Comparative Study on different Machine Learning techniques for stock price forecasting

Introduction:

ML has become a very important technology in time series forecasting over various fields where researchers apply it to real world challenges. These fields include Healthcare [1], Energy [2], Agriculture [3], Climate & Weather [4] and financial data. Especially in financial data people have a huge interest in making accurate forecasts about developments of for example companies and stock prices given the huge potential for profit in trading.

In this paper we want to evaluate different Machine Learning models against each other based on their performance of forecasting different stock prices and indices. We therefore observe the current literature in this field:

Literature review:

The paper [5] from Kumbure et al. (2022) showed in a comprehensive review the technological development in the field of stock forecasting. The review includes 138 articles that have been published between 2000 and 2019. It looks on machine learning techniques that have been applied, features that were considered for training and metrices with which results have been measured. Like that they propose a differentiation of features into 4 categories which are “Technical Indicators”, “Macro-Economy”, “Fundamental Indicators” and “others”. They explain the importance and use frequency of these features. In section 5.4.8 that paper [5] illustrates what families of machine learning models have been applied to the task of forecasting stock prices. It shows that at least since the year 2000 Artificial Neural Networks (ANNs) in various forms were experimented with excluding Deep Learning models that are listed separately. That differentiation shows that deep learning models have especially been investigated heavily in the more recent years with the first reviewed paper applying them in 2017.

One representative of Deep Learning is mentioned very regularly in research – Long Short-Term Memory (LSTM). The paper [6] by Matharasi et al. (2025) evaluates two models against each other which are LSTM and XGBoost. Both delivered promising accuracy in forecasting AMD inc. stock data. While the LSTM model delivered slightly better accuracy in forecasts, the XGBoost model could excel in computational efficiency. Both models have been shown to have outstanding predictive performance when forecasting certain stock or index data. Teixeira, D. M., & Barbosa, R. S. (2025) have conducted another experiment [13] that shows their effectiveness in capturing the complexity of stock prices. They evaluate the models LSTM and XGBoost as well as other architectures such as GRU, CNN, RNN, but also different hybrid combinations of these like LSTM + CNN, RNN + GRU, GRU + CNN, LSTM + GRU, and RNN + LSTM. The study trains all of these models on historical stock data from Apple inc. and comes to the result that the standalone models of GRU, LSTM and XGBoost perform the best for the Apple inc. stock data. This is a little counterintuitive since one might think that hybrid models usually outperform their standalone component models since they might merge strengths of both models but as evidenced that is not generally the case. Under section 5 they discuss that the performance depends furthermore on the timeframe of the training data. They state that the gap of the performance between the models is smaller for a shorter time frame of training data. They state that the reason for that is the lower complexity of that time frame with fewer large amplitude oscillations. When choosing a longer time frame for training with a more complex data course, the three earlier mentioned models GRU, LSTM and XGBoost outperform the other models. Another paper [7] by Li, Siyuan. (2024) investigates the performance of a Kalman Filter and different types of LSTM models such as a single layer LSTM, a stacked LSTM, a bidirectional LSTM and a hybrid convolutional neural network (CNN)-LSTM. From those the bidirectional LSTM performed best for low-volatility stocks and the CNN-LSTM model performed best for high volatility stocks. Here the hybrid CNN-LSTM model in fact outperformed the standalone LSTM model. XGBoost models as mentioned in the two papers above seem to have a reasonable performance in forecasting stock prices under certain circumstances. This is evidenced by another experiment [10] by Aiyegbeni Gifty, & Dr. Yang Li. (2024) that was conducted to compare the performance of LSTM, ARIMA and XGBoost models. They also come to the conclusion that the XGBoost model outstands in performance under certain circumstances. They trained and evaluated the models on Google inc. stock data. This again emphasizes the impact that the data has on the performance of each model and it shows as the other studies mention as well, that certain models have advantages in dealing with certain characteristics in data like volatility making the choice of a suitable model very much not trivial. They also emphasize the importance of hyperparameter tuning. Like that they could reduce the Mean Absolute Error (MAE) from 17.63 without hyperparameter tuning down to 15.98 and the Root Mean Squared Error (RMSE) from 30.24 down to 27.34.

While the mentioned approaches of deep learning and ensemble methods have been looked into particularly heavy in the last years as shown in the previously mentioned papers and under section 5.4.8 of paper [5], the new transformer-based architecture has been proven effective in forecasting stock prices. The paper [14] by Yao, Y. (2025) shows its superiority over the previous mentioned models such as XGBoost, LSTM and CNN under certain circumstances.

Conclusion of Literature review:

In general, the advantages and superiorities of different ML algorithms depend strongly on circumstances such as dynamics in the data, feature selection, architecture tuning and hyperparameter tuning. This said, in this study we want to further diversify the results in this area in a way where we can evaluate predictive performance in relation to the characteristics of the data. Out of that we define our research question in the following paragraph.

Research question:

As mentioned in the previous section, to make useful statements about predictive performance of ML algorithms, we need to look on the relation of the performance of the predictions to the data which is used. We observed the dependency of predictive performance on data characteristics during our literature review where we recognized that different ML models can be claimed to be best performing depending on the parameters, input data and setting of the study. For our experiment we want to look on the performance of ML algorithms in forecasting stock prices based on the volatility of the stock data. We want to understand how volatility in the course impacts the forecasting performance of different ML algorithms and we also want to understand which model is most suitable for a certain degree of volatility in the data. To be more precise we are looking for results about the difference in performance of forecasts when using one ML algorithm and stocks of different volatility as input and we want to draw conclusions about the difference in predictive performance when using stock data of a certain volatility as input to train different ML models to see which is best suitable for a certain degree of volatility.

Machine Learning: (This section will talk about the bullet points as general topics but it will focus only on what’s necessary to understand later parts of the thesis, how important the parts are for the different models will be concretized in the experimental setup under methodology)

Artificial Intelligence refers to systems that are designed to simulate aspects of human intelligence such as decision, reasoning, perception and adaptation. The important part here is that these systems are capable of learning based on outcomes. With learning we mean that the system can update itself to make better predictions in response to the difference of the predicted outcome and the actual outcome. They don’t have to rely on silicon-based hardware but often do when referred to AI. Machine Learning is a subset of Artificial Intelligence. As IBM puts it [48], “Machine learning is a branch of [artificial intelligence](https://www.ibm.com/think/topics/artificial-intelligence) focused on enabling computers and machines to imitate the way that humans learn, to perform tasks autonomously, and to improve their performance and accuracy through experience and exposure to more data.“. To understand that further we look at an example that clarifies where the difference between any algorithm and ML algorithms comes from. Let’s say we have two algorithms that are designed to tell you how many years you can expect to live. The first one retrieves the average life expectancy for your country from the internet and then returns the difference between the life expectancy and your age as the number of years you have left to live. This algorithm would adapt in a sense where it updates its input which is the life expectancy but it still would not be considered a machine learning algorithm. In other words, although the input changes, the algorithm itself never updates so it’s considered non-ML. If the algorithm instead would get the number of years the individual actually had left to live once it died and then update its parameters based on how much the prediction was off, then the algorithm would be considered Machine Learning. So, the important difference is that our algorithm directly learns and gets better in its predictions using the value and direction of the error between the predicted and the actual outcome.

Machine Learning is widely accepted to be divided into 3 main subcategories. These subcategories are defined as Supervised Learning, Unsupervised Learning and Reinforcement Learning. There also exist hybrid approaches of these but we don’t need to understand those right now. We just look at these 3 main subcategories. These categories are also referred to as paradigms or learning paradigms.

Supervised Learning:

Supervised Learning is a machine learning technique where labeled data is used for the training. The model makes a prediction for the target variable based on the input and compares the predicted outcome with the actual outcome. This actual outcome is referred to as “label”. The direction and the amount of the error is then processed by the algorithm to learn. We can imagine supervised learning very well as a linear function with multiple input variables and coefficients for every input variable. We are aiming for a certain result value and we want to find the correct coefficients

In that way the algorithm adapts to the actual patterns and relations in the data allowing for better predictions. [48]

Unsupervised Learning:

Unsupervised Learning is a machine learning technique where data is used for the training that is not labeled. So we have no target variable that is to be predicted but instead we just have input data. That means that the algorithm is not designed to predict a certain value based on an input such as in the example with the life expectancy but instead it’s supposed to just work with the input. The algorithm aims for detecting patterns among the data points. We look at an example to get a sense for its usefulness.

Let’s say we have an online shop and we want to give recommendations for items that the customer would be likely to buy so that we sell more products. How can we know which products the customer might buy? Unsupervised learning can be used to improve these recommendations. There are relations or patterns among our items in terms of how they are bought together or separately. Of course, this is based on the taste and preferences of the customers. So, what we are learning is not an objective relation of items but rather how the customers choose them. Some of these patterns might be obvious such as “these chairs match with this table”, but there are many of patterns some of which are very complex and hard to grasp for humans. As we are constantly adding and removing products from our store it would be infeasible to manually explore and then pick these patterns for a recommendation. So, what we do instead is clustering customers into groups. In our example scenario we could say that customers within one cluster share the same taste or preference. The algorithm locates all customers in a multidimensional space where every information a customer can be described with makes up one dimension. the more similar customers are in terms of the information that we use to describe them the closer they are in this space. Areas where many customers are located close together are called clusters. We look at one example for a cluster. Let’s say for whatever reason many customers who buy item a and b also buy item c two weeks later. For humans it can be hard to find patterns as this or much more complex ones. The algorithm would see that there is a higher density of customers in the area of our multidimensional model space for which “bought item a”, “bought item b” and “bought item c” is true. The algorithm looks at how this information fit together and sees that item c is always bought after item a and b was bought and only if both were bought. Like that the simple conclusion is to recommend item c to customers about 2 weeks after they bought item a and b.

The ways unsupervised learning algorithms work differs from architecture to architecture. One common way is to locate the data points in a multidimensional space for which every information about the data is one dimension. Clusters are then defined as areas where the density of data points is higher than elsewhere.

Reinforcement Learning:

Reinforcement learning is a little bit similar to Supervised Learning but the algorithm doesn’t use labeled input data. Instead, the algorithm works with trial and error. Successful results will be rewarded and, in that way, reinforced so the algorithm strengthens that behavior while at the same time bad moves are punished with a penalty and the algorithm learns to avoid that certain behavior.

These 3 Subsets describe *how* we train the system. They specify the data we see, what feedback we get and what objectives to optimize. There is a clear distinction to the ML algorithms. We will discover the 3 algorithms that we are using in this study under methodology. So while the 3 subsets we just mentioned, specify how the algorithm learns in a conceptualized way, the algorithms themselves defines the rules and operations that happen during that learning.

The technique of machine learning that we are using is Supervised Learning. This makes sense because we have an input of stock data and market circumstances and we want the algorithm to learn to predict the next stock price based on that.

The performance of a ML algorithm is measured with by the error. This is usually some way to measure the difference of the predicted value for the target and the actual value of the target. If they differ strongly, we would say that the error is greater and the performance is worse. The same vice versa – if the difference between predicted and actual value is small, we say that we have a small error and a better performance. Concrete ways to measure the performance will be explored under Methodology.

(Methodology):

In our experiment we will evaluate different ML algorithms based on their predictive performance in regards of the data used. We choose an LSTM, an XGBoost and a CNN architecture for this evaluation since they have been shown to be relevant algorithms in the field of stock price forecasting as shown in the literature review. We use non-hybrid, vanilla versions of these models to have more meaningful results. We tune their hyperparameters separately.

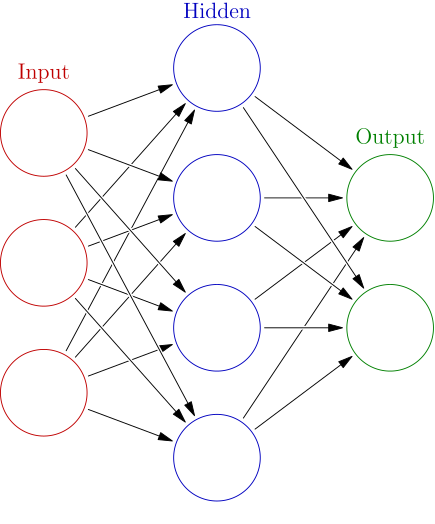
Model selection:

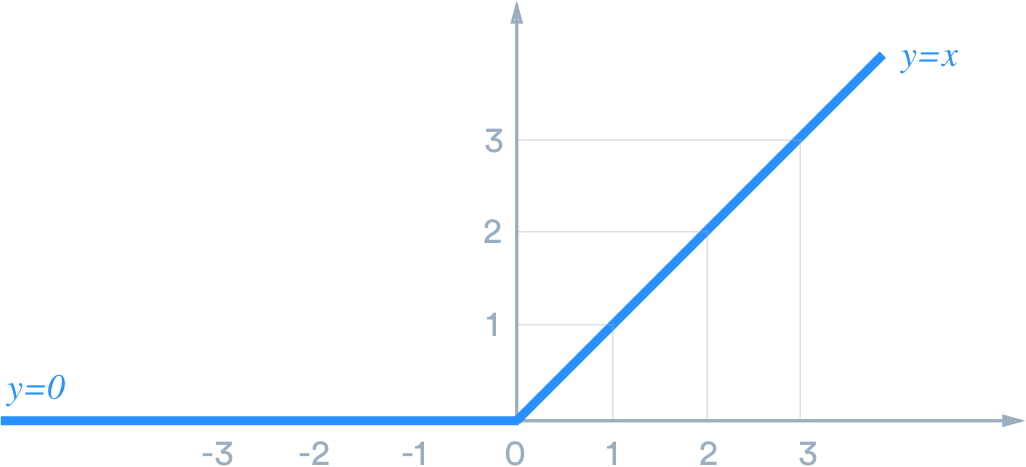
As we understood before Machine Learning can be divided into 3 subsets. Supervised Learning, Unsupervised Learning and Reinforcement Learning. For our task we are looking at Supervised Learning. LSTM, XGBoost and CNN for time series data are some of the best performing Machine Learning algorithms in stock price forecasting as we conclude from our literature review. We will evaluate all three models on our stock data.

We learned earlier that there are 3 main learning paradigms within Machine Learning. For our purposes we are looking at Supervised Learning at the moment. All paradigms can be further divided into different Machine Learning families. These families are groups of ML algorithms. All algorithms within one group or family rely on the same basic idea or architecture of learning. There are many families we could look into but this would be out of the scope of this thesis. The 2 families under Supervised Learning that we are interested in right now are Neural Networks and Ensemble Learning.

Neural Networks:

Neural networks are systems that are inspired by the structure and functionality of the human brain. They consist of neurons which are connected. The artificial neural network adjusts these connections between the neurons when it learns from data. A neural network typically looks like this:

It is important to mention that there are different architectures of neural networks two of which we will explore in more detail under section Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN). They can vary strongly in their functionality, use cases and structure.

The basic version of a neural network is called a feed forward neural network. It always has one input and one output layer. In addition to those the network can consist of an arbitrary number of hidden layers between input and output layer. Each layer including input and output layer consists of at least one neuron. The number of neurons in the input layer needs to match the size of our input. The input necessarily consists of one or more values. So, if our neural network takes images of pixel size (28 x 28) as input then we have 784 values per image and need 784 neurons in the input layer. This applies in our case of a feed forward neural network. We will later see that other architectures like a convolutional neural network for example have a different way of dealing with 2Dimensional input.   
Each neuron is connected with other neurons. These connections are defined by their weight. In our feed forward neural network every neuron has a connection to every neuron of the next layer. Again, this is just the case for our standard feed forward neural network. There exist more specialized structures for which this rule doesn’t apply. The value of a neuron is fed forward to all other neurons it has a connection to. In our basic case the neurons only have connections to neurons of the next layer so the values only move from left to right as the directed arrows between the neurons in the image suggest. When a value is fed forward it is multiplied by the weight of the connection. A neuron receives the weighted values from all neurons that have a connection to it. Within the neurons all these weighted values are added up and the bias of the neuron is added. The value of the bias is learned during training. Before the value is given forward to the next neurons, a function is applied. This happens in each neuron. The function is called activation function. It has this name because the function is what decides whether a neuron is “activated”.  
This is very much inspired by nature. The neurons in our brains receive an input which arrives as electrical signals. Only when the membrane potential exceeds a certain threshold does the neuron “fire” an action potential. Artificial neural networks simulate this behavior with an activation function which also is designed to decide whether and how strong a neuron “fires”. One widely used activation function is called Rectified Linear unit (ReLU). It looks like this:

It “rectifies” or cuts off the negative part and sets every value in it to zero. Every value greater than or equal to zero is retained by a linear function. That’s a very simple understanding of the activation behavior.

We need to introduce the concept of non-linearity here. A linear relation between two variables x and y always has this structure:

Linear functions let us solve linear problems. They always are a straight line when drawn as a graph. For example, the relation of euros to cents is a linear function. You always multiply the amount of euros by 100 to get the number of cents with the same worth.

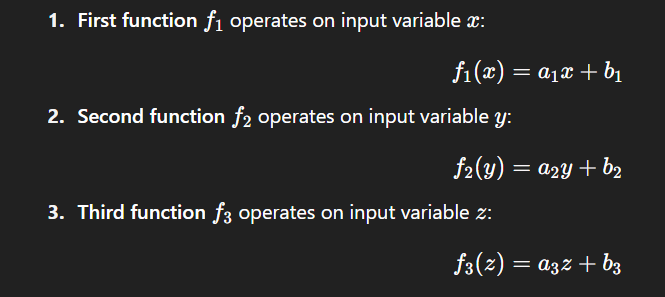
A nonlinear relationship between two variables is everything but a linear relationship. All of those functions are nonlinear.



If we want to model nonlinear relationships, we need a nonlinear function to do that. One example that actually fits nicely to the stock market is compound of interest. If you want to model the course of an investment given a certain interest rate greater than zero, you are facing a nonlinear problem which is only solvable with a non-linear function.

In the fewest cases the problem we want to solve using a neural network is linear. More precisely we usually don’t know the exact relation between the input and output data so we have to assume nonlinearity. Even in the case that the relation is perfectly linear, then we can still use nonlinear functions since they can also model linear relations.

Let’s assume we are having only linear activation functions which is the case that includes having no activation function at all because simply passing on the values would be synonymous to the identity function which is a linear function. Then our whole neural network would only be able to capture linear relationships between input features and the output. This is due to the nature of stacked linear functions. If you stack n linear functions, then no matter how big n is, the resulting function always collapses down to a linear function with n input variables. We look at a simple example that illustrates that.



Stacking:

f1(f2(f3(z))) = f1(f2(a3\*z+b3)) = f1(a2\*(a3\*z+b3) +b2) = a1\*(a2\*(a3\*z+b3) +b2) +b1

= a1\*(a2\*a3\*z+a2\*b3+b2) +b1 = a1\*a2\*a3\*z+a1\*a2\*b3+a1\*b2 +b1

Since a1, a2, a3, b1, b2 and b3 are fixed values, we can compute them together to their effective values.

Weff = a1\*a2\*a3

beff = a1\*a2\*b3+a1\*b2+b1

So, the resulting function is f4(z) = Weff \* z + beff.

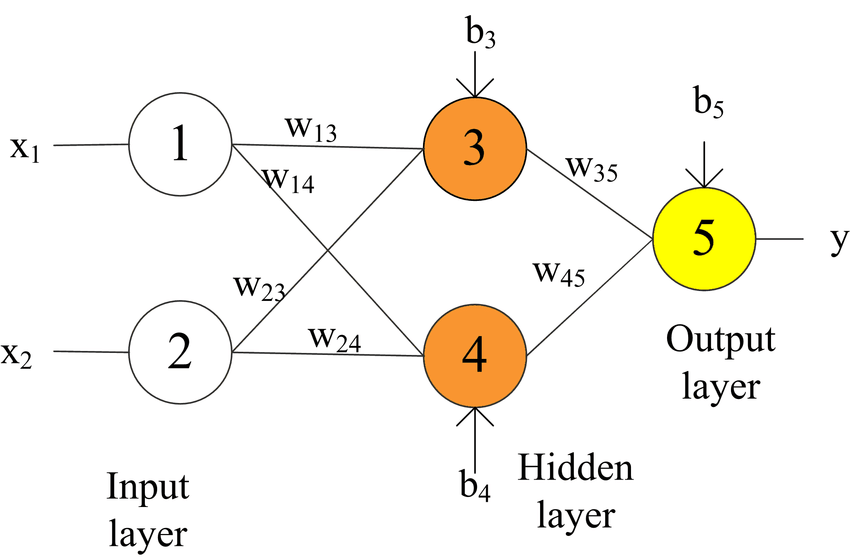
No matter how often we stack linear functions or in the case of neural networks no matter how many layers of neurons with linear activation functions we stack we can never capture non linear relations between input and output.

That’s why we need nonlinear activation functions like ReLU.

We talked about the connections between the neurons and we understood that these connections are defined by their weight and their bias. The weights and biases are learned during training through backpropagation.

To understand the concept of backpropagation we will walk through the process of one prediction using an example network. One prediction or the process of walking the input from the input layer through the network to the output layer is called forward propagation.

The example neural network we are using looks like this:



Where…:

X1 – is the input feature 1

X2 – is the input feature 2

1,2,3,4,5 are the neurons

bn – is the bias in neuron n

wi,j – is the weight of the connection from i to j

y – is the output value

One forward propagation leaves an output. If you have labeled training data and labeled outputs for each input, then you can compare the predicted output with the actual one to learn better weights and biases. We will first only do the process of one forward propagation and then show how the network refines its weights and biases comparing the predicted target value with the actual one.

Example:

X1 = 1.0

X2 = 2.0

Value in neuron 1 = 1.0

Value in neuron 2 = 2.0

W1,3 = 0.5; w2,3 = 0.9; b3 = 0.5

W1,4 = 0.3; w2,4 = -0.4; b4 = 0.6

W3,5 = 0.7; w4,5 = 0.3; b5 = 0.8

The activation function in neuron 3 and 4 is ReLU and the output layer has no activation function.

1. Value x1 and x2 simply arrive in neuron 1 and 2.
2. Neuron 3 receives two values and together with its bias b3 adds them up.

That’s:

X1 \* w1,3 + x2 \* w2,3 + b3

= 1.0 \* 0.5 + 2.0 \* 0.9 + 0.5 = 2.8

Now the activation function is applied on 2.8

Value in neuron 3 = max(0, 2.8) = 2.8

1. Neuron 4 receives two values and together with its bias b4 adds them up.

That’s:

X1 \* w1,4 + x2 \* w2,4 + b4

= 1.0 \* 0.3 + 2.0 \* -0.4 + 0.6 = 0.1

Now the activation function is applied on 0.1

Value in neuron 4 = max(0, 0.1) = 0.1

1. Neuron 5 receives two values and together with its bias b5 adds them up.

That’s:

X3 \* w3,5 + x4 \* w4,5 + b5

= 2.8 \* 0.7 + 0.1 \* 0.3 + 0.8 = 2.79

1. The calculated output y is 2.79

Our calculated output y with 2.79 is what our neural network computes us as result for the input x1 = 1.0 and x2 = 2.0.

Let’s now say that we have an actual output value of 2.1 for this input. Then we can calculate the loss and perform a backpropagation.

The loss E is calculated as:



Where…:

E – is the loss

A5/ y – is the predicted outcome

T – Is the actual outcome

In our case that’s:



To perform backpropagation we need to calculate the derivates of the

to the identity function which and we pass values through our neural network and at every pass apply the activation function after multiplying them by the weight of the connection

The activation function is central to why neural networks are powerful systems.

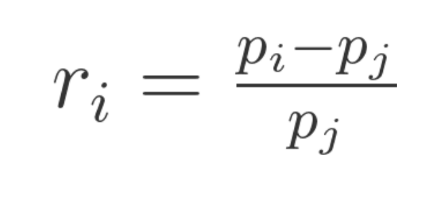
* Machine Learning
  + Supervised Learning
    - Deep Learning
      * Feed Forward (CNNs)
      * Recurrent (RNNs)
        + LSTM
    - Ensemble Learning
      * Gradient Boosting
        + XGBoost
  + Unsupervised Learning
  + Reinforcement Learning

Volatility:

Volatility is known as the degree to which data disperses over time or in other words “Volatility is a statistical measure of the dispersion of returns for a given security or market index. It is often measured from either the standard deviation or variance between those returns.”[15]. We understand that the volatility has to be measured to deliver meaningful results. The most common way to measure the volatility of stock courses in finance is by calculating the standard deviation or more precise the sample standard deviation of logarithmic returns [16]. If we do that we get a measure that tells us how strongly the data points differ on average from the mean of the values. That’s quite good to compare the volatility of different stocks or ETFs.

To do so, we first need to calculate the logarithmic returns. We choose to calculate logarithmic returns instead of simple returns. We can understand why we choose the logarithmic return over the simple return by looking at a simple example.

We calculate the simple return with



… where:

Ri = stands for the current data point’s simple return

Pi = stands for the current data point’s value

Pj = stands for the previous data point’s value

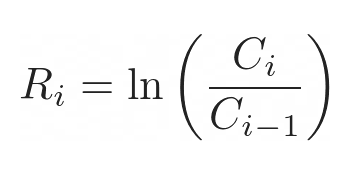
Let’s say we have a stock price development for a company X of the following:

|  |  |  |  |
| --- | --- | --- | --- |
|  | Month 1 | Month 2 | Month 3 |
| Stock price | 100$ | 150$ | 100$ |
| Simple returns | - | +50.00% | -33.33% |

Since the price ends up at 100$ again we know that the total return is 0%. But when looking at the returns we have Month 1-2: +50% and Month 2-3: -33.33%. So, we could assume that the average return is (-33.33%+50%)/2 = 8.335% which is clearly wrong. The mistake we made in our calculation is not considering the compound of interest. We need to understand that the 50$ change from Month 2 to Month 3 is already based on a starting value of 150$ which is different than the starting value for the change in value from Month 1 to Month 2, which was again 50$ but this time based on 100$. To make our numbers make sense, we would need to calculate the total return by considering compound of interest by multiplying the returns instead of adding them up. Then we would get the correct 0% total return. The part where the log returns is a more intuitive way of doing it, is when it comes to looking at returns over single time steps as a human. Let’s extend our course of the stock price by another 4 Months:

Our returns now would be

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | Month 1 | Month 2 | Month 3 | Month 4 | Month 5 | Month 6 | Month 7 |
| Price | 100$ | 150$ | 100$ | 150$ | 100$ | 150$ | 100$ |
| Simple Return | - | +50.00% | -33.33% | +50.00% | -33.33% | +50.00% | -33.33% |

If we look at returns like these, we could easily think that we end up with a positive return overall but when looking at the actual stock price we see, that we are just oscillating between two values. When we use the logarithmic return all that gets much more intuitive and easier to use. We calculate the logarithmic return with: [17]

… where:

Ri = stands for the logarithmic return at the current data point

ln = stands for the natural logarithm

Ci = stands for the current data point’s value

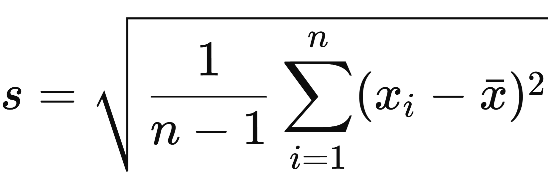
Ci-1 = stands for the previous data point’s value

Let us now also calculate the logarithmic return of our stock course.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | Month 1 | Month 2 | Month 3 | Month 4 | Month 5 | Month 6 | Month 7 |
| Price | 100$ | 150$ | 100$ | 150$ | 100$ | 150$ | 100$ |
| Simple Return | - | +50.00% | -33.33% | +50.00% | -33.33% | +50.00% | -33.33% |
| ln Return | - | 0.405 | -0.405 | 0.405 | -0.405 | 0.405 | -0.405 |

If we now add up the logarithmic returns, we are left with 3\* (0.405) – 3\* (0.405) which is 0. So using the logarithmic return instead of actual stock prices itself or simple returns of the stock prices, leaves us with numbers that are detached from the compound of interest effect and give us a much more intuitive understanding of the volatility. We now have our logarithmic returns, which leads us to the next step which is calculating the sample standard deviation based on them.

To calculate the sample standard deviation, we use this formula.



… where:

n = stands for the number of data points that we calculate the sample standard deviation for

xi = stands for the currently observed data point (for us it’s the current logarithmic return)

= stands for the mean of all data points (for us it’s the mean of all logarithmic returns)

In our codebase we write our own pipeline to calculate the volatility in the way we just discussed. For that we use a pre-implemented function for the sample standard deviation which is located in *pandas.DataFrame.std()*.

The standard deviation gives information about how strongly the data points are deviated from the statistical mean. If the standard deviation is lower it means that the data points are on average closer to the mean and if the standard deviation is higher, it means that the data points are spread wider.

We now have defined our metric for volatility and we can start choosing the stock data we want to train the algorithms on.

So far so good. We now have a measure that tells us how volatile the stocks have been in the past. The volatility score is averaged over our time frame which is 5 years. We could go ahead and select the stocks based on that score. If we do so, we might see, that stocks with the same volatility score seem to have much different characteristics in the data.

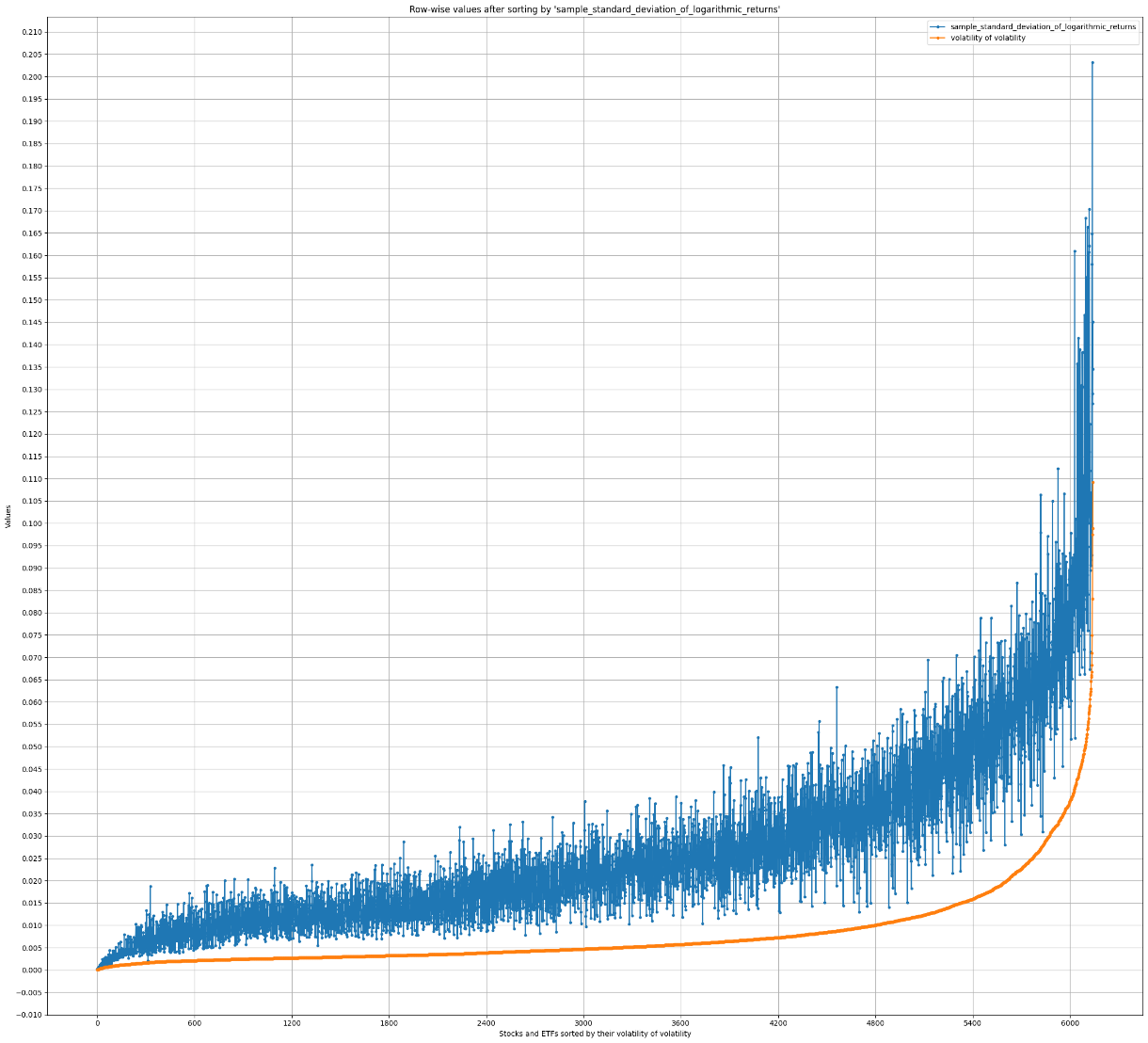
To understand that using an example we take two stocks. One stock is oscillating moderately strong throughout the whole course let’s say its volatility score is 5 at every point in time. The other stock oscillates compared to the first one very little during the first half but a lot during the second half. Let’s say during the first half it has a volatility score of 1 and during the second half it has a volatility score of 9. The average volatility of these two stocks is 5 even though they have very different characteristics and the first stock has a more constant oscillation which doesn’t change as much with time. To account for that problem and to make sure that the stocks we chose are as similar as possible in terms of their volatility we look at another metric called the volatility of the volatility. As one might think this metric simply measures how much the volatility itself changes over time. To measure that we calculate the pure volatility just as described above but not for the whole set of data but instead multiple times for rolling windows. So, we basically compute the volatility for every 75 consecutive data points in the data set. After having the volatility for each of these windows we again calculate, just as explained above, the volatility of these volatility measures. Like that we get the volatility of the volatility for a stock or ETF.

Stock selection:

We have defined how we measure the volatility of a stock course. That enables us now to choose stock data based on which we want to train our models. In the codebase the Jupyter Notebook file ‘Volatility\_Pipeline.ipynb’ completely contains this process. At first, we are using the alpaca-trade-api to retrieve our historical stock data. This API requires you to verify yourself with an API\_KEY and an API\_SECRET. After we created ourself an account and retrieved the credentials, we now create a list which contains common stocks and ETFs listed on AMEX, ARCA, BATS, NYSE, NASDAQ or NYSEARCA [18]. After that we define the time frame for which we want to retrieve the historical data, we choose it to be the past 5 years until 2025-05-07 (yyyy-mm-dd). We then start to make calls to retrieve the data. We batch the call so that we get 200 stock courses with one call. This is due to the rate limit of the alpaca api [19]. Like that we retrieve the historical prices of about 11500 stocks and ETFs.

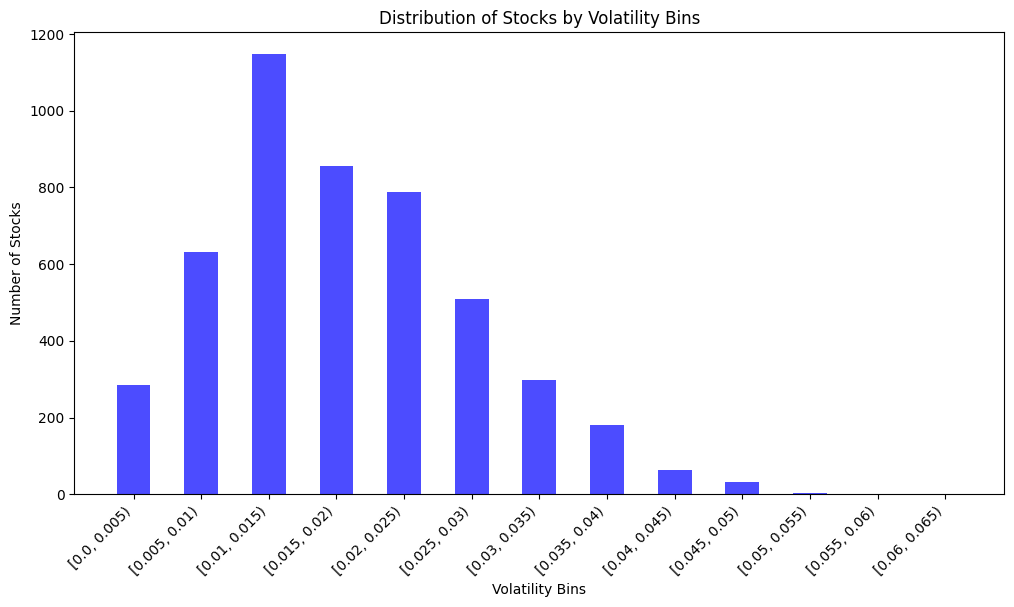
We further process this data to be only left with a table with the stock symbols as columns, the timestamp as index and the close price as a column as well. During preprocessing we would need to account for missing values. It would be much easier to already now just chose stocks and ETFs without missing values. So, we look how many stocks and ETFs have missing values and its about 5000. That means we have about 6500 stocks and ETFs left with no missing values. Since we only need handful of historical courses, we simply decide to drop all that have missing values and just proceed with the ones without any missing value. Besides that, we also drop all historical courses that have the same closing price over at least 30 days. When a stock or ETF has the same closing price over a number of days it can have different reasons but usually means that the asset hasn’t been traded in that time. For whatever reason the price stays the same for at least 30 days, we don’t want such asset courses in our data because it is obviously not natural behavior of the asset price and it gives the algorithm a hard time to learn.

We now want to extract information regarding volatility. To do so we apply the methods of calculating the volatility and calculating the volatility of the volatility for our stocks as described under methodology.Volatility. We apply the functions and store the returned values in a table. As we understood before we the volatility of the volatility to be as low as possible for all stock and ETF courses while at the same time having a wide range of different volatilities of which we use stocks and ETFs to train our model. To filter out stocks and ETFs that have a higher volatility of volatility we need to visualize our data set. For that we draw a graph. The graph shows the measure of volatility (blue) and volatility of volatility (orange) on the y-axis for each stock or ETF and the number of the stock on the x-axis. We sort the stocks by the volatility of their volatility in increasing order.



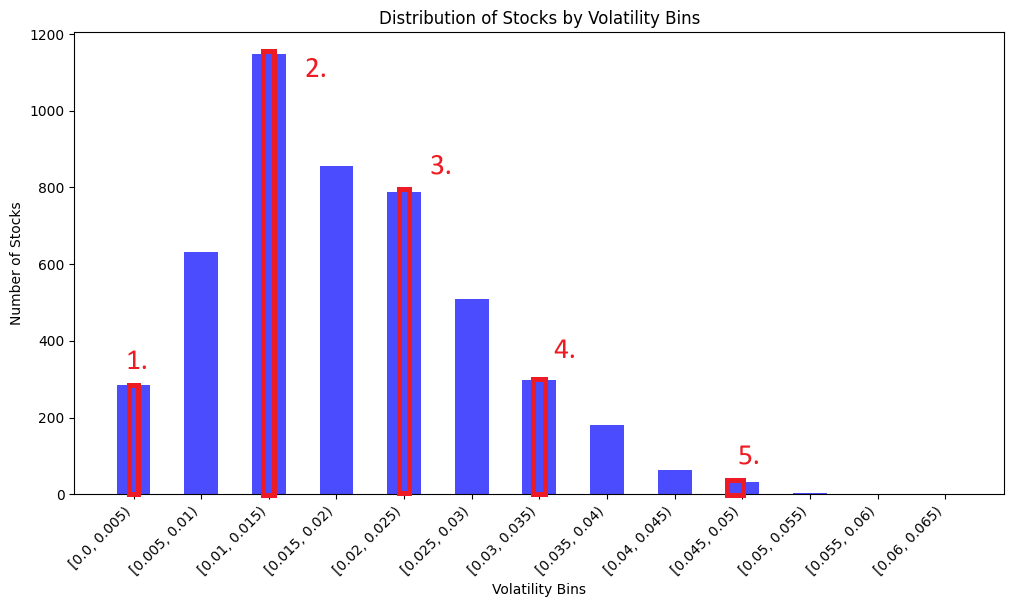
We see that the volatility of the volatility seems to correlate on average with the volatility. The greater the volatility of the volatility the greater the pure volatility. Now, for us two things are most important. The first one is that we want to have stocks from volatilities within a range that is as wide as possible to have a more meaningful result of our experiment. The second important thing is that we want the volatility of the volatility to be as low as possible. We explained before why we want that. Since the volatility seems to correlate with the volatility of the volatility, we need to make a compromise when deciding for a value of the volatility of the volatility which serves as a threshold. We will just drop every stock or ETF that has a volatility of volatility greater than that threshold. We take into consideration that we only need a relatively small number of stocks and ETFs. Besides that we take into consideration that the volatility of volatility seems to increase dramatically on the right side of the graph so we definitely want to cut off at some point before that dramatic increase. After careful consideration we decide to cut off all stocks and ETFs that have a volatility of their volatility of more than 0.01. This is pretty much at stock 4800 in the graph. Like that we ensure to have constant oscillation based on the given volatility while still being able to capture a wide range of stocks and ETFs with different volatilities.

Across the range of volatility, we want to evenly pick 5 values for each of which we again pick 15 stocks or ETFs that are as close as possible to the values in terms of volatility of the historical data. To get a sense for that we first create bins of volatility and sort our stocks and ETFs into these bins. We plot that distribution.



We now want to manually choose 5 bins and 15 stocks or ETFs for each bin for training. To make the results as meaningful as possible we define the ranges of our bins in a way so that we capture the widest possible range of volatility. In other words, we want bin1 and bin5 to be as far apart as possible on the graph and the remaining 3 bins to be in between them while having equal distances to their neighbors. At the same time, we want the stocks and ETFs within one bin to be as similar as possible in terms of their volatility. Based on the distribution which is visible in the plot, we choose our volatility steps to be:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Volatility score interval | 0.00235  – 0.0027 | 0.01243  - 0.01248 | 0.022425  - 0.0225 | 0.032416  - 0.0326 | 0.045  - 0.046 |



This will allow us to train and evaluate the models based on multiple stock data for each value of volatility which we expect to give us a statistically better and closer to the average measurement compared to just using one stock for each step which is susceptible to outliers. We especially expect the models to have a similar predictive accuracy for stocks within the same volatility interval and to show clear jumps in performance when trained based on stocks of different intervals.

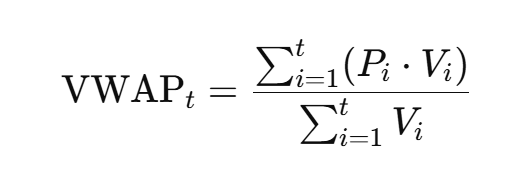
Data Preprocessing:

During the previous section (‘stock selection’) we selected the stocks that can be grouped into 5 intervals or bins of different volatility and which we want our models to be evaluated on. Since we already dropped stocks with missing values, we don’t need to perform any further imputation.

Our historical data so far has the features: open, high, close, low, vwap, volume, trade\_count, symbol – where symbol is the ticker symbol of the stock and will not be used for training.

The other ones are:

* trade\_count, which tells how many transactions have been made in a period.
* Volume, which is the number of shares that have been traded within a period.
* Volume Weighted Average Price (VWAP) is the typical price of a stock or ETF weighted by its volume [36]



Where…

Pi – is the price at which the asset was traded

Vi – is the volume at which the trade executed

t – is the number of trades in the period.

So, if within one period particularly many trades executed at a certain price than this price is weighted more than a price at which few trades executed. That means while the close price only tells you the price at which price the last trade executed, VWAP is averaged over all trades in that day.

The next step is to preprocess the historical data from each asset by adding other features. Some of those are retrieved from APIs and some are calculated using the existing features.

We choose the features based on which the review study by Kumbure et al. [5] has shown to be mainly used in stock price forecasting. We also add some indicators mentioned in the articles “Template:Technical analysis” from Wikipedia [20] and “Technical Indicator: Definition, Analyst Uses, Types and Examples” from Investopedia [21].

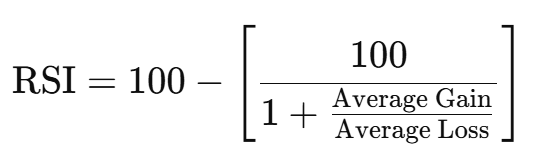
Feature Engineering:

Technical Indicators:

Relative Strength index (RSI):

The RSI is a way to measure speed and directions of price movements. The RSI always lies in the range of zero to 100 and it is commonly considered overbought when above 70 and oversold when below 30. The RSI formula is:

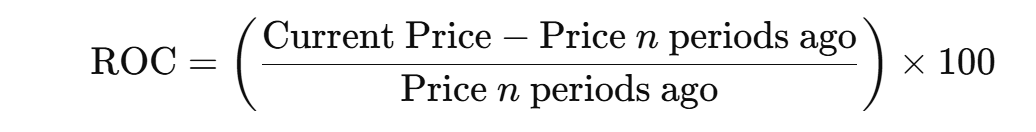
RSI = 100 – [100 / (1 + (Average of Upward Price Change / Average of Downward Price Change))]



Where Average Gain and Average Loss are Exponentially weighted moving averages. [22]

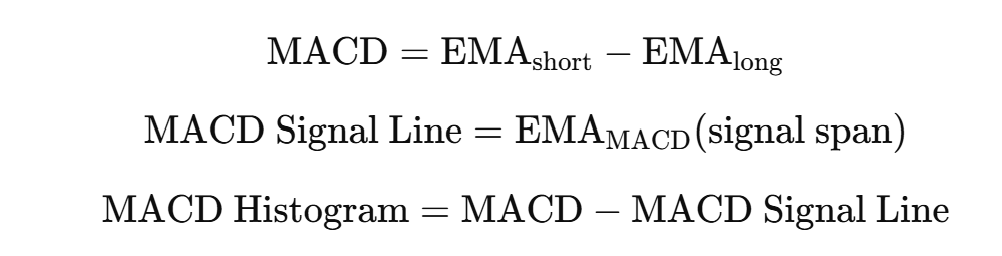
Rate of Change (ROC):

The ROC is an indicator that shows the return in percent not compared to the previous period but to the price n periods ago. A common number for n is 14. [23]



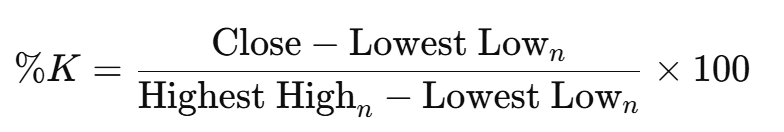
Moving Average Convergence Divergence (MACD):

The MACD is used to measure both the momentum and direction of a price movement. It consists of a the MACD line and the signal line. The MACD line measures the difference between a shorter exponential moving average and a longer exponential moving average. The signal line is again an exponential moving average of the MACD line. Due to the fact that both lines crossing has implications for the price movement and we want the model to better identify that relation, we also add a histogram column that simply is calculated as the difference between MACD line and signal line. [24]



Stochastic Oscillator:

The stochastic Oscillator is another momentum indicator that measures where the current closing price lies in the range of the highest high of a certain past period and the lowest low of that same period in percent. This value is called %K. A second value which is called %D contains the moving average of %K for a short period. Since again the relation of those 2 lines is of importance to us and we need to make the machine learning model consider this relation even though it cannot see the the lines on a chart we add a stochastic difference value that is calculated as the difference of these 2 values. [25]

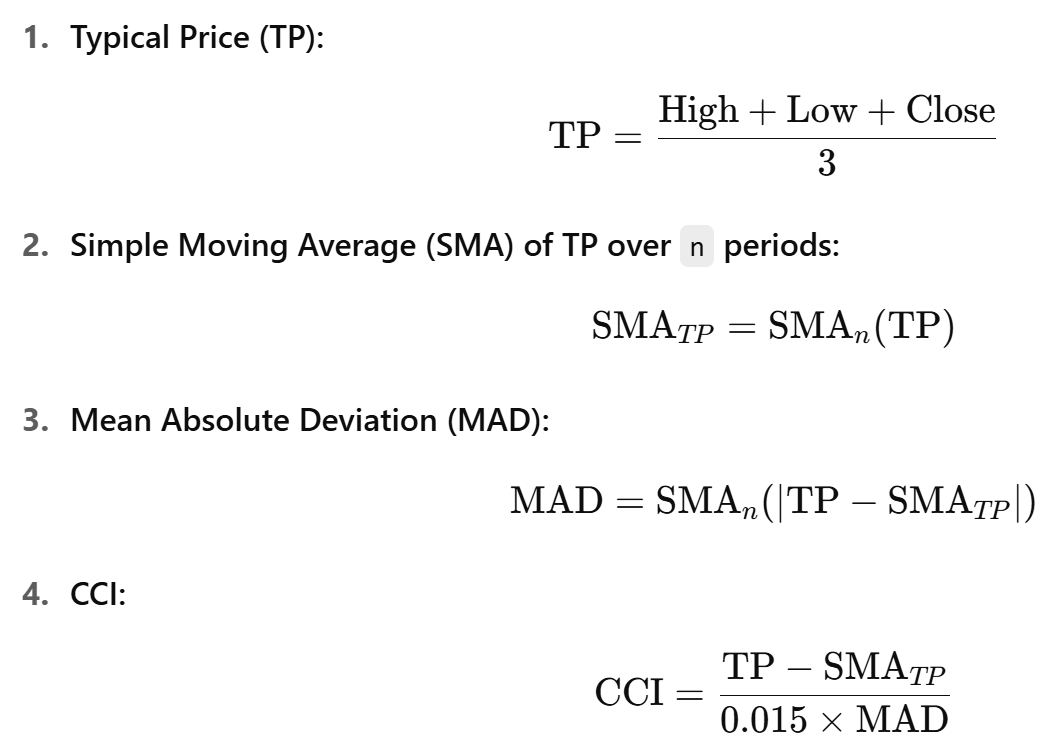






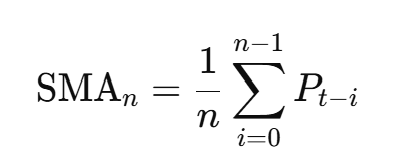
Commodity Channel Index (CCI):

The CCI measures how far a price is from its statistical average indicating overbought or oversold market conditions. [26]



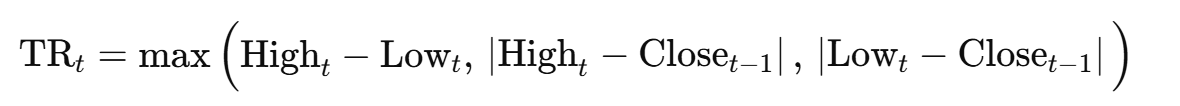
Moving Averages:

We add multiple simple moving averages with different window sizes. Moving averages smooth out price data and indicate an upwards trend when increasing and a downwards trend when decreasing. Besides that they can indicate overbought or oversold conditions. [27]



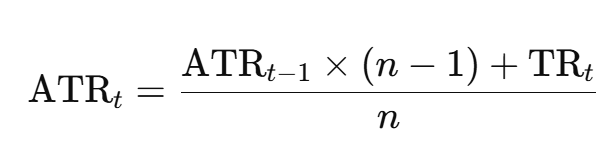
Average True Range (ATR):

The ATR is a volatility indicator that tells how much the price moves on average per period. We therefore first look at the True Range (TR) for every period. This is the maximum price difference within that period. We add that difference to our feature set.



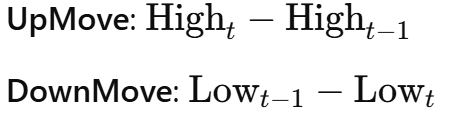
We use the previous day’s close price because the current day’s open price can differ from the previous day’s close price due to overnight news that led to changes in the sentiment. [30]

After that we use wilder’s smoothing to smooth out the True Range over a certain windows size, usually 14, so that we understand how volatile certain periods are. [31]

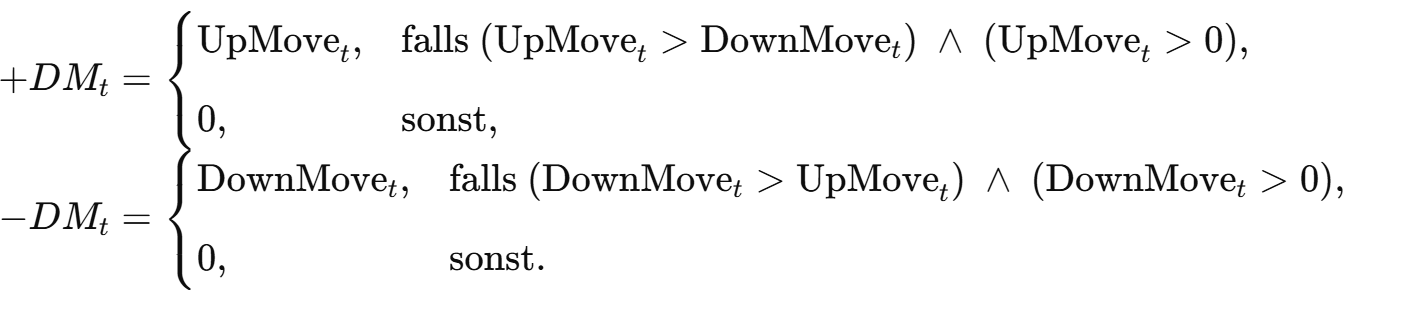


Average Directional Index (ADI):

The ADI uses the ATR as a component. The ADI and its components measure how much of the Average movement within a certain window which we derive from the ATR is upwards movement and how much is downwards movement. For that we calculate our up and downwards movement like this. [32]



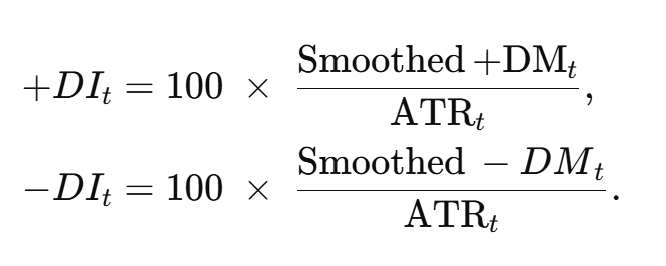
UpMove contains the difference of the high values so that increases have a positive value. DownMove contains the difference of low values in a way that downward movements have positive values and upwards movements have negative values.



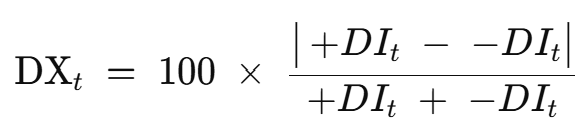
+DM now stores all absolute increases in the high value for periods in which the low value decreased less than the high value increased.

-DM works vice versa.

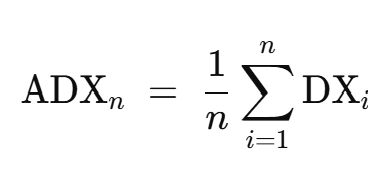
We now average these 2 values over a window that must have the same size as the window size n from our ATR. Like that we get the average up and down movement in absolute values for the given window. We calculate the percent to which our over all movement which we derive from the ATR is upwards movement or downwards movement.



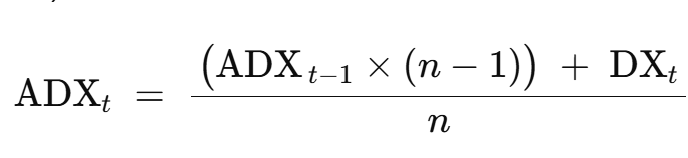
The next step lets us calculate the Directional Movement Index (DX). DX tells us in percent how one-sided a movement is. If up and down movement have the same portion of the overall movement then DX is 0%.



The last step is to calculate the actual ADX. We again use wilder’s smoothing. That is a recursive function so we need to calculate the first ADX value manually by simply averaging the previous n DX values.



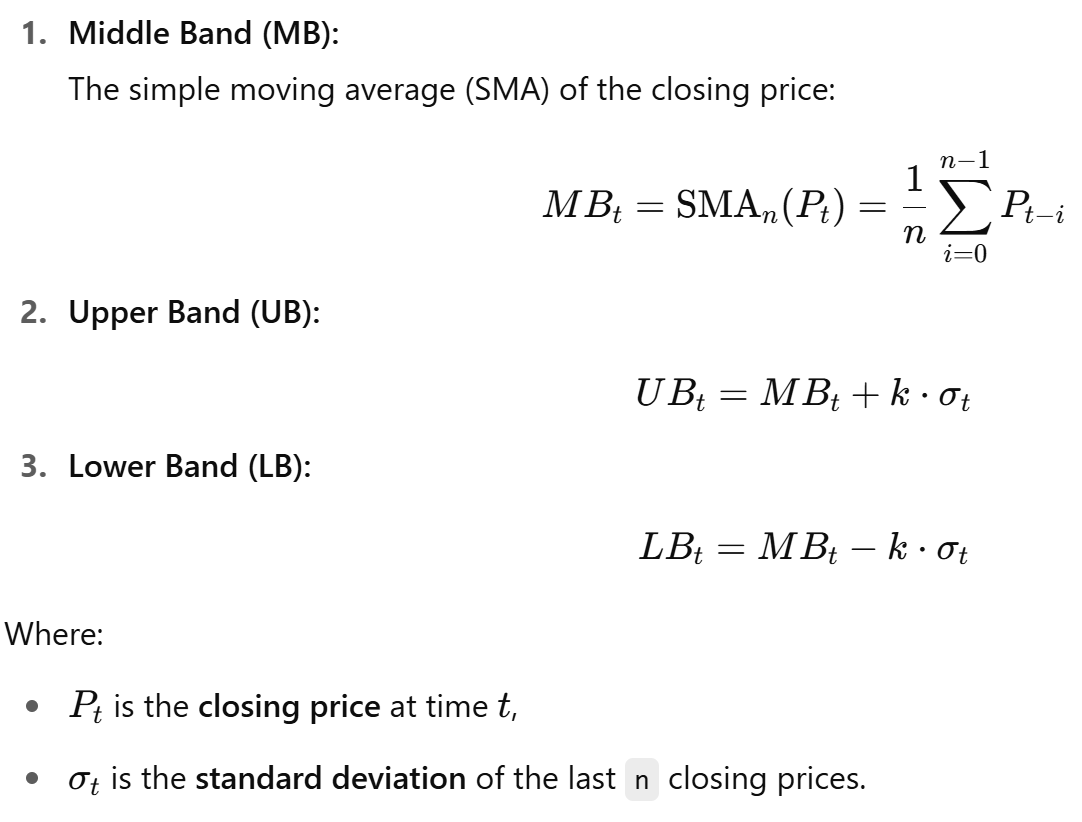
Any further ADX value is calculated recursively.



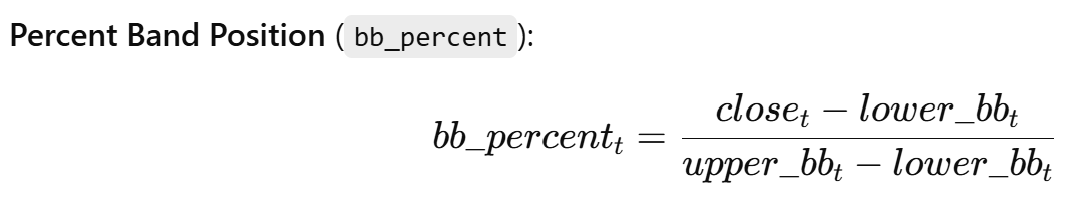
Bollinger Bands:

The Bollinger Bands are indicators to gauge the volatility of a stock to understand whether they are over or undervalued. [33]

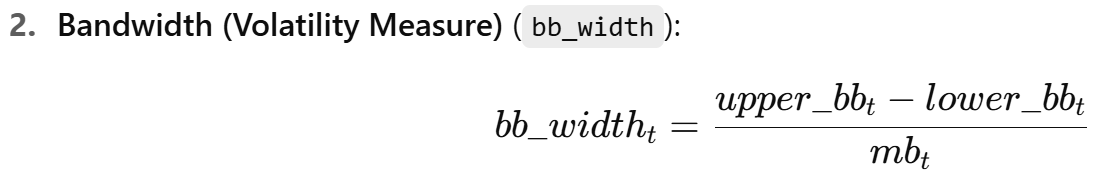
They consist of 3 lines:



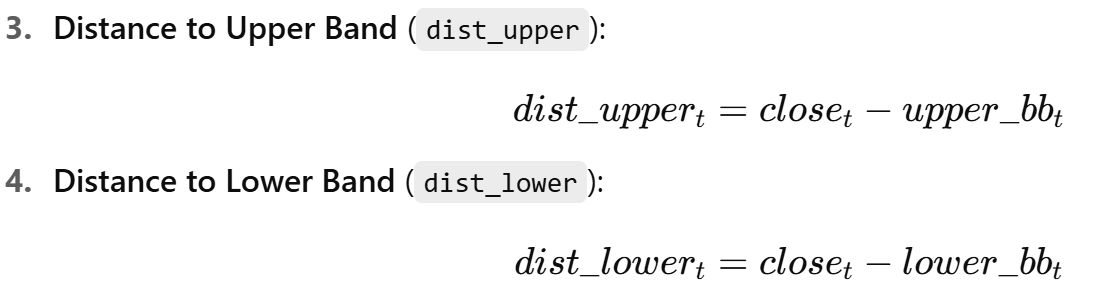
Since we use this indicator for machine learning purposes, we will add the following features to emphasize relations between the bands or our close price and the bands.



* Measures from 0 to 1 where the close price is within lower and upper band

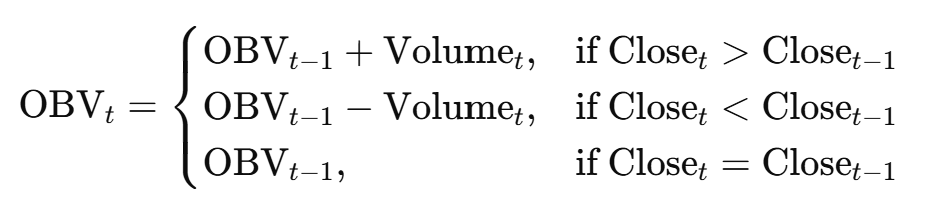


* The band width tells how volatile the course is.

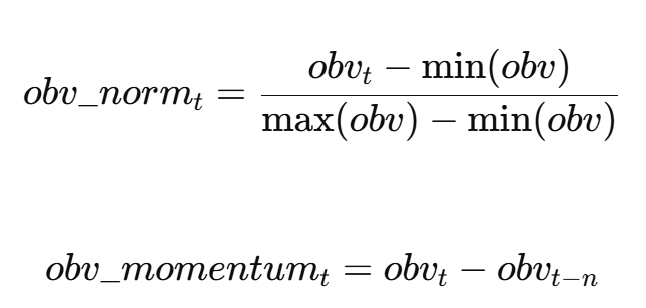


On-Balance Volume (OBV):

The On-Balance Volume Indicator is a momentum indicator that uses volume flow to predict price movement. It assumes that volume precedes the price – so a rising OBV signals buying pressure and a falling OBV signals selling pressure. [34]

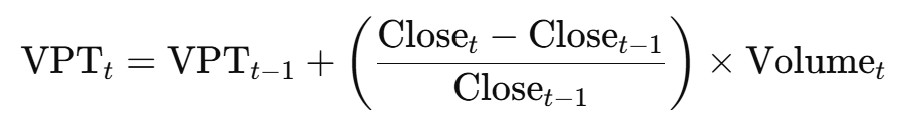


Besides the absolute OBV we add a normalized OBV for better machine learning suitability and an OBV momentum that compares the OBV to the OBV n periods before.

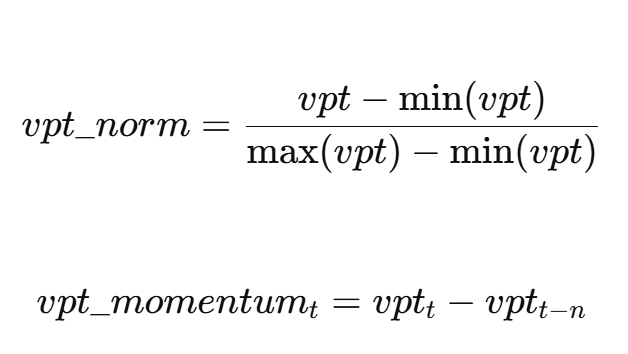


Volume Price Trend (VPT):

The VPT is a momentum indicator that combines the price change with volume. Its purpose is to track how strongly volume aligns with or contradicts price changes. [35]



For Machine Learning purposes we also add the VPT in a normalized way and the VPT momentum.



Macro-economic features:

We add Macro-economic features to capture global or US wide circumstances and market context [38]. We use the “FRED API” version 0.5.2 to retrieve them [37]. Some of the indicators are not published daily. For example, the GDP is published quarterly. We therefore use the interpolate function that comes with the pandas library. It looks for brackets of NaN values and draws a line from the valid value before and the valid value after the bracket to fill the rows in between. So, if we have a list such as [10, NaN, NaN, NaN, 18, NaN, 26] then the interpolation of this list would result in this list: [10, 12, 14, 16, 18, 22, 26]. This allows us to simulate a realistic and smooth course of the features.

S&P 500:

One important macro-economic indicator is the S&P500 index. Since it includes the biggest 500 US companies it is an important measure of the health of the overall us economy.

GDP(USA):

The Gross domestic Product is the value of all good and services produced by a country in a given period. It is a great indicator since it reflects the economic performance of a country [38].

Unemployment rate:

The unemployment rate can capture strengths and weaknesses in the economy. It is a great indicator for economic activity [38].

Consumer price index (CPI):

The consumer price index measures the monthly change in prices paid by urban US customers for different basic products and services [39].

Personal consumption expenditures (PCE):

The personal consumption expenditures is an indicator that measures how much US households spend on goods and services [41].

Industrial production index (IPI):

The industrial production index measures the output in manufacturing, gas, oil, mining and electric industries [42].

federal funds rate:

The federal fund rate is the target interest rate range at which commercial banks are supposed to borrow money [43].

10Y treasury rate:

The 10-year treasury is the interest rate which the US government pays to borrow money over a decade. It is an important benchmark for other interest rates and it tells about expectations of the US government about inflation and economic growth [44].

Retail sales:

Retail sales is a main indicator for economic health because it provides information about the buying power of consumers and bigger retail sales usually lead to more profit for companies which has a positive effect on the stock price [40].

Housing starts:

Housing starts is the number of newly started construction projects in a given period that provides information about the housing market and general economic activity [45].

Exchange rates:

Exchange rates are a good way to measure the economic health in comparison to economies from other countries [46] [47]. We include the exchange rates USD-EUR, USD-GBP and USD-JPY.

Calendar Features:

We also add the following calendar features to capture patterns for example the Monday effect [28] and the January effect [29].

* Day of week (1-7)
* Day of year (1-365)
* Month (1-12)
* Year (yyyy)
* Quarter (1-4)

In total we now have included 60 features in our data set that are products or byproducts of our calculations.

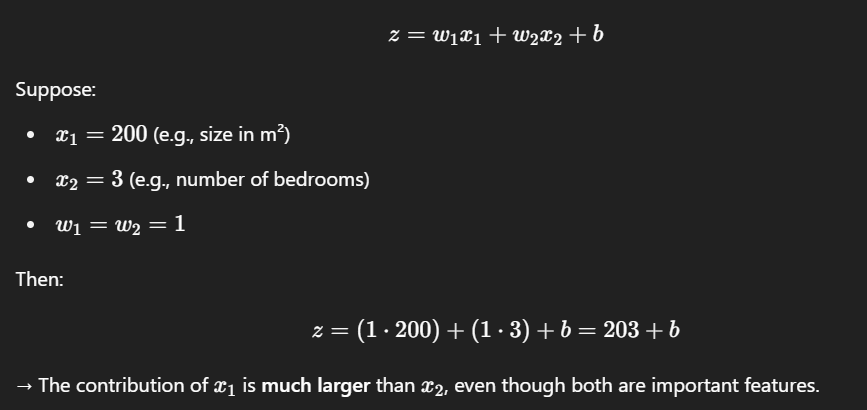
We also already add a ‘target’ column with the next days close price for training.

We continue with performing further preprocessing steps, but we have to perform them in separate pipelines since the LSTM and the CNN model need distinct preprocessing steps compared to our XGBoost model.

Further Pipeline for LSTM and CNN:

One important step we need to perform on data for neural networks is normalization. This is due to the nature of neural networks – they are sensitive to the scale of input features. Without normalization features with large values would dominate features with small values which would lead to uneven learning. We look at an example to understand that dynamic. Neural networks as we learned before work by taking vectorized inputs. That means they take a list of numerical values as input. Each of these values is multiplied by the according weight and then typically added together.

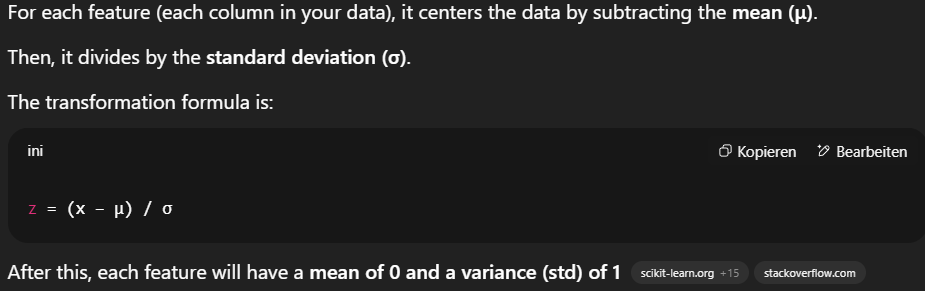
Let’s say we have the following equation for one neuron and we assume that features x1 and x2 are equally important to the result:



As we can see. The contribution of x1 to the result is much larger even though we know that both features are equally important, it’s just that x1 has a larger scale. One might argue that the network could compensate this larger scale by using a much smaller weight for input feature x1, but then we are interfering with the nature of the neural network which really is to weigh particular features heavier because they have been observed to have a greater impact on the result. This is not the case for us because we assume that our features both have an equal impact on the result. If we already have different scales for our inputs at the beginning of the network, it would be as if we predefine an importance for each feature. In case we know that particular features are in fact more important than others and we know the relation of this importance among the features, than the practice to weigh the more impactful ones heavier would make sense, but usually the network is unbeatable in figuring out the individual importance of each feature or combination of features. Now it is totally true that you could simply have much smaller weights for those much larger inputs. But the problem with that lies in the nature of how the network learns its weights. They are computed based on a fixed learning rate which is an absolute value for the whole network and for the full training process. The learning rate tells us how much a weight is updated. If the learning rate is very small it means that we can converge our weights to very precise values with a fine granularity but it also means that we need more iterations to get to this correct value because we are doing much smaller steps. So, if the weights are forced to lie within different ranges because our input features have different scales, then the learning process within the whole network would be asymmetrical and some weights would learn very slow and barely reach a good value while others constantly overshoot and never converge to an accurate enough number.

This is why normalization is needed.

A scaler scales every input feature so that all have the same scale. We use the StandardScaler() from the sklearn.preprocessing library in python. [49]



Like that the mean is 0 and 68% of the values lie within -1 and 1.

To apply the scaler on our features we first have to fit it or in other words make it learn the scale by which it has to recalculate our values. If we would fit it on the whole data set then information about the scale of our validation and test data sets would leak through into the scaler. So, to maintain a clean pipeline we need to first split our data into training, validation and test sets, then fit the scaler only on the training set and after that apply it on all data sets. The target variable hereby is the only feature that doesn’t need to be scaled. In fact, it’s much easier to not scale it because we would otherwise need to revert the scaling for our predictions.

The normalization or scaling is actually the only preprocessing step we are undertaking here. Another important step for neural networks for time series data is windowing. Windowing allows us to have a series of past x periods as input. We want to optimize the window size as a hyperparameter so we decide to implement the windowing under section hyperparameter tuning.

Further pipeline for XGBoost:

The XGBoost model requires a different preprocessing pipeline. As we learned earlier the input for a tree-based model looks different to the input of our LSTM or CNN model. For our XGBoost model the input data is not a collection of windows that have the shape (n\_periods x n\_features) but instead it’s a collection of single row features or 1D vectors that contain all features. That means we can’t simply use past periods as input. The way to work around that and still use XGBoost models for time series forecasting is to add lag values. Lag values always belong to a specific feature and they invoke the value of a past period of that feature. So, a lag value of 3 for the feature “close” would mean that we add 3 columns as new features where one is the “close” price 3 days ago, one is the “close” price 2 days ago and the third one is the “close” price from the previous day. Like that we can add different lag sizes for each feature and in that way add the necessary temporal context for our current period. Our concrete approach is documented in the codebase.

As we learned before XGBoost is a tree-based model and tree-based models only care for the proportions of the data matter but not for their absolute value. When we normalize, the proportions of the values within one feature column don’t change but only their absolute value gets resized. As we learned

### Functionality of Tree based models and why normalization is not needed.

Since we have no windowing to perform on the data for the XGBoost model, the last preprocessing step is to split the data into train, validation and test set.

Hyperparameter tuning:

When we looked into the different Machine Learning models that we are using, we understood what adjustable hyperparameters there are. We will tune these hyperparameters for each combination of model and data set separately so that we conduct our experiment based on optimal performance.

Optuna:

To do so we use the optuna library in python, which has a very straight forward workflow. It allows us to define a function that returns a float value and a direction in which we want to optimize that returned value. The directions can be to minimize or to maximize.   
In the function which’s return value is to be optimized ranges for variables can be specified. The function later will be executed a number of times that is predefined and during every iteration the values from the specified ranges for the variables will be selected. The way these values are selected depends on the algorithm that is specified for the hyperparameter suggestion. It can simply suggest random combinations of hyperparameters or it chooses them based on prior performance.  
The function is executed multiple times with different variable values. The outer object which is called study and which executes the function stores the returned value and hyperparameter combination for each iteration and especially for the one iteration that led to the best result. That’s the general workflow of the optuna optimization library.

Our optuna use case:

In our case the function which’s return value we want to optimize is defined to be the training and evaluation step for each model-stock combination. The variables that the study will pick values for are our hyperparameters. The returned value is the forecast error and the optimization direction is to minimize. Like that the study will look for the combination of hyperparameters that lead to the smallest error – exactly what we are looking for.

In our case the study object takes 4 parameters.

* # 5.2. CNN study
* study = optuna.create\_study(
* direction="minimize",
* study\_name="cnn\_regression\_study",
* sampler=optuna.samplers.TPESampler(),
* pruner=optuna.pruners.MedianPruner(n\_startup\_trials=5, n\_warmup\_steps=10)
* )
* Direction … which defines whether the float value of the function should be minimized or maximized.
* Sampler … Which defines the algorithm that suggests new parameters.
* Pruner … which defines the mechanism to abort bad trials

Our sampler tries to pick combinations that have the highest probability to be another “good” guess. A “good” guess is a combination with a performance above a certain threshold and a “bad” guess is a combination with a performance below that threshold.

The pruner aborts a trial instantly when it foresees it to not be a good trial. After n\_startup trials it checks every trial whether after 10 reports of one trial this trial is better or worse than the median trial so far. If worse than the median trial, it prunes the current trial, if better it keeps going. Like that computational efficiency is ensured and the search space is further focused on promising combinations.

Depending on the ML algorithm that we use, we need to tune different hyperparameters.

LSTM:

* N\_layers:
* N\_units:

CNN:

* N\_layers:
* Filter\_size:

XGBoost:

* Max\_tree\_depth

Metrices:

Execution times:

XGBoost: 59.455 minutes

LSTM: 1887.202minutes

CNN: 280.319 minutes

To evaluate the performance of our trials during the hyperparameter tuning we use decide for one main performance metric. This is the mape. The reason we use the mape for our performance lies within the nature of historical stock price data.

Mape:

RMSE:

The Root Mean squared error (rmse) is a performance metric. It takes the predicted value and the true val and calculates the difference from it. Then it squares this difference for all pairs of predicted and true value and takes the mean of these squares of differences. That mean is the rmse value. The best possible value is 0.0.

Example:

>>> y\_true = [3, -0.5, 2, 7]  
>>> y\_pred = [2.5, 0.0, 2, 8]  
>>> mean\_squared\_error(y\_true, y\_pred) = 0.375

MAE:

The Mean Absolute Error (mae) calculates the absolute difference of predicted and true value and takes the mean of these differences. The best possible value is 0.0.

Example:

>>> y\_true = [3, -0.5, 2, 7]  
>>> y\_pred = [2.5, 0.0, 2, 8]  
>>> mean\_absolute\_error(y\_true, y\_pred) = 0.5

* R2

Results & Discussion:

Future Research:

* Add other variables as hyperparameters and tune them as well, like lag sizes for xgboost

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Words to explain:

Average  
Exponentially weighted moving averages (EWMA or EMA) with formula  
Simple moving average (SMA) with formula  
period. I would say when you read the whole thing you just write down every word you need to explain.

* A system updates itself (same as third, learning)
* Error (in prediction)
* To learn (when a system updates itself and learns from error)
* Data point
* Period
* Data sets (big tables of periods x features)
* Adding a feature (equals adding a column with that value)