Bitcoin candlestick predictions using lagged features and machine learning algorithm in R

Training various machine learning algorithms to predict the next candlestick of the bitcoin price using various lagged features

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Abstract

This report explores how to get the best accuracy on predicting the next candlestick of the bitcoin chart using the previous ones. It compares different algorithms: Generalized Linear Model, Decision Tree, Random Forest, KNN and Gradient boosting and different number of lagged features. This project is part of the 'Data Science: Capstone' module of HarvardX PH125.9x from the edx platform.

Contents

List of Figures

List of Tables

1 Overview

In this study we will try to predict the direction of the next candlestick of the bitcoin chart. Before starting, it's important to understand: what are Bitcoin and candlesticks and the goal of this study.

1.1 Introduction to Bitcoin

This last years Bitcoin (BTC) has been gaining attention not only by retail investors but also by institutional investor. In 2024 we've seen the emergence of spot Bitcoin exchange-traded funds (ETF) from institutions such as BlackRock, VanEck, Grayscale [1]. With a market capitalization of about 1.68 billion in dollars at the time of writing, Bitcoin started as a peer-to-peer currency, a free alernative to centralized currencies controlled by central banks. Now it is often used as an investment, a store of value and even considered as a strategic reserve assets by some countries [2], [3].

Bitcoin ows its decentralization to its data structure, the blockchain — a chain of block that contains transactions, and to its consensus, the proof of work. Without going too much into details, it makes Bitcoin a currency that does not rely on a centralized server. Proof of work is a cryptographic algorithm, that enables a competition between bitcoin servers (called nodes) to decide which transactions will be part of the next block added to the blockchain. They go through a process called mining where nodes have to use their computing power to find a number called nonce. This computing power is called the hashrate. The node who succeed at "mining" successfully gets rewarded for that [4].

Bitcoin is defined by its source code, and that's quite facinating. Its ledger is visible and publicly available, which gives a lot of data available to analyze. Moreover unlike stocks BTC can be traded any time, there is no opening or closing hours, the bitcoin market never stops and it is very easy for anyone to buy and sell bitcoin. Those are two reasons worth studying bitcoin's candlestick charts instead of other asset.

1.2 What are candlesticks?

Let's talk about the candlestick. The price of assets such as Bitcoin is described by a timeserie of candle stick defined by, an opening price, a close price a high and a low also called OHLC. A candlestick can be "up" (often green and also called bullish) or "down" (often red and also called bearish). You can see this visually with the following figure.

The candle stick chart is defined as a time serie of candles, each candle is defined at a defined time and have a time duration. We will explain more in detail in the exploratory analysis.

1.3 Candlesticks pattern

Some of the technical analyist study candlestick pattern to try to predict the direction of the market, this field is known as candlestick pattern. It consist at knowing a set of patterns and the outcome of them.

Traders look for specific patterns like "Doji", "Hammer", "Engulfing patterns", and many others to make trading decisions. Each pattern has a specific interpretation based on market psychology and historical tendencies [6].

If they really exist we believe that machine learning algorithms would be able to detect them.

1.4 Goal of the study

The goal of the study is to find a model able to predict the direction of a candlestick using N previous candles. This number N will be also part of the research. We will have to not only find N but also find what are the best features to achieve the best accuracy.

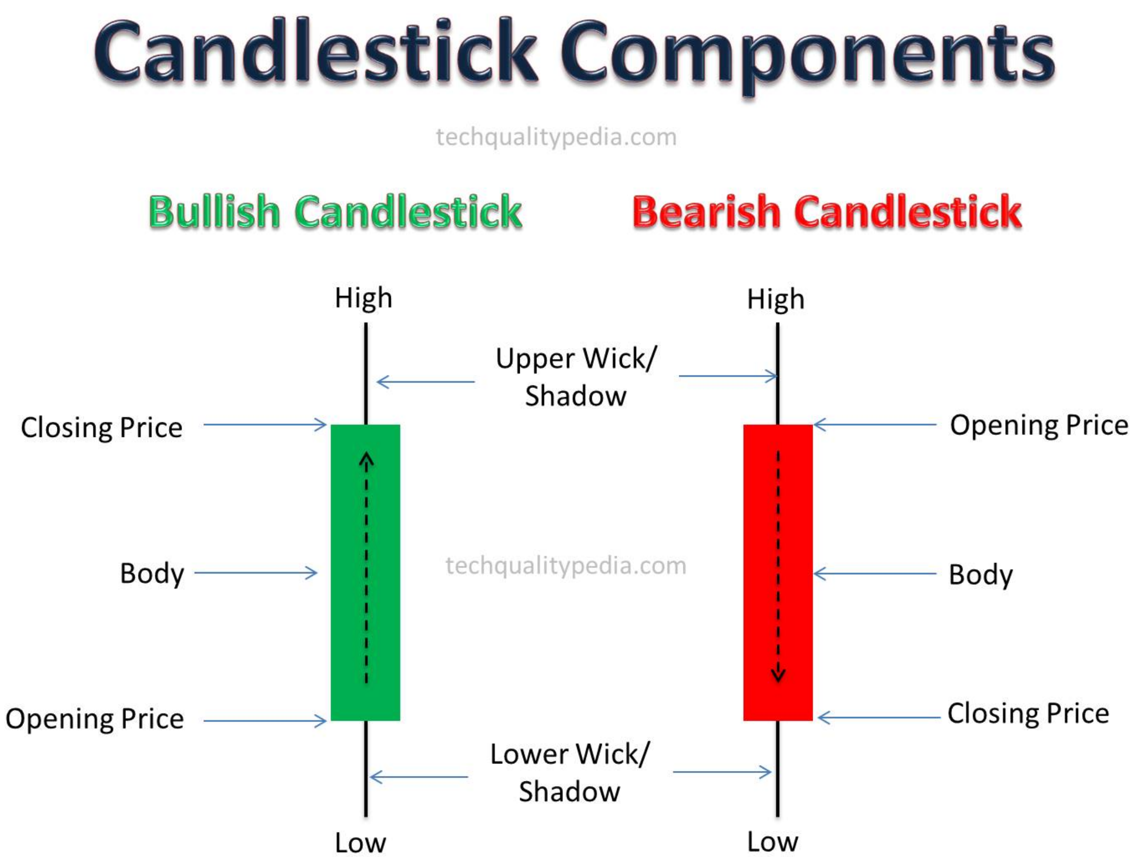


Figure 1: Candlestick components [5]

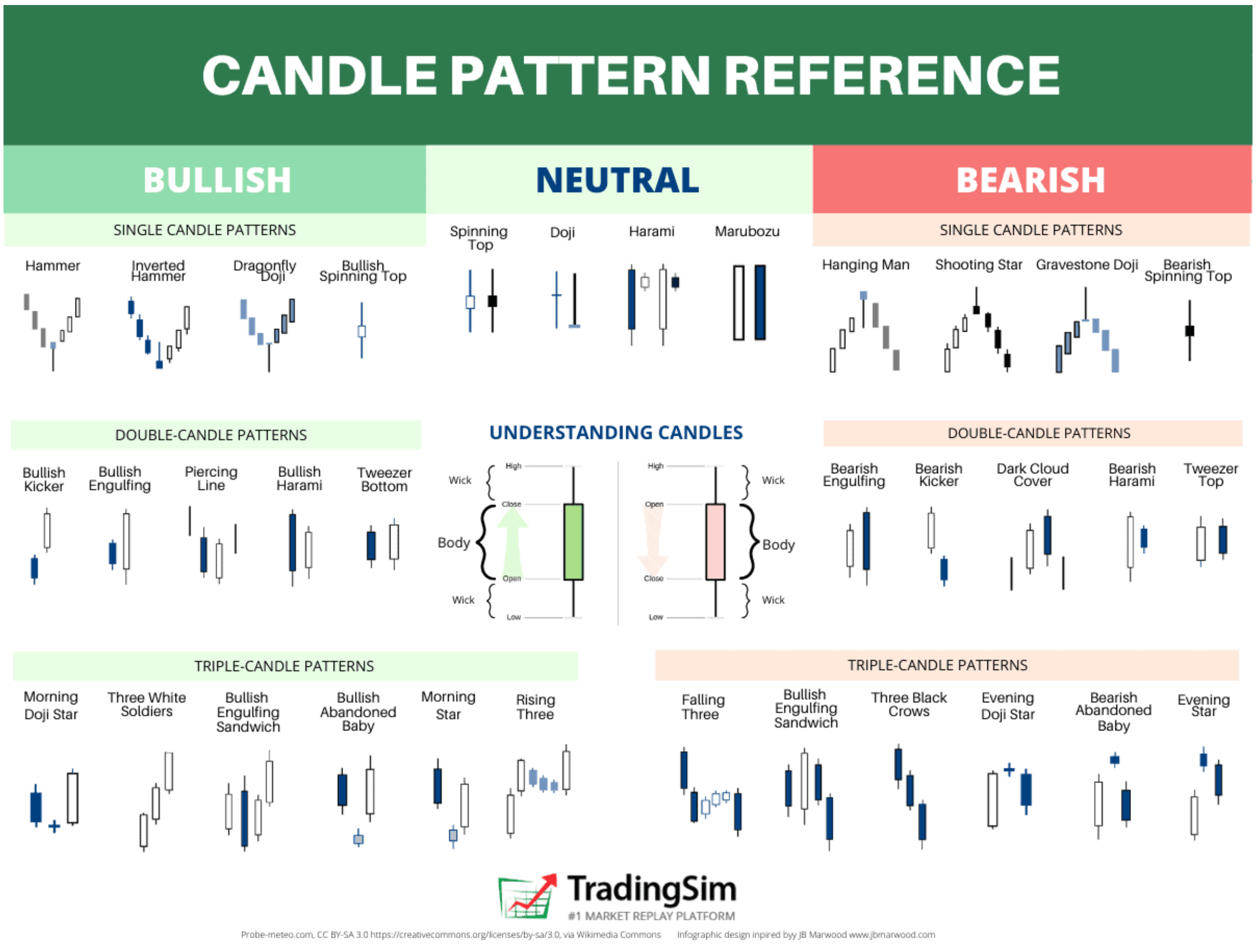


Figure 2: Common candlestick patterns guide [6]

1.5 Applications

Why does the direction of a candlestick matter? Because being able to predict the direction of the next candle could enable traders to buy and sell on spot market when the predicted candle is green. Also perpetual futures trader can go both ways, they can long when the prediction says "up" and "short" when the predictions says "down".

2 Exploratory data analysis

In this section we will see what are the are the different datasets available. We will see what features are available to train the different models. Then we will prepare the data, verify it, and choose which machine learning algorithms we are going to train.

2.1 Data sets

In order to conduct this study we used as a the main data set the historic rates for the trading pair BTC-USD using Coinbase API.

We used the following global variables for the full project:

```
trading_pair <- "BTC-USD"
start_date <- "2024-01-01"
end_date <- "2025-03-29"
candlestick_period <- 3600
set.seed(1)
```

The timeframe is the entire year 2024 and the start of the year 2025 until the day we started the study. Note that since January 2024, Bitcoin ETF has officially been approved. The period `candlestick_period <- 3600` is the time of a candle, the candle closes 1h after it starts. Which means we have 24 candles per day [7].

I choose this settings to have a dataset of around 10,000 candles but also since Bitcoin ETF has been approved the market may have taken a different dynamic than the previous years.

Let's see how the dataset looks like.

Table 1: Overview of the BTC-USD candlestick dataset

time	low	high	open	close	volume
2024-01-01 00:00:00	42261.58	42543.64	42288.58	42452.66	379.1973
2024-01-01 01:00:00	42415.00	42749.99	42453.83	42594.68	396.2019
2024-01-01 02:00:00	42488.03	42625.68	42594.58	42571.32	227.1412
2024-01-01 03:00:00	42235.00	42581.26	42571.32	42325.11	306.0057
2024-01-01 04:00:00	42200.00	42393.48	42325.10	42389.77	296.2336
2024-01-01 05:00:00	42175.65	42396.09	42389.78	42231.47	188.1280

We have 10,873 entries in our candle stick dataset. As described in the overview it contains the OCLH data, timestamp and the volume of each candles.

Bitcoin is used by 3 types of users:

- Traders — they are interested by the price and make profit

- Users — using the currency to do payments or to transfer money around the world
- Miners — they mine bitcoin to sell it, their interest is that the price of bitcoin is higher than the cost of mining bitcoin

Keeping this in mind, I tried to find other dataset that could represent each of the type of users that could eventually help in our predictions and I picked the following:

- Fear and greed index — represents the overall mood of the market (traders)
- Hash-rate — defines the overall mining power (miners)
- Average block size — the higher it is the more transactions are happening (users)
- Number of transactions — defines the activity of the network (users)
- Number of unspent transaction outputs (UTXO) — defines how many addresses contains bitcoin, and reflects the network activity (users)

Table 2: Overview of the BTC fear and greed index dataset

value	value_classification	timestamp
26	Fear	2025-03-29
44	Fear	2025-03-28
40	Fear	2025-03-27
47	Neutral	2025-03-26
46	Fear	2025-03-25
45	Fear	2025-03-24

This dataset is a time serie of the daily fear and greed index, it is a value between 0 and 100, 0 being the most fearful and 100 being the most greedy. The data set contains 453 entries.

The blockchain data (hash rate, average block size, number of transactions, and UTXO count) was sourced from Blockchain.com Explorer [8], while the fear and greed index was obtained from Alternative.me [9].

Table 3: Overview of the BTC hash rate dataset

timestamp	hash_rate
2024-01-01	501122294
2024-01-02	509303882
2024-01-03	505213088
2024-01-04	520042217
2024-01-05	545098332
2024-01-06	538450791

This dataset is a time serie of the daily hash rate, it is a value in TH/s. The data set contains 454 entries.

Table 4: Overview of the BTC average block size dataset

timestamp	avg_block_size
2024-01-01	1.653640

timestamp	avg_block_size
2024-01-02	1.718455
2024-01-03	1.771466
2024-01-04	1.782402
2024-01-05	1.774551
2024-01-06	1.847959

This dataset is a time serie of the daily average block size, it is a value in bytes. The data set contains 454 entries.

Table 5: Overview of the BTC number of transactions dataset

timestamp	n_transactions
2024-01-01	657752
2024-01-02	367319
2024-01-03	502749
2024-01-04	482557
2024-01-05	420884
2024-01-06	382140

This dataset is a time serie of the daily number of transactions, it is a value in transactions. The data set contains 454 entries.

Table 6: Overview of the BTC UTXO count dataset

timestamp	utxo_count
2024-01-01	135878807
2024-01-02	136204295
2024-01-03	136536575
2024-01-04	136871780
2024-01-05	137209298
2024-01-06	137552822

This dataset is a time serie of the daily number of UTXO, it is the count of UTXO in the network. The data set contains 454 entries. We had to group by timestamp since some dates had more than 1 value.

As we can see `fear_and_greed_index` seems to miss one data point. We will see fix that in the next sections.

We have different dataset that we will use for the predictions but we are still missing one important data used by traders, technical analysis indicator.

Based on a previous research and blog post I wrote [10], I decided to include a few indicators that are very common in trading :

- Moving average convergence divergence (MACD)
- Rate of change (ROC)
- Bolinger Bands (BB)
- Relative Strenght Index (RSI)

Before preparing the dataset let's see what would be the features we can extract from the OHLC candlestick data.

2.2 Features

Our candlesticks dataset from coinbase gives us values that are based on the price of bitcoin, but used itself for a machine learning algorithm it will be hard to use those raw absolute values since the price always fluctuate, so we have to think about what defines the candlesticks we have seen above?

If we isolate a candle we can see the following features:

- Size of the body
- Size of the upper shadow / wicks
- Size of the lower shadow / wicks
- Direction of the candle (up or down)
- Closing price
- Volume

We are now ready to prepare the dataset for the study.

2.3 Preparation

Preparation of the dataset is done in the following function:

```
enhance_dataset <- function(candles_data, fear_and_greed_index_data, hash_rate_data, average_block_size_
  candles_enhanced <- candles_data %>%
    mutate(date_only = as.Date(time)) %>%
    left_join(fear_and_greed_index_data, by = c("date_only" = "timestamp")) %>%
    left_join(hash_rate_data, by = c("date_only" = "timestamp")) %>%
    left_join(average_block_size_data, by = c("date_only" = "timestamp")) %>%
    left_join(n_transactions_data, by = c("date_only" = "timestamp")) %>%
    left_join(utxo_count_data, by = c("date_only" = "timestamp")) %>%
    mutate(
      body_size = abs(close - open),
      upper_shadow_size = high - pmax(close, open),
      lower_shadow_size = pmin(close, open) - low,
      direction = ifelse(close > open, "up", "down"),
    ) %>%
    tq_mutate(
      select = close,
      mutate_fun = ROC,
      n = 14,
      col_rename = "roc"
    ) %>%
    tq_mutate( # https://www.keenbase-trading.com/find-best-macd-settings/#t-1719588154943
      select = close,
      mutate_fun = MACD,
      nFast = 12,
      nSlow = 26,
      nSig = 9,
      col_rename = c("macd", "signal")
    ) %>%
    tq_mutate(
```

```
      select = close,
      mutate_fun = RSI,
      n = 14,
      col_rename = "rsi"
    ) %>%
    tq_mutate(
      select = close,
      mutate_fun = BBands,
      n = 20,
      sd = 2,
      col_rename = "bband"
    )

  candles_enhanced
}

candles_enhanced <- enhance_dataset(candles, fear_and_greed_index, hash_rate, average_block_size, n_tran
names(candles_enhanced)
```

```
##  [1] "time"                "low"                 "high"
##  [4] "open"                "close"               "volume"
##  [7] "date_only"           "value"               "value_classification"
## [10] "hash_rate"           "avg_block_size"      "n_transactions"
## [13] "utxo_count"          "body_size"           "upper_shadow_size"
## [16] "lower_shadow_size"   "direction"           "roc"
## [19] "macd"                "signal"              "rsi"
## [22] "dn"                  "mavg"                "up"
## [25] "pctB"
```

We have now a table with all the features discussed above. Before adding the lagged features let's explore our set.

First let's see if we have NAs.

```
na_indexes <- which(apply(candles_enhanced, 1, function(x) any(is.na(x))))
knitr::kable(head(candles_enhanced[na_indexes, ] %>%
    select(direction, roc, macd, signal, rsi, mavg, pctB, value)),
    format = "simple", caption = "NAs of the dataset")
```

Table 7: NAs of the dataset

direction	roc	macd	signal	rsi	mavg	pctB	value
up	NA	NA	NA	NA	NA	NA	65
up	NA	NA	NA	NA	NA	NA	65
down	NA	NA	NA	NA	NA	NA	65
down	NA	NA	NA	NA	NA	NA	65
up	NA	NA	NA	NA	NA	NA	65
down	NA	NA	NA	NA	NA	NA	65

```
knitr::kable(tail(candles_enhanced[na_indexes, ] %>%
    select(direction, roc, macd, signal, rsi, mavg, pctB, value)),
    format = "simple", caption = "NAs of the dataset")
```

Table 8: NAs of the dataset

direction	roc	macd	signal	rsi	mavg	pctB	value
down	0.0012887	-0.1426441	-0.1844117	47.95418	66866.20	0.6227201	NA
up	0.0007626	-0.1086808	-0.1692655	52.68220	66893.00	0.8544387	NA
up	0.0012911	-0.0721331	-0.1498390	54.72628	66919.90	0.9343443	NA
down	0.0024273	-0.0527284	-0.1304169	51.93706	66944.51	0.7779949	NA
down	-0.0002377	-0.0424873	-0.1128310	50.40502	66960.23	0.6689238	NA
down	0.0005901	-0.0375443	-0.0977736	49.39916	66970.03	0.5904000	NA

We can see in the table above that there are 2 types of NAs:

1. Technical analisis indicators
2. Fear and greed index

The technical analysis indicators are located at the start of the table which is normal since to calculate these indicators you need to have a certain number of previous values. Clearing those NAs will be enough.

As concern the fear and greed index missing value we can notice that we are missing the values of the day `2024-10-26` so we will add the values of the average between the day before and after manually.

It's important to do so to have coherant lagged values.

```
date_na <- as.Date("2024-10-26")
fear_and_greed_index_date_before_na <- fear_and_greed_index %>%
    filter(timestamp == as.Date("2024-10-25"))
fear_and_greed_index_date_after_na <- fear_and_greed_index %>%
    filter(timestamp == as.Date("2024-10-27"))
fear_and_greed_value_date_na <- mean(c(fear_and_greed_index_date_before_na$value,
    fear_and_greed_index_date_after_na$value))

fear_and_greed_index_corrected <- fear_and_greed_index %>%
    bind_rows(tibble(timestamp = date_na, value = fear_and_greed_value_date_na,
        value_classification = "Greed"))

fear_and_greed_index %>%
    filter(timestamp == date_na) %>%
    nrow()
```

```
## [1] 0
```

```
fear_and_greed_index_corrected %>%
    filter(timestamp == date_na) %>%
    nrow()
```

```
## [1] 1
```

Let's check the NAs again.

```r
candles_enhanced_cleaned <- enhance_dataset(candles, fear_and_greed_index_corrected,
    hash_rate, average_block_size, n_transactions, utxo_count)
```

```
## Warning in coerce_to_tibble(ret, date_col_name, time_zone, col_rename): Could not rename columns. The
##   Is the length of ‘col_rename‘ the same as the number of columns returned from the ‘mutate_fun‘?
```

```r
na_indexes <- which(apply(candles_enhanced_cleaned, 1, function(x) any(is.na(x))))
knitr::kable(tail(candles_enhanced_cleaned[na_indexes, ] %>%
    select(direction, roc, macd, signal, rsi, mavg, pctB, value)),
    format = "simple", caption = "NAs of the dataset cleaned")
```

Table 9: NAs of the dataset cleaned

direction	roc	macd	signal	rsi	mavg	pctB	value
down	0.0625693	2.103478	NA	83.37869	43483.53	1.0029836	71
down	0.0588336	2.115233	NA	76.65897	43616.84	0.8874993	71
down	0.0549824	2.098952	NA	76.59357	43745.10	0.8455368	71
down	0.0560958	2.060150	NA	76.37608	43871.11	0.8093231	71
up	0.0604901	2.058537	NA	78.83895	44011.84	0.8389528	71
up	0.0604520	2.086971	NA	81.02236	44169.85	0.8654968	71

We can see now the only NAs are the missing TA values that we can clean with a simple line of code.

```r
candles_enhanced_cleaned_no_na <- candles_enhanced_cleaned %>%
    drop_na()
sum(is.na(candles_enhanced_cleaned_no_na))
```

```
## [1] 0
```

2.4 Visual analysis

First of all let’s plot the data to visually verify the data.

Find below the plot of the different TA.

Comparing with the data from TradingView it seems that all the charts are correct.

Let’s now see how is the distribution of “up” and “down” candles.

Table 10: Distribution of up and down candles

up	down	total	up_percentage	down_percentage
5538	5302	10840	0.5108856	0.4891144

We can notice that the distribution is not exacly 50%.

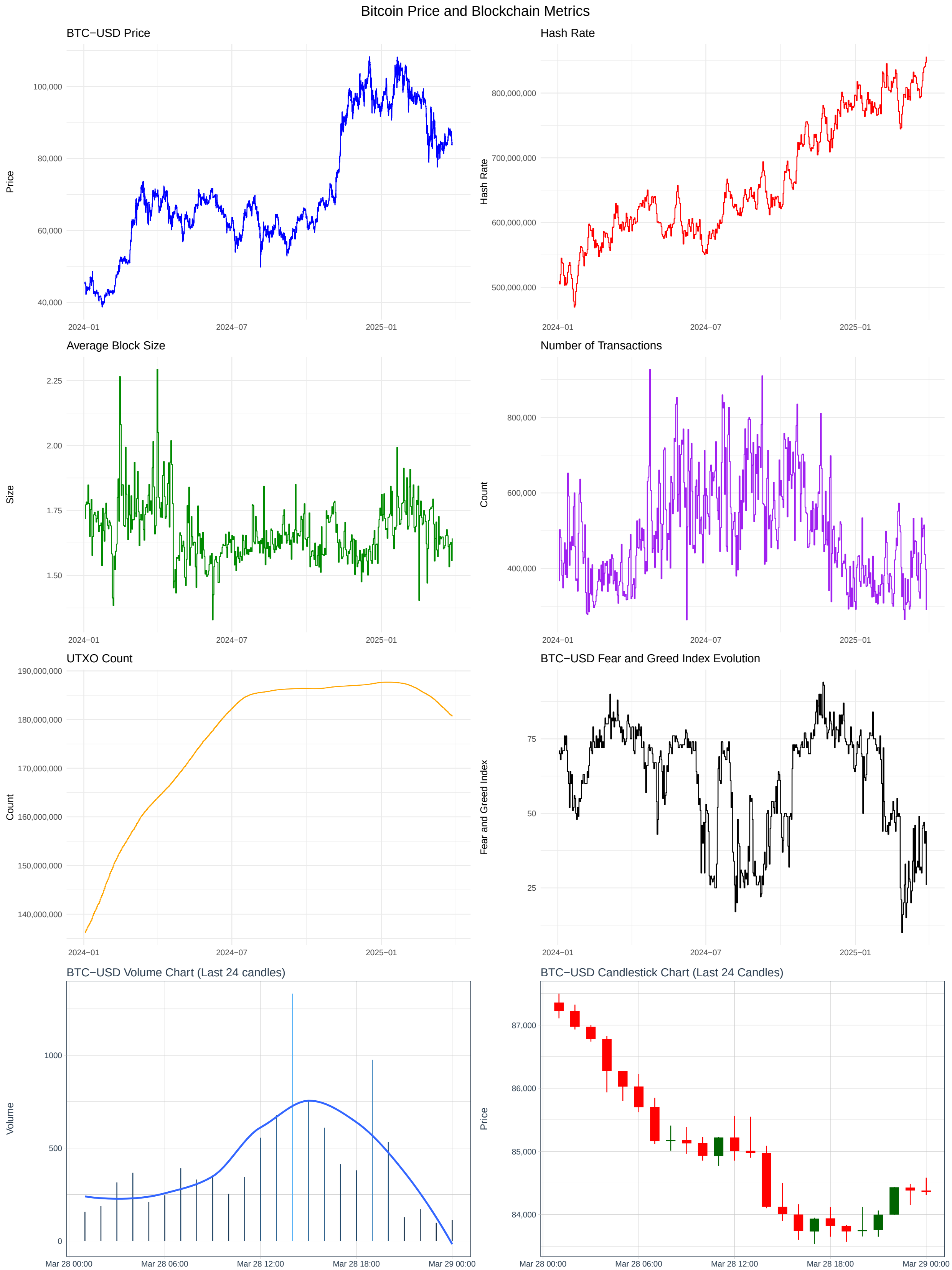


Figure 3: Visual analysis of BTC-USD data

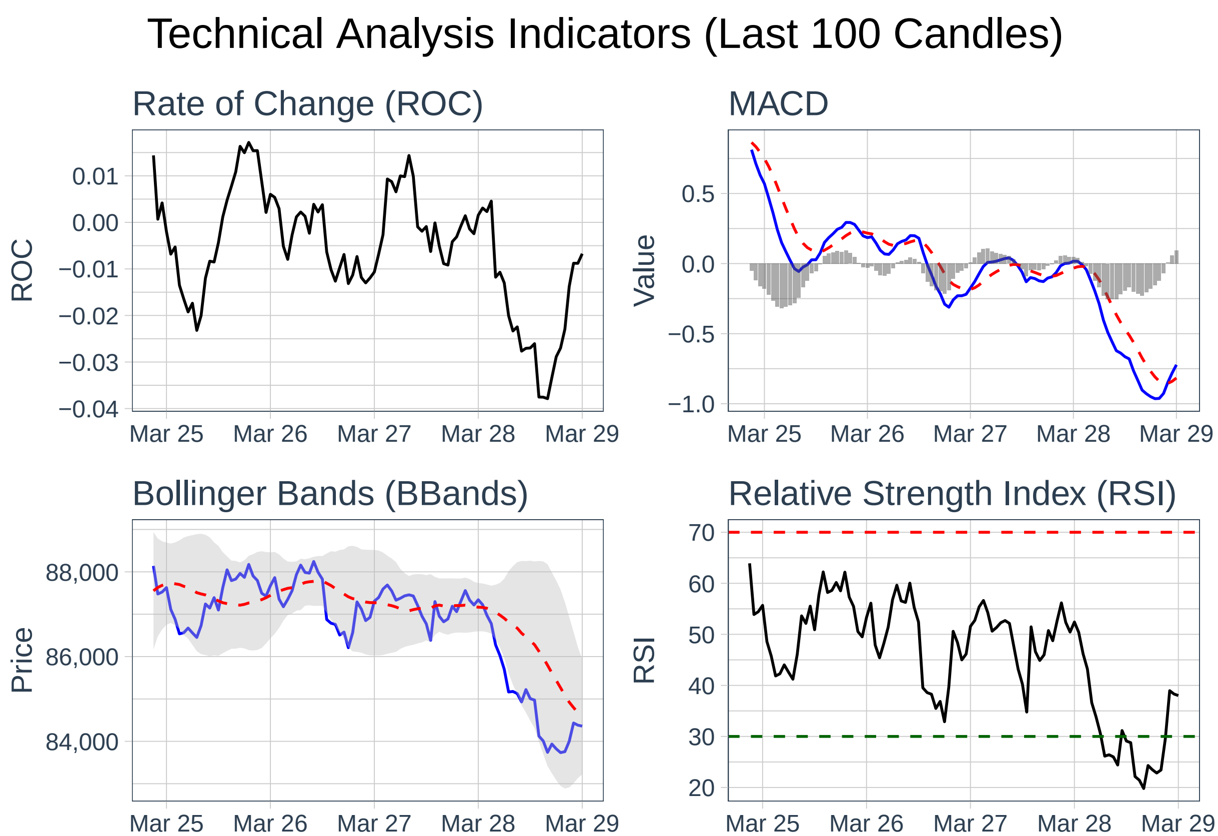


Figure 4: Technical analysis indicators of BTC-USD

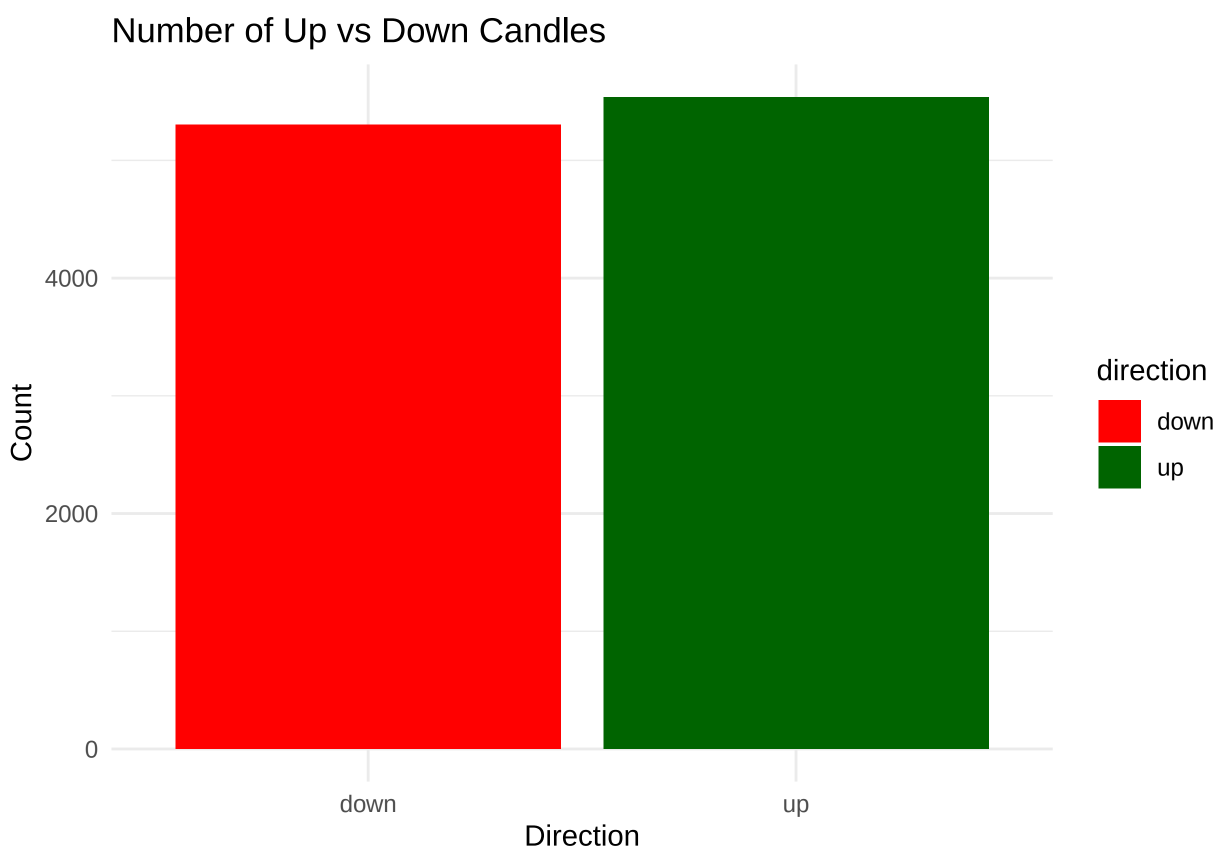


Figure 5: Distribution of up and down candles in the dataset

2.5 Adding lagged candles

Our study aim at predicting the direction of a candle using the previous candle's data and other features.

So we need to create a function to create a dataset containing lagged candles. We also created another function to directly prepare the right data.

```
add_lagged_candles <- function(enhanced_clean_dataset, n_lag) {
    dataset_with_lagged_candles <- enhanced_clean_dataset

    for (i in 1:n_lag) {
        dataset_with_lagged_candles[[paste0("body_size_lag_",
            i)]] <- lag(dataset_with_lagged_candles$body_size,
            i)
        dataset_with_lagged_candles[[paste0("upper_shadow_size_lag_",
            i)]] <- lag(dataset_with_lagged_candles$upper_shadow_size,
            i)
        dataset_with_lagged_candles[[paste0("lower_shadow_size_lag_",
            i)]] <- lag(dataset_with_lagged_candles$lower_shadow_size,
            i)
        dataset_with_lagged_candles[[paste0("direction_lag_",
            i)]] <- lag(dataset_with_lagged_candles$direction,
            i)
        dataset_with_lagged_candles[[paste0("volume_lag_", i)]] <- lag(dataset_with_lagged_candles$volu
            i)
        dataset_with_lagged_candles[[paste0("value_lag_", i)]] <- lag(dataset_with_lagged_candles$value
            i)
        dataset_with_lagged_candles[[paste0("close_lag_", i)]] <- lag(dataset_with_lagged_candles$close
            i)
        dataset_with_lagged_candles[[paste0("hash_rate_lag_",
            i)]] <- lag(dataset_with_lagged_candles$hash_rate,
            i)
        dataset_with_lagged_candles[[paste0("avg_block_size_lag_",
            i)]] <- lag(dataset_with_lagged_candles$avg_block_size,
            i)
        dataset_with_lagged_candles[[paste0("n_transactions_lag_",
            i)]] <- lag(dataset_with_lagged_candles$n_transactions,
            i)
        dataset_with_lagged_candles[[paste0("utxo_count_lag_",
            i)]] <- lag(dataset_with_lagged_candles$utxo_count,
            i)
        dataset_with_lagged_candles[[paste0("open_lag_", i)]] <- lag(dataset_with_lagged_candles$open,
            i)
        dataset_with_lagged_candles[[paste0("high_lag_", i)]] <- lag(dataset_with_lagged_candles$high,
            i)
        dataset_with_lagged_candles[[paste0("low_lag_", i)]] <- lag(dataset_with_lagged_candles$low,
            i)
        dataset_with_lagged_candles[[paste0("roc_lag_", i)]] <- lag(dataset_with_lagged_candles$roc,
            i)
        dataset_with_lagged_candles[[paste0("macd_lag_", i)]] <- lag(dataset_with_lagged_candles$macd,
            i)
        dataset_with_lagged_candles[[paste0("signal_lag_", i)]] <- lag(dataset_with_lagged_candles$signa
            i)
        dataset_with_lagged_candles[[paste0("rsi_lag_", i)]] <- lag(dataset_with_lagged_candles$rsi,
```

```
            i)
        dataset_with_lagged_candles[[paste0("up_bband_lag_",
            i)]] <- lag(dataset_with_lagged_candles$up, i)
        dataset_with_lagged_candles[[paste0("mavg_lag_", i)]] <- lag(dataset_with_lagged_candles$mavg,
            i)
        dataset_with_lagged_candles[[paste0("dn_bband_lag_",
            i)]] <- lag(dataset_with_lagged_candles$dn, i)
        dataset_with_lagged_candles[[paste0("pctB_lag_", i)]] <- lag(dataset_with_lagged_candles$pctB,
            i)
    }

    dataset_with_lagged_candles
}

prepare_dataset <- function(candles_data, fear_and_greed_index_data,
    hash_rate_data, average_block_size_data, n_transactions_data,
    utxo_count_data) {
    enhanced_clean_dataset <- enhance_dataset(candles_data, fear_and_greed_index_data,
        hash_rate_data, average_block_size_data, n_transactions_data,
        utxo_count_data)
    enhanced_clean_dataset_without_na <- enhanced_clean_dataset %>%
        drop_na()
    dataset_with_lagged_candles <- add_lagged_candles(enhanced_clean_dataset_without_na,
        15)
    dataset_with_lagged_candles_without_na <- dataset_with_lagged_candles %>%
        drop_na()
    dataset_with_lagged_candles_without_na
}
```

Using the function `prepare_dataset` and the we can have directly the final dataset with lagged data.

2.6 Test and training datasets

We put together the code to fix the fear_and_greed_index and to prepare the datasets and split them in train and test sets.

```
date_na <- as.Date("2024-10-26")
fear_and_greed_index_date_before_na <- fear_and_greed_index %>%
    filter(timestamp == as.Date("2024-10-25"))
fear_and_greed_index_date_after_na <- fear_and_greed_index %>%
    filter(timestamp == as.Date("2024-10-27"))
fear_and_greed_value_date_na <- mean(c(fear_and_greed_index_date_before_na$value,
    fear_and_greed_index_date_after_na$value))

fear_and_greed_index_corrected <- fear_and_greed_index %>%
    bind_rows(tibble(timestamp = date_na, value = fear_and_greed_value_date_na,
        value_classification = "Greed"))

project_dataset <- prepare_dataset(candles, fear_and_greed_index_corrected,
    hash_rate, average_block_size, n_transactions, utxo_count)

sum(is.na(project_dataset))
```

```
## [1] 0
```

```r
nrow(project_dataset)
```

```
## [1] 10825
```

```r
nrow(candles)
```

```
## [1] 10873
```

```r
test_index <- createDataPartition(y = project_dataset$direction,
    times = 1, p = 0.2, list = FALSE)
train_set <- project_dataset[-test_index, ]
test_set <- project_dataset[test_index, ]
```

The number of rows reduced since adding lags introduced a lot of NAs in the first rows, NAs that we removed. Also we decided not to use cross validation to reduce the time of training for the different machine learnings algorithms. Note that we initiated already the project using `set.seed(1)` part of the global variables.

2.7 Machine learning algorithms

Based on some shallow research on the press, we selected the following machine learnings algorithms that seems to work better with our type of dataset [11], [12]:

- Generalized Linear Model (GLM)
- Decision Tree (DT)
- Random Forest (RF)
- K-nearest neighbor (KNN)
- Gradient boosting (GBM)

We will also compare these algorithms with Random guess as a reference.

2.8 Utility functions

Since we want to compare each algorithms for a different set of features we need a function to create the formula that we will pass to the machine learning function.

```r
create_feature_formula <- function(feature_names, n_lags) {
    features <- c()

    for (feature_name in feature_names) {
        for (i in 1:n_lags) {
            features <- c(features, paste0(feature_name, "_lag_",
                i))
        }
    }
```

```r
    formula_str <- paste("direction ~", paste(features, collapse = " + "))

    as.formula(formula_str)
}


train_with_cache <- function(formula, train_set, method) {
    formula_hash <- digest::digest(formula)
    filepath <- paste0("models/", method, "_", formula_hash,
        ".rds")
    if (file.exists(filepath)) {
        model <- readRDS(filepath)
        print(paste("Model loaded from cache:", filepath))
    } else {
        start_time <- Sys.time()
        if (method == "rf") {
            model <- train(formula, data = train_set, method = "rf",
                ntree = 100)
        } else if (method == "glm") {
            model <- train(formula, data = train_set, method = "glm",
                family = "binomial")
        } else if (method == "rpart") {
            model <- train(formula, data = train_set, method = "rpart")
        } else if (method == "knn") {
            model <- train(formula, data = train_set, method = "knn",
                preProcess = c("center", "scale"), tuneGrid = data.frame(k = seq(3,
                  15, 2)))
        } else if (method == "gbm") {
            model <- train(formula, data = train_set, method = "gbm")
        } else {
            stop("Invalid method")
        }
        end_time <- Sys.time()
        print(paste("Training time:", format(end_time - start_time,
            digits = 2)))

        saveRDS(model, filepath)
    }

    model
}

evaluate_models <- function(feature_set, test_set, lags = c(1,
    3, 5, 7, 15)) {
    # Define model types
    model_types <- c("glm", "rf", "rpart", "knn", "gbm")

    # Create a data frame to store results
    results <- data.frame(model = character(), model_type = character(),
        lag = numeric(), accuracy = numeric(), stringsAsFactors = FALSE)

    # Evaluate each model type and lag combination
    for (model_type in model_types) {
```

```
        for (lag in lags) {
            model_name <- paste0(model_type, "_model_", feature_set,
                "_lag_", lag)

            if (exists(model_name)) {
                # Get the model object
                model <- get(model_name)

                # Make predictions
                predictions <- predict(model, test_set)

                # Calculate accuracy
                accuracy <- mean(predictions == test_set$direction)

                # Add to results
                results <- rbind(results, data.frame(model = model_name,
                  model_type = model_type, lag = lag, accuracy = accuracy,
                  stringsAsFactors = FALSE))
            }
        }
    }

    # Sort by accuracy in descending order
    results <- results[order(-results$accuracy), ]

    # Add rank column
    results$rank <- 1:nrow(results)

    results
}
```

3 Training machine learnings algorithms

We are now going to train and compare various machine learning algorithms with different set of selected features and different number of lag.

Before starting with those algorithms we will start with very simple ones to have a reference to compare.

3.1 Simple algorithms

3.1.1 Random guess

We will run a montecarlo simulation of `1000` random guesses of direction and compare it with the test set.

```
random_guess_simulations <- replicate(1000, {
    estimated_direction <- replicate(nrow(test_set), sample(c("up",
        "down"), 1))
    mean(estimated_direction == test_set$direction)
})

mean_accuracy <- mean(random_guess_simulations)
```

```r
standard_deviation <- sd(random_guess_simulations)
print(paste("Mean accuracy:", round(mean_accuracy, 4)))
```

```
## [1] "Mean accuracy: 0.5002"
```

```r
print(paste("Standard deviation:", round(standard_deviation,
    4)))
```

```
## [1] "Standard deviation: 0.0109"
```

3.1.2 Always up

We can also compare this with an always up strategy:

```r
always_up <- function(test_set) {
    replicate(nrow(test_set), "up")
}
always_up_accuracy <- mean(always_up(test_set) == test_set$direction)
print(paste("Always up accuracy:", round(always_up_accuracy,
    4)))
```

```
## [1] "Always up accuracy: 0.5111"
```

3.1.3 Previous direction

Now let's see how it compares with returning the same direction as the previous (lag_1):

```r
previous_direction <- function(test_set) {
    test_set$direction_lag_1
}
previous_direction_accuracy <- mean(previous_direction(test_set) ==
    test_set$direction)
print(paste("Previous direction accuracy:", round(previous_direction_accuracy,
    4)))
```

```
## [1] "Previous direction accuracy: 0.4658"
```

3.1.4 Opposite direction to previous one

```r
opposite_direction <- function(test_set) {
    ifelse(test_set$direction_lag_1 == "up", "down", "up")
}
opposite_direction_accuracy <- mean(opposite_direction(test_set) ==
    test_set$direction)
print(paste("Opposite direction to the previous one accuracy:",
    round(opposite_direction_accuracy, 4)))
```

```
## [1] "Opposite direction to the previous one accuracy: 0.5342"
```

We can see that giving the opposite direction to the previous one has the highest accuracy so far: `0.5342`, let's see how it compares with machine learning algorithms.

3.2 Machine learning algorithms

For each of these machine learning algorithms we will use either 1, 3, 5, 7 or 12 lagged data. We will later fine tune that number of lagged candles to see what works the best.

3.2.1 OHLC features

We will first try to use the lagged OHLC features got directly from the coinbase dataset:

- open
- high
- low
- close
- volume

Table 11: Model comparison for OHLC features

model	model_type	lag	accuracy	rank
glm_model_OHLC_lag_1	glm	1	0.5429363	1
glm_model_OHLC_lag_3	glm	3	0.5397045	2
glm_model_OHLC_lag_7	glm	7	0.5337027	3
glm_model_OHLC_lag_5	glm	5	0.5323176	4
glm_model_OHLC_lag_15	glm	15	0.5212373	5
rpart_model_OHLC_lag_1	rpart	1	0.5110803	6
rpart_model_OHLC_lag_7	rpart	7	0.5110803	7
rpart_model_OHLC_lag_3	rpart	3	0.5096953	8
gbm_model_OHLC_lag_15	gbm	15	0.5069252	9
knn_model_OHLC_lag_1	knn	1	0.5064635	10
gbm_model_OHLC_lag_3	gbm	3	0.5060018	11
rf_model_OHLC_lag_15	rf	15	0.5050785	12
gbm_model_OHLC_lag_1	gbm	1	0.5004617	13
rf_model_OHLC_lag_3	rf	3	0.4967682	14
rpart_model_OHLC_lag_15	rpart	15	0.4958449	15
knn_model_OHLC_lag_15	knn	15	0.4935365	16
rf_model_OHLC_lag_1	rf	1	0.4930748	17
knn_model_OHLC_lag_7	knn	7	0.4921514	18
rpart_model_OHLC_lag_5	rpart	5	0.4912281	19
gbm_model_OHLC_lag_5	gbm	5	0.4898430	20
gbm_model_OHLC_lag_7	gbm	7	0.4884580	21
rf_model_OHLC_lag_5	rf	5	0.4879963	22
rf_model_OHLC_lag_7	rf	7	0.4773777	23
knn_model_OHLC_lag_5	knn	5	0.4750693	24
knn_model_OHLC_lag_3	knn	3	0.4699908	25

Table 12: Summary statistics for OHLC features

Model Type	Mean Accuracy	SD Accuracy	Max Accuracy
gbm	0.4983	0.0088	0.5069
glm	0.5340	0.0083	0.5429
knn	0.4874	0.0148	0.5065
rf	0.4921	0.0103	0.5051
rpart	0.5038	0.0095	0.5111

3.2.2 Candle features

Now let's try to use the lagged candle features:

- body_size
- upper_shadow_size
- lower_shadow_size
- direction
- close
- volume

Table 13: Model comparison for candles features

model	model_type	lag	accuracy	rank
gbm_model_candles_lag_1	gbm	1	0.5470914	1
rpart_model_candles_lag_1	rpart	1	0.5447830	2
glm_model_candles_lag_7	glm	7	0.5433980	3
glm_model_candles_lag_5	glm	5	0.5401662	4
glm_model_candles_lag_3	glm	3	0.5397045	5
rpart_model_candles_lag_3	rpart	3	0.5341644	6
rpart_model_candles_lag_7	rpart	7	0.5341644	7
gbm_model_candles_lag_7	gbm	7	0.5313943	8
glm_model_candles_lag_1	glm	1	0.5300092	9
rpart_model_candles_lag_5	rpart	5	0.5286242	10
knn_model_candles_lag_3	knn	3	0.5277008	11
gbm_model_candles_lag_15	gbm	15	0.5258541	12
glm_model_candles_lag_15	glm	15	0.5249307	13
rf_model_candles_lag_1	rf	1	0.5244691	14
knn_model_candles_lag_1	knn	1	0.5235457	15
rf_model_candles_lag_7	rf	7	0.5230840	16
gbm_model_candles_lag_3	gbm	3	0.5221607	17
knn_model_candles_lag_7	knn	7	0.5212373	18
gbm_model_candles_lag_5	gbm	5	0.5184672	19
knn_model_candles_lag_15	knn	15	0.5143121	20
rpart_model_candles_lag_15	rpart	15	0.5110803	21
rf_model_candles_lag_5	rf	5	0.5092336	22
knn_model_candles_lag_5	knn	5	0.5055402	23
rf_model_candles_lag_3	rf	3	0.5036934	24

model	model_type	lag	accuracy	rank
rf_model_candles_lag_15	rf	15	0.5036934	25

Table 14: Summary statistics for candles features

Model Type	Mean Accuracy	SD Accuracy	Max Accuracy
gbm	0.5290	0.0112	0.5471
glm	0.5356	0.0078	0.5434
knn	0.5185	0.0087	0.5277
rf	0.5118	0.0114	0.5254
rpart	0.5306	0.0124	0.5448

3.2.3 Candles features and fear and greed index

Now let's try to use the lagged candles features and the fear and greed index:

- body_size
- upper_shadow_size
- lower_shadow_size
- direction
- close
- value
- volume

Table 15: Model comparison for candles features and fear and greed index

model	model_type	lag	accuracy	rank
rpart_model_candles_fg_lag_1	rpart	1	0.5447830	1
glm_model_candles_fg_lag_7	glm	7	0.5438596	2
glm_model_candles_fg_lag_5	glm	5	0.5429363	3
glm_model_candles_fg_lag_3	glm	3	0.5410896	4
rpart_model_candles_fg_lag_3	rpart	3	0.5341644	5
rpart_model_candles_fg_lag_5	rpart	5	0.5341644	6
rpart_model_candles_fg_lag_7	rpart	7	0.5341644	7
rpart_model_candles_fg_lag_15	rpart	15	0.5341644	8
rf_model_candles_fg_lag_3	rf	3	0.5337027	9
gbm_model_candles_fg_lag_7	gbm	7	0.5332410	10
gbm_model_candles_fg_lag_3	gbm	3	0.5318560	11
gbm_model_candles_fg_lag_1	gbm	1	0.5290859	12
glm_model_candles_fg_lag_15	glm	15	0.5286242	13
glm_model_candles_fg_lag_1	glm	1	0.5277008	14
gbm_model_candles_fg_lag_5	gbm	5	0.5249307	15
rf_model_candles_fg_lag_15	rf	15	0.5216990	16
knn_model_candles_fg_lag_1	knn	1	0.5175439	17

model	model_type	lag	accuracy	rank
rf_model_candles_fg_lag_5	rf	5	0.5170822	18
rf_model_candles_fg_lag_1	rf	1	0.5166205	19
knn_model_candles_fg_lag_7	knn	7	0.5106187	20
knn_model_candles_fg_lag_5	knn	5	0.5064635	21
knn_model_candles_fg_lag_15	knn	15	0.5041551	22
gbm_model_candles_fg_lag_15	gbm	15	0.5041551	23
knn_model_candles_fg_lag_3	knn	3	0.4967682	24
rf_model_candles_fg_lag_7	rf	7	0.4949215	25

Table 16: Summary statistics for candles features and fear and greed index

Model Type	Mean Accuracy	SD Accuracy	Max Accuracy
gbm	0.5247	0.0119	0.5332
glm	0.5368	0.0080	0.5439
knn	0.5071	0.0077	0.5175
rf	0.5168	0.0140	0.5337
rpart	0.5363	0.0047	0.5448

3.2.4 Candles features, fear and greed index and chain data

We will try to use the lagged candles features, the fear and greed index and the chain data:

- body_size
- upper_shadow_size
- lower_shadow_size
- direction
- close
- value
- hash_rate
- avg_block_size
- n_transactions
- utxo_count
- volume

Table 17: Model comparison for candles features, fear and greed index and chain data

model	model_type	lag	accuracy	rank
rpart_model_candles_fg_chain_lag_15	rpart	15	0.5447830	1
rpart_model_candles_fg_chain_lag_1	rpart	1	0.5341644	2

model	model_type	lag	accuracy	rank
rpart_model_candles_fg_chain_lag_3	rpart	3	0.5341644	3
rpart_model_candles_fg_chain_lag_5	rpart	5	0.5341644	4
gbm_model_candles_fg_chain_lag_1	gbm	1	0.5290859	5
glm_model_candles_fg_chain_lag_3	glm	3	0.5258541	6
glm_model_candles_fg_chain_lag_7	glm	7	0.5235457	7
rf_model_candles_fg_chain_lag_7	rf	7	0.5235457	8
gbm_model_candles_fg_chain_lag_15	gbm	15	0.5221607	9
glm_model_candles_fg_chain_lag_15	glm	15	0.5203139	10
glm_model_candles_fg_chain_lag_5	glm	5	0.5198523	11
gbm_model_candles_fg_chain_lag_5	gbm	5	0.5184672	12
rf_model_candles_fg_chain_lag_3	rf	3	0.5161588	13
rpart_model_candles_fg_chain_lag_7	rpart	7	0.5110803	14
gbm_model_candles_fg_chain_lag_3	gbm	3	0.5101570	15
knn_model_candles_fg_chain_lag_15	knn	15	0.5087719	16
glm_model_candles_fg_chain_lag_1	glm	1	0.5069252	17
rf_model_candles_fg_chain_lag_15	rf	15	0.5069252	18
knn_model_candles_fg_chain_lag_5	knn	5	0.5064635	19
knn_model_candles_fg_chain_lag_7	knn	7	0.5055402	20
knn_model_candles_fg_chain_lag_3	knn	3	0.5036934	21
gbm_model_candles_fg_chain_lag_7	gbm	7	0.5023084	22
rf_model_candles_fg_chain_lag_1	rf	1	0.5013850	23
rf_model_candles_fg_chain_lag_5	rf	5	0.5004617	24
knn_model_candles_fg_chain_lag_1	knn	1	0.4986150	25

Table 18: Summary statistics for candles features, fear and greed index and chain data

Model Type	Mean Accuracy	SD Accuracy	Max Accuracy
gbm	0.5164	0.0104	0.5291
glm	0.5193	0.0073	0.5259
knn	0.5046	0.0038	0.5088
rf	0.5097	0.0099	0.5235
rpart	0.5317	0.0124	0.5448

3.2.5 Candles features, fear and greed index, chain data and technical analysis indicators

Finally let's add the technical analysis indicators to the model, so we will use the following lagged features:

- body_size
- upper_shadow_size
- lower_shadow_size
- direction
- close
- value
- hash_rate

- avg_block_size
- n_transactions
- utxo_count
- volume
- roc
- macd
- signal
- rsi
- up_bband
- mavg
- dn_bband
- pctB

Table 19: Model comparison for candles features, fear and greed index, chain data and technical analysis indicators

model	model_type	lag	accuracy	rank
gbm_model_candles_fg_chain_ta_lag_1	gbm	1	0.5498615	1
gbm_model_candles_fg_chain_ta_lag_7	gbm	7	0.5424746	2
rpart_model_candles_fg_chain_ta_lag_1	rpart	1	0.5383195	3
glm_model_candles_fg_chain_ta_lag_3	glm	3	0.5364728	4
glm_model_candles_fg_chain_ta_lag_5	glm	5	0.5327793	5
gbm_model_candles_fg_chain_ta_lag_3	gbm	3	0.5304709	6
glm_model_candles_fg_chain_ta_lag_15	glm	15	0.5295476	7
gbm_model_candles_fg_chain_ta_lag_5	gbm	5	0.5295476	8
rf_model_candles_fg_chain_ta_lag_7	rf	7	0.5277008	9
rpart_model_candles_fg_chain_ta_lag_3	rpart	3	0.5272392	10
rpart_model_candles_fg_chain_ta_lag_5	rpart	5	0.5272392	11
rpart_model_candles_fg_chain_ta_lag_7	rpart	7	0.5272392	12
rpart_model_candles_fg_chain_ta_lag_15	rpart	15	0.5272392	13
glm_model_candles_fg_chain_ta_lag_7	glm	7	0.5253924	14
glm_model_candles_fg_chain_ta_lag_1	glm	1	0.5235457	15
gbm_model_candles_fg_chain_ta_lag_15	gbm	15	0.5203139	16
rf_model_candles_fg_chain_ta_lag_3	rf	3	0.5198523	17
rf_model_candles_fg_chain_ta_lag_15	rf	15	0.5156971	18
knn_model_candles_fg_chain_ta_lag_5	knn	5	0.5096953	19
rf_model_candles_fg_chain_ta_lag_1	rf	1	0.5078486	20
knn_model_candles_fg_chain_ta_lag_3	knn	3	0.5078486	21
rf_model_candles_fg_chain_ta_lag_5	rf	5	0.5064635	22
knn_model_candles_fg_chain_ta_lag_1	knn	1	0.5041551	23
knn_model_candles_fg_chain_ta_lag_7	knn	7	0.4912281	24
knn_model_candles_fg_chain_ta_lag_15	knn	15	0.4852262	25

Table 20: Summary statistics for candles features, fear and greed index, chain data and technical analysis indicators

Model Type	Mean Accuracy	SD Accuracy	Max Accuracy
gbm	0.5345	0.0116	0.5499
glm	0.5295	0.0053	0.5365
knn	0.4996	0.0108	0.5097
rf	0.5155	0.0088	0.5277
rpart	0.5295	0.0050	0.5383

3.3 Models comparison

Table 21: Top models across all feature sets

model	model_type	lag	accuracy	rank
gbm_model_candles_fg_chain_ta_lag_1	gbm	1	0.5498615	1
gbm_model_candles_lag_1	gbm	1	0.5470914	1
rpart_model_candles_lag_1	rpart	1	0.5447830	2
rpart_model_candles_fg_lag_1	rpart	1	0.5447830	1
rpart_model_candles_fg_chain_lag_15	rpart	15	0.5447830	1
glm_model_candles_fg_lag_7	glm	7	0.5438596	2
glm_model_candles_lag_7	glm	7	0.5433980	3
glm_model_OHLC_lag_1	glm	1	0.5429363	1
glm_model_candles_fg_lag_5	glm	5	0.5429363	3
gbm_model_candles_fg_chain_ta_lag_7	gbm	7	0.5424746	2

Table 22: Summary of feature sets

	feature_set	avg_accuracy	sd_accuracy
2	candles	0.5254663	0.0123088
3	candles_fg	0.5241736	0.0144663
5	candles_fg_chain_ta	0.5215512	0.0155503
4	candles_fg_chain	0.5163989	0.0128327
1	OHLC	0.5027331	0.0195974

As we can see the best models are the ones using `Gradient boosting` and the `candles` feature set seems to perform better overall.

Also as expected the OHLC didn't perform well since it just uses raw data that are hard to use to train a machine learning algorithm.

But in order to proceed to the fine tuning we will use `gbm_model_candles_fg_chain_ta_lag_1` since it's outperforming the other models with an accuracy of `0.5498615`.

4 Fine tuning

Before proceeding to the fine tuning it's worth checking if the GBM model is not performing better with the same features and 2 lags instead of one.

```
## [1] "Model loaded from cache: models/gbm_42d3a7ed8ef45c8b47ea08a3f199fd00.rds"
```

```
## [1] 0.5369344
```

As we can see the GBM model with `candles_fg_chain_ta` feature set and 1 lag `gbm_model_candles_fg_chain_ta_lag_1` is still performing better.

Let's use its tuning values and let's fine tune it.

```
##   n.trees interaction.depth shrinkage n.minobsinnode
## 1      50                 1       0.1             10
```

We will use values around those values to fine tune this algorithm. Also unlike all the others algorithms we will use cross-validation for avoiding overfitting and having a more robust prediction algorithm, that would perform better with any dataset than only the `test_set`.

```r
# Define the tuning grid with the best values
gbm_grid <- expand.grid(n.trees = c(45, 46, 47, 48, 49, 50, 51,
    52, 53, 54, 55), interaction.depth = c(1, 2), shrinkage = c(0.05,
    0.1, 0.15), n.minobsinnode = c(8, 9, 10, 11, 12))

# Set up cross-validation
train_control <- trainControl(method = "cv", number = 5, verboseIter = TRUE,
    classProbs = TRUE, summaryFunction = twoClassSummary)

# Train the fine-tuned model with cross-validation
formula_candles_fg_chain_ta_lag_1 <- create_feature_formula(c("body_size",
    "upper_shadow_size", "lower_shadow_size", "direction", "close",
    "value", "hash_rate", "avg_block_size", "n_transactions",
    "utxo_count", "roc", "macd", "signal", "rsi", "up_bband",
    "mavg", "dn_bband", "pctB", "volume"), 1)


if (!file.exists("models/gbm_model_candles_fg_chain_ta_lag_1_tuned.rds")) {
    gbm_model_candles_fg_chain_ta_lag_1_tuned <- train(formula_candles_fg_chain_ta_lag_1,
        data = train_set, method = "gbm", trControl = train_control,
        tuneGrid = gbm_grid, metric = "ROC")
    saveRDS(gbm_model_candles_fg_chain_ta_lag_1_tuned, "models/gbm_model_candles_fg_chain_ta_lag_1_tune
} else {
    gbm_model_candles_fg_chain_ta_lag_1_tuned <- readRDS("models/gbm_model_candles_fg_chain_ta_lag_1_tur
}

# Evaluate the fine-tuned model on the test set
accuracy_gbm_model_candles_fg_chain_ta_lag_1_tuned <- mean(predict(gbm_model_candles_fg_chain_ta_lag_1_t
    test_set) == test_set$direction)
print(paste("Fine-tuned model accuracy:", accuracy_gbm_model_candles_fg_chain_ta_lag_1_tuned))
```

```
## [1] "Fine-tuned model accuracy: 0.545706371191136"
```

As we can see the result the model is performing slightly less good than the one without fine tuning, but it's still better than the third best model.

We can see below the values of the different parameters:

```
##    n.trees interaction.depth shrinkage n.minobsinnode
## 90      46                 2      0.05             11
```

Now let's compare the results and analyse what we have got.

5 Results

We will compare the best model for each feature set.

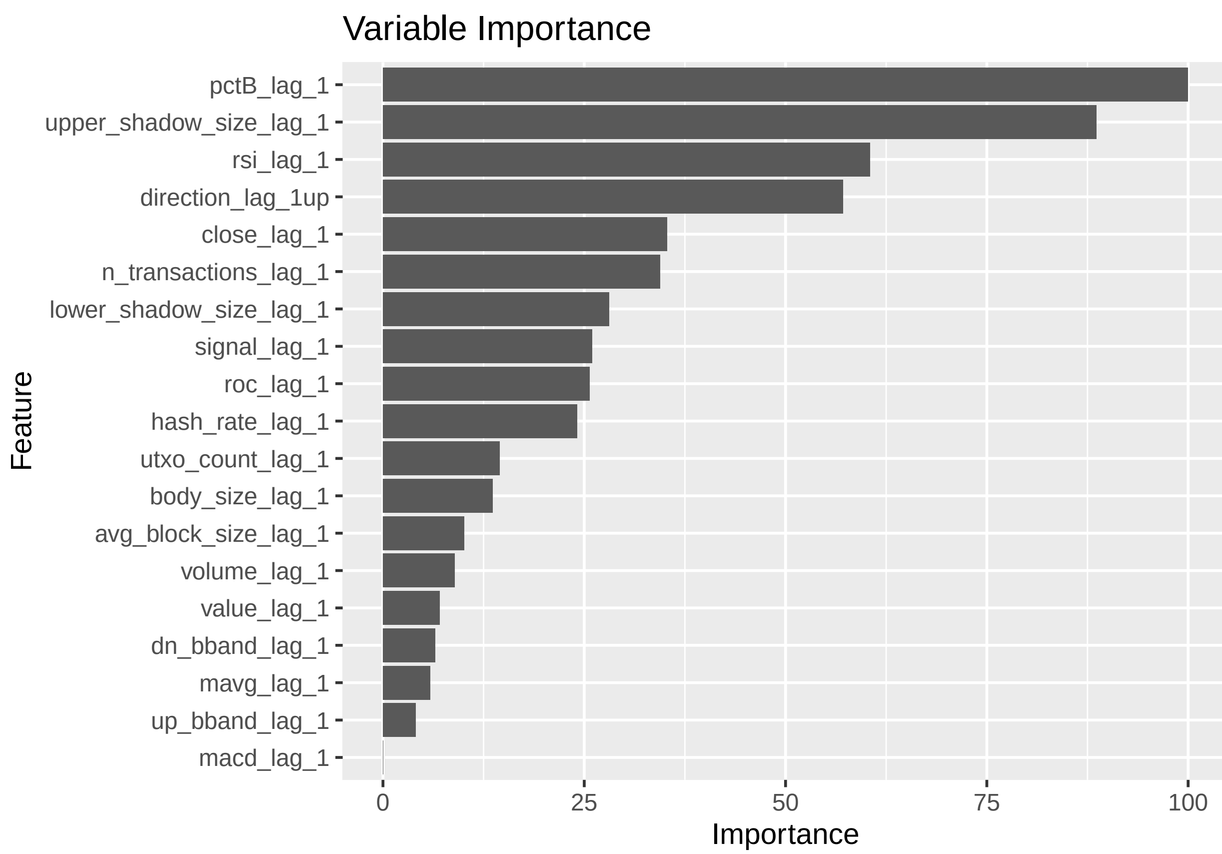
Table 23: Comparison of best models from each feature set and baseline methods

	Model	Features	Model Type	Lag	Accuracy
211	gbm_model_candles_fg_chain_ta_lag_1	Candles, F&G, Chain, TA	gbm	1	0.5499
21	gbm_model_candles_lag_1	Candles	gbm	1	0.5471
12	gbm_model_candles_fg_chain_ta_lag_1_tuned	Candles, F&G, Chain, TA	gbm	1	0.5457
11	rpart_model_candles_fg_lag_1	Candles, F&G	rpart	1	0.5448
15	rpart_model_candles_fg_chain_lag_15	Candles, F&G, Chain	rpart	15	0.5448
5	glm_model_OHLC_lag_1	OHLC	glm	1	0.5429
4	opposite_direction	simple	simple	1	0.5342
2	always_up	simple	simple	NA	0.5111
1	random_guess	simple	simple	NA	0.5002
3	previous_direction	simple	simple	1	0.4658

While our best model has an accuracy of `0.5499`, we would still consider the fine tuned algorithm more robust with an accuracy of `0.5457`.

5.1 Most relevant features

Now let's see what are the most important features of the algorithm.



Interestingly the features with an importance higher than 25 are related to TA, Chain Data and Candles data.

5.2 Confusion matrix

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  up down
##       up   816  693
##       down 291  366
##
##                Accuracy : 0.5457
##                  95% CI : (0.5245, 0.5668)
##     No Information Rate : 0.5111
##     P-Value [Acc > NIR] : 0.0006755
##
##                   Kappa : 0.0834
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.7371
##             Specificity : 0.3456
##          Pos Pred Value : 0.5408
##          Neg Pred Value : 0.5571
##              Prevalence : 0.5111
```

```
##          Detection Rate : 0.3767
##    Detection Prevalence : 0.6967
##       Balanced Accuracy : 0.5414
##
##        'Positive' Class : up
##
```

We can notice that the model is slightly better at predicting `down` than `up` at least with the `test_set`. Which means that in in future trading it would potentially get a better success rate at shorting rather than longing.

6 Conclusion

We have learned in this study that predictions using a trained model are better than luck.

With an accuracy of `0.5457` it would be important for a trader to use the predictions along with a well defined target for take-profit and stop-loss where the profit targeted should be higher than the stop-loss targeted.

Let's see what are the limitations of this study and what could be done next.

6.1 Limitations

As mentioned in the report, most of the training have been done without cross-validation, in order to save computation time, therefore some other algorithm may have performed better than the current one.

6.2 Potential improvements

A deeper study of the existing research could be used as a base to improve this algorithm, also there may be some other algorithms working even better than GBM that may be worth be trained.

Also, some other Technical Analysis indicator could be used to have better predictions maybe by coupling our hourly candles to a smaller time frame of candles.

Last but not least, using different algorithm depending on the type of market could also be a good solution. By comparing how algorithms performs in a different type of market, bearish, bullish or sideway and switching to the right model depending on the type of market could also improve the accuracy.

6.3 Trading application

In order to be closer to the trading reality and test the ability of the model to make profit, I would recommend to start with backtesting to see how it performs setting good stop loss / take profit targets. Then after tuning the trading algorithm it would be worth doing some paper trading before doing actual real trading.

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