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Noise reduction and feature extraction with principal component analysis for cryptocurrency price modeling

Bachelor's thesis

Author: Tomáš Barhoň

Study program: Economics and Finance

Supervisor: prof. PhDr. Ladislav Krištoufek Ph.D.

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Declaration of Authorship

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Prague, February 25, 2025

Tomas Barhon

Abstract

The abstract should concisely summarize the contents of a thesis. Since potential readers should be able to make their decision on the personal relevance based on the abstract, the abstract should clearly tell the reader what information he can expect to find in the thesis. The most essential issue is the problem statement and the actual contribution of described work. The authors should always keep in mind that the abstract is the most frequently read part of a thesis. It should contain at least 70 and at most 120 words (200 when you are writing a thesis). Do not cite anyone in the abstract.

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Author's e-mail	tomas.barhon@hotmail.cz
Supervisor's e-mail	ladislav.kristoufek@fsv.cuni.cz

Abstrakt

Nutnou součástí práce je anotace, která shrnuje význam práce a výsledky v ní dosažené. Anotace práce by neměla být delší než 200 slov a píše se v jazyce práce (tj. česky, slovensky či anglicky) a v překladu (tj. u anglicky psané práce česky či slovensky, u česky či slovensky psané práce anglicky). Anotace práce by neměla být delší než 200 slov a píše se v jazyce práce (tj. česky, slovensky či anglicky) a v překladu (tj. u anglicky psané práce česky či slovensky, u česky či slovensky psané práce anglicky). V abstraktu by se nemělo citovat.

Klasifikace JEL	C01, G00, F23, H25, H71, H87
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Název práce	Redukce šumu a extrakce rysů pomocí analýzy hlavních komponent pro modelování cen kryptoměn
E-mail autora	`tomas.barhon@hotmail.cz`
E-mail vedoucího práce	`ladislav.kristoufek@fsv.cuni.cz`

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Acronyms

BTC Bitcoin

ETH Ethereum

LTC Litecoin

AI Artificial Intelligence

ML Machine Learing

DL Deep Learing

ANN Artificial Neural Network

SGD Stochastic Gradient Descent

LR Linear Regression

SVM Support Vector Machines

SVR Support Vector Regression

RNN Recurrent Neural Network

LSTM Long Short-Term Memory

PCA Principal Component Analysis

SVD Support Vector Decomposition

ARIMA Autoregressive Integrated Moving Average

PoW Proof of Work

Bachelor's Thesis Proposal

Author	Tomáš Barhoň
Supervisor	prof. PhDr. Ladislav Krištoufek Ph.D.
Proposed topic	Noise reduction and feature extraction with principal component analysis for cryptocurrency price modeling

Motivation Crypto assets have always been exceptionally volatile compared to traditional assets such as stocks or gold. The historical window is relatively short, thus modeling their price or volatility proposes quite a difficult challenge. It is generally believed that noise in any data decreases the precision of predictions. This effect might be reduced, which will improve the performance of traditional models that are used for cryptocurrency price modeling.

The main motivation for researching this topic is that there is still an ongoing discussion about the role of different features in crypto pricing dynamics. (Kukacka; Kristoufek 2023) have shown that a lot of the pricing dynamic emerges from complex interactions between fundamental and speculative components. They also show the different correlations between all of the explanatory variables which have a direct connection to principal component analysis. It is crucial to study the real impact of those variables in different models as many of them might turn out to be obsolete.

There is currently little use of this dimensionality reduction technique in the academic literature about cryptocurrencies. However, for more traditional financial series this technique is already quite established as a preprocessing technique to reduce noise and dimensionality from which financial data inherently suffer (Chowdhury, U. ; Chakravarty, S. and Hossain, M. 2018). Moreover (Bouri, E.; Kristoufek, L.; Ahmad, T. et al. 2022) studied the effect of microstructural noise on idiosyncratic volatility in cryptocurrencies which further supports the need for a technique that will mitigate this effect on the predictions.

The research will address the problem of variable selection for different types of predictive models with respect to the analysis of the principle components aiming to reduce the dimensionality and simultaneously increase precision. The second question is whether it is more appropriate to transform the high dimensionality with

PCA into lower dimensionality or simply omit the variables with high multicollinearity from the models. These approaches are fundamentally different and the answer is not clear.

Methodology The data will come from various sources because the aim is to look at all the possible variables even if they might not seem useful at first glance. As already mentioned the dynamic is driven by a lot of completely different effects. Most of it will be collected from: coinmetrics.io, studio.glassnode.com, and for macroeconomic indicators https://fred.stlouisfed.org/. Some of the data might need to be interpolated to daily observations. Lastly, the observations will need to be sliced to different window sizes and shifted by one so that the predictions can be made for the next day with the data available on that day.

Afterward, the multicollinearity in the data will be examined and different approaches to solve it will be used. The two main ones are using only a smaller set of uncorrelated variables (simple dimensionality reduction) and the second being employing PCA transformation to preserve a predefined threshold of variance or directly targeting the number of principal components.

All the different setups will be compared across three models: linear regression, SVM, and LSTM neural network. The hypothesis is that PCA transformation will substantially lower the measured errors for linear regression and SVM although for LSTM it will result in lower performance as it will only decrease the capacity of the model as the model is powerful enough to create such uncorrelated features without the PCA transformation.

Expected Contribution Existing research agrees that financial data and especially cryptocurrency data are significantly affected by noise. The main goal is to extend the research on the topic of variable selection for algorithmic trading models as there are still a lot of unanswered questions. It will most likely become clearer which approach to dimensionality reduction is the most efficient concerning cryptocurrencies.

Also, not only the underlying pricing dynamics will be detected but the results can be used for investors that are trying to lower their risk of loss which is relatively high in crypto markets. The effect of having a more stable and precise model might significantly cut the transaction costs that are associated with more frequent exchanges as the predictions will become less volatile. That is a desirable property needed to maximize profit and increase credibility towards its customers.

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Author

Supervisor

Chapter 1

Introduction

Since the introduction of the first cryptocurrency Bitcoin (BTC) associated with the unknown author Satoshi Nakamoto (2008) cryptocurrencies have become part of our everyday life. Their high volatility, futuristic name and alternative nature are of interest to the media and the general public. According to **coinmarketcap.com** the overall cryptocurrency market capitalization peaked at around 2.8 trillion $USD in the year 2022 which makes them a substantial part of the financial sphere. The initial idea of BTC was to establish an alternative to traditional fiat currencies. The BTC whitepaper pointed out the weakness of the current trust-based model that relies on a third-party instance responsible for verifying transactions. A different approach was suggested to validate transactions known as the proof-of-work which utilizes the computational power of miners in the network. The fact that the power is distributed across the network ensures that it becomes exponentially harder with an increasing number of blocks to generate blocks faster than the rest of the miners (Nakamoto 2008, pg. 6). The mining process is interconnected with the creation of new coins which is a crucial parameter in all monetary systems. This fact gives researchers such as Kukacka & Kristoufek (2023) the possibility to use various attributes of the network to study the pricing dynamics of cryptocurrencies. However, there are a couple of substantial drawbacks that make price modeling relatively challenging. Those are non-stationarity of the target prices, relatively short historical window, the limited power of proxies for speculative components and as pointed out by many researchers such as Bouri *et al.* (2022), Dimpfl & Peter (2021), WÄ...torek *et al.* (2023) an idiosyncratic noise in volatility. Addressing these issues might potentially lead to better-performing models, especially with longer forecasting periods. Likewise in other fields, the recent rise of machine learning has also affected the cryptocurrency area where various Machine Learing (ML) and Deep Learing (DL) models are often being used to model the price Khedr *et al.* (2021) or volatility Kristjanpoller & Minutolo (2018).

The main objective of this thesis is to try to tackle the problem of idiosyncratic noise in the high dimensional data used for price and returns modeling across three ML models: Ridge Linear Regression (LR), Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) Recurrent Neural Network (RNN). We will examine the effect of a method known as Principal Component Analysis (PCA) which was according to Farebrother (2022) developed in 1933 by Harold Hotelling. However, others often refer to the fact that the idea was already introduced before by Karl Pearson in the article *On lines and planes of closest fit to systems of points in space* Pearson (1901). This technique aims to compress data from a higher dimensionality space into a lower space while retaining a maximum amount of variance. It utilizes linear transformation of the covariance matrix to do that. Nevertheless, despite the initial focus on dimensionality reduction different types of PCA are often being used as noise reduction techniques in signal or image processing. Interestingly many studies in recent years have incorporated PCA for time series data as a part of their preprocessing pipeline Chowdhury *et al.* (2018), Kristjanpoller & Minutolo (2018). The idea stems from the fact that removing the most idiosyncratic components might help with capturing clear dynamics that enter the price-making process. We perceive that there is currently a lack of literature that would examine the effects of noise reduction techniques on the performance ML based models for cryptocurrency modelling. We want to mitigate most of the identified challenges using the currently available academic knowledge and focus exclusively on the effect of noise in the data. Admittedly it is always intricate to establish a ceteris paribus relationship in such a scenario where many variables change, the randomness of the training process using Stochastic Gradient Descent (SGD) plays a crucial role and the size of the dataset is relatively limited. We want to contribute with an alternative approach, especially in the preprocessing pipeline that can be used in future studies to decrease the volatility of predictions. We do not aim to provide a universally applicable approach, as different techniques can produce varying outcomes on different datasets. This phenomenon partially corresponds to the *No Free Lunch Theorem* Wolpert *et al.* (1995) which has turned into a buzzword in the ML community over the years.

The remainder of the thesis is organized as follows: The following chapter introduces the fundamentals of cryptocurrencies and their unique characteristics. It also covers the usage of ML methods in this field and especially focuses on the literature about the usage of PCA in various areas. The data chapter explains in detail which data were used and elaborates on the basic resampling methods that we used. In methodology, we focus on each specific ML method and explain the core concepts that are crucial for understanding the training process. Similarly, we propose our complete forecasting framework. Chapter results and discussion evaluates the findings for each currency-model pair across different settings. We also include a limitations section which is especially crucial for our study where we acknowledge those problematic parts of our approach that might be improved in the future. The conclusion focuses on the overall impact and proposes paths that should be explored in the years to come. All the tables, source codes and visualizations can be found in the appendices.

Chapter 2

Literature Review

2.1 Cryptocurrencies

2.1.1 Bitcoin

In the year 2008, an unknown author with the pseudonym Satoshi Nakamoto introduced the idea of a purely peer-to-peer electronic cash system. Interestingly the author mentions small casual transactions as something that the current model relying on third-party financial institutions fails to deliver because of unavoidable transaction costs Nakamoto (2008). In contrast, from today's perspective, Bitcoin is a relatively slow medium for micro-transactions because technically the receiver has to always wait for a certain amount of blocks to be mined such that it becomes statistically unlikely that double-spending has been committed by the payer Conti *et al.* (2018). This phenomenon can be demonstrated on the data from **coinmetrics.io** which show that the mean size of a BTC transaction ranges in thousands of USD$. Another important aspect is that the miners prioritize transactions with higher fees in the block which introduces considerable costs to each payment. MĂ¶ser & BĂ¶hme (2015) have shown the relationship between the transaction fee and the transaction latency meaning the time it takes for the transaction to be almost surely valid. Even though there has been some divergence from the original idea of small transactions all of the security measures regarding the double spending problem in the original whitepaper have turned out to be relatively well-defined in a medium time horizon.

Despite the fact, that Bitcoin is generally regarded as the first cryptocurrency it relies on many older ideas and technologies that are mostly mentioned in the original whitepaper. First and foremost stands the conference paper *How* *to Time-Stamp a Digital Document* Haber & Stornetta (1991) which focuses on the problem of third parties responsible for verification of digital documents. It makes use of an already established family of functions known as hashes that surpass privacy concerns and generally surpass the need for a third party to be involved in the verification process when combined with the correct consensus algorithm. They define a hash function as follows:

Definition 2.1 (Hash). This is a family of functions $h : \{0, 1\} \rightarrow \{0, 1\}^l$ compressing bit-strings of arbitrary length to bit-strings of a fixed length l, with the following properties:

1. The functions h are easy to compute, and it is easy to pick a member of the family at random.
2. It is computationally infeasible, given one of these functions h, to find a pair of distinct strings x, x' satisfying $h(x) = h(x')$. (Such a pair is called a collision for h)(Haber & Stornetta 1991, see Chapter 4.1)

And suggest hashing documents together with the time of their creation. However, the time-stamping might fail if the users can tweak the time of their machines. Interestingly, the authors have already mentioned that and introduced the idea of chaining the data together with their metadata sequentially in a long chain so that the user can trust that something was not overwritten (Haber & Stornetta 1991, see Chapter 5). This is possible due to the properties of the hash functions. Meaning that we can concatenate arbitrarily long inputs and always produce a fixed-size output. Another significant influence came from b-money which was an idea for an anonymous digital cash system presented in Dai (1998). B-money proposed the concept of Proof of Work (PoW) which is a validation protocol that many cryptocurrencies still use. The idea was to solve computationally challenging puzzles where it can be determined how much effort was used to do so (see Dai 1998, pg. 1). However, certain worries were being raised about how to regulate a system if the computational power of computers is increasing every year (see Dai 1998, pg. 3). This has been addressed by Bitcoin with the regulation of difficulty based on the average time it takes to solve the puzzle rather than the difficulty itself (see Nakamoto 2008, pg. 3).

Since many characteristics of the network are often being used by researchers such as: (Kukacka & Kristoufek (2023), Kristoufek (2023), Kubal & Kristoufek (2022) or Jay *et al.* (2020)) in their research, it is critical to understand the underlying mechanics that form them. Bitcoin takes a completely adverse approach to the general financial system. Whereas traditionally, banks and other institutions try to keep every transaction encrypted Bitcoin makes all the transactions publicly visible and available but hashing the addresses of the sender and receiver. The process of sending Bitcoins to someone else essentially means adding a digital signature to the previous transaction from which you received that money. However, as (see Chapter 2 Nakamoto 2008, pg. 2) suggests this only mitigates the privacy concerns but the double spending risk needs to be dealt with a smarter design. This is solved by the introduction of the PoW algorithm. The idea is that transactions are collected into blocks by the miners who try to solve a computationally difficult task that can only be solved by a brute-force search. It is simply a race to find a hash with a certain amount of leading zeros which is adjusted based on the mining power of the network. The miners are incentivized by BTC price for winning the race and also by the transaction fees that can be added to each transaction as a reward for being prioritized. The leading concept is that the blocks are connected sequentially in a chain through the hash. If we assume that most of the nodes/miners are honest their profit-maximizing behavior should always be working on the longest chain and thus transactions that have already been spent do not get included in the chain. After the puzzle is solved by a node it can be validated by all other nodes in a linear time and they move on to the next block. Despite that, there remains the risk of an attacker forking a malicious block and sending his money back or elsewhere. Nakamoto (2008) claims that the probability of an attacker catching up (or reaching breakeven from the memoryless property of Poisson distribution) drops exponentially with each block if the mining power (probability of solving the puzzle) of the attacker is lower than the power of honest nodes. This mechanism is the root of the Bitcoin security. However, it also implies that there is an implicit tradeoff between security and the desired liquidity of cash. Another important property is that there will ever exist only a limited amount of 21 million of BTCs which makes it inherently a deflationary currency at least after all of the BTCs are mined. Technically there will be less as some wallets do get lost together with their contents. Limiting supply might be an intentional design choice to contrast the traditional model where banks issue money and cause inflation.

As cryptocurrencies are a relatively new phenomenon they are currently a frontier topic of academic research in many different aspects. They are being studied on multiple levels such as law, technology, cryptography, security, economics or machine learning. Generally, the area of economics and machine learning will be of interest as we want to uncover whether there exist some determinants of the bitcoin price or at least features that can be used to estimate the pricing dynamics. We assume that there are theoretically three simplified possibilities of the pricing model of BTC and other cryptocurrencies. Firstly, it might be a purely efficient market and the price technically follows a random walk process with a potential drift. The second model is that the price is entirely driven by speculative components and lastly, it might be a combination of speculative and fundamental components.

2.1.2 Ethereum

At the time of writing according to the data from **coinmarketcap.com**, Ethereum (ETH) is the second cryptocurrency based on the market capitalization standing at 318 billion USD. Although, there are a lot of similarities with BTC the idea behind ETH is much more profound and builds an entire technological infrastructure on top of blockchain which provides easily scriptable smart contracts. Tikhomirov (2018) defines smart contracts as follows:

> *Turing-complete programs that are executed in a decentralized network and usually manipulate digital units of value.*

We might want to reformulate this definition for the purposes of this thesis to cover a broader meaning.

Definition 2.2 (Smart contract). A program that is running on the blockchain infrastructure as an endpoint with a specific address that other entities on the platform can interact with in order to execute a transaction for a cost proportional to the number of computational steps. The contract usually has a predefined set of rules which is applied to the input data and automatically executes on hold whenever called. This allows developers to build applications on top of blockchain infrastructure that is run by the distributed network and grants them the unique benefits of the blockchain model.

According to the original whitepaper, the main purpose of ETH was not to create another cryptocurrency but build a simple-to-use scripting language that would allow developers to create custom applications running on the blockchain that share the benefits of the distributed nature of the system but reduce the need for hardware as the transactions are handled by the network and also software as the transactions can be defined in a few lines of code. Notably it describes cryptocurrencies as a state transition system:

Definition 2.3 (Digital currency ledger). From a technical standpoint, the ledger of a cryptocurrency such as BTC can be thought of as a state transition system, where there is a *state* consisting of the ownership status of all existing coins and a *state transition function* that takes a *state* and a *transaction* and outputs a new state *state-new* which is the result.

In this view, we can understand building smart contracts, see Definition 2.2, as creating use case specific *state transition functions* ((Buterin *et al.* 2013, see Chapter Bitcoin As A State Transition System),(Tikhomirov 2018, see Chapter 2)).

We can observe the fundamental difference in philosophy between the BTC and ETH from their respective whitepapers. ETH is much more focused on its role as an application platform whereas BTC was mainly intended to work as a currency. The ETH whitepaper even presents many ideas for future applications that might benefit from this framework. This fact is crucial in understanding the underlying price-making mechanics as investments into ETH might be affected by its perceived potential as a technological product rather than a typical currency that might be valued mostly as a medium of exchange.

Even though there are a lot of similarities in the blockchain architecture, there have been many functional and implementation differences. The most notable is the ETH scripting language which is a Turing-complete counterpart to the BTC scripting language that did not support infinite looping (Buterin *et al.* 2013, see Chapter Scripting). The second fundamental implementation variation is that each Ethereum block saves the entire *state* of the whole network and thus does not need to store the whole history of the blockchain. On the contrary, BTC is doing exactly that, as the blocks are state-unaware and only validate blocks based on the transactions and the wallet software usually calculates the balances (Tikhomirov 2018, see Chapter 2). As Buterin *et al.* (2013) pointed out there is a workaround that makes this implementation roughly equally efficient which utilizes the propagation properties of the Merkle tree with the fact that only a small part of the state changes with each block allowing for efficient state change using pointers to the specific branches and leaves of this data structure, see Figure 2.1. The data are stored at the bottom of this infrastructure and there is an efficient algorithm that allows the ETH software to reference the affected addresses and paths leading to them.

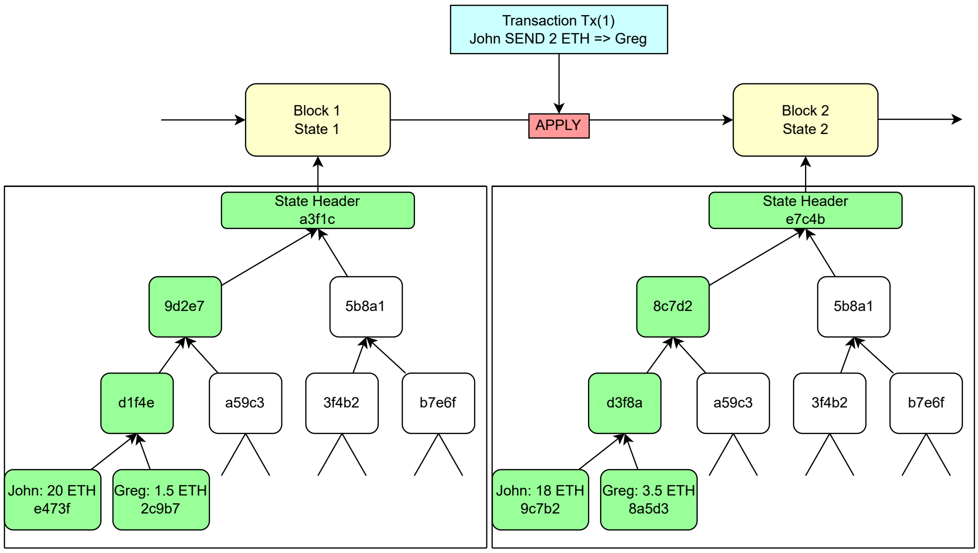


Figure 2.1: Merkel tree with pointers allows efficient state change

Lastly, there is a difference in the supply of new coins. Contrasting the model of BTC where the supply is limited ETH introduces a model of an infinite linear supply of coins to provide incentives for future users to join the network as they might still obtain new coins and thus limit the wealth concentration common in BTC (Buterin *et al.* (2013), Tikhomirov (2018)). Note that ETH already switched to the proof-of-stake model in September 2022 but our dataset does not include this period and thus this fact is not especially relevant to this thesis.

On the outside ETH acts similarly to BTC. It is a ledger that stores the coin balances of accounts where each has a designated unique address. There are two types of accounts: externally owned accounts which are essentially the typical users and contract accounts which are the abstraction on top of which smart contracts can be built with contract code that executes when the account receives a message from another account (externally owned or a different contract account). Because of the presence of infinite loops in the scripting language ETH employs a strategy that prevents users from essentially exploiting the Denial-of-service attack. Nonetheless stands the Halting problem. That can be simplified to the fact that for a Turing-complete model, there is no way of saying ex-ante whether the program will halt or run indefinitely. As Lucas (2021) suggests the Halting problem is usually attributed to Alan Turing's paper (Turing *et al.* 1936, On computable numbers, with an application to the Entscheidungsproblem), however, the problem was reformulated in various forms by others. This implies that this undecidability also holds for any ETH contract code. This is fixed by introducing a gas currency that acts as a cost of computation and the maximum has to be predefined in each message so that the recipient knows what is at stake Buterin *et al.* (2013). We can think of this as a type of timeout based on a currency. If gas runs out all of the state changes are reverted. This also explains the origin of the term transactions which typically refers to a set of instructions in SQL or other databases that are bundled together and executed in an all-or-nothing fashion Kleppmann (2017). The last important fact, as the whitepaper describes, is that the contract code is run by all of the miners verifying the block which essentially means applying all of the transactions and reverting in case of an error.

2.1.3 Litecoin

In comparison to ETH, the goal of Litecoin (LTC) was pronounced from the beginning as building a better version of BTC that shines where BTC has failed. We might say that LTC is a tweaked version of BTC with different parameters or a hard fork of the BTC protocol. To our best understanding, the only document that is wildly considered the original whitepaper is a transcript of a forum post by the founder Charlie Lee where he suggests reading the BTC whitepaper. Essentially, two main differences address the problems BTC embodies. The first one is faster confirmation time that allows LTC to be used truly in a fashion that was intended for BTC as digital cash with high liquidity sacrificing a bit of security. Achieving that mostly through four times faster block generation. And second one is a different proof-of-work algorithm. As Padmavathi & Suresh (2018) suggests the intention was most likely since BTC mining was dominated by GPU and ASIC miners which led to a concentration of mining power in pools and thus more centralized distribution of BTC. Despite the initial promises Litecoin has most likely not fulfilled its envisaged role and does not currently belong even to the ten most popular cryptocurrencies by market capitalization.

2.2 Machine Learning Methods for Cryptocurrencies

Thanks to transformer-based architectures that are the backbone of most chatbots. ML and artificial intelligence have gotten a lot of public spotlight during the last two years. However, ML methods have been especially prevalent in research in the last decade. Particularly in data-driven fields of academia, there have been various use cases where ML shines and outperforms traditional statistical models. Forecasting has always been an area of interest in many different fields as the idea of predicting the future based on historical data provides intrinsic value in itself. The field of cryptocurrencies is no exception as the significant volatility is a thought-provoking problem to tackle and an opportunity to win against the rest of the market.

In order to use ML or any other data-driven method we implicitly have to assume that there are some underlying dynamics of which we can make sense. This argument is hard to make without the proper data and might have to be studied separately for different time horizons. Thankfully, Kukacka & Kristoufek (2023) argue that some cryptocurrencies especially BTC are driven by the interaction of speculative and fundamental components and thus provide an incentive for us to untangle and study these relationships. Disturbingly, even though there are many other papers focusing directly on the practical implementation of forecasting frameworks for cryptocurrency prices a significant amount of them do not compare their model to a random walk or other simple statistical model. We suggest that their approaches should not be condemned but we strongly emphasize that their results should be interpreted cautiously.

We believe that there is currently an upsetting trend in the studies focusing on modelling the price or returns of cryptocurrencies using ML methods. There seem to be a lot of inconsistencies in terms of splitting the data into training and testing sets, making the results robust using some forms of cross-validation, comparably presenting the results and contrasting the models to a meaningful baseline model. This fact arguably contributes to the fact that the results of most of the studies are relatively underwhelming and have stagnated in the last few years. The other side of the coin, arguably worse, are studies that present overly optimistic results. A similar critique of the generalizability of results was presented by Akyildirim *et al.* (2020). We propose an idea for future research that would imaginably help the field advance further and stimulate innovation.

The suggestion lies in the creation of a standardized dataset with set splits between train, validation and test data that would allow for the comparison of different approaches and would encourage researchers to make their models generalizable. Taking inspiration from the field of image recognition where the Image-net is a state-of-the-art dataset to compare models for image recognition. This would allow for a competitive environment boosting innovation and development. We acknowledge that there is a fundamental difference between a dataset that consists of an unordered series of images and an especially challenging non-stationary time-series. Some compromises would undeniably have to be introduced in terms of set prediction horizons, different data granularity and artificially set splitting points. However, there is always a place for variation and this dataset could have multiple versions. Even though, this solution is sub-optimal we firmly believe the current scattered state of knowledge in this field makes it extremely difficult for further development to blossom.

Despite that, we would like to provide a brief overview of the methods that are often incorporated in price or returns modelling pipelines. As we already mentioned in order for ML to work as a forecasting algorithm there has to exist a possibility of drawing information about the future from the past. That is a non-trivial assumption because it contradicts The Efficient market hypothesis that was formulated for capital markets by Fama (2017). It is thus no oddity that Ren *et al.* (2022) have found out that across 395 scientific articles about the use of ML in cryptocurrencies the most cited article was Urquhart (2016) that studied the efficiency of BTC and concluded that the BTC market is inefficient but may become efficient in the future. And that the keyword inefficiency was the one with the highest burst of emergence among the articles.

There are generally two types of the problem formulation. Either the price is being modelled as a regression problem or the movement of the market is predicted as a binary classification. Although modelling market movement is easier it is also much more comparable across studies. If we can assume that there are approximately the same amounts of ups and downs we can work against the 50% baseline Akyildirim *et al.* (2020). Khedr *et al.* (2021) pointed out that cryptocurrencies lack seasonal trends which makes them challenging to predict for traditional statistical models. They also distinguish four types of factors influencing cryptocurrency price. Namely: demand and supply, crypto market, macro-economic and political. Our work will cover the first three types of factors as the political factors are hard to quantify. Later Ren *et al.* (2022) suggested that future researchers should study measurement tools for political factors. If you want to find out more about research in this field from 2010-2020 please view Khedr *et al.* (2021) which provides a comprehensive review. However, as we suggested earlier the aspect of comparison between studies is rather limited.

Alessandretti *et al.* (2018) compared multiple models from the perspective of portfolio management comparing them using return on investment and suggested that all of the ML models outperformed the moving average baseline. They also introduce the idea of predicting cryptocurrencies prices in BTC rather than USD to filter out the effect of overall cryptocurrency market growth and ease the effects of spurious correlation. In their study LSTM outperformed the gradient-boosting decision trees with longer time horizons and vice versa. Lastly, they pinpointed the fact that expressing prices in terms of BTC helped the predictions and concluded that forecasting only the trend of individual currencies might be easier than also predicting the overall market trend. Chowdhury *et al.* (2020) used ensemble methods to predict the prices of multiple cryptocurrencies. Utilizing the fact that combining multiple weaker models with uncorrelated errors with voting can increase the overall performance (Bishop & Nasrabadi 2006, see Chapter 14.2). Unfortunately however impressive their results might seem they have been evaluated only on a month of predictions which is in our view insufficient.

2.3 Principal Component Analysis

2.3.1 PCA in Time Series

PCA is a widely adopted signal processing technique that is typically used to lower dimensionality of input features and to mitigate noise in the signal by transforming the data into a different feature space while ensuring that the new principal components remain uncorrelated. Traditional usecases include dimensionality reduction for visualization purpouses (word embedding vectors), noise reduction in ECG, dimensionality reduction for performance reasons of different ML methods and many other signal processing pipelines.

Thanks to its valuable properties it has been recognized also as a tool to simplify and bring insights into multivariate time-series data concretely in the financial sector. However, using PCA in time-series usually comes with many identified challenges. Especially the need for the data to be normalized before being processed by the PCA layer might turn to be almost impossible to fulfill with non-stationary time-series. Despite these shortcoming many researchers have used PCA in their predictive work with a substantial success.

Most notably Nadkarni & Ferreira Neves (2018) designed a technical analysis based trading strategy for stocks and indexes that used PCA to reduce the dimensionality of input features from 6 to 31 that enabled the genetic NeuroEvolution algorithm to design much simpler Artificial Neural Network (ANN), reduce noise in the data and decrease the risk of overfitting the training datasetset. Their approach significantly outperformed the Buy and Hold strategy and they conclude that PCA was vital to achieve such results. Their work is especially important because of generalizability for future work as their approach used the broad population of ANNs even making each neuron dynamically choose different activation function and thus introduces no constrains on the generality of the results. Lastly they concluded that PCA led to lower risk, less days spent with capital in the market and higher daily profits.

Similarly, Chowdhury *et al.* (2018) used PCA and Independent Component Analysis as a preprocessing layer for stock prediction and found out that the proposed framework outperformed the approach where only the final Support Vector Regression (SVR) was used for prediction. Many other works use PCA only as a dimensionality reduction technique such as Toledo & Souza (2022).

An alternative novel approach used by some researchers (Shah *et al.* (2021), Mohsin *et al.* (2021), Smales (2020)) focuses on creating a cryptomarket wide index using PCA to capture the overall market trends. Smales (2020) found that the first principal component explains a large portion of the variation and is highly correlated with the BTC returns and thus support the notion of BTC returns being an important driver for other cryptocurrencies. Shah *et al.* (2021) critique the use of rule based indexes that do not rely on any fundamental mathematical reasoning and thus create a dynamic index using PCA that captures the overall market trends. However, they discourage the use of the index as an ETF highlighting the fact that the maximal variance optimization may be associated with higher volatility.

2.4 Web Search Data in Financial Applications

The phenomenon of Google Trends has drawn attention of many researchers. First and foremost stands the idea of Google Flu Trends. A project launched by Google which aimed at predicting flu epidemics using the symptom related searches by the users Ginsberg *et al.* (2009). However, as Lazer *et al.* (2014)

pointed out there have been many underlying issues both in the data construction and the dynamic nature of the search engine changing with years of development. We should highligh the importance of the correlation-causation fallacy in the use of Google Trends or other search based services. It is even worsened by the Google Trends weekly data granularity which makes it especially challenging to assess any kind of causality and its direction. We have to take into account the possibility that there is a bidirectional influence between Google Trends and BTC prices. Despite these challenges, research suggest that there is an underlying value in using web search data for modelling financial time series.

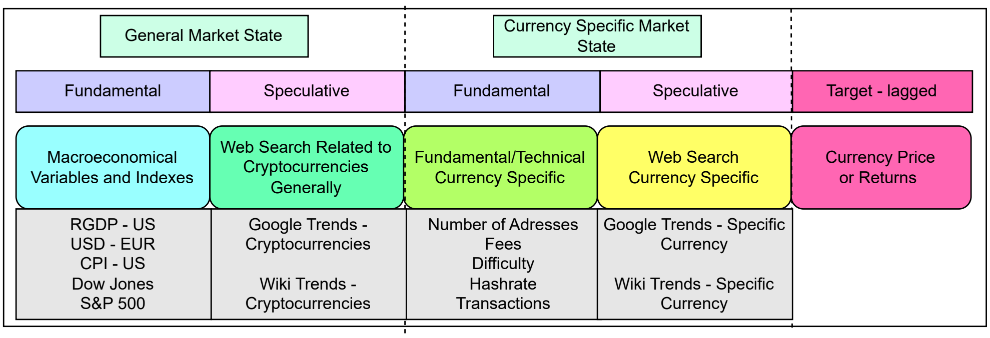
Hu *et al.* (2018) used ANN to predict the direction of the stock market indexes and compare two setups with and without Google Trends and conclude that inclusion of Google Trends improves the performance of their models. Similarly, Huang *et al.* (2019) studied the effect of investor attention measured by Google Trends as a potential market signal. Interestingly, they do not find evidence that market movements cause changes in search volumes. However, they conclude that search terms are useful in predicting stock market movements and as a proxy variable for investor attention. Most notably they emphasize that the effect is conditional on the sentiment of the search. Suggesting that we need to distinguish between positive and negative searches. This idea was adressed before in Kristoufek (2013) that found an asymmetric effect of positive and negative searches which were discriminated based on whether the price over or underperformed compared to a moving average of 4 days for Google Trends and 7 days for Wikipedia visits. Furthermore, Arratia & LĂłpez-Barrantes (2021) studied both linear and nonlinear effect between Google Trends and BTC returns and also conclude that Google Trends can be used to improve accuracy when forecasting BTC prices.

Chapter 3

Data

Compared to traditional financial data cryptocurrency data tend to be easier to obtain. However, many data providers have already identified the bussiness potential of selling advanced data and have started to monetize them. Since some websites monetize only their APIs we could obtain data from multiple sources and merge them to get to our desired number of features. We have desired to use as many relevant variables as possible and we build on an existing research in the field. Our dataset can be split into 2 main categories and 4 subcategories. We utilize the data that describe the overall market trends in the traditional sense. These data were mostly obtained from **Federal Reserve Bank of St. Louis** and from the **Yahoo Finance** API. To balance fundamental indicators with speculative side we used **Google Trends** and **Wikipedia Page Views** that act as a proxy for market attention about cryptocurrencies in general and should help us to model the market hype periods. These explanatory variables are then used to forecast the price or returns of the specific cryptocurrency of interest lagged back in time.

Figure 3.1: Dataset Variables Overview



The data were collected between December 2023 to February 2024 varying based on the different sources but they are further shortened to utilize the most overlapping region between data sources for each unique cryptocurrency. This results in a time series from 17.9.2014 to 1.11.2022 for Bitcoin, 4.2.2016 to 27.7.2022 for Ethereum ensuring that the end of the series is before the change to proof-of-stake algorithm and series from 17.9.2014 to 1.11.2022 for Litecoin. The shifted versions of the datasets are of variable length based on the forecasting horizon.

3.1 Cryptocurrency Specific Technical Data

Despite the fact, that we have framed this data as fundamental/technical we should acknowledge that fundamental in our case stands far from its traditional meaning. They are fundamental in a way that they are the typical data researchers and practitioners employ to model cryptocurrencies and that they objectively describe the system. However, as the fundamental factor is very limited in this case it only makes sense for the typical variables such as capitalization, volatility, hashrate and others. But we also used a lot of technical variables that are derived from these fundamental variables or the price itself. These help to identify trends in certain variables from pure mathematical transformation of the original series. All of these data were collected from **coinmetrics.io** and further processed by our pipeline.

We incorporate many variables describing specific technical characteristics of the network. Starting with number of active addresses which acts as a measure of user activity on a particular day that is a cruical parameter potentially capturing the strength of bull or bear market behaviour. However, it does not reflect the direction itself. The difficulty of the network is adjusted dynamically to counteract the changes in the mining power and thus act as a proxy for current mining power of the network or the current efforts of the miners. The size of the block is another characteristic of the network describing the size of the block (in bytes) and has been steadily increasing overtime with significant fluctuation that depend on many other changes in the network. Hashrate is a measure of how fast do the miners solve the hash for one block. In the long term the mean hashrate should be proportional to the difficulty at least that is how the BTC protocol was designed however there are some fluctuation in the short term as the difficulty is adjusted every 2016 blocks to match the average hashrate over that period.

Other variables focus on the economics of the currency and model the market behaviour not the network itself. Beginning with traditional market signals such as capitalization indicating the overall price of all coins and volatility of returns as a standart deviation of log-returns. Furthermore, we employ many other variables about the price of fees provided by the users, revenues of the miners, distribution of wealth in the network and the number of transactions for that interval.

Following is the list of technical variables on the example of BTC. The definitions were taken directly from **coinmetrics.io** to avoid any misconceptions:

- *BTC / Addresses, active, count* - The sum count of unique addresses that were active in the network (either as a recipient or originator of a ledger change) that interval. All parties in a ledger change action (recipients and originators) are counted. Individual addresses are not double-counted if previously active.
- *BTC / NVT, adjusted, 90d MA* - The ratio of the network value (or market capitalization, current supply) to the 90-day moving average of the adjusted transfer value. Also referred to as NVT.
- *BTC / NVT, adjusted, free float, 90d MA* - The ratio of the free float network value (or market capitalization, free float) to the 90-day moving average of the adjusted transfer value.
- *BTC / NVT, adjusted* - The ratio of the network value (or market capitalization, current supply) divided by the adjusted transfer value. Also referred to as NVT.
- *BTC / NVT, adjusted, free float* - The ratio of the free float network value (or market capitalization, free float) divided by the adjusted transfer value. Also referred to as FFNVT.
- *BTC / Flow, in, to exchanges, USD* - The sum USD value sent to exchanges that interval, excluding exchange to exchange activity.
- *BTC / Flow, out, from exchanges, USD* - The sum USD value withdrawn from exchanges that interval, excluding exchange to exchange activity.
- *BTC / Fees, transaction, mean, USD* - The USD value of the mean fee per transaction that interval.

- *BTC / Fees, transaction, median, USD* - The USD value of the median fee per transaction that interval.
- *BTC / Fees, total, USD* - The sum USD value of all fees paid by transactors that interval. Fees do not include new issuance.
- *BTC / Miner revenue, USD* - The USD value of the mean miner reward per estimated hash unit performed during the period, also known as hashprice. The unit of hashpower measurement depends on the protocol.
- *BTC / Capitalization, market, free float, USD* - The ratio of the free float market capitalization to the sum realized USD value of the current supply.
- *BTC / Capitalization, realized, USD* - The sum USD value based on the USD closing price on the day that a native unit last moved (i.e., last transacted) for all native units.
- *BTC / Capitalization, market, current supply, USD* - The sum USD value of the current supply. Also referred to as network value or market capitalization.
- *BTC / Capitalization, market, estimated supply, USD* - The sum USD value of the estimated supply in circulation. Also referred to as network value or market capitalization.
- *BTC / Volatility, daily returns, 30d* - The 30D volatility, measured as the standard deviation of the natural log of daily returns over the past 30 days.
- *BTC / Volatility, daily returns, 180d* - The 180D volatility, measured as the standard deviation of the natural log of daily returns over the past 180 days.
- *BTC / Difficulty, last* - The difficulty of the last block in the interval. Difficulty represents how hard it is to find a hash that meets the protocol-designated requirement (i.e., the difficulty of finding a new block) that day. The requirement is unique to each applicable cryptocurrency protocol. Difficulty is adjusted periodically by the protocol as a function of how much hashing power is being deployed by miners.

- *BTC / Difficulty, mean* - The mean difficulty of finding a hash that meets the protocol-designated requirement (i.e., the difficulty of finding a new block) that interval. The requirement is unique to each applicable cryptocurrency protocol. Difficulty is adjusted periodically by the protocol as a function of how much hashing power is being deployed by miners.

- *BTC / Hash rate, mean* - The mean rate at which miners are solving hashes that interval. Hash rate is the speed at which computations are being completed across all miners in the network. The unit of measurement varies depending on the protocol.

- *BTC / Hash rate, mean, 30d* - The mean rate at which miners are solving hashes over the last 30 days. Hash rate is the speed at which computations are being completed across all miners in the network. The unit of measurement varies depending on the protocol

- *BTC / Revenue, per hash unit, USD* - The USD value of the mean miner reward per estimated hash unit performed during the period, also known as hashprice. The unit of hashpower measurement depends on the protocol.

- *BTC / Supply, Miner, held by all mining entities, USD* - The sum of the balances of all mining entities in USD. A mining entity is defined as an address that has been credited from a transaction debiting the 'FEES' or 'ISSUANCE' accounts.

- *BTC / Block, size, mean, bytes* - The mean size (in bytes) of all blocks created that day.

- *BTC / Block, weight, mean* - The mean weight of all blocks created that day. Weight is a dimensionless measure of a blockâ€™s â€śsizeâ€ť. It is only applicable for chains that use SegWit (segregated witness).

- *BTC / Issuance, continuous, percent, daily* - The percentage of new native units (continuous) issued over that interval divided by the current supply at the end of that interval. Also referred to as the daily inflation rate.

- *BTC / Network distribution factor* - The ratio of supply held by addresses with at least one ten-thousandth of the current supply of native units to the current supply.

- *BTC / Transactions, count* - The sum count of transactions that interval. Transactions represent a bundle of intended actions to alter the ledger initiated by a user (human or machine). Transactions are counted whether they execute or not and whether they result in the transfer of native units or not (a transaction can result in no, one, or many transfers). Changes to the ledger mandated by the protocol (and not by a user) or post-launch new issuance issued by a founder or controlling entity are not included here.

- *BTC / Transactions, transfers, count* - The sum count of transfers that interval. Transfers represent movements of native units from one ledger entity to another distinct ledger entity. Only transfers that are the result of a transaction and that have a positive (non-zero) value are counted.

- *BTC / Transactions, transfers, value, mean, USD* - The sum USD value of native units transferred divided by the count of transfers (i.e., the mean size in USD of a transfer) between distinct addresses that interval.

The datasets for Ethereum and Litecoin look similar with the exception of a few variables missing, look at (Figure 3.2, Figure 3.3):

Figure 3.2: Ethereum missing variables

- *Hash rate, mean, 30d*
- *Supply, Miner, held by all mining entities, USD*
- *Block, weight, mean*

3.2 Macroeconomical Data

As the macroeconomical condition is a cruical factor for investor behaviour we decided to include relevant variables that might deliver valuable insights. We utilize five macroeconomical indicators that affect invesment choices. Real Gross Domestic product of the United States represents the overall growth trend of the largest economy in the world with closely related real gross domestic product per capita telling more about individual resouces which gives

Figure 3.3: Litecoin missing variables

- *Hash rate, mean, 30d*
- *Supply, Miner, held by all mining entities, USD*
- *Flow, in, to exchanges, USD*
- *Flow, out, from exchanges, USD*
- *Revenue, per hash unit, USD*

a more complex picture of the state of the US economy despite the fact that americans are not the main cryptocurrency investors by nation. Furthermore we incorporate Consumer Price Index in the United States that acts as an inflationary measure to capture the spurious correlation between prices of USD and BTC-USD exchange rate. M2 base acts as a measure of dollar liquidity in the circulation. Lastly, the USD-EUR exchange rate can be thought of as a market state information or its returns as an opportunity costs for potential investors. To further adress the problem of spurious correlation and add the information about growth of other markets we include various closing prices and other measures of the stock market and other investment opportunities.

Following is the full description of the macroeconomical variables used:

- *Close_DJI* - Dow Jones Industrial Average
- *Close_GSPC* - S&P 500
- *Close_GC=F* - Gold Futures
- *Close_VIX* - CBOE Volatility Index
- *Close_IXIC* - NASDAQ Composite
- *Close_SMH* - VanEck Semiconductor ETF
- *Close_VGT* - Vanguard Information Technology Index Fund
- *Close_XSD* - SPDR S&P Semiconductor ETF
- *Close_IYW* - iShares U.S. Technology ETF

- *Close_FTEC* - Fidelity MSCI Information Technology Index ETF
- *Close_IGV* - iShares Expanded Tech-Software Sector ETF
- *Close_QQQ* - Invesco QQQ Trust
- *RGDP_US* - Real Gross Domestic Product of the United States
- *RGDP_PC_US* - Real Gross Domestic Product per capita of the United States
- *CPI_US* - Consumer Price Index: All Items: Total for United States
- *M2_US* - M2 Base US
- *USD_EUR_rate* - U.S. Dollars to Euro Spot Exchange Rate

3.3 Web Search Data

As mentioned earlier following many other researchers we aimed to obtain a proxy for the market attention. We specifically used **Wikipedia Page Views** to get the page views for Wikipedia pages: Bitcoin, Ethereum, Litecoin and Cryptocurrency and use them respectively for each coin dataset combining the overall Cryptocurrency views with the specific currency. Similarly we hoped to obtain similar data from **Google Trends** but they turned out to be quite cumbersome to use. As West (2020) mentioned there are three main obstacles when using Google Trends. Firstly, the scale is always normalized into the range 0-100 based on the selected region and time. Secondly, this implicitly means that the results are rounded to integers and thus loosing a lot of precision. Lastly, there is a limit of 5 queries that you can use at a time. This not only means that you cannot compare more search terms but it also means that when there are over five variations how the term might be searched for one cannot do that effectively. Another problem, that we faced is that the data can be obtained only in weekly granularity for longer periods and thus needs to be interpolated to daily which most likely sacrifices a lot of interesting dynamics on the daily level which is significant regarding the volatility of cryptocurrencies. These reasons, except the weekly sampling frequency, were solved in the **g-tab** Python library, created by West (2020), which uses a two step query sampling process that estimates the searches on a universally common scale with floating precision and allows us to use as many word formulation as needed. We would then sum the popularity for each word formulation that is related to the same thing. We acknowledge that there is a risk that we ommited some word formulations but hopefully we covered all the significant ones.

Following is the list of the variables from this section and their word forms for Google Trends: https://cs.wikipedia.org/wiki/Bitcoin

- *Wiki_btc_search* - Wiki pageviews for **Bitcoin**
- *Wiki_eth_search* - Wiki pageviews for **Ethereum**
- *Wiki_ltc_search* - Wiki pageviews for **Litecoin**
- *Wiki_crypto_search* - Wiki pageviews for **Cryptocurrency**
- *Google_btc_search* - Google Trends summed from terms: *Bitcoin, bitcoin, BTC*
- *Google_eth_search* - Google Trends summed from terms: *Ethereum, ethereum, ether, ETH*
- *Google_ltc_search* - Google Trends summed from terms: *Litecoin, litecoin, LTC*
- *Google_crypto_search* - Google Trends summed from terms: *Cryptocurrency, cryptocurrency, Cryptocurrencies, cryptocurrencies, crypto, Crypto*

3.4 Preprocessing

Forecasting from historical data comes with many identified challenges. These were especially pronounced in our case as we incorporate data from many different sources with different sampling frequencies. Despite the fact that our focus is on forecasting daily price and returns we use data that come in weekly and monthly frequencies. We suggest two general concerns with such data. As we are using historical explanatory variables to predict a response variable in the future we need to ensure that our explanatory variables are already published at the time of forecasting and not use data from the future. We implement forward filling after the data is resampled to daily frequencies as a remedy. Especially for the macroeconomical data we implicitly match those indicators to future dates that they do not trully corespond to. Concretely, the Consumer Price Index for January is published at the beginning of February but as we forward fill this variable the Consumer Price Index from January will actually be in February. This ensures that when we are forecasting with a 10 day horizon at the beginning of February we only use data that was present at that time. The second concern is the fact that there is a lot of lost signal during those interpolated periods and the daily dynamics are not incorporated in the model. Unfortunately, this is the nature of economic research as especially the macroeconomical indicators come typically in such sampling frequencies. As already suggested these preprocessing steps were applied to the macroeconomical indicators, Google Trends that come in weekly frequency and for ETFs and indexes that are not traded on the weekends, see Figure 3.4.

As some of the variables are missing at the beginning of the time frame there is no clear solution how to impute them without leaking the future distribution. Even though we could say that this rule might be violated on the training set but we opted for a different approach. We start by visually inspecting the structure of the missing values and set the start of the series as such that "almost all" variables are already being collected. The aim is to keep as much data as possible but avoid having a lot of data points at the beginning with different distribution changed by imputation. After that we fill the data that is missing only at the start with zeros in order to avoid imputing future data. There is also a second reason as generaly these variables are increasing and thus imputing zeros makes even mathematical sense. Especially for data like Googe Trends or Wikipedia Pageviews this is a reasonable imputation. Finally we cut the ETH series at the switch to proof-of-stake as this completely changes the modeling perspective and we merge all the data from different sources on the date column.

The most cruical step is the transformation of this dataset into a supervised learning problem. We will proceed with the example of BTC price, however the same will hold for other coins and returns forecasting. We employ forecasting with 1, 5 and 10 day horizon h. We denote the number of observations $\mathbf{x_i}$ as n and the number of features j as k.

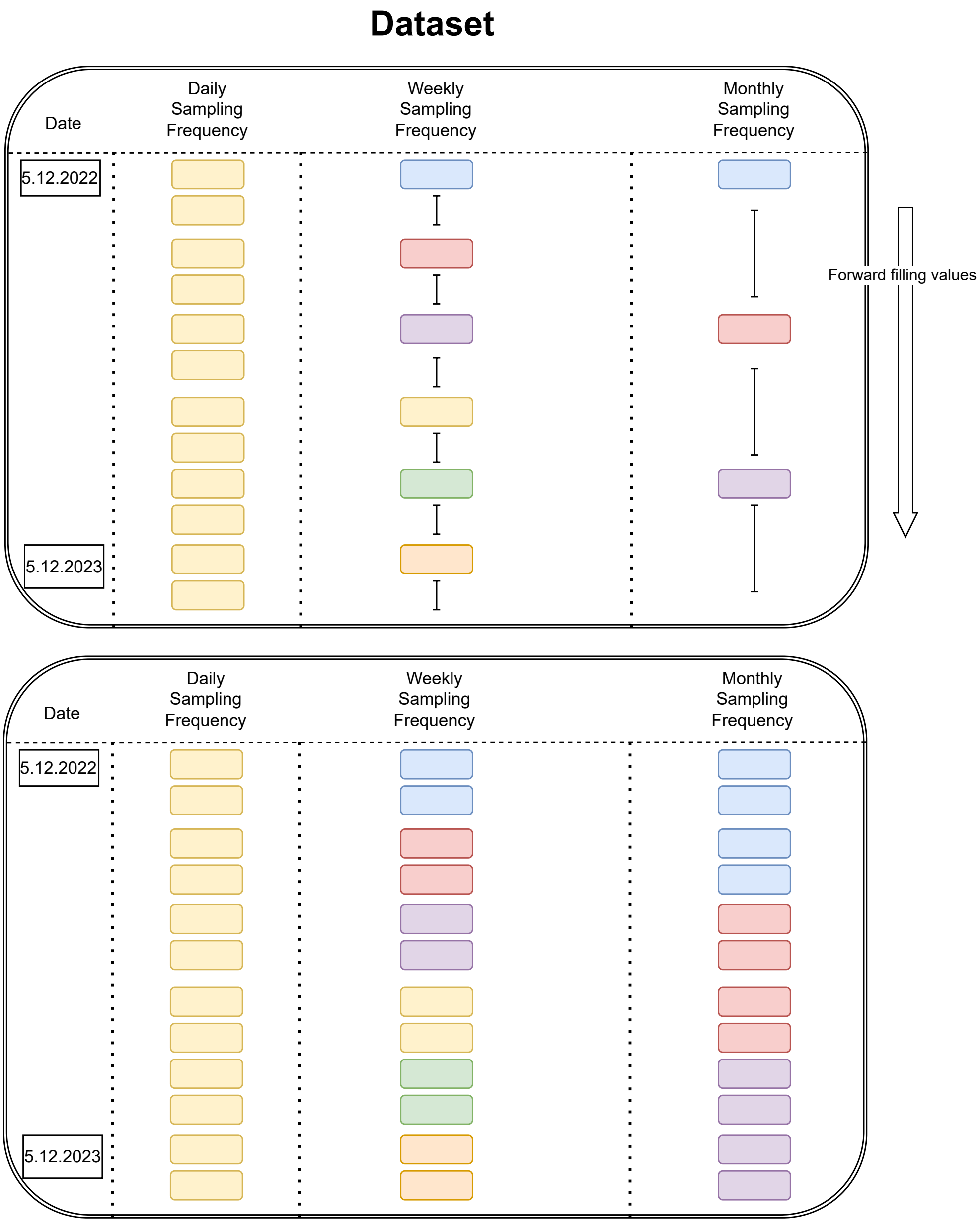
$$h \in \{1, 5, 10\} \tag{3.1}$$

$$j \in \{1, ..., k\} \tag{3.2}$$

$$i \in \{1, ..., n\} \tag{3.3}$$

We start by denoting the original dataset $\mathbf{X} \in \mathbb{R}^{n \times k}$. Now assuming

Figure 3.4: Dataset Feature Interpolation



$\mathbf{X_{:,k}} = [\mathbf{x}_{1k}, ..., \mathbf{x}_{nk}]$ is the BTC price feature vector we shift it back in time by h and drop the data without corresponding counterpart. Concretely, we drop all $\mathbf{X_{n-h:n,1:k-1}}$ and $\mathbf{X_{1:h,k}}$. With this technique we always sacrifice $2h$ observations from the original dataset. If we further split the dataset into the explanatory and target features and reset the indexation such that we denote

$m = n - 2h$ we end up with the following matrices where the target matrix Y is essentially only a vector where $y^\top = \mathbf{X}_{:,\mathbf{k}}$, see Figure 3.5.

$$\mathbf{X} \in \mathbb{R}^{m \times k-1} = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1k-1} \\ x_{21} & x_{22} & \dots & x_{2k-1} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mk-1} \end{pmatrix} \tag{3.4}$$

$$\mathbf{Y} \in \mathbb{R}^{m \times 1} = \mathbf{y}^\top = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{pmatrix} \tag{3.5}$$

We can now observe that modeling y_i as a function of explanatory variables x_i is a forecasting with horizon h into the future. Where we essentially try to estimate the function $f_{foreacast}$.

$$y_i = f_{forecast}(\mathbf{x_i}) \tag{3.6}$$

The final preprocessing step is specific to the LSTM network which is a type of architecture that requires the input to be of the shape (num timesteps, num features). This means that it can use for example 10 day history for each variable and forecast the target variable. This is a really strong feature and makes it a viable option for our usecase. In order to use it, the input dataset has to be reshaped in such a way that for observation $\mathbf{x_i}$ concatenates values from $\mathbf{x_i}$ up to $\mathbf{x_{i-lag}}$, see Figure 3.6

$$\mathbf{X_{i,:}} = [[x_{i1}, ..., x_{ik}], [x_{i-11}, ..., x_{i-1k}], [x_{i-lag1}, ..., x_{i-lagk}], ...] \tag{3.7}$$

Figure 3.5: Dataset Shifting for Supervised Learning

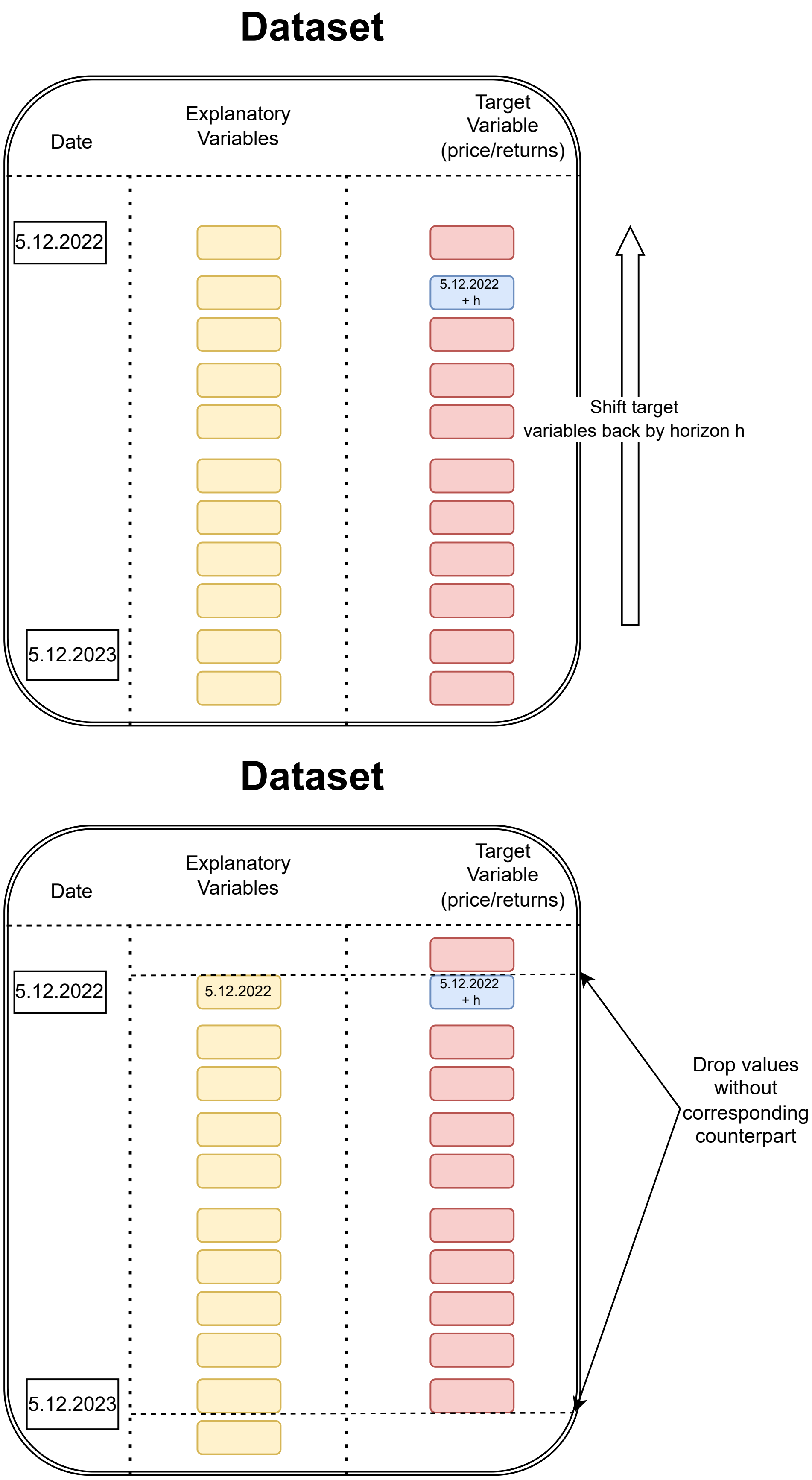
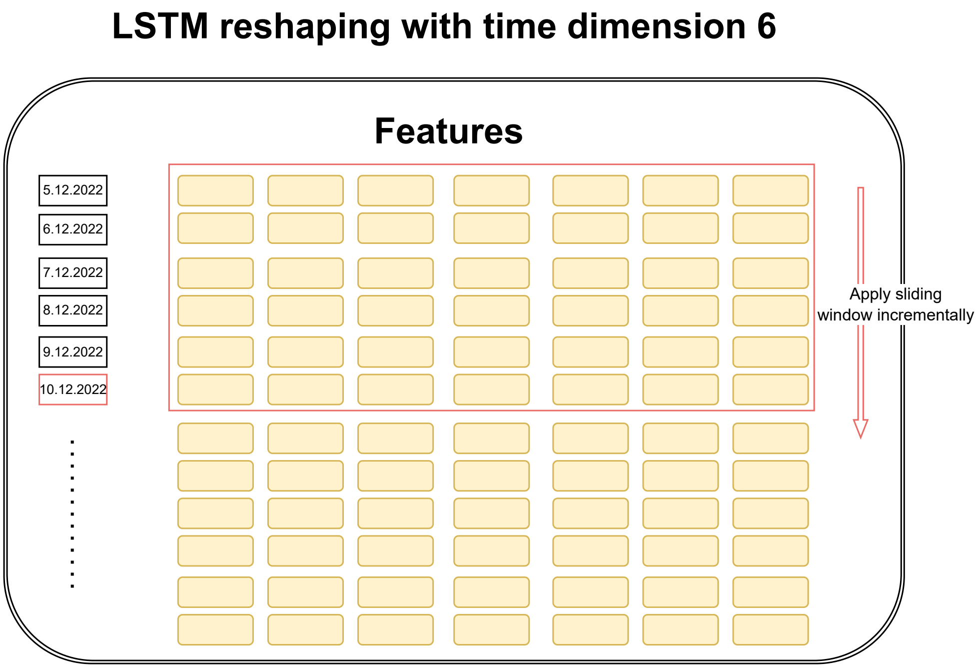


Figure 3.6: LSTM Reshaping



Chapter 4

Methodology

4.1 Machine Learing

It is generally agreed upon that the term ML refers to the field of study that gives computers the ability to learn without being explicitly programmed. This fact was first introduced by Arthur Samuel in 1959 Samuel (1959). However, note that the reference to this paper is used loosely, as the term ML was not directly used in the paper and it is rather a retrospective interpretation of the paper.

The term ML was more explicitly introduced by Tom M. Mitchell in 1997 Mitchell (1997):

Definition 4.1 (Machine Learning). A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

Typically, the experience E is represented by a dataset, which is used to train the model. We can generally say that ML is the ability to get better at specified task by learning from provided relevant data without problem domain specific programming of the computer.

Nowadays ML is at the core of many applications that we use daily. The usecases range from spam filters, recommendation systems, medical diagnosis, stock trading, and many more. Currently, machine learning is dominated by deep learning, which is a subfield of ML that focuses on deep neural networks that rely on large datasets in order to be able to generalize well. On the other, hand traditional ML algorithms are still widely used and are often the first choice when the dataset is small or the problem is low dimensional. Whereas deep learning models can be used in high frequency data, where the datasets are large enough to train the model, daily closing stock price prediction is a task that can be successfully solved with traditional ML algorithms. As the datasets are much smaller.

In general, cryptocurrencies lie somewhere in the middle of the spectrum. Exactly as stocks, either high frequency or low frequency data can be chosen based on the research question. The difference however is that cryptocurrencies are much more volatile than stocks, and they can have much higher dimensionality as we can use many technical analysis indicators to predict the price. That is why we will use a combination of traditional ML algorithms and deep learning models to predict the closing prices or returns of various cryptocurrencies.

ML algorithms can be divided into three main categories: supervised learning, unsupervised learning, and reinforcement learning. As mentioned earlier, we will focus on supervised learning as the process of forecasting can be easily transformed into a supervised learning problem where the input features are historical or current data and the output is the future price or return.

It is important to note on the fundamental difference between machine learning and traditional econometric models. In econometrics the focus is to uncover the underlying relationship between the variables and to understand the size of contribution of each feature. In machine learning, the focus is mainly on maximizing the performance metric for predictions and the magnitude of the effects usually remains unknown. This is definitely a weakness of machine learning which researchers try to adress by developing new field of explainable Artificial Intelligence (AI). Where they focus on developing models that are able to explain their predictions in a human understandable way. They provide a significant promise for the use of ML methods in finance in the future where the interpretability of the model is crucial for customers or regulators in specific subfields.

4.2 Ridge Linear Regression

The simplest model that we can use for forecasting is the LR model. Generally, there exists a closed form solution for the LR model.

$$\hat{y} = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n \tag{4.1}$$

But in practice, we use gradient descent to find the optimal parameters. Gradient descent is an optimization algorithm used to minimize the cost function provided to the model. The idea is that we compute partial derivation of the error function with respect to each parameter of the model and update the parameters in the opposite direction of the gradient where the learning rate is the step size of the update. Usually, minibatch gradient descent is used where the gradient is averaged over a small batch of randomly sampled data.

The update rule for the parameters θ using gradient descent is given by:

$$\theta_j := \theta_j - \alpha \frac{\partial J(\theta)}{\partial \theta_j} \tag{4.2}$$

where α is the learning rate and $J(\theta)$ is the cost function.

4.3 Support Vector Machines

4.4 Long Short-Term Memory Recurrent Neural Networks

4.5 Principal Component Analysis

4.6 Stationarity in Time-Series

We would like to explicitly adress the concept of stationarity as there seems to be a lot of confusion around the topic especially because the boundary between traditional econometric models and machine learning models is not always clear.

Stationarity is a crucial concept in time-series analysis. Despite the fact, that there exist many tests and rigid definitions for it, it is often reduced to the concept of constant mean and variance or generally to the fact that the parameters of the distribution do not change in time. Without this property the errors of the model become function of time which is not desirable for proper inference.

Econometrics usually prefers stationary data for aforementioned reasons because it is cruicial for inference and interpretation of the results. That is why econometricians like to model returns instead of prices, as returns should generally be stationary. Imporantly, there is always the possibility to transform the predictions back to the original prices by adding the forecasted returns to the last observed price and potentially reversing some normalization steps.

This is different for ML as the focus is on prediction and the models are fundamentally different. As the models are trained using gradient descent and not using the analytical solutions, the stationarity is not as crucial. Clearly, the models will perform better on stationary data because it requiers much less capacity for the model as some of the information removed by differencing. However, models with enough capacity can easily learn non-stationary data and capture information about trends, seasonalities, and other patterns. Thus we decided to test our models on both prices directly and on returns where the results are much less dependent on changes in the distribution of the data.

4.7 Proposed Forecasting Framework

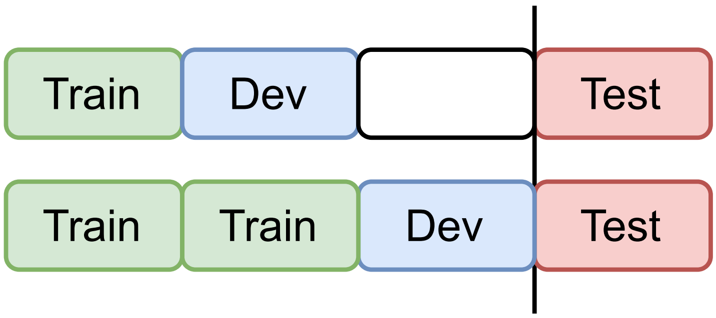
We propose a forecasting framework which is designed to compare the performance between using PCA as a dimensionality reduction technique and using the raw data. The framework is shown in Figure 4.2. The preprocessing layer is responsible for cleaning the data, filling in missing values and tranforming the problem to supervised learning as described in 3. Following stage is responsible for reducing the number of features. The first PCA step transforms the data onto n principal components and the filtering step chooses the most important features such that their cumulative variance adds up to 95%, 98% or 99%. Following is the LSTM reshaping layer that is responsible for transforming the data into a 3D tensor for the LSTM RNN as described in 3. The most crucial layer is the forecasting layer that essentially consists of 3 parts. Firstly, it normalizes the variables using robust scaler to ensure that the input features come from the same value range. Secondly, it uses grid search to search for the best hyperparameters for the model. This is a cruical step as the change of dimensionality changes the optimal hyperparameters. Without this step it would be hard to establish any real effects as the change in performance might be attributed to the change in suitability of hyperparameters. Lastly, it trains the model and evaluates the performance using the best found model. This is the reason why we abstract the metrics layer seperately to make it apparent that the metrics are calculated on the best model found by the grid search. The metrics layer is also the layer where we can statistically compare the significance of the difference between the models. It is important to note that this framework is executed across all specified forecasting models, cryptocurrencies of interest, and forecasting horizons as we expect the effects to be quite different for different models and forecasting horizons.

As we have already noted the fact that that the target price is clearly non-stationary, has important implication for the choice of splitting strategy for the grid search hyperparameter optimization. There are two main strategies for splitting the data into training and testing sets. The first one is traditional train, development, and test split where the model is trained on the training set, hyperparameters are optimized on the development set, and the model is evaluated on the test set. This approach is generally sufficient when the dataset is large enough and we believe that the distributions of the three datasets are similar. A more robust approach is to use grid search with cross-validation. This approach makes sure that we have not overfitted the model to the development set. Firstly, we split the data into training and testing set. And then we iteratively split the training set into training and validation set. Train the model on the training part of the train set and evaluate on the validation set. Finally we average over the results across all validation sets and take the best hyperparameters from the provided grid. This approach avoids overfitting and is typically used when we have enough compute to train the models.

Note that the goal of grid search is to create a robust representation of a reasonable test set distribution as it samples randomly the points into the training and validation set. This approach works if the data is stationary and the distribution of the data does not change drastically in time. But time series rarely have this property and cryptocurrencies suffer especially profound changes in the distribution as they have grown in popularity. The difference between the training and test set is extreme but that is something that we can do very little about as we want the test set to be as close to the future as possible.

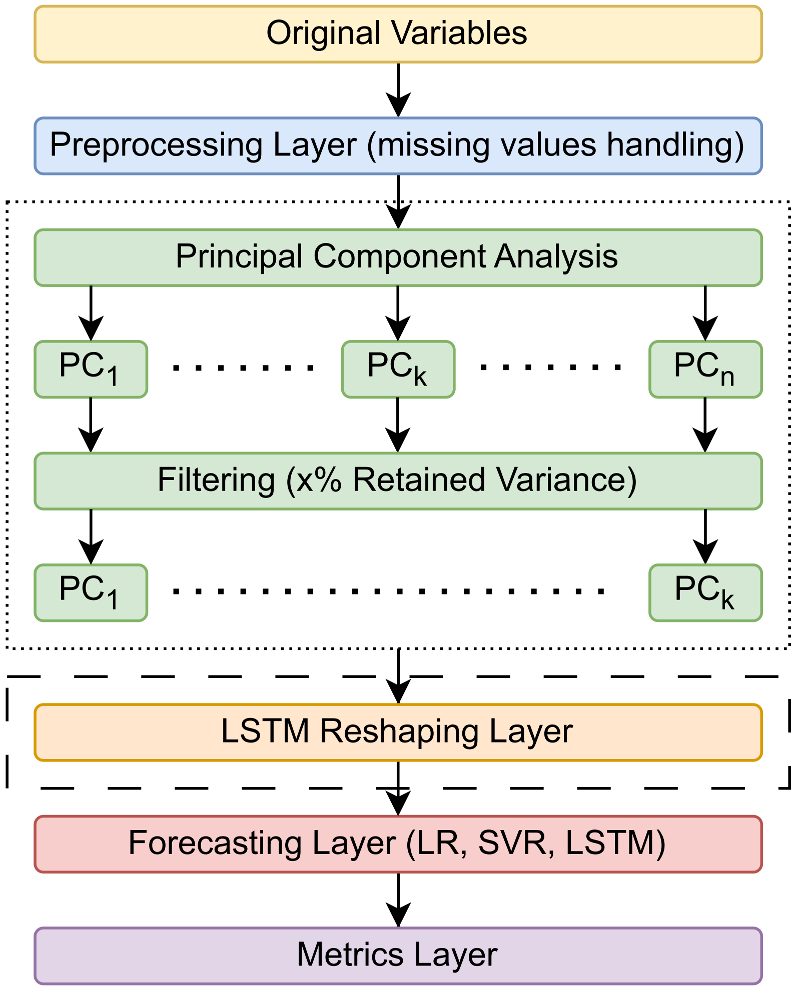
Additionally, there is an extremely common mistake that researchers make when they use grid search for time series data. This problem is called data leakage and it occurs when future distribution of the data is used to optimize the hyperparameters. As ML models typically require data to be scaled and normalized, the parameters for the normalization need to be learned only on the historical data not on the future data otherwise the results will be biased and suggest higher quality of the model than it actually is. Theoretically, this could be relaxed on the training set as the normalization might be fitted on the whole training set but it is crucial that the test set distribution is never leaked to the fitting procedure. However, we believe that the correct methodology is to use a rolling window approach for the grid search where the normalization parameters are fitted on the training set and the validation set. This is why we use time series split for the grid search without randomly shuffling the data. This approach splits the training set into k folds and iteratively trains the model on *k-1* folds and evaluates on the *k-th* fold. This approach has the advantage that the model is actually trained with different sized training sets which is useful for generalization properties but has the disadvantage that the difficulty of the splits is extremely volatile. This is definitely a limitation as the performances between splits can vary significantly and averaging over the results might be prone to noise. However, we believe that this is the methodologically correct approach. We opted to use only two splits as the the

Figure 4.1: Time Series Split with k=*2*



data size is relatively small and the results were extremely noisy when using more splits.

Figure 4.2: Proposed Forecasting Framework



Dimensionality reduction section is either used or not for comparison

Specific only to LSTM Forecasting Layer

k - is chosen such that 95/98/99% of variance is retained

Chapter 5

Results and Discussion

5.1 Results Intepretation

5.1.1 Basline Autoregressive Integrated Moving Average

5.1.2 Linear Regression

5.1.3 Support Vector Machines

5.1.4 Long Short-Term Memory

5.2 Limitations

Chapter 6

Conclusion

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Appendix A

Detailed Results Tables

Appendix B

Additional Figures

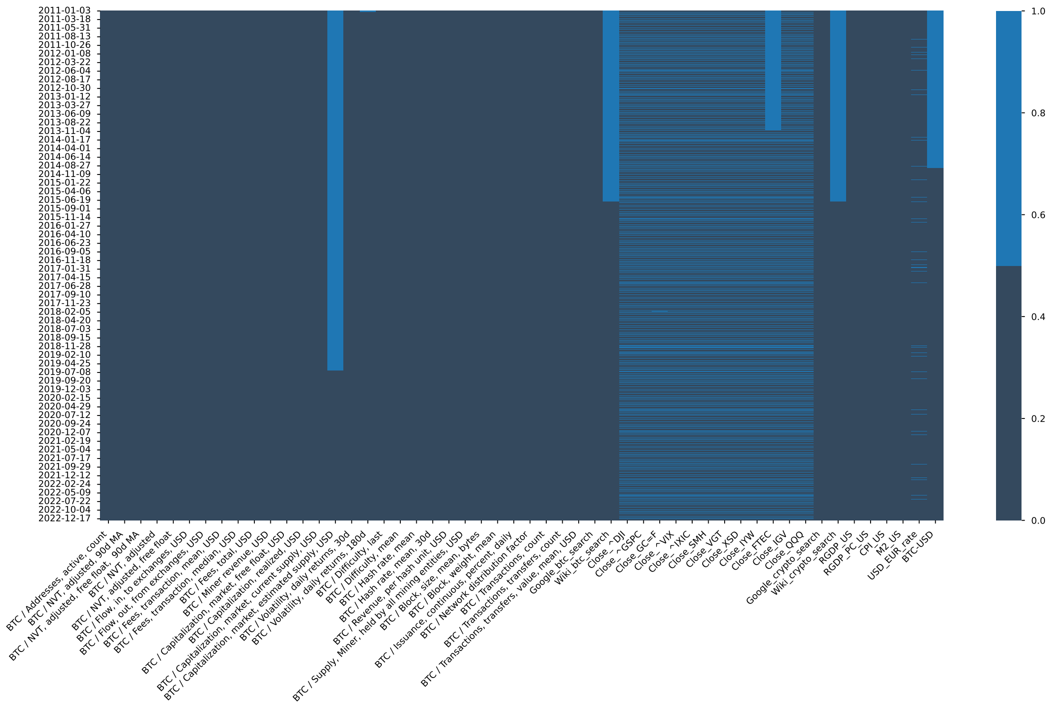

Figure B.1: Missing Values BTC before subsetting

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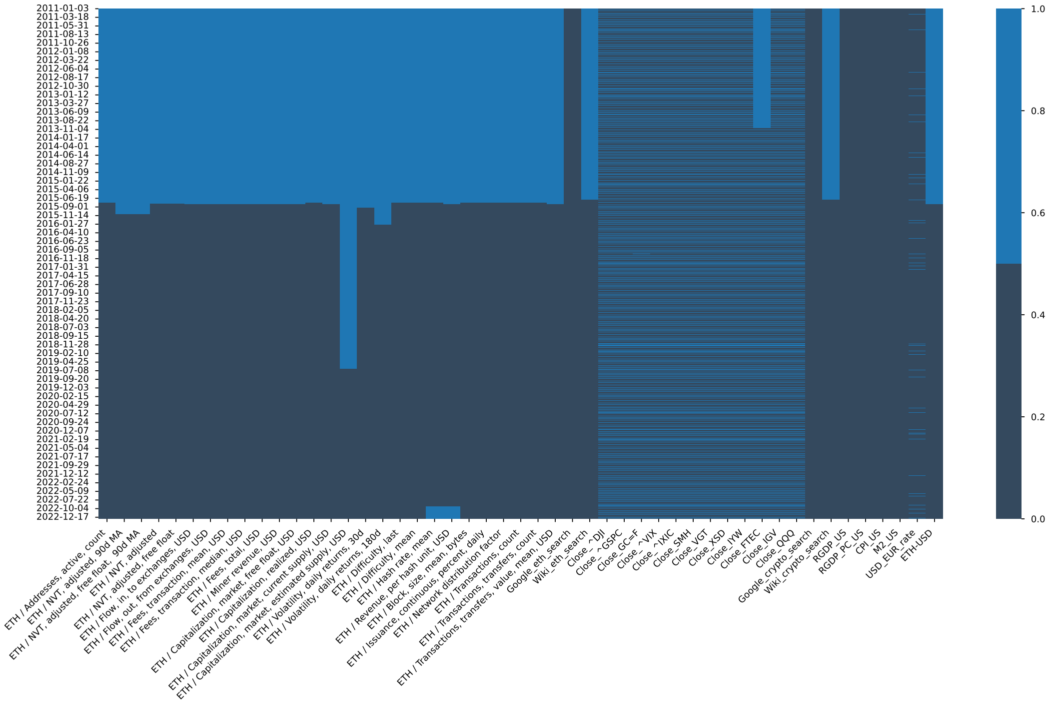

Figure B.2: Missing Values ETH before subsetting

Source: Author

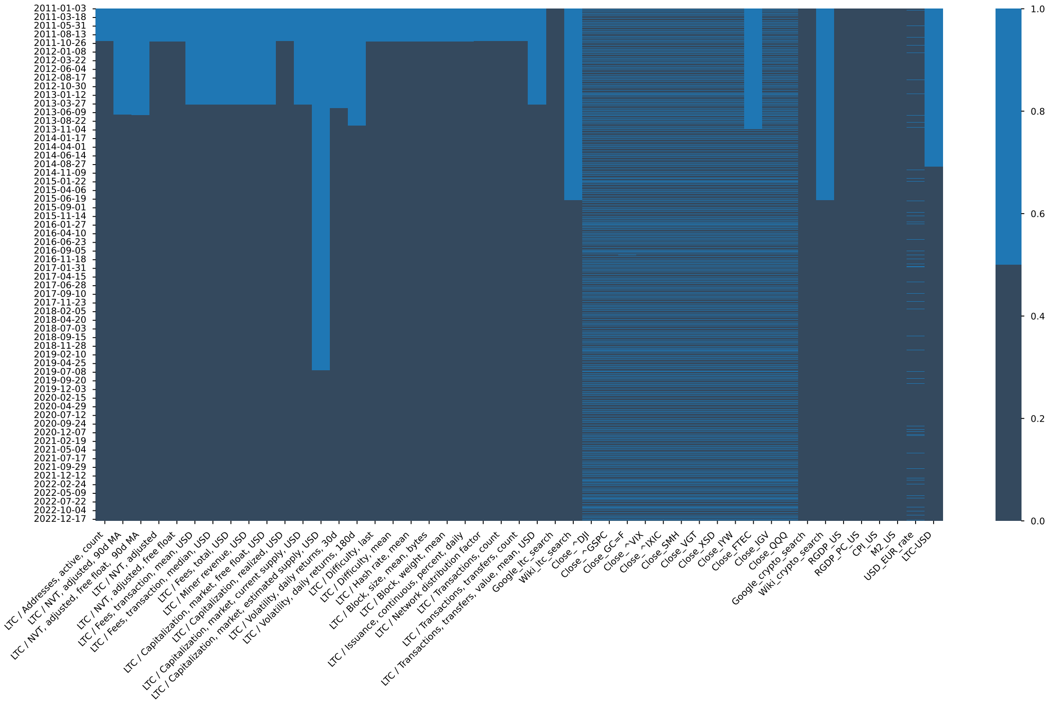

Figure B.3: Missing Values LTC before subsetting

Source: Author

Appendix C

Aditional Contents

All of the source codes and data to reproduce the results are available at https://github.com/Tomas-Barhon/Noise-reduction-and-feature-extraction. Including all the instructions on how to install the necessary dependencies.