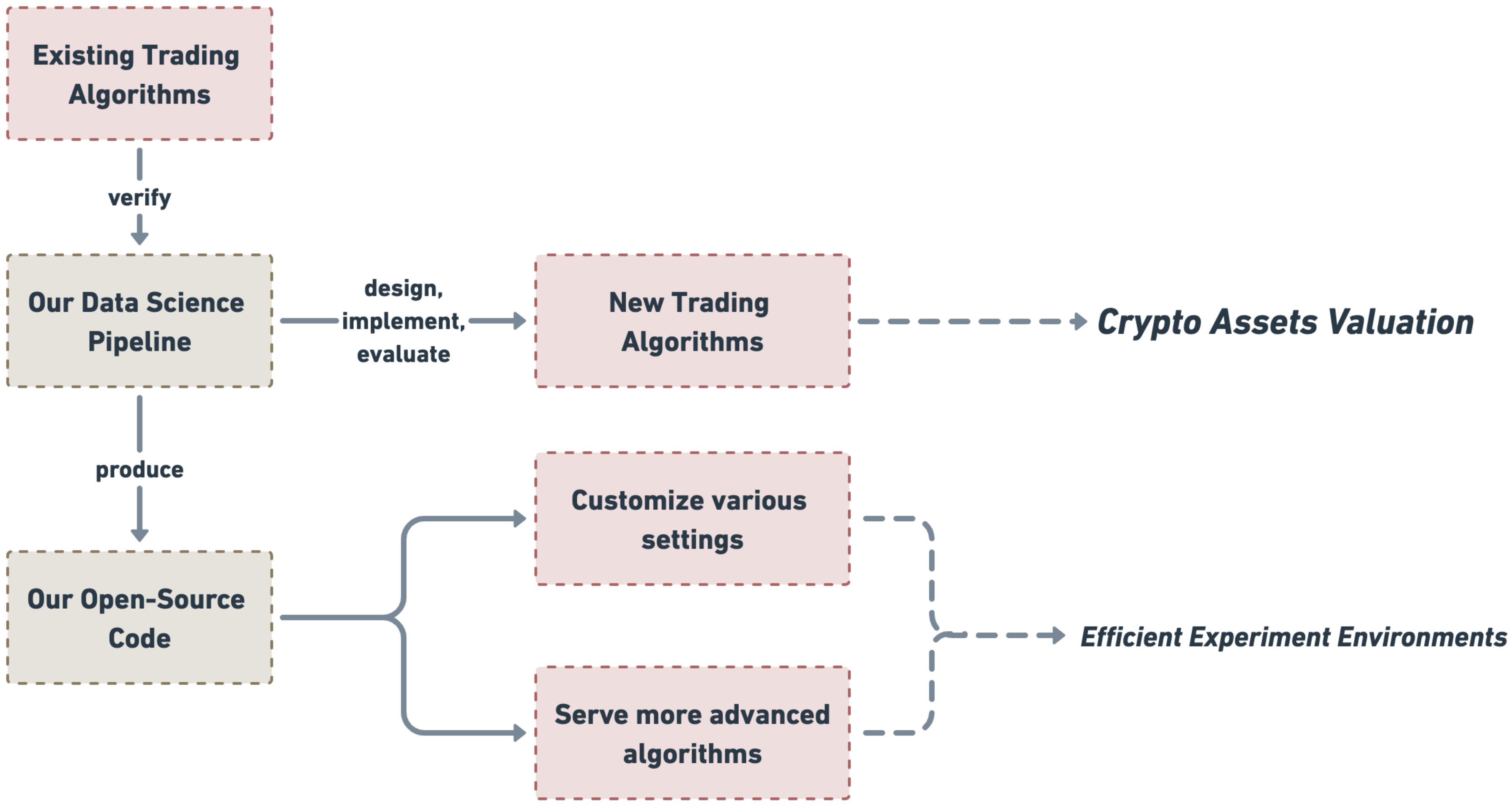
Future Research and Practices

Future Research and Practices



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Thank you

Working Paper: https://arxiv.org/abs/2206.14932

Data and Code: https://github.com/sciecon/srs2021

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