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Master's Degree Program in

Data Science and Advanced Analytics

TREND FOLLOWING ALGORITHMIC TRADING WITH A REDUCED UNIVERSE OF CRYPTOCURRENCIES

Using unsupervised learning for universe reduction and trend following strategies to generate profits

André Otão Pereira

Dissertation

presented as partial requirement for obtaining the Master Degree Program in Data Science and Advanced Analytics

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Dissertation presented as partial requirement for obtaining the Master's Degree in Data Science and Advanced Analytics, with a Specialization in Data Science

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledge the Rules of Conduct and Code of Honor from the NOVA Information Management School.

André Otão Pereira

Lisboa, May 2024

DEDICATION

I want to express my gratitude to my parents for always believing in me and encouraging me to aim higher than ever I thought possible. To my brothers, I want to express my heartfelt gratitude for the paths you've chosen, which have served as a constant source of inspiration and guidance for me.

I want to extend my sincere thanks to Ahmed Assad and Tomás Juhos for their incredible patience and willingness to help me through the ups and downs of professional life. Lucas Carvalho and Duarte Caldas, your insightful talks on finance have been incredibly influential in shaping the direction of this project.

To all my friends, thank you for your unwavering support and friendship throughout this journey. Your kindness and hard work inspire me. Here's to many more adventures together.

ABSTRACT

Cryptocurrencies have revolutionized trading with their decentralized and volatile nature, presenting unique opportunities for trend-following strategies. This study investigates the enhancement of such strategies by implementing a reduction in the universe of cryptocurrencies based on their similarities, aiming to improve trading performance. Additionally, a market momentum classification will be constructed to analyze and compare performance across different market momentum environments.

By utilizing Support Vector Machines (SVM) and Principal Component Analysis (PCA), the overall universe of cryptocurrencies is reduced to the most similar cryptocurrencies based on metrics of momentum, growth, and technical analysis. This approach aims to address market overload caused by the considerable number of available cryptocurrencies, removing the most erratic cryptocurrencies.

To assess the efficacy of two trend-following trading strategies—an equally weighted portfolio approach and a time-weighted portfolio approach—we will utilize a momentum-based trading strategy serving as our benchmark. All strategies will be used with the reduced universes produced by our method. Additionally, a market momentum classification will be constructed using market capitalization data of the crypto market, with the goal of gaining relevant insights into the effects of the overall market momentum environment on the performance of the algorithmic trading strategies and reduced universe combinations.

The innovation lies in the method of reducing the cryptocurrency universe by identifying the most similar tokens during the same period while asserting the value of unsupervised learning models like SVM and PCA in enhancing trend-following trading strategies by reducing complexity.

In summary, this research underscores the critical differences in short and long trend formation periods, the effectiveness of trend-following approaches, and the superior performance of time-weighted portfolios, demonstrating how SVM and PCA can enhance algorithmic trading strategies by reducing complexity and optimizing profitability in the dynamic cryptocurrency market.

KEYWORDS

Crypto Currencies; Machine Learning; Unsupervised Learning; Algorithmic Trading; Trend Following

Sustainable Development Goals (SGD):

Content

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LIST OF ABBREVIATIONS AND ACRONYMS

ML	Machine Learning
SVM	Support Vector Machine
PCA	Principal Component Analysis
RSI	Relative Strength Index
BB	Bollinger Bands
CV	Coefficient of Variance
MA	Moving Average
SMA	Simple Moving Average
EMA	Exponential Moving Average
FE	Feature Engineering
APL	Average Profit and Loss
MDD	Maximum Drawdown

1. Introduction

The rapid growth of cryptocurrencies has been attracting attention from both novice and seasoned investors into this financial. With thousands of cryptocurrencies actively traded against other cryptocurrencies or fiat money, the cryptocurrency exchange market has become a global phenomenon known for its volatility and diversity. As financial markets play a pivotal role in global economic development, forecasting financial time series has garnered increasing interest among traders and researchers.

Financial time series forecasting has presented itself as a challenge due to the uncertainties inherent in market movements, influenced by factors such as political events, economic conditions, and investor sentiment. While traditional approaches like technical and fundamental analysis have long been employed, the Efficient Market Hypothesis (EMH) states that no analysis can consistently outperform a buy and hold strategy, as market prices reflect all available information instantaneously. However, evidence suggests that markets may be predictable, challenging the validity of the EMH (Borges & Neves, 2020).

In recent years, machine learning and data mining techniques became popular for forecasting financial markets, offering promising results compared to static analysis strategies. This dissertation aligns with technical analysis and employs machine learning methods to detect promising trading pairs for forecasting in the cryptocurrency exchange market. Unlike previous studies focused primarily on Bitcoin (Farell, 2015), this research broadens the scope to include a more diverse range of cryptocurrencies, aiming to measure and compare the performance of 2 machine learning methods, Principal component analysis (PCA) and Support vector machines (SVM).

With the cryptocurrency market's exponential growth and increasing adoption, the need for effective prediction strategies has become more pressing (Hitam, Ismail , & Saeed, 2019). By leveraging machine learning algorithms, this thesis aims to design and evaluate algorithmic trading strategies based on trend-following approach, comparing them against a benchmark momentum-based trading strategy approach. By exploring the potential of machine learning in cryptocurrency market prediction, this research contributes to advancing our understanding of this rapidly evolving financial landscape.

1.1 Motivation

The motivation behind this research stems from the unique characteristics of the cryptocurrency market, characterized by its high volatility. With price fluctuations of 5 to 10% in a single day common, the cryptocurrency market presents an exciting opportunity to apply machine learning methods, leveraging insights from traditional stock markets while exploring problem-specific features.

The primary objective of this work is to design a profitable strategy tailored to the cryptocurrency market. From an engineering perspective, developing a machine learning system capable of uncovering patterns in dynamic, non-linear, and chaotic signals pose a significant challenge.

The European Central Bank (2019) notes that algorithmic trading has been on the rise since the early 2000s, estimating that it accounts for approximately 70% of total orders in some markets. However, there remains a vast unexplored territory. In this work, the research introduces a universe reduction procedure for selecting cryptocurrencies to act on, based on a similarity metric. A novel approach that lacks comparison or experimentation in the existing literature.

1.2 Aim and Objectives

The primary aim of this project is to develop a machine learning model capable of accurately predicting cryptocurrency price movements and generating profits, even after accounting for general trading fees.
The first objective is to explore the reduction of the universe, parameterized in four ways:

- *Metrics Groups*: Providing information for each cryptocurrency.
- *Lookback Period*: Dictating the amount of historical data accessed during the selection process.
- *Universe Size*: Expressing the reduction factor of the universe.
- *Selection Method*: Determining which cryptocurrencies will be removed.

The algorithms under consideration include Support Vector Machine (SVM) One-Class and Principal Component Analysis (PCA). The performance of this procedure will be analyzed by focusing on key portfolio metrics such as the Sharpe Ratio, Maximum Drawdowns, and Average Profit & Loss (APL).
The exploration of algorithmic trading strategies will be conducted by predicting cryptocurrency price movements as a binary classification problem using tabular data, relying on 1-hour candlestick grouping to capitalize on the high volatility and frequent significant price changes inherent in the cryptocurrency market. This procedure will employ momentum and trend-following trading strategies to identify potential entry and exit points for trades over a 4-hour rebalancing period, aiming to exploit the market's directional movements and capture profitable opportunities.
Additionally, a daily market momentum classification of the cryptocurrency market will be constructed as a multiclass classification task, parameterized using a confidence level threshold. Using daily historical market capitalization data, the model will classify market momentum conditions as bullish, bearish, or neutral. With the flexibility provided by the confidence level parameterization, we aim to optimize the classification's sensitivity, assisting traders in making informed decisions amidst market volatility.
Through these objectives, this project aims to contribute to the development of effective machine learning-driven strategies for cryptocurrency trading, enhancing understanding and performance in this dynamic and rapidly evolving financial landscape.

1.3 Research Questions

Research Question 1

How effectively can SVM and PCA aid in reducing the overall universe of tokens based on similarity? What combination of parameters is most pertinent for profitability?
In this experimentation phase, we will explore different combinations of metric groups, lookback periods, universe size and selection methods to construct several reduced universes of cryptocurrencies. Our aim is to enhance performance by reducing the universe into similarly behaving cryptocurrencies, which entails decreasing complexity and associated transaction costs.

Research Question 2

How do trend-following based trading strategies perform when coupled with the constructed reduced universes? Additionally, how does this performance compare to a momentum-based benchmark trading strategy?

In the context of this work, a comprehensive grid search will be conducted across all reduced universes created against our three trading strategies. Our objective is to identify the most efficient combination of reduced universe and algorithmic trading strategy and find any relevant patterns by evaluating performance metrics such as the Sharpe Ratio, Maximum Drawdowns and Average Profit & Loss.

Research Question 3

What is the most effective market momentum class and level of confidence in terms of profitability? Can we identify variations in performance of the same combinations of reduced universe and trading strategy during different market classes and levels of confidence, or is the performance independent of these factors?

To evaluate the performance of each market momentum classification, we will conduct a grid search across all combinations of reduced universes, trading strategies, and market momentum classifications. Our goal is once more to determine the most effective algorithm as well as understanding if different market classifications have an impact on the results.

1.4 Outline of the Research

In the context of this thesis's framework, the structure and content of the research endeavor are delineated. The first chapter encompasses the introduction, providing clear goals and objectives. It culminates with the articulation of three pivotal research questions. Moving to the second chapter, it dives into background information, providing relevant descriptions of cryptocurrencies, algorithmic trading, and the unsupervised ML models considered in the thesis. Additionally, this chapter offers insights into relevant metrics pivotal to the thesis. The subsequent chapter, Chapter 3, is dedicated to data preparation, encompassing data ingestion, feature engineering, and normalization processes essential for the study's progression. Chapter 4 delves into methodology, detailing the reduced universe formation process, strategy definition, and market momentum signaling. Moreover, this chapter delineates the performance metrics utilized to assess the experimental results. Chapter 5 engages in an in-depth discussion of the main findings, as well as the limitations inherent in this work. Finally, Chapter 6 serves as the platform for presenting the conclusions and outlining avenues for future research.

2. Literature Review

This chapter presents the fundamental concepts put into practice throughout this thesis.

2.1. Crypto

2.1.1. Crypto Currencies

Cryptocurrency, a digital currency that is completely decentralized and works based on peer-to-peer transactions, has catalyzed innovative models of payment and financing within the global economic landscape. Originating from the work of Chaum (1983) who intended to mitigate issues like double-spending while ensuring user anonymity.

Cryptocurrencies similarly to gold, offered an alternative for those who lost confidence in the banking system during the financial crisis (Acharya, Philippon, Richardson, & Roubini, 2009).

In a study conducted by Yermack (2015), an assessment of Bitcoin as a currency concluded that it fails to satisfy all the requirements of a currency. Yermack argued that Bitcoin behaves more like a speculative investment than a currency, as it does not fulfill the criteria of being a store of value, a medium of exchange, and a unit of account, which are essential attributes of fiat money. Instead, the author suggested that Bitcoin occupies a position somewhere between money and a commodity. This view is supported by Dierksmeier & Seele (2018), who found that cryptocurrency prices exhibit significant volatility on a daily basis, challenging their suitability for classification as currency.

Nakamoto (2009) outlines that ownership of Bitcoin entails the storage of a private key. A bitcoin, in essence, represents a record of transactions between different addresses within the Bitcoin network, a design structure that has been closely emulated by other cryptocurrencies.

2.1.2. Crypto Market

The cryptocurrency market operates through decentralization and peer-to-peer transactions, facilitated by blockchain technology. This decentralized setup, coupled with limited regulatory oversight, fosters a volatile and speculative environment, prompting careful trading strategies. However, liquidity and market efficiency remain subject to ongoing assessment (Dierksmeier & Seele, 2018).

Studies on cryptocurrency market dynamics reveal the intricate connections between liquidity, price predictability, and market efficiency. Brauneis & Mestel (2018) observe that as liquidity in the cryptocurrency market increases, the predictability of price movements diminishes. This relationship suggests that higher liquidity leads to more efficient markets, where the bid-ask spreads, which represent the difference between the prices buyers are willing to pay and sellers are asking, also play a role in enhancing this efficiency.

While cryptocurrencies offer short-term diversification benefits for investors, their long-term viability is heavily influenced by macro-financial indicators. The debate over their classification as money continues, with scrutiny on their effectiveness as mediums of exchange, units of account, and stores of value. Dierksmeier & Seele (2018) highlight that these aspects are still under significant examination, reflecting the ongoing uncertainty surrounding the true utility and stability of cryptocurrencies in the financial

system.
In conclusion, the cryptocurrency market signifies a fundamental shift in currency and financial transactions. With its decentralization, innovation, and volatility, it presents both opportunities and challenges in the global economic landscape.

2.2. Algorithmic Trading

Algorithmic trading has become a fundamental component of investing strategies in the global financial markets (European Central Bank, 2019). It signifies a shift away from manual techniques by automating the execution of trades, hence removing the impact of human emotions and biased decision-making that frequently result in irrational outcomes (Narang, 2009). Moreover, algorithmic trading facilitates the immediate examination of extensive datasets, permitting traders to swiftly react to market dynamics and capitalize on opportunities. Having originated more than thirty years ago, its extensive acceptance has significantly increased since the mid-1990s, infiltrating the methods of traders, investment banks, and funds alike. Algorithmic trading is based on the automation and optimization of trading strategies, using computational algorithms to execute deals accurately and quickly (European Central Bank, 2019).
In the future, algorithmic trading is expected to undergo substantial development. The progress in artificial intelligence and machine learning is poised to transform trading techniques, allowing computers to adjust and develop coordinated with changing market conditions.

2.2.1. Time Series

Time series analysis is central to algorithmic trading, representing the realization of stochastic processes. Stochastic processes encompass a range of time-indexed random variables, while time series consist of sequential observations gathered through continuous measurements over time. This framework is instrumental in deriving insights from historical price data (Hillmer, 1991).
In this thesis, we consider only discrete time series perceived in equal time intervals.

2.2.2. Trend Following

Trend following strategies represent a fundamental pillar of algorithmic trading methodologies, capitalizing on the momentum of market trends to generate profits. These strategies, pioneered by industry luminaries like Ed Seykota, utilize sophisticated patterns to identify and exploit sustained price movements in the market. By aligning trades with prevailing trends, traders aim to ride the momentum and capture significant gains. However, the challenge lies in accurately identifying and sustaining trends, as markets tend to exhibit trending behavior only a fraction of the time. Despite this, trend-following strategies have demonstrated significant efficacy, particularly in capturing substantial gains during trending market phases. (Narang, 2009)

2.3. Machine Learning Methods

A significant branch of AI, machine learning (ML) allows computers to improve their performance by analyzing data and applying their learnings, all without human intervention. ML allows for automated decision-making, forecasting, and spotting of

patterns by utilizing statistical models and algorithms.
There are main categories of machine learning algorithms, each with its unique way of analyzing data.
Supervised learning algorithms are taught using labeled data, in which each training instance is linked to a specific goal or result. The objective is for the algorithm to be able to anticipate outcomes based on previously unseen data by learning a mapping function that connects input variables to output variables. Supervised learning is commonly employed in tasks such as diagnosing medical conditions based on patient data and forecasting stock prices using historical and financial indicators. (Kotsiantis, 2007)
Unsupervised learning is the training of an algorithm to identify patterns or structures in data without the use of labels or any human interaction. The algorithm autonomously discovers novel insights and connections within the dataset, without requiring any human input or predefined target variables. Unsupervised learning often encompasses tasks such as grouping and dimensionality reduction. Dimensionality reduction techniques, such as principal component analysis (PCA), uncover latent patterns in data with a large number of dimensions (Gentleman & Carey, 2008).
Semi-supervised learning algorithms aim to optimize the performance of supervised learning models by leveraging the additional information provided by unlabeled data. This approach excels in scenarios when there is a scarcity of labeled data and a surplus of unlabeled data, a circumstance that is frequently seen in real-world contexts (van Engelen & Hoos, 2020).

2.3.1. Support vector machine

Support Vector Machine (SVM) is a supervised learning model adept at handling data classification and regression tasks. Operating effectively in high-dimensional spaces, SVM identifies the optimal hyperplane to maximize the margin between different classes of data points, exhibiting capabilities in both linear and nonlinear classification (Pisner & Schnyer, 2020). However, SVM's performance may suffer with large datasets or in the presence of noise.
One-Class SVM, a specific case of the support vector machine, exemplifies unsupervised machine learning. It can train with unlabeled data, distinguishing between inliers and outliers. One-Class SVM achieves this by separating all data points from the origin and maximizing the distance from this hyperplane to the origin (Schölkopf, Williamson, Smola, John , & Platt, 1999).

2.3.2. Principal component analysis

Principal Component Analysis (PCA) is a widely used technique for dimensionality reduction, enhancing interpretability by extracting significant features from high-dimensional datasets. By projecting data onto a lower-dimensional subspace, PCA improves computational efficiency and minimizes information loss. This method is invaluable for exploratory data analysis, feature extraction, and visualization tasks across diverse domains (Song, Guo, & Mei, 2010).

2.3.3. Anomalies and outliers

While the terms "outliers" and "anomalies" are often used interchangeably, their distinction is nuanced yet crucial in data analysis, as they represent distinct concepts

with subtle differences in meaning and interpretation.
Outliers, as defined by Grubbs (1969), are data points that significantly deviate from the majority of data points in a dataset. These deviations are typically characterized by exceptional values or placements relative to the distribution of the data. Outliers may arise due to measurement inaccuracies, inherent variability, or infrequent occurrences within the data. They are often identified using statistical metrics such as standard deviation, z-scores, or interquartile range, with a focus on the distributional properties of the data. Importantly, outliers do not necessarily imply deviant behavior or pose significant threats to the underlying system or process. As such, they may be treated as benign data points that can be safely ignored or removed from the dataset without significant consequences.
On the other hand, anomalies encompass a broader range of atypical or unforeseen observations within a dataset. While outliers represent a subset of anomalies, anomalies can include various types of irregularities, patterns, or behaviors that deviate from expected norms or distributions (Chandola, Banerjee, & Kumar, 2009). Anomalies may arise from systemic failures, fraudulent activities, unexpected events, or emerging trends that are not adequately captured by the existing data model. Consequently, more sophisticated algorithms may be required to identify anomalies that are not readily apparent through simple statistical analyses.
The distinction between outliers and anomalies underscores the importance of considering the broader context, domain knowledge, and specific objectives when analyzing data and identifying irregularities. By understanding these distinctions, data analysts and decision-makers can effectively interpret the results of anomaly detection methods and make informed decisions to address potential risks or opportunities within their datasets.

2.3.4. Anomaly Detection

Anomaly detection, also known as outlier detection, is a critical task in various fields, including cybersecurity, finance, healthcare, and industrial monitoring (Singh & Upadhyaya, 2012).
Anomaly detection techniques leverage various methods, including statistical analysis, machine learning algorithms, and domain-specific knowledge. One common approach is to use machine learning algorithms to automatically learn patterns from data and detect anomalies based on deviations from those patterns.
Supervised anomaly detection involves training a model on labeled data, where anomalies are explicitly marked. The model learns to distinguish between normal and anomalous instances based on the provided labels. This approach is effective when labeled data is readily available and when anomalies are well-defined. However, it may not perform well in cases where labeled data is scarce or when anomalies are not clearly defined.
Unsupervised anomaly detection, on the other hand, does not require labeled data. Instead, it relies on identifying instances that are significantly different from most of the data. Clustering algorithms, density estimation techniques, and distance-based methods are commonly used in unsupervised anomaly detection. While unsupervised methods are more versatile and applicable to a wide range of scenarios, they may struggle to accurately detect anomalies in complex datasets with high-dimensional features (Guthrie, Guthrie, Allison, & Wilks, 2007).

Anomaly detection methods must be carefully selected based on the characteristics of the data and the specific requirements of the application. Factors such as the type of anomalies present, the availability of labeled data, and the computational resources required for training and inference play crucial roles in determining the most suitable approach.

2.4. Metrics Relevance

2.4.1. Momentum

Time-series momentum, a strategy focusing on an asset's absolute performance over a historical period, has garnered attention in financial research. Moskowitz et al. (2012) found compelling evidence supporting this strategy across various securities, suggesting that past returns positively predict future returns. This phenomenon, known as the time-series momentum effect, is attributed to significant autocovariance in returns, particularly during periods of market volatility. However, skepticism exists regarding the robustness of these findings, with some researchers attributing the observed returns to volatility scaling rather than true predictive power (Kim, Tse , & Wald, 2016). Despite its popularity, time-series momentum rules often underperform moving average rules, indicating the complexities of implementing this strategy effectively.

2.4.2. Technical Indicators

Technical analysis is a methodology that use historical market data to forecast future price changes. The idea behind its operation is that market activity encompasses all accessible information and that previous pricing patterns tend to recur. Analysts employ a range of techniques and indicators, including moving averages and chart patterns, to discern trends and provide trade recommendations.

While technical analysis offers a systematic approach to market analysis, its effectiveness remains unregular over time (Zakamulin, 2014). Some studies suggest that market timing with moving averages can outperform passive strategies, highlighting the potential value of technical analysis in investment decision-making (Kilgallen, 2012).

3. Data

3.1. Data Source

The foundation of the proposed system relies on a curated collection of time series data, which is fundamental for extracting meaningful features. This study utilizes cryptocurrency time series data sourced from Binance's API, a leading data provider renowned for its extensive coverage of cryptocurrencies. Each time series corresponds to a cryptocurrency exchange pair, consisting of a base currency and a quote currency, and is acquired for a predefined timeframe and frequency. The study focuses exclusively on cryptocurrency pairs with the quote currency USDT (Tether) to ensure that all data points are standardized. While Binance offers a range of time resolutions from one minute to one month, this thesis focuses exclusively on hourly intervals. This strategic decision strikes a balance between granularity and space efficiency, aligning with the objectives of this thesis. This work tracks a total of 457 symbols during the analysis period aiming to achieve a comprehensive yet manageable exploration of cryptocurrency market dynamics.

3.2. Data Ingestion

Candle Stick Charts

Candlestick charts serve as valuable tools for gaining insights used in various technical indicators. They visually depict the relationship between two assets values over time, typically involving at least one currency. Technical analysis frequently centers on examining these charts to discern patterns and trends. The fundamental unit of a candlestick chart is a candle, which represents a consistent time length. Each candle provides information on the highest, lowest, opening and closing prices for that specific period. Additionally, separate graphs often depict the total asset volume traded and the total number of trades associated with each period.

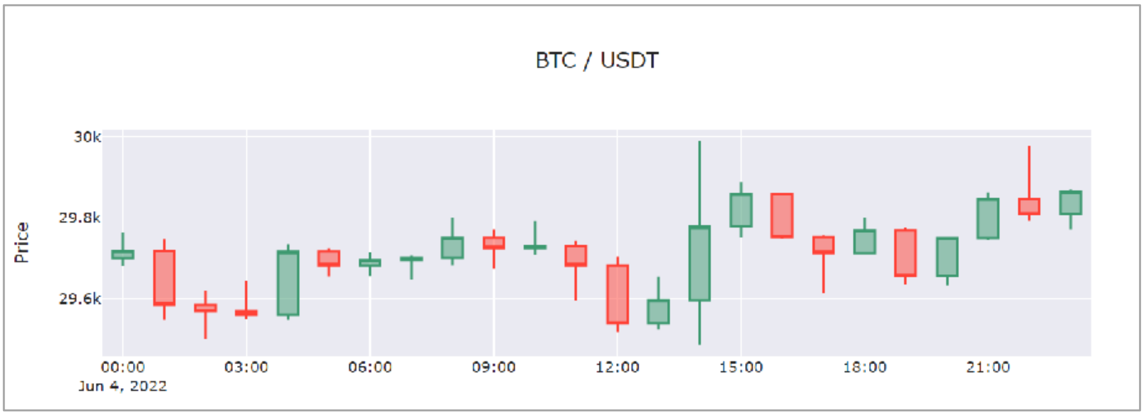


Figure 3.1: Candlestick chart with hourly candles of the pair Bitcoin / USD Tether.

3.2.1. Raw Field Descriptions

In the following table, we can observe the description and type of data for all fields ingested each hour.

Table 3.1: Description and Type of Data for All Fields Ingested Each Hour

Field Name	Field description	Data Type
symbol	A trading pair composed of a base currency and a quote currency	Text
Open Time	The start time of the candlestick	Timestamp
Open Price	The price of the asset when the candlestick opened	Numeric (25,10)
High Price	The highest price of the asset during the candlestick's duration	Numeric (25,10)
Low Price	The lowest price of the asset during the candlestick's duration	Numeric (25,10)
Close Price	The price of the asset when the candlestick closed	Numeric (25,10)
Close Time	The closing time of the candlestick	Timestamp
Quote Asset Volume	The volume of the asset traded in terms of the quote asset during the candlestick's duration	Numeric (25,10)
Number of Trades	The number of trades executed during the candlestick's duration	Integer
Taker Buy Base Asset Volume	The volume of the asset bought by takers during the candlestick's duration	Numeric (25,10)
Taker Buy Quote Asset Volume	The volume of the quote asset bought by takers during the candlestick's duration	Numeric (25,10)

3.3. Data Preparation

A dataset comprises multiple observations, termed a sample, characterized by a set of values referred to as features. Missing data is a prevalent source of errors in code, often triggering exceptions. Attempting to remove missing values may significantly reduce the available data while distorting the truth, a scenario detrimental in machine learning. One of the most familiar challenges encountered in data cleaning and exploratory analysis is managing missing values.

To maintain fidelity to Binance's provided truth, this thesis opts not to manage any missing values. Instead, missing data is interpreted as indicative of periods of market or cryptocurrency trading pair inactivity. The dataset undergoes preprocessing and normalization before analysis to optimize the data for said analysis.

3.3.1. Feature Engineering

Feature engineering (FE) is a machine learning technique aimed at enhancing the effectiveness of models by transforming raw data into more meaningful variables known as features. By extracting domain-specific features from the data, FE not only accelerates the learning process but also elevates the model's performance, ensuring a more accurate representation of the underlying problem.

Simple Percentage Change

This work adopts a methodology that calculates percentage changes in variables by means of different speeds (or lookback periods):

$$R^c_{t,t-h} = \frac{P^c_t}{P^c_{t-h}} - 1$$

Figure 3.2: Simple Percentage Change Equation

- $R^c_{t,t-h}$ is the return of cryptocurrency c between hour $t-h$ and t
- P^c_{t-h} is the price of cryptocurrency c at close of hour $t-h$
- P^c_t is the price of cryptocurrency c at close of hour t

Moving Averages

The moving average (MA) is a widely employed technical indicator in financial analysis (Glendrange & Tveiten, 2016). Its primary role is to smooth out short-term fluctuations, improving the interpretation of trends through a line derived from successive averages. As new trading periods unfold, the moving average is recomputed by introducing current information while discarding the oldest information, thereby shifting the average along the time scale. This indicator is therefore classified as a lagging indicator due to its reactive nature relying solely on past prices to confirm trends even though it aids in trend prediction by filtering out noise from random price fluctuations, achieved through averaging a fixed size of historical price levels known as the lookback period. In this thesis, two types of MA are employed: the Simple Moving Average (SMA), which assigns equal weights to all time scales, and the Exponential Moving Average (EMA), which uses exponential weighting with a decay factor λ as a sensitivity adjustment to recent prices.

$$SMA_{t,l} = \frac{1}{l+1}\sum_{i=0}^{l} P^c_{t-i}$$

Figure 3.3: Simple Moving Average Equation

$$EMA_{t,l} = \frac{\sum_{i=0}^{l} \lambda^i P^c_{t-i}}{\sum_{i=0}^{l} \lambda^i}$$

Figure 3.4: Exponential Moving Average Equation

- P^c_{t-i} is the price of cryptocurrency c at close of hour $t-i$
- λ is the decay factor , $0 \prec \lambda \preccurlyeq 1$
- l is the lookback period in hours

Bollinger Bands

Bollinger Bands (BB) focus on volatility as a key by using standard deviation in band calculations. The bands are made by a central line using SMA, and upper and lower bands mirroring this average by standard deviations creating non-symmetric bands unlike moving average envelopes, which shift bands relative to the average. Aimed at creating bands sensitive to extreme deviations with quick reaction to large price fluctuations, this approach suggests a lookback period of twenty units with two standard deviations (Williams, 2006). Bollinger Bands are versatile, applicable to various data frequencies from intraday to monthly. Rather than giving absolute buy or sell signals, Bollinger Bands assess whether prices are high or low relative to recent history. They offer a framework for understanding price movements in relation to indicators, emphasizing a relative perspective.

$$MB_{t,h} = \frac{\sum_{i=0}^{h} P_{t-i}^{c}}{h}$$

$$UB_{t,h} = MB_{t,h} + D\sqrt{\frac{\sum_{i=0}^{h}\left(P_{t-i}^{c} - MB_{t,h}\right)}{h}}$$

$$LB_{t,h} = MB_{t,h} - D\sqrt{\frac{\sum_{i=0}^{h}\left(P_{t-i}^{c} - MB_{t,h}\right)}{h}}$$

$$BBP_{t,h} = \frac{P_{t}^{c} - LB_{t,h}}{UB_{t,h} - LB_{t,h}}$$

Figure 3.5: Bollinger Band Equations

- P_{t-i}^{c} is the price of cryptocurrency c at close of hour $t - i$
- h is the number of hours in the lookback period
- t is the current hour
- $MB_{t,h}$, $UB_{t,h}$ and $LB_{t,h}$ are respectively the Middle, Upper and Lower Band values at the close of hour t having a lookback period of h hours
- $BBP_{t,h}$ is the Bollinger Bands Percentage (BBP), which is a metric used to gauge where the current price is relative to the Bollinger Bands.

Relative Strength Index

The Relative Strength Index (RSI) serves as a momentum oscillator, evaluating the speed and size of price changes to determine if a market is overbought or oversold. Typically calculated using a lookback period of fourteen units, the RSI compares the average gain of up periods to the average loss of down periods within this timeframe. Its values range from 0 to 100, with readings above 70 indicating overbought conditions and those below 30 suggesting oversold conditions with divergence between RSI and price often anticipating a potential trend reversal (Rani, 2020).

$$RS_{h} = \frac{Average\ Gain_{h}}{Average\ Loss_{h}}$$

$$RSI_h = 100 - (\frac{100}{1 + RS_h})$$

Figure 3.6: Relative Strength Index Equation

- h is the number of hours in the lookback period
- t is the current hour
- $Average\ Gain_h = \frac{Sum\ of\ Gains_t}{h}$
- $Average\ Loss_h = \frac{Sum\ of\ Losses_t}{h}$
- $Gains_t = \{\Delta P_t^c \mid P_t^c > 0\}$
- $Losses_t = \{\Delta P_t^c \mid P_t^c < 0\}$

Coefficient of Variance

The coefficient of variation (CV) measures the relative variability of a dataset compared to its average, i.e.

$$CV = \frac{\sigma}{\mu}$$

Figure 3.7: Coefficient of Variance Equation

- Where σ is the average of the dataset,
- And μ is the measure of the dispersion or variability of the dataset.

3.4. Data Normalization

Dataset scaling, or normalization, is a critical preprocessing step in machine learning pipelines aimed at harmonizing feature scales to ensure uniformity. This adjustment is essential for enhancing the performance of classification models.

Equalizing the scales of features prevents attributes with larger or wider numerical ranges from dominating those with narrower or lower ranges. This prevents biases that could otherwise arise, ensuring that attributes contribute proportionally to the analysis regardless of scale. Consequently, dataset scaling mitigates bias and improves classification performance.

Research consistently supports the idea that scaling data before model training significantly boosts performance compared to using non-scaled data. Selecting the most suitable technique is a crucial methodological decision, as studies have shown that an inappropriate scaling method can be more detrimental than not scaling the data at all. Thus, careful consideration is necessary to optimize model performance (Amorim, Cavalcanti, & Cruz, 2023).

Min-max Scaler

The Min-max Scaler is a technique used to transform feature scales, ensuring that the transformed values fall within the interval [0,1]. In this method, the scaling factor is determined by the attribute's range, while the minimum value determines the translational vector. As a result, this technique guarantees a new minimum of zero and a new maximum of one. However, it is important to consider that the Min-max Scaler may encounter difficulties in equalizing means and variances of distributions, particularly when dealing with data containing outliers. This limitation should be considered when deciding whether to use this method in data preprocessing.

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}}$$

Figure 3.8: Min-max Formula

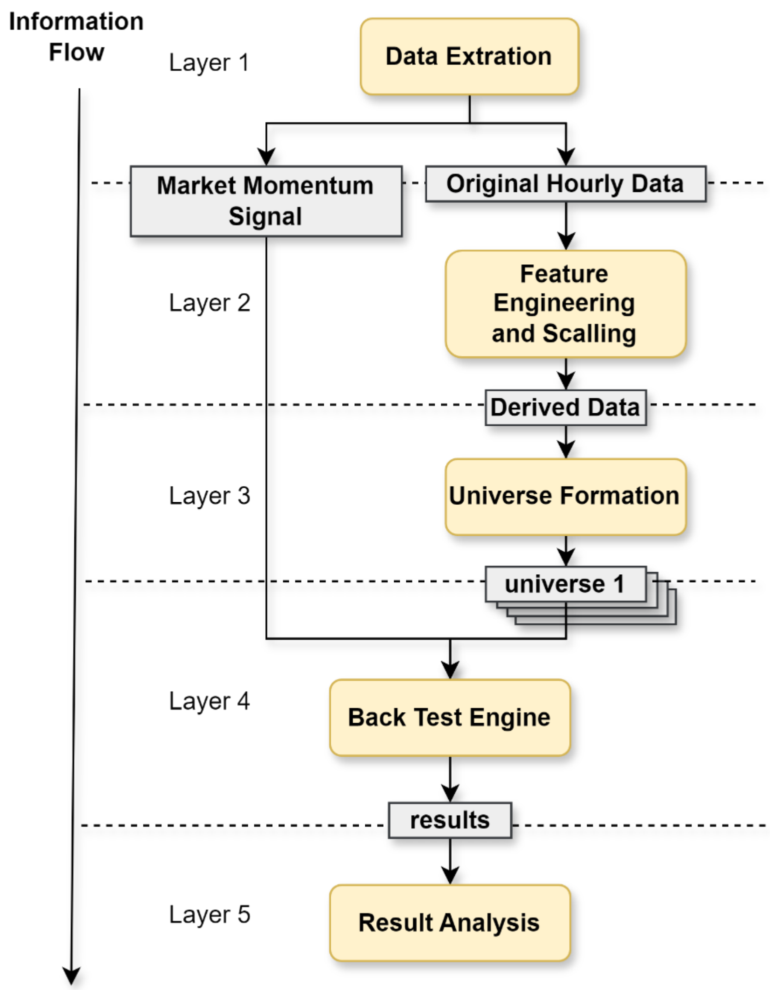
4. Methodology

The methodology section of this thesis delves into the comprehensive architecture of the framework employed for the analysis. It begins with an overview of the overall design, providing insight into how the various components interact and function cohesively. Following this, each section of the framework is examined in detail, highlighting the specific roles and operations that contribute to the system's performance. By systematically breaking down the architecture and its components, this section aims to offer a clear and precise understanding of the methodology underpinning the research.

4.1. Architecture

The system's architectural framework is organized into five hierarchical layers, each designed to support specific stages of data processing and analytical inquiry. Figure 4.1 provides a visual representation of the flow of information within the proposed solution. As depicted, the output of each layer serves as the input for the subsequent layer.

Figure 4.1: Hierarchical Flow of Information in the Proposed Solution.



1. Data extraction (Layer 1)
2. Feature engineering and scaling (Layer 2)
3. Universe construction and parameterization (Layer 3)
4. Algorithmic strategy testing (Layer 4)
5. Analysis of results (Layer 5)

In the first layer, the focus is on extracting relevant data, including 1-hour candle data from Binance's API spanning January 1, 2021, to March 31, 2024. Additionally, daily crypto market capitalization data is ingested to generate a momentum signal based on a 5-day percentage change simple moving average, elaborated further in Section 4.4.

Transitioning to the subsequent layer, attention shifts to feature engineering and scaling. Computational operations are performed to derive key metrics such as Relative Strength Index (RSI), Bollinger Bands (BB), Simple Moving Average (SMA), Exponential Moving Average (EMA), Coefficient of Variation (CV), and Previous Returns from the hourly binned dataset. Normalization procedures using Min-max Scaler are then applied, and metrics are categorized into momentum, growth, and technical indicators.

The third layer orchestrates the construction of universes and their parameterization. Diverse universes are created through combinations of metric groups, lookback periods, universe size, and selection methodologies with a deep dive in Section 4.2.

The fourth layer is dedicated to the systematic evaluation of algorithmic trading strategies. Three distinct strategies are analyzed: a benchmark strategy based on momentum and two variations of trend-following strategies, an equally weighted portfolio approach and a time-weighted portfolio approach. These strategies undergo back testing across the various universes generated in the preceding layer, further explored in Section 4.3.

In the final layer, results analysis takes place. Performance metrics, described in Section 4.5 are assessed over a three-year trading horizon, with a focus on their performance during bullish, bearish, and neutral market conditions classified using the market momentum signal.

This structured approach provides a methodologically robust framework for systematically evaluating diverse trading strategies under varied market conditions, offering valuable insights into their effectiveness and resilience.

4.2. Parameterized Universe Formation

Parameterization is a critical aspect of universe formation in the analysis, enabling us to systematically explore the efficiency and robustness of each of the parameter's value decision. Rather than arbitrary selection, this methodical approach aims to inform future work and enhance strategy effectiveness. In the upcoming section, this thesis will present the range of values for each parameter under consideration. These values are meticulously chosen to encompass various market scenarios and trading strategies. While also providing a brief rationale for including each value range, outlining the logic behind our selection process. Through this thorough exploration, the goal is to highlight the diverse range of parameter combinations and their potential impact on strategy performance.

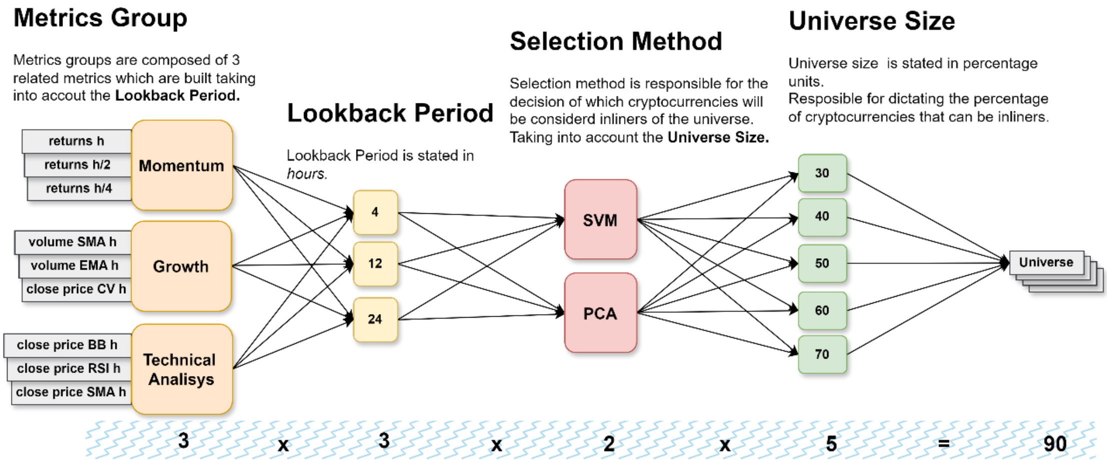


Figure 4.2: Parameterization Exploration for Universe Formation

4.2.1. Metrics Groups

From the spectrum of metrics described in Section 3.3 of this thesis, three distinct metric groups were constructed, each composed of three different metrics. The decision criteria for coupling the metrics are based on the similarity of the information they provide while maintaining their individuality.

The first group of metrics, referred to as momentum, is constructed using three metrics of past returns, each with a different lookback period. This enables a thorough examination of momentum dynamics across various temporal scales.

For the study of growth, a group of metrics is composed of the Simple Moving Average (SMA) and the Exponential Moving Average (EMA) of the quote currency volume for each trading pair, along with the Coefficient of Variation (CV) of the price. This combination aims to capture various facets of growth dynamics within the market, enabling a nuanced analysis of evolving trends and patterns.

Finally, a technical analysis group is formed using Bollinger Bands (BB), the Relative Strength Index (RSI), and the SMA of the cryptocurrency price. This group offers valuable insights into market momentum, volatility, and trend direction, facilitating a comprehensive evaluation of technical indicators and their influence on trading strategies.

Table 4.1: Metrics Groups for Universe Formation

Metrics Group	Feature 1	Feature 2	Feature 3
Momentum	SIMPLE PERCENTAGE CHANGE h	SIMPLE PERCENTAGE CHANGE $h/2$	SIMPLE PERCENTAGE CHANGE $h/4$
Growth	VOLUME SMA h	VOLUME EMA h	CLOSE PRICE CV h
Technical Analysis	BBP h	RSI h	CLOSE PRICE SMA h

- Where h is the lookback period

4.2.2. Lookback Period

In the parameterization of lookback periods, we are assessing three distinct intervals: 4, 12 and 24 hours. These intervals determine the historical data window used in our analysis to assess market trends and inform trading decisions. It is worth noting that these lookback periods are selected based on their relevance to our strategy, particularly in the context of rebalancing portfolios every 4 hours.

- $h \in \{4, 12, 24\},\ in\ hours.$

4.2.3. Selection Method

For the selection method, we begin by organizing all symbols within the universe during the observation timeframe into a cube of 1x1x1, considering that the data has already been scaled.
Subsequently, we employ one of two methods. The first method utilizes Support Vector Machines (SVM), employing one-class classification to delineate a polynomial function defining the highest-density area encapsulating symbols classified as inliners. Due to computational constraints, we refrain from conducting a parameter grid search to optimize decision-making. Instead, we utilize specific parameters for both kernel and degree parameters:

- $kernel = poly$
- $degree = 3$
- $nu = pct$

As an alternative, we consider implementing a higher-dimensional decision-making function or reducing dimensionality. Given roughly 400 symbols per rebalance period on average, we opt for dimensionality reduction. To achieve this, we pass the three-dimensional data through Principal Component Analysis (PCA), reducing it to one dimension. Subsequently, a Euclidean-based algorithm detects the minimal range within this one-dimensional space capable accommodating pct of all cryptocurrencies.

- pct is the value used to state the universe size.

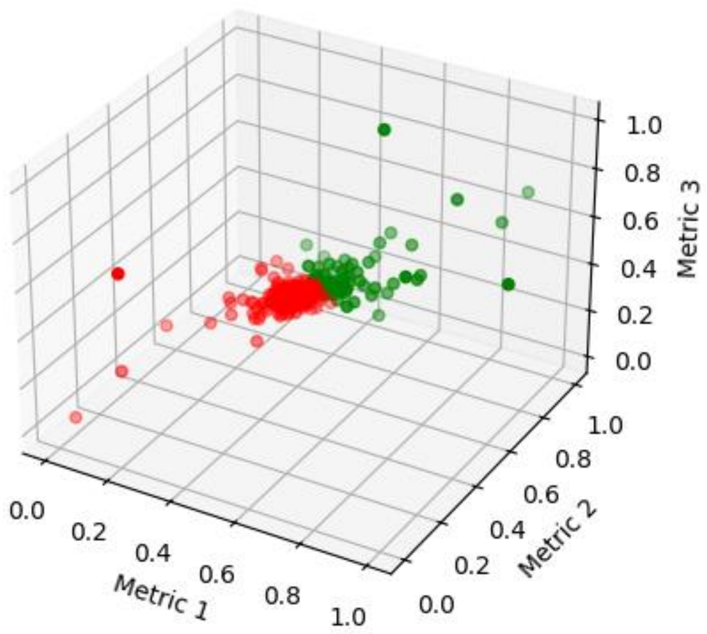


Figure 4.3: SVM selection method example.

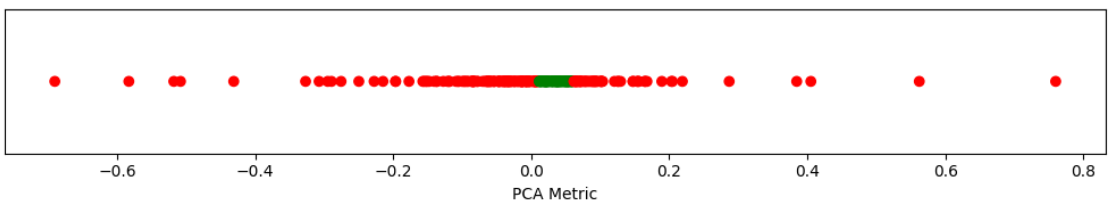


Figure 4.4: PCA selection method example.

4.2.4. Universe Size

In the selection of values for the universe size, the range has intentionally been made very wide. This parameter dictates the percentage of inliners to keep from the original universe of cryptocurrencies existent during the rebalance period. By creating a range from high to low, we aim to study the performance from a very strict rule of admission into the universe—based on finding the highest density cluster possible—all the way to a rule that resembles outlier removal, aimed at eliminating only those cryptocurrencies that deviate significantly from the main cluster of cryptocurrencies. This research methodology has been chosen due to the lack of experimental research in this topic.

- $pct \in \{30, 40, 50, 60, 70\}$ in percentage units

4.3. Algorithmic Trading Strategies Back Testing

The back testing process enables us to evaluate the effectiveness and profitability of a spectrum of trading strategies using historical data provided by each reduced universe already computed. This section of the thesis aims to describe the workflow of the back test engines and the specific actions unique to each one. The main framework shared by all back test engines can be depicted in the figure below:

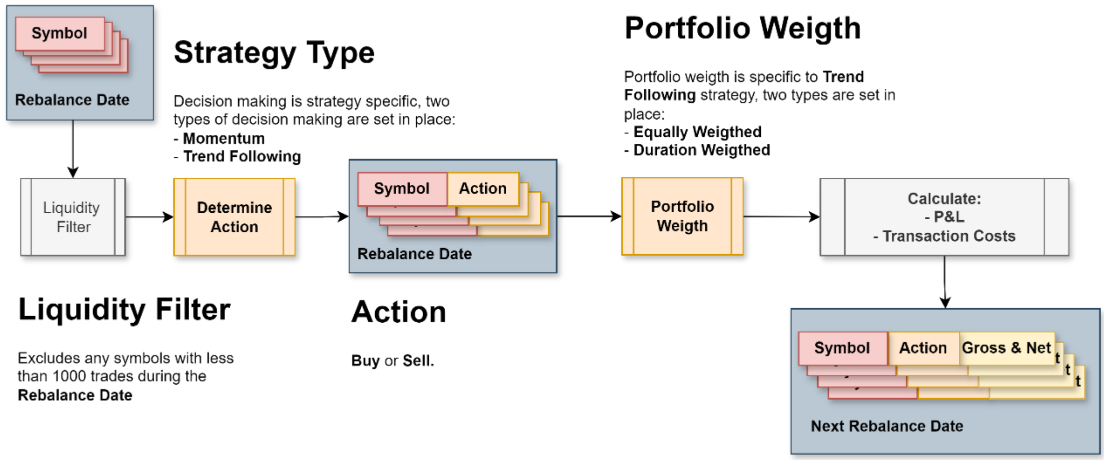


Figure 4.5: Algorithmic Trading Strategy workflow.

Two processes are agnostic to each iteration of the back test engine. First, a liquidity filter is applied, responsible for removing any cryptocurrency that does not have enough trades during the rebalance hour. Utilizing a threshold of at least one thousand trades during the 1-hour period. Second, the calculation of profit or loss during the rebalancing period and the calculation of transaction costs associated with the reshuffling of cryptocurrencies in the portfolio and their weights, with a transaction cost of five basis points (bps). Transaction costs play a crucial role in evaluating the performance of trading strategies (Lesmod, Schill, & Zhou, 2004). In this study, a transaction cost of 5 bps was established based on an estimate of a 15 to 20 million USDT trade volume during a 30-day period with an initial capital of 150 to 200 thousand USD.

4.3.1. Strategy Type

Momentum Strategy

This thesis opts to utilize the time-series momentum methodology as the benchmark strategy for generating trading signals in the cryptocurrency market. Following closely the approach proposed by (Levine & Pedersen, 2015) in their Time Series Momentum Strategy (TSMOM), which involves creating trading signals based on historical returns for predetermined lookback periods of 1, 3, and 12 months.

However, recognizing the fast-paced nature of the cryptocurrency market, we have decided to adopt a strategy with a shorter lookback period of 4 hours. This adjustment allows us to better capture and respond to the rapid price movements characteristic of the cryptocurrency space.

Under this strategy, a signal to initiate a long position is generated when the asset's price has exhibited upward movement over the specified 4-hour period. Conversely, a signal to go short is triggered when the price has demonstrated a downward trend within the same timeframe. This approach enables us to leverage time-series momentum analysis to inform our trading decisions in the dynamic cryptocurrency market environment.

$$signal_t^c = \begin{cases} 1, & P_t^c - P_{t-i}^c \geq 0 \\ -1, & P_t^c - P_{t-i}^c < 0 \end{cases}$$

- P_{t-i}^c is the price of cryptocurrency c at close of hour $t - i$
- P_t^c is the price of cryptocurrency c at close of hour t
- t is the current hour
- $signal_t^c$ is the signal for the action to perform on cryptocurrency c on the hour t

Trend Strategies

Trend-following strategies have demonstrated profitability by correlating market actions with bullish movements prompting buying and selling during bearish markets (Rozario, Evans, Holt, & West, 2020). These strategies have been assessed across various markets over the past century, typically over 12-month periods. In this thesis, a short lookback period is chosen based on findings from previous studies, particularly those focused on the crypto market.

Trend analysis often employs tools such as trend lines to depict directional and strength information of trends, typically characterized by the duration and slope of the line. The strategy adopted for this project closely follows this rationale. Hourly price data for cryptocurrencies within a reduced universe are considered, with a historical lookback extending to the earliest consecutive appearance of each cryptocurrency in the reduced universe.

Cryptocurrencies that have appeared only once, in the previous rebalancing period, indicating instability or lack of confidence, are discarded. A regression line will then be constructed using the hourly data to determine the slope (or strength) of the trend, as well as the duration of the trend, representing the number of consecutive periods the cryptocurrency has been included in the universe.

Cryptocurrencies exhibiting a positive slope are bought, while those with a negative slope are sold. The duration will come into play in the portfolio weighting section of the thesis, as outlined in Section 4.3.2.

$$LR_c^N = \alpha x + \beta$$

$$Action_c = \begin{cases} 1, & \alpha \geq 0 \\ -1, & \alpha < 0 \end{cases}$$

- LR_c^N is the linear regression of cryptocurrency c with number of consecutive rebalance periods N

- α is the slope of linear regression
- $Action_c$ is the action for cryptocurrency c

4.3.2. Portfolio Weight

The portfolio weight is responsible for determining the weight of each cryptocurrency with the same action of buy or sell until the next rebalancing period of 4 hours.
In this thesis, two types of decision criteria were implemented. First, an equally weighted approach was utilized, where all cryptocurrencies are given the same amount of relevance in our portfolio. This method is employed in both the momentum and trend-following trading strategy approaches, and the portfolio weight is defined as:

$$PortfolioWeigth_c = \frac{1}{\sum c}$$

- Where $\sum c$ is the summation of cryptocurrencies in the portfolio.

Second, the time-weighted approach is solely used with the trend-following strategy. In this approach, the weight of each token in the portfolio is determined by the number of consecutive rebalancing periods it has remained an inlier, it's duration. This method aims to adjust the portfolio dynamically based on both the trend direction and the token's stability. Additionally, a maximum time limit of five periods is implemented to prevent overly stable coins from dominating the portfolio dynamics, ensuring a balanced allocation. The portfolio weight is defined as:

$$Time_c = min(N_c, 5)$$

$$PortfolioWeigth_c = \frac{Time_c}{\sum Time_c}$$

- Where N_c is the number of consecutive rebalance periods with cryptocurrency c considered inliner
- And $\sum Time_c$ is the summation of all $Time_c$ for all cryptocurrencies in the same rebalance period

4.4. Market Momentum Signal

In addition to evaluating a reduced universe and a trading strategy component, we aim to assess the combinations' performance across temporal spaces defined as bullish, bearish, or neutral, across multiple confidence levels. These confidence levels serve as parameters that introduce sensitivity regulators for the classification of market momentum. This assessment will help us understand if there is relevant information to be obtained from the overall market momentum that can significantly impact our decision of reduced universe and trading strategy combination, and if so, how important it is.
The classification task begins by computing the daily percentage change of the market capitalization data, followed by the calculation of its 5-day simple moving average.

Following a systematic approach, we evaluate five confidence levels for classifying daily market momentum. It is important to note that the classification provided for day d are used on day $d + 1$ to avoid introducing lookahead bias. The market classification can be defined as:

$$Market\ Class^{d+1} = \begin{cases} Bull, & SMA_5^d \geq\ bps \\ Neutral, & -bps \leq SMA_5^d \leq\ bps \\ Bear, & SMA_5^d \leq -bps \end{cases}$$

- $Market\ Class^{d+1}$ is the market momentum classification for the day $d + 1$
- SMA_5^d is the simple moving average of the percentage change over 5 days on the day d
- bps is the level of confidence in the classification provided
- $bps\ \in\ \{10, 20, 30, 40, 50\}$ in basis points.

4.5. Evaluation Metrics

To gauge the strategies' effectiveness, we have crafted a systematic evaluation method. This includes tracking key metrics, namely Average Profit and Loss (APL), Sharpe Ratio, Sortino Ratio, Max Draw Down (MDD), Kurtosis and Skewness which we describe next.

Average Profit and Loss

Average Profit and Loss (APL) quantifies the gain or loss from a series of trades by averaging the profits and losses of individual rebalancing periods. A high APL suggests a profitable strategy, while a low APL may indicate a less successful approach.

$$APL = \frac{\sum R_i}{n}$$

Figure 4.6: Average Profit & Loss Equation

- $\sum R_i$ is the time series containing returns on investment
- n is the number of rebalancing periods.

Sharpe Ratio

The Sharpe Ratio is a metric used to evaluate risk-adjusted returns by comparing the excess return of an investment to its risk. While not statistically significant on its own, it serves as a valuable tool for comparing the performance of assets or portfolios. Higher Sharpe ratios indicate better risk-adjusted returns, which is typically preferred by investors (Sharpe, 1998).

$$SR = \frac{ROI_p - R_f}{\sigma_p}$$

Figure 4.7: Sharpe Ratio Equation

- ROI_p is the average return of the asset/portfolio
- R_f is the risk-free rate
- σ_p is the standard deviation of the asset/portfolio

Sortino Ratio

The Sortino ratio offers a nuanced alternative to the Sharpe ratio. While the Sharpe ratio considers all volatility, including positive volatility, the Sortino ratio focuses solely on negative volatility. This adjustment addresses a limitation of the Sharpe ratio, where positive volatility can unfairly penalize the ratio. The Sortino ratio replaces the standard deviation with the downside deviation, which measures the volatility of returns below a specified minimum acceptable return (MAR), typically set to zero (Sortino, 1994).

$$DownsideDeviation(R_x) = \sqrt{\frac{\sum(R_i - MAR)^2 \quad where\ R_i \prec MAR}{n}}$$

$$SortinoRatio(x) = \frac{ROI_p - R_f}{DownsideDeviation(R_x)}$$

Figure 4.8: Sortino Ratio Equation

- ROI_p is the average return of the asset/portfolio
- R_f is the risk-free rate
- R_i is the time series containing returns on investment

Max Draw Down

Maximum drawdown is crucial for assessing downside risk in investments or strategies, representing the largest decline in a portfolio's value from peak to trough before a new peak is established. It provides insight into relative downside risk and is particularly relevant in volatile cryptocurrency markets. Considering maximum drawdown alongside volatility is essential when evaluating investment risks. (Magdon-Ismail, 2004)

$$MDD = max_{t \in (StartDate,\ EndDate)}\left[max_{t \in (StartDate,\ T)}(ROI_t) - ROI_T\right]$$

Figure 4.9: Max Draw Down Equation

Kurtosis

Kurtosis describes the tail shape of data distributions by comparing the weight of the tails to the center of the distribution. It is not a measure of the peakedness of the distribution. High kurtosis values indicate that the tails extend further from the center, while low kurtosis values indicate shorter tails and a sharper peak (Chouksey, 2018).

$$Kurtosis = \frac{\sum_{i=0}^{N}(Y_i - \bar{Y})^4/N}{S^4}$$

Figure 4.10: Kurtosis Equation

- $\bar{Y}$ is the mean
- S is the standard deviation
- N is the number of data points

Skewness

Skewness describes the symmetry of a distribution. Negative values indicate left skewness, while positive values indicate right skewness. When skewness is close to zero, the distribution approximates to symmetric (Chouksey, 2018).

$$Skewness = \frac{\sum_{i=0}^{N}(Y_i - \bar{Y})^3/N}{S^3}$$

Figure 4.11: Skewness Equation

- $\bar{Y}$ is the mean
- S is the standard deviation
- N is the number of data points

5. Results and Analysis

5.1. Results

For the discussion of results, we will have access to a total of 16,200 records. The rationale behind this number of records can be found in the table below, which describes each parameter used during the study, its relation to a process and the number of different values used.

Table 5.1: Parameter Overview

Parameters	Combinations
Universe Formation	90
Lookback Period	3
Metrics Group	3
Selection Method	2
Universe Size	5
Strategy Definition	12
Action	2
Strategy	3
Transaction Costs	2
Market Momentum Signal	15
Confidence Level	5
Market Class	3
Total Results	16200

The systematic approach of introducing parameters to test several values at each decision-making step of the algorithm has left us with a high dimensionality problem that can be assessed in a large variety of ways. This project adopts three different perspectives deemed relevant for the research questions proposed.

Firstly, the examination of the average performance metrics for each parameter's values, remaining agnostic to all other parameters in the study. This involves analyzing how each parameter independently influences the outcome, providing a clear understanding of their isolated effects.

Secondly, an analysis of the flow of the optimal set of parameter values across various organizational structures. This analysis includes a comprehensive examination of both the net and gross returns of the portfolios, factoring in transaction costs.

Finally, the third viewpoint focuses on the top 20 percent of records ranked by Average Profit and Loss (APL). This high-performing subset is scrutinized to identify common characteristics that lead to superior performance, providing insights into the most effective parameter configurations.

5.1.1. Best overall value per parameter

In this section, 16,200 combinations generated throughout this project are grouped solely on individual parameters.

Universe Formation Parameters

PCA consistently outperforms SVM across various return metrics as well as volatility and risk metrics, leaving no room for doubt about its overall superiority. Momentum metrics emerge as the top performers, while growth-oriented metrics exhibit the least skewness. A clear positive correlation is observed between universe size and performance, revealing low significance for the universe reduction effort. A mid-term lookback period of 12 hours proves to be the most reliable, offering balanced returns and risk management (see Appendix A).

Table 5.2: Selection Method Analysis.

Method	Trades	Sharpe	Sortino	MDD	APL	Kurtosis	Skewed	Count
PCA	2328	-1.1234	-0.0304	-0.7944	-0.0005	13.8905	-0.0411	8100
SVM	2328	-1.4739	-0.0395	-0.8329	-0.0007	26.8080	-0.2784	8100

Strategy Definition Parameters

Both equally weighted and time-weighted trend-following trading strategies surpass the benchmark momentum strategy, exhibiting similar risk levels. Notably, the weighted option stands out with superior return metrics and a higher Sharpe ratio (see Appendix B). A substantial performance differential is observed within the portfolio action decision, short portfolios outperform long portfolios, despite slightly higher kurtosis.

Table 5.3: Portfolio Action analysis.

Action	Trades	Sharpe	Sortino	MDD	APL	Kurtosis	Skewed	Count
Buy	2329	-2.4704	-0.0681	-0.9314	-0.001184	17.2754	-0.2824	8100
Sell	2329	-0.1269	-0.0018	-0.6959	0.000001	23.4231	-0.0371	8100

Market Momentum Signal Parameters

The neutral market class demonstrates the most promising values in terms of returns and risk metrics. However, it is important to note that the sample size for the neutral market is significantly smaller compared to the bull and bear markets, which reduces our confidence in these results. The bull market, with a sample size twice as large, ranks second, slightly outperforming the bear market in APL (see Appendix C). The analysis of market classification confidence levels indicates a negative correlation with performance metrics. In other words, as market confidence levels rise, performance tends to decrease.

Table 5.4: Market Class Confidence Level Analysis

Conf. Level	Trades	Sharpe	Sortino	MDD	APL	Kurtosis	Skewed	Count
10	2329	-1.2214	-0.0322	-0.7712	-0.0005	19.9119	-0.1135	3240
20	2329	-1.2912	-0.0350	-0.8033	-0.0006	20.4440	-0.1574	3240
30	2329	-1.3094	-0.0352	-0.8197	-0.0006	21.0207	-0.1912	3240
40	2329	-1.3290	-0.0359	-0.8323	-0.0006	20.3526	-0.1737	3240
50	2329	-1.3423	-0.0364	-0.8416	-0.0006	20.0170	-0.1630	3240

In summary, PCA, trend-following strategies with weighted portfolios, and lower confidence level market classifications emerge as the top performers in their respective categories.

5.1.2. Parameter Combination Analysis

In this section, the approach gradually reduces the combinations in the subgroups deemed most worthy of further analysis, proceeding in the order of market momentum signal parameters to strategy definition parameters to universe formation parameters.

Best Combinations for Long Portfolios

In this section, 8100 combinations of long portfolios are analyzed to determine the optimal parameter configuration for buying strategies.

The results indicate that the bull market class should be used for further analysis. While the neutral market class exhibits better risk factors, its smaller sample size and lower returns make it less suitable as the best approach. Within the bull market, the highest confidence level consistently outperforms across all metrics, except for skewness, which shows an interesting negative correlation by improving with lower confidence levels.

For the strategy component, the time-weighted trend-following trading strategy emerges as the best choice. The strategy is selected due to its high returns' potential and balanced risk factors, clearly outperforming other strategies in terms of both return metrics and risk management. Both the metrics group and selection method show no ambiguity, with the growth metrics group and PCA selection method performing the best among their peers. Although these combinations indicate a more risk-prone approach, they offer higher rewards.

When it comes to the universe size parameter, reducing the universe does not seem effective for long portfolios. Performance shows a clear trend of improvement as the size of the universe increases. This suggests that a larger universe provides better diversification and opportunities for higher returns. The lookback period, whether mid-term or short-term, performs similarly, allowing for some flexibility in this parameter's choice.

Amongst the long portfolios, this approach ranks 35th in terms of APL and 355th after accounting for transaction costs.

Figure 5.1: Net and Gross Returns of Best Long portfolio.

In conclusion, the best parameters combination for long portfolios in a buying strategy involves operating within a bull market, using a high confidence level, and employing a time-weighted trend-following strategy. The growth metrics and PCA method should be applied, with flexibility in the lookback period, although larger universes tend to yield better performance.

Best Combinations for Short Portfolios

In this section, 8100 combinations of short portfolios are analyzed to determine the optimal parameter configuration for selling strategies.
The results reveal that the best configuration appears in a bear market. This configuration achieves the highest Sharpe ratio and APL, although it does suffer from the highest kurtosis. The chosen strategy is a trend-following approach with a time-weighted portfolio, which effectively captures market trends and manages risks.
In terms of universe selection, the universe is reduced using SVM methodology. SVM proves to be superior overall, despite exhibiting higher skewness and kurtosis. This suggests that while SVM may introduce some additional risk, its overall performance benefits outweigh these drawbacks.
Returns are the preferred metrics in this analysis, consistently performing better across the board. Performance shows a clear trend of improvement as the size of the universe decreases despite resulting in higher maximum drawdowns and worse skewness.
For the lookback period parameter, longer timeframes demonstrate better performance overall, suggesting that an extended historical view aids in identifying more reliable trends.
Amongst the short portfolios, this approach ranks 10^{th} in terms of mean P&L and 29^{th} after accounting for transaction costs.

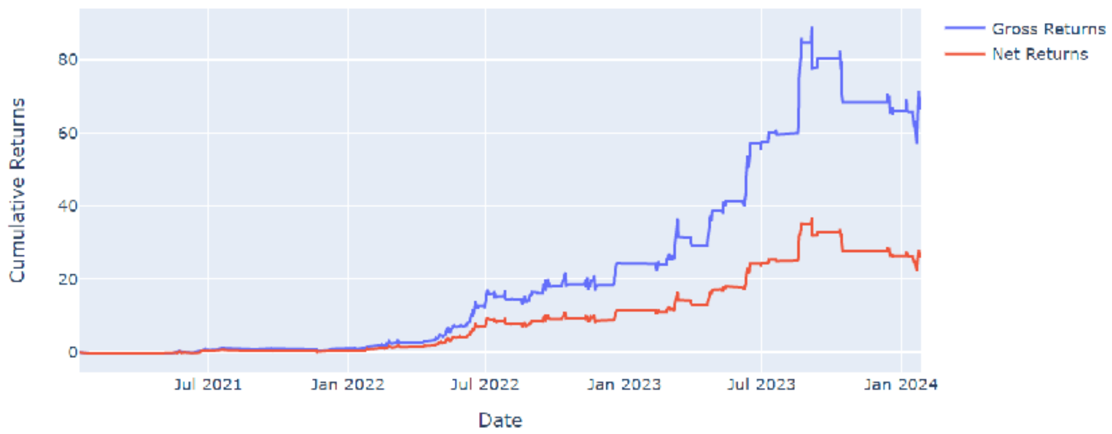


Figure 5.2: Net and Gross Returns of Best Short portfolio.

In conclusion, the best parameter combination for short portfolios in a selling strategy involves operating within a bear market employing a trend-following strategy with a time-weighted portfolio. The SVM method should be used to reduce the universe, with a focus on returns and keeping universe size low. Longer timeframes should be utilized to enhance performance.

Best Combinations per Market Class

With a focus on identifying the most effective configurations for varying market conditions, 5400 combinations for each market class are analyzed.

The level of confidence parameter shows a positive correlation with the performance metrics suggesting a stronger reliability on market trends.

The analysis consistently shows that short portfolios are the top performers in all market classes. This finding highlights the effectiveness of short selling strategies.

In bull markets, trend-following time-weighted portfolios exhibit slightly better performance compared to momentum portfolios. The trend-following approach, especially when used with a time-weighted portfolio, is adept at capturing upward trends, leading to better returns. The weighted aspect of the strategy allows for a more nuanced and responsive approach to market movements (see Appendix D).

The performance gap between strategies widens in the neutral market, with time-weighted trend-following portfolios significantly outperforming momentum portfolios. In these market conditions, where the direction is not clearly defined, the adaptability of trend-following strategies proves advantageous (see Appendix E).

During bear markets, the trend-following time-weighted portfolio stands out as the superior choice. This strategy not only delivers better returns but also manages risk more effectively in declining markets.

Across all market classes, the use of SVM and a smaller universe size is a common theme. This methodological choice ensures that the strategy is applied to a well-selected subset of cryptocurrencies, enhancing overall performance. The SVM methodology aids in identifying the most relevant and high-potential cryptocurrencies, while the reduced universe size maintains a focus on quality over quantity.

Momentum metrics are preferred in market classes experiencing substantial shifts. These metrics are effective at quickly capturing and exploiting rapid changes in the

market, providing an edge in highly dynamic environments.
Growth metrics are employed in the neutral market, emphasizing stability and consistent performance. These metrics are less reactive to short-term volatility, which is crucial in a market where clear trends are absent.
The importance of the lookback period varies across market conditions. In bull markets, shorter lookback periods are favored as they help in quickly identifying and capitalizing on upward trends. Conversely, in bear markets, longer lookback periods are preferred. They offer a comprehensive view of long-term downward trends, aiding in more strategic decision-making.

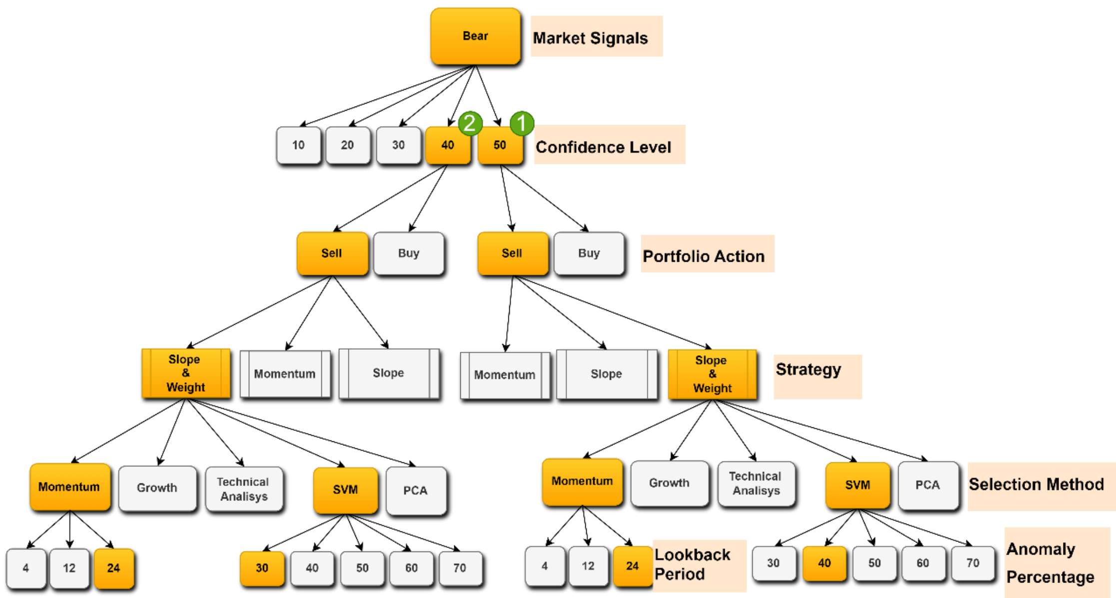


Figure 5.3: Bear Market Optimal Combination Flow

5.1.3. Top Ranked Combinations Analysis

In this section, the top 20 percent of combinations ranked by APL, accounting for 3240 combinations are analyzed. This subset represents the most profitable and promising parameter configurations, offering valuable insights into the factors contributing to their success.
When examining the top combinations, it is crucial to analyze the percentages of use for each parameter and strategy. Among the top combinations, SVM emerges as the preferred method, being utilized 60% of the time. This finding contradicts the analysis of the dataset but suggests that in the top-performing subset, SVM may offer better returns despite involving slightly more risk.
Furthermore, returns are the most frequent metrics choice, present in 50% of the cases with higher APL. Growth metrics are slightly less utilized but provide better skewness.
Additionally, a clear trend emerges regarding the size of the universe, with smaller universes being associated with better performance, excluding risk factors such as skewness and kurtosis. This trend diverges from the overall dataset analysis but indicates that among the top-performing combinations, a smaller universe may lead to

more profitable outcomes.
A mid to long-term lookback timeframe shows similar results among the top combinations. This suggests that the timeframe choice does not significantly impact the profitability of the top-performing strategies.
The time-weighted trend-following strategy appears to be used more frequently than the other strategies among the top combinations. This strategy demonstrates improvements in both returns and risk, indicating its effectiveness in generating profits while managing downside risk.
Short portfolios dominate the results, constituting 95% of the combinations among the top-performing subset. This indicates that short portfolios are highly effective in generating profits, especially within the top-performing parameter configurations.
Both bear and neutral markets share the frequency of occurrence among the top combinations. While the bear market exhibits better returns metrics, it is also more prone to risk. Additionally, it is worth noting that the neutral market sample size is significantly smaller, potentially influencing the analysis outcomes.
Contrary to the overall analysis, there is a tendency for better results with higher confidence levels of market classification.

5.2. Discussion

A noteworthy observation in our analysis is the presence of Simpson's Paradox, a statistical phenomenon where combined results of different subgroups contradict the results of individual subgroups. This paradox arises due to the influence of a third variable, known as a confounder, on the relationship between two variables (Sprenger & Jan and Naftali, 2021).
During our analysis, we observed Simpson's Paradox particularly in the evaluation of selection methods and universe size. When examining grouped performance metrics, PCA appeared to be more favorable, consistently outperforming SVM on most metrics. However, the best combinations consistently relied on SVM as their selection method. This discrepancy suggests that evaluating results solely based on the selection method without considering other parameters can lead to misleading conclusions.
To mitigate the influence of confounding variables, we opted to separate the analysis into various relevant subsets. Additionally, we focused on analyzing the top 20% of combinations based on the most relevant metric, APL, gaining a clearer understanding of optimal configurations.

Key Findings

In this thesis, Trend-following strategies were primarily employed, showcasing notable differences in performance between short and long portfolios. This disparity arises partly due to the limitations in shorting all tokens. It is crucial to highlight the distinct formation periods and windows of opportunity between short and long trends in cryptocurrency trading. The study unveils that short to mid-term lookbacks hold relevance during bull markets, indicating a propensity for shorter-term trends to materialize during periods of market optimism. Conversely, mid to long-term lookbacks exhibit predictive power during bear markets, suggesting that longer-term trends tend to emerge and persist amidst market downturns. This observation underscores the

significance of tailoring trading strategies to suit prevailing market conditions, thereby maximizing opportunities for profitable trades in both bullish and bearish environments.
Time-weighted portfolios significantly outperformed equally weighted portfolios, with comparable results to the momentum strategy. This underscores the informational value of cryptocurrency stability within our universe and the effectiveness of trend-following strategies in capturing market trends.
Optimal results were achieved when market classifications indicating significant changes were confirmed with high confidence levels. Similarly, confidently classifying stable markets as neutral also yielded favorable outcomes.
Market classification indecision periods could be leveraged as inactive periods for specific fallback strategies, highlighting their strategic importance.
Different universe formation methods and lookback periods were found to be more effective depending on market conditions. For instance, momentum metrics were favored during periods of market volatility, while growth metrics were suitable for stable markets.
The selection method exhibited notable differences in performance characteristics. SVM results showed higher kurtosis, indicating more volatile returns, while PCA presented a more right-skewed approach.
The universe size varied in its impact on portfolio performance, with larger universes performing better in long portfolios and more reduced universes proving profitable for short portfolios.
Through this comprehensive analysis, we gained valuable insights into the behavioral differences of bullish and bearish trends, the significance of trend duration, and the influence of selection methods and universe formation on portfolio performance. These findings provide a deeper understanding of optimal algorithm configurations and inform strategic decision-making in cryptocurrency trading.

5.3. Limitations

In the theoretical context of this thesis, there are limitations that restrict its application to live trading and its reproducibility in the real world. The study does not address the feasibility of short selling. Some trading pairs may not be feasible for short selling due to several reasons, such as exchange restrictions or borrowing availability. Thorough research and consideration of factors such as liquidity, borrowing costs, and regulatory implications are necessary before implementing short selling strategies. Additionally, risk management measures should be in place to mitigate the elevated risks associated with these strategies.
Furthermore, the liquidity filter applied in this study was a basic liquidity cutoff for each cryptocurrency. In the next iteration, it would be beneficial to replace this with a more sophisticated liquidity filter that considers not only the number of trades but also the volume of the cryptocurrency during a moving average of a specified lookback period. This would provide a more comprehensive assessment of liquidity.
To enhance the adaptability of the algorithm in situations of limited cryptocurrency selection, fallback strategies could be implemented. Furthermore, exploring the utilization of specific order types such as stop-loss orders, triggered to limit potential losses and take-profit orders, activated to secure profits, could provide potential performance enhancements. Understanding the nuances of these orders and their

impact on trade execution is crucial for optimizing trading strategies.
A contrary study to the trend-following strategy, such as a mean reversion strategy aimed at exploiting short-term deviations from historical averages, could complement existing strategies and cater to different market conditions and timeframes. Exploring these strategies could provide additional opportunities for optimizing trading performance.
Furthermore, limitations in the form of data ingestion can be addressed. This thesis relied solely on two types of data. Expanding the data sources to include market sentiment data from social media platforms or derivatives data could potentially improve the algorithm's performance.

6. Conclusions

6.1. Academic Contribution

This thesis represents a comprehensive exploration into the development of machine learning models for cryptocurrency trading, focusing on universe reduction and predictive analytics to enhance profitability. By addressing key portfolio performance metrics and evaluating unsupervised machine learning algorithms, this study aimed to identify optimal configurations for cryptocurrency trading strategies.

At its core, the project aims to develop a model adept at accurately predicting cryptocurrency price movements and generating profits, while factoring in general trading fees. To achieve this, the study focused on identifying the most suitable unsupervised machine learning model for anomaly detection, including SVM One-Class and PCA. These algorithms were evaluated alongside other parameters responsible for creating reduced universes of cryptocurrencies, such as metrics group, lookback period, and universe size.

The research employed trend-following strategies to capitalize on cryptocurrency price movements, highlighting notable differences in performance between short and long portfolios. This analysis revealed the importance of understanding the different formation periods and windows of opportunity for short and long trends. Additionally, time-weighted portfolios were found to significantly outperform equally weighted portfolios, emphasizing the informational value of cryptocurrency stability within the reduced universe.

Furthermore, the study explored the construction of a daily market momentum classification system for cryptocurrencies, utilizing a multiclass classification approach. By adjusting the confidence level parameter, the model aimed to optimize sensitivity and assist traders in making informed decisions amid market volatility.

Key findings from this research include the strategic importance of leveraging market classification indecision periods as inactive periods for fallback strategies. Additionally, the study revealed that different universe formation methods and lookback periods were more effective depending on market conditions, with momentum metrics favored during periods of volatility and growth metrics suitable for stable markets. Furthermore, the selection method exhibited notable differences in performance characteristics, with SVM presenting higher volatility compared to PCA.

In summary, this thesis contributes valuable insights into the behavioral differences of bullish and bearish trends in the cryptocurrency market, the significance of trend duration, and the influence of selection methods and universe formation on portfolio performance. These findings advance understanding and inform strategic decision-making in cryptocurrency trading, contributing to the development of effective machine learning driven trading strategies.

6.2. Future Work

In future research endeavors, in addition to improving the framework already developed, the main intention is to incorporate a decision-making process tailored for paper trading. This process would involve utilizing the results provided by the current study to produce a rolling performance tester capable of providing a score for each unique combination of universe formation, strategy decision, and market momentum classification components combination. This would involve creating a dynamic scoring algorithm where the parameterization would be implemented on the lookback period of performance and the equation that produces the computed score.

Accompanying this development would be the creation of a process responsible for terminating and initiating the strategy that is the best fit for the market momentum classification provided. This adaptive strategy aims to optimize trading strategies by continuously adapting to changing market dynamics.

Lastly, improvements to the framework would involve adding more depth to the types of strategies and the implementation of various order types to replicate a trading experience closer to reality. These enhancements would contribute to refining the framework and making it more robust for future research and potential real-world applications.

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Appendix A

Lookback	Trades	Sharpe	Sortino	MDD	APL	Kurtosis	Skewed	Count
4	2330	-1.8623	-0.0501	-0.8469	-0.000890	21.3508	-0.3753	5400
12	2329	-0.8744	-0.0243	-0.7899	-0.000370	20.0291	0.1157	5400
24	2328	-1.1593	-0.0304	-0.8042	-0.000518	19.6678	-0.2197	5400

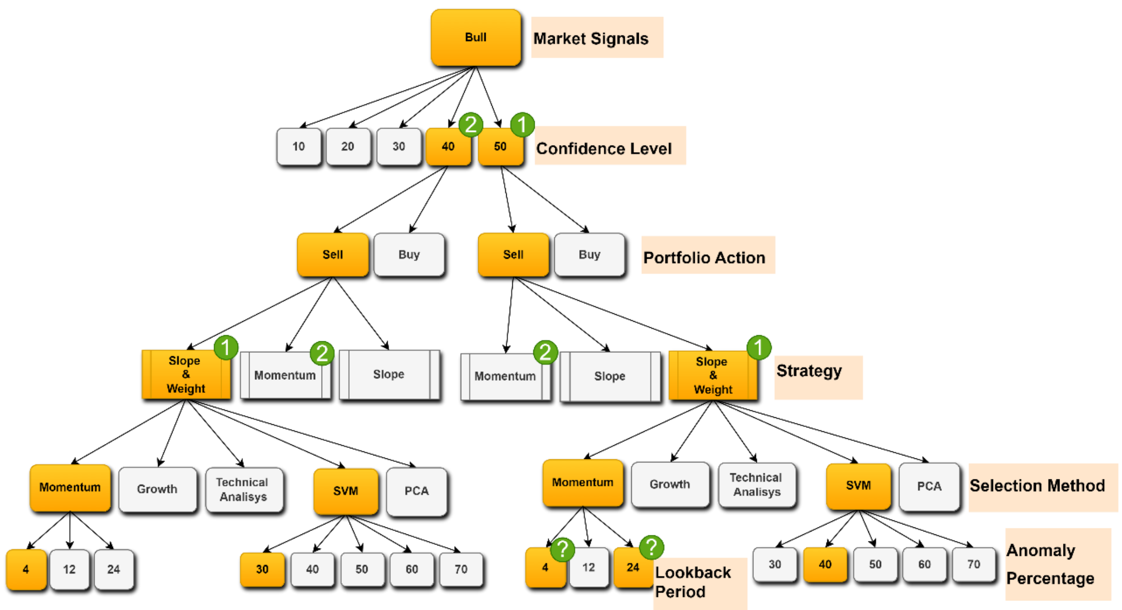
Appendix B

Strategy	Trades	Sharpe	Sortino	MDD	APL	Kurtosis	Skewed	Count
Momentum	2329	-1.8570	-0.0491	-0.8256	-0.000849	27.3525	-0.4492	5400
Trend	2329	-1.1472	-0.0313	-0.8119	-0.000518	16.7198	-0.0361	5400
Trend Weighted	2329	-0.8918	-0.0244	-0.8034	-0.000410	16.9754	0.0061	5400

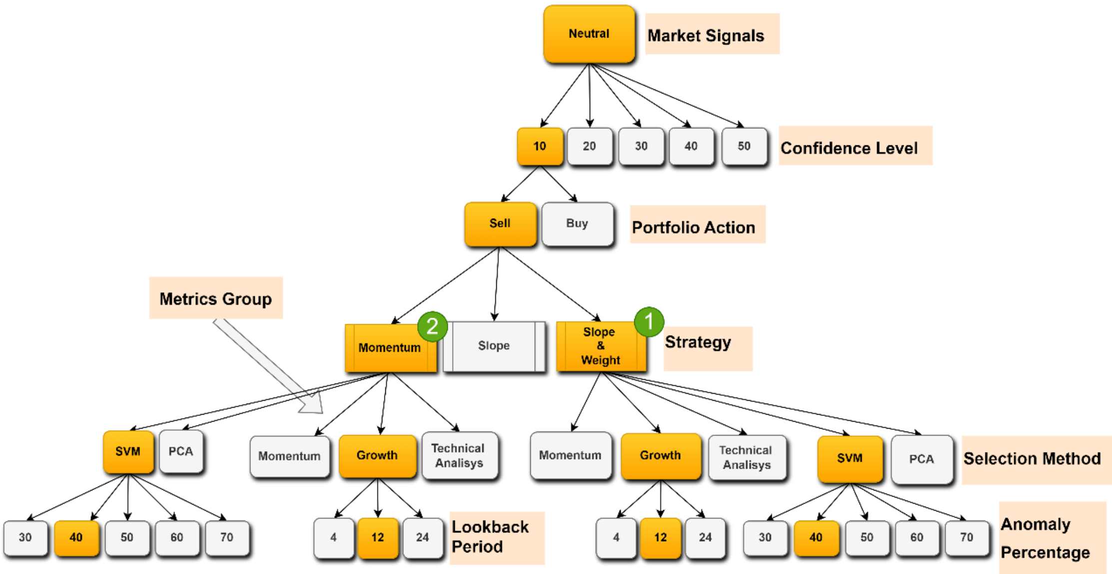
Appendix C

Market	Trades	Sharpe	Sortino	MDD	APL	Kurtosis	Skewed	Count
Bear	2258	-1.5059	-0.0378	-0.8497	-0.000834	27.1663	-0.1143	5400
Bull	3175	-1.3971	-0.0334	-0.9092	-0.000499	17.1102	-0.1734	5400
Neutral	1553	-0.9929	-0.0337	-0.6820	-0.000444	16.7713	-0.1915	5400

Appendix D



Appendix E


Neutral
Market Signals
10
20
30
40
50
Confidence Level
Sell
Buy
Portfolio Action
Metrics Group
Momentum
2
Slope
Slope & Weight
1
Strategy
SVM
PCA
Momentum
Growth
Technical Analisys
Momentum
Growth
Technical Analisys
SVM
PCA
Selection Method
30
40
50
60
70
4
12
24
Lookback Period
4
12
24
30
40
50
60
70
Anomaly Percentage

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