CRYPTO PREDICTOR

1. Introduction

The aim of this project is to create a model that can predict whether the closing price of Bitcoin will be higher or lower the following day and that, by acting on these predictions, the model can get higher returns on investment than simply buying and holding Bitcoin.

I. Why is it relevant?

Bitcoin and other cryptocurrencies have established themselves as relevant inversion vehicles, attracting the interest of mainly small investors, but also some investment funds and regulators.

Cryptocurrencies are highly volatile, very often suffering big swings in prices, which in turn makes them potentially highly profitable investments.

Cryptocurrencies are still relatively new and have a much higher ratio of non-professional investors than stocks. This might mean that, unlike stocks, they might be somewhat predictable.

Potential predictability and high profitability make Bitcoin and other cryptos very interesting targets for machine learning models.

II. Previous works – state of the art

Most existing works about using machine learning for Bitcoin price prediction try to predict the actual future price:

- Short-term bitcoin market prediction via machine learning
- Bitcoin Price Prediction Using Recurrent Neural Networks and LSTM
- Bitcoin price prediction using Machine Learning
- BITCOIN PRICE PREDICTION USING MACHINE LEARNING
- Automated Bitcoin Trading via Machine Learning Algorithms

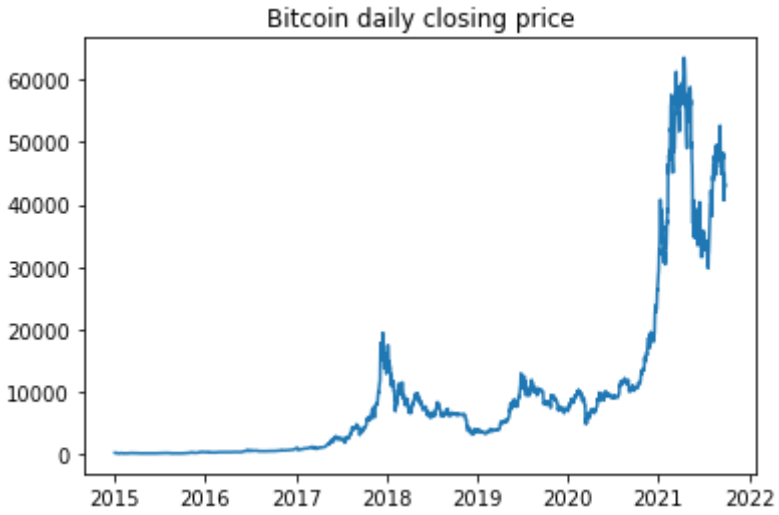
Very few of these works offer results of using the models to try to beat the market. When they do, the results are negative, like in this case: Using machine learning to predict future bitcoin prices

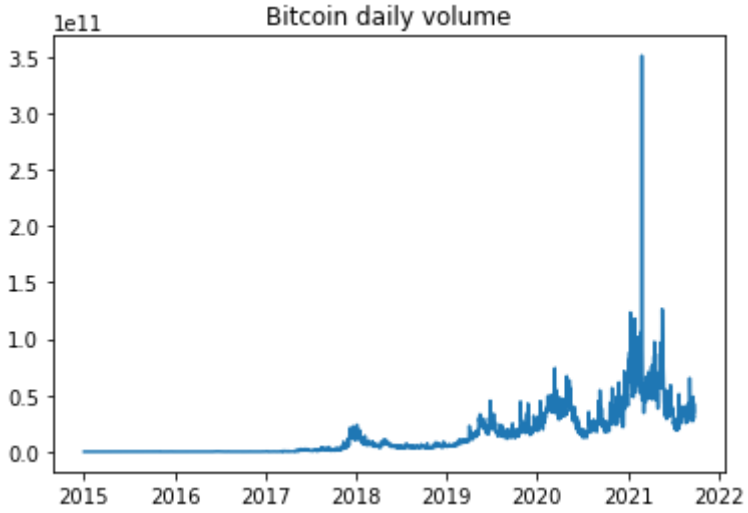
2. Raw data description

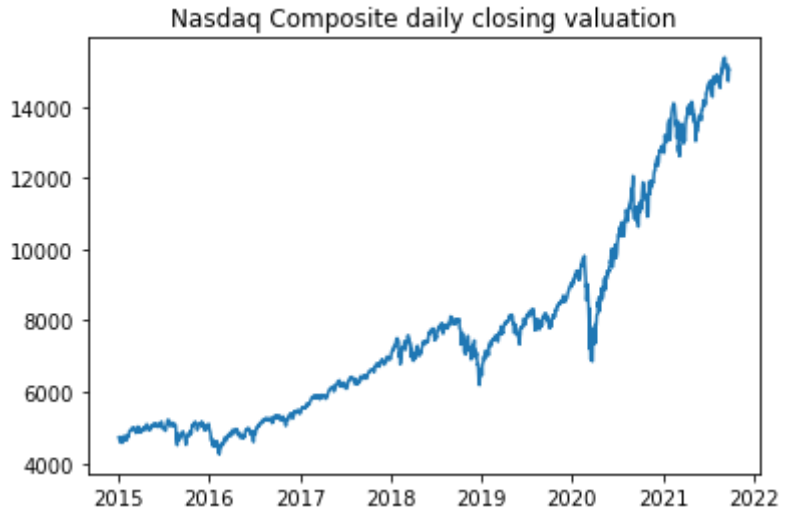
The data used in this project is very simple:

- Bitcoin closing price and volume traded daily from 01/01/2015. Note that bitcoin exchanges are always open, so the closing price is just the last price of the day.

- Gold closing price daily from 01/01/2015.
- Nasdaq Composite closing valuation daily from 01/01/2015.







3. Methodology

I. Approach

The whole project follows the approach that in trading is called “technical analysis”. This means that the model will try to predict future movements of prices using only past prices. It will never try to take into account the underlying causes of price movements (for example investor sentiment, published articles or the global economy).

In order to assess the models I use a naive model as reference. The naive model is just buying Bitcoin at the beginning of the evaluated period and holding it until the end of that period. The performance of the naive model is the same as the price evolution of Bitcoin.

All the evaluated models use the following assumptions:

- If the model indicates that I should buy or sell, the price is the closing price for that day.

- Each transaction (buying or selling) means a fee of 0.15% (a little bit higher than the minimum transaction fee at Binance – 0.1%).

II. Feature engineering

For ARIMA models, no feature engineering is needed, only daily closing prices of Bitcoin.

For classification models the feature engineering used is based on variations:

- For Bitcoin, and for every day, I compute the variation of closing price and volume since the previous day, the previous week (7 days) and the previous month (30 days).
- For Gold and Nasdaq Composite I calculate the same variations as for Bitcoin for closing price. But Gold and Nasdaq Composite don't have closing prices for every day (because of weekends and holidays), so previously I fill the missing values with the first previous real closing value.

I wanted to take into account variations over the previous year for each date, but I also wanted to keep the number of features for each date to a minimum. Therefore, each register for classification models includes:

- Variation from the previous the day for each of the last 30 days.
- Variation from the previous week for days 30, 37, 44, 51, 58, 65, 72, 79, 86 (counting backwards from the date of the register).
- Variation from the previous month for days 93, 123, 153, 183, 213, 243, 273, 303, 333 (counting backwards from the date of the register).

For Bitcoin, the variations in closing price and volume are included, for Gold and Nasdaq Composite only the variations in closing price are included. In all cases the date of the first register is 01/01/2016, as 1 year of previous data is needed to fill the features for the first register.

III. Model selection

a. ARIMA

As previously stated, for the ARIMA models I use only the closing price of Bitcoin.

The results from running the Augmented Dickey-Fuller test and checking Autocorrelation and Partial Autocorrelation suggest that the best [p, d, q] values are [10, 1, 10].

I divide the data into training, cross validation and testing and use a walk forward validation approach. This means that, every time the model is run, it only predicts the following day (d+1). For predicting day d+2, the real data from day d+1 is added to the training set and the model is trained again.

I try two different decision-making algorithms for the model:

- 2-options algorithm: if the model predicts an increase in price, Bitcoin is bought or held. If the model predicts a decrease in price, Bitcoin is sold or not bought.
- 3-options algorithm: if the increase predicted by the model is higher than the transaction fee (>0.15%), then Bitcoin is bought or held. If the model predicts an absolute variation less or equal to the transaction fee (>-0.15% and <0.15%), Bitcoin is held or not bought (ie I maintain the same position). If the decrease predicted by the model is higher than the transaction fee (<-0.15%) , Bitcoin is sold or not bought.

The results for the cross validation set for the [10,1,10] model are negative: the naive model (just hold model) obtains a 63% return, the 2-options algorithm obtains a -33% return and the 3-options algorithm obtains a -28% return.

After that I decided to try changing the [p,d,q] values. I tried all combinations of p=[9,10,11], d=[0,1] and q=[9,10,11]. The best result was a -5% return on the cross validation set (vs 63% of the naive model). These results indicated that ARIMA models cannot beat the market, so I decided to discard them.

b. Classification models

For classification models I use variations in price and volume, as explained in 3.II.

I divide the data into training, cross validation and testing and use a walk forward validation approach. This means that, every time the model is run, it only predicts the following day (d+1). For predicting day d+2, the real data from day d+1 is added to the training set and the model is trained again.

A large number of models have been tried on the cross-validation sets. These models include all combinations of the following data, transformers and classifiers:

- Data:
  - data_for_use_w_vol: Bitcoin closing price and volume variations
  - data_for_use_w_gold: Bitcoin closing price and volume variations and Gold closing price variations.
  - data_for_use_w_nasdaq: Bitcoin closing price and volume variations and Nasdaq Composite closing price variations.
  - data_for_use_w_all: Bitcoin closing price and volume variations, Gold closing price variations and Nasdaq Composite closing price variations.
  - data_for_use_basic: Bitcoin closing price variations
  - data_for_use_basic_w_gold: Bitcoin closing price variations and Gold closing price variations.
  - data_for_use_basic_w_nasdaq: Bitcoin closing price variations and Nasdaq Composite closing price variations.

    - data_for_use_basic_w_all: Bitcoin closing price variations, Gold closing price variations and Nasdaq Composite closing price variations.
    - data_for_use_bone_deep: only Bitcoin closing price daily variations for the last 30 days.
- Transformers (there are only numeric columns in the data):
    - StandardScaler
    - MinMaxScaler
    - PowerTransformer, method='yeo-johnson'
    - QuantileTransformer, output_distribution='normal'
    - MaxAbsScaler
- Classifiers:
    - KneighborsClassifier, with n_neighbors between 1 and 20
    - DecisionTreeClassifier, with max_depth between 1 and 20
    - AdaBoostClassifier, with n_estimators between 1 and 20
    - RandomForestClassifier, with min_samples_split between 2 and 20

The results of running all these models on the cross validation set are stored in all_models_CV_results.csv. The inspection of this file reveals that only 482 out of 3556 models beat the naive model on the cross validation set and that, when results are different for different transformers, models that have used the PowerTransformer overwhelmigly obtain the best results.

In order to decide between the 107 models that beat the naive model and use PowerTransformer, I perform backtesting on the training data, using all those models to predict Bitcoin evolution since 2018. The results of the models that manage to beat Bitcoin evolution during the backtesting are stores in back_testing_results.csv

44 of these models beat the naive model during backtesting. The most repeated classifier is KneighborsClassifier (43 out of 44) and the most repeated dataset is data_for_use_basic (18 out of 44).

The following table presents a summary of the results of the models that beat the naive model both in backtesting and cross validation using data_for_use_basic, PowerTransformer and KneighborsClassifier:

dataset	model	model_boost_bt	f1_score	accuracy	model_boost_cv
data_for_use_basic	KNeighbors_2	0.273368	0.296296	0.491071	0.038458
data_for_use_basic	KNeighbors_3	0.276004	0.486322	0.497024	0.17485
data_for_use_basic	KNeighbors_4	0.497313	0.369231	0.511905	0.195834
data_for_use_basic	KNeighbors_5	0.205694	0.468085	0.479167	0.381945

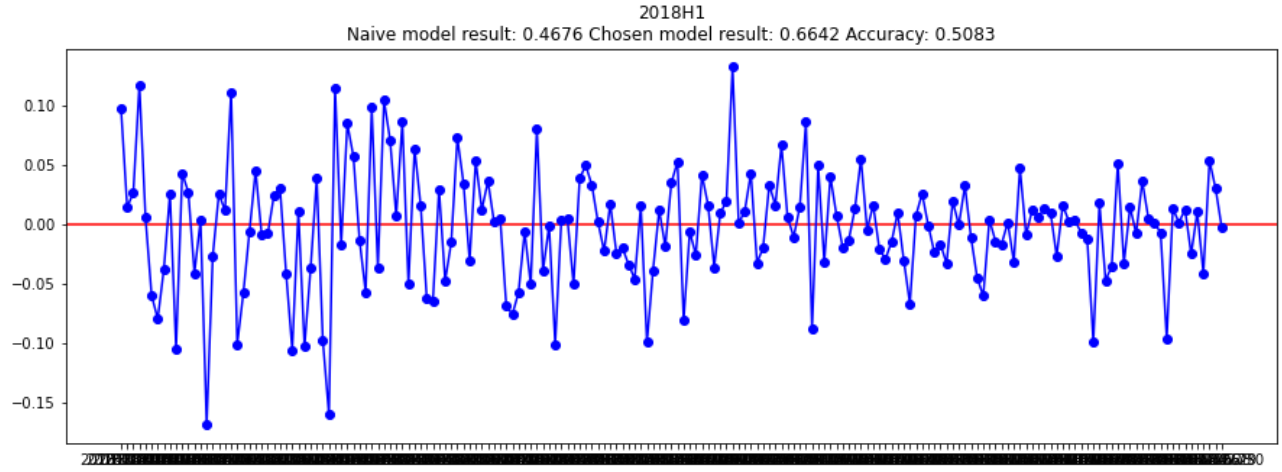
data_for_use_basic	KNeighbors_7	0.423383	0.449231	0.467262	0.010775
data_for_use_basic	KNeighbors_8	0.375538	0.416961	0.508929	0.427289
data_for_use_basic	KNeighbors_9	0.704103	0.504451	0.502976	0.673785
data_for_use_basic	KNeighbors_10	0.99751	0.450331	0.505952	0.537804
data_for_use_basic	KNeighbors_11	0.596276	0.530259	0.514881	0.463674
data_for_use_basic	KNeighbors_12	1.334393	0.471338	0.505952	0.127442
data_for_use_basic	KNeighbors_13	0.731507	0.538682	0.520833	0.277382
data_for_use_basic	KNeighbors_14	0.801408	0.503067	0.517857	0.198657
data_for_use_basic	KNeighbors_15	0.702536	0.561111	0.529762	0.23614
data_for_use_basic	KNeighbors_16	0.542663	0.511905	0.511905	0.072797
data_for_use_basic	KNeighbors_18	0.992195	0.520231	0.505952	0.029453
data_for_use_basic	KNeighbors_19	0.533433	0.55643	0.497024	0.060268
data_for_use_basic	KNeighbors_20	0.487056	0.548476	0.514881	0.165602

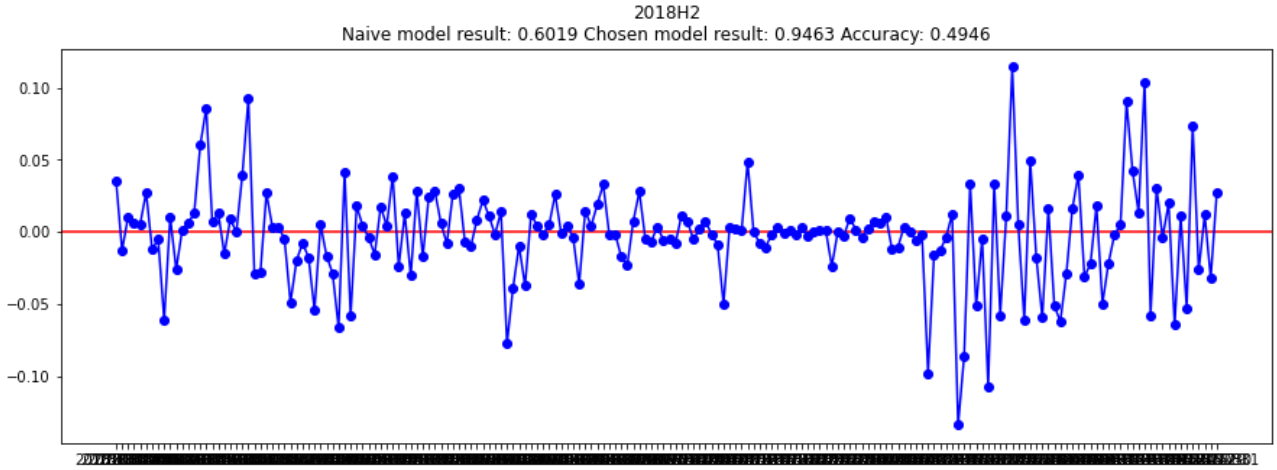
There is no clear winner between these models, it depends on the metric used. I think the chosen model should do better with more training data, so I choose to go with the model with the highest performance increase in cross validation (column model_boost_cv), and that is KNeighbors_9.

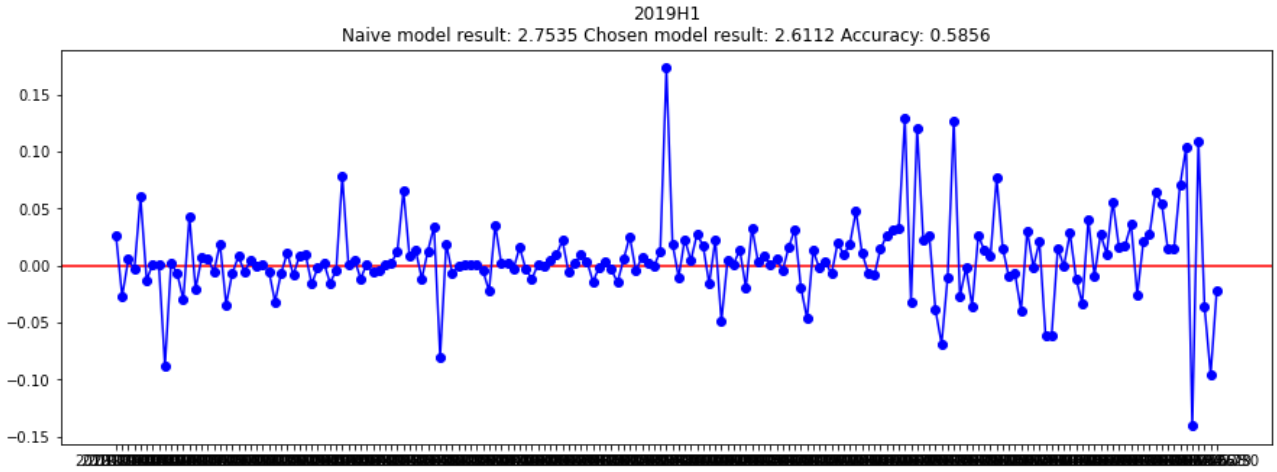
4. Summary of main results

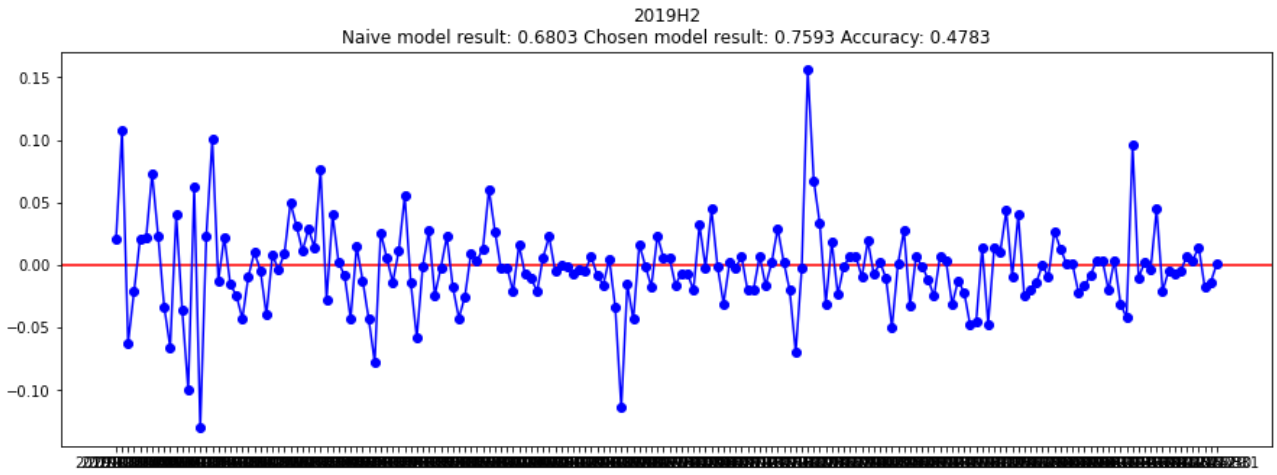
As stated above, the chosen model is Kneighbors_9 with transformer PowerTransformer, for the data data_for_use_basic (Bitcoin closing price variations).

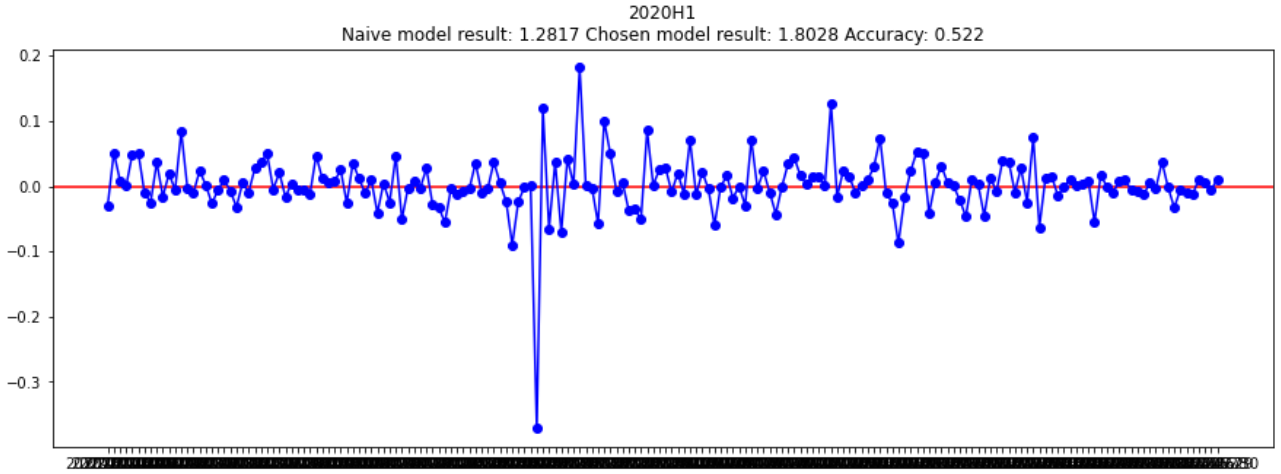
The results of running this model, separated by half-years, since 2018 are shown below, with the plotting of the daily price variations during those periods.

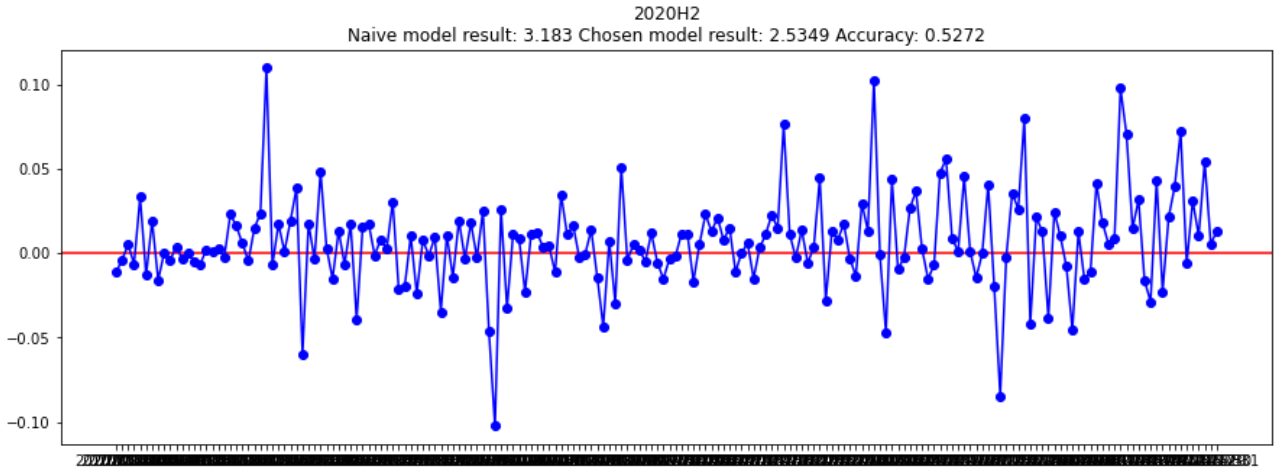


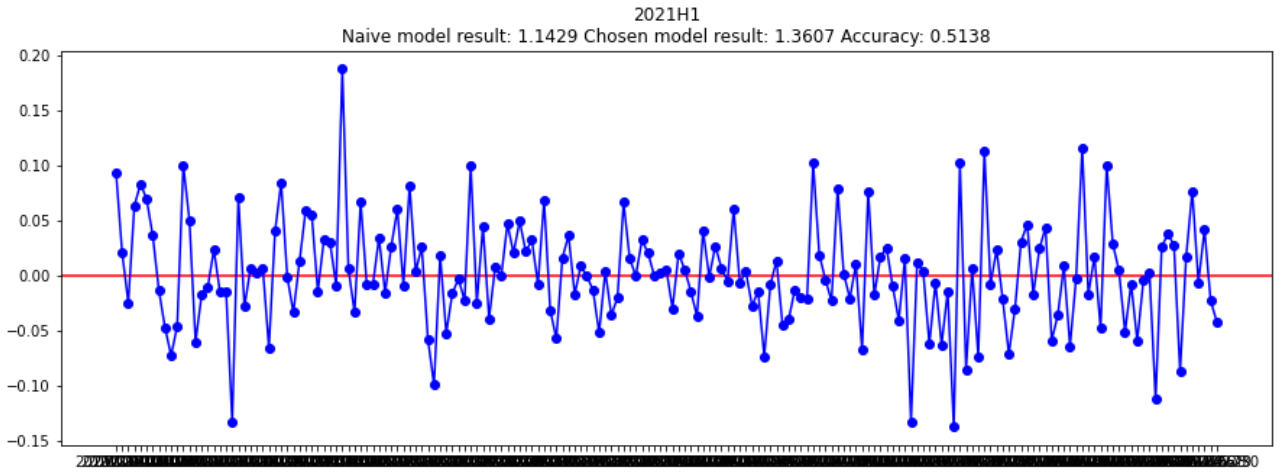

2018H2
Naive model result: 0.6019 Chosen model result: 0.9463 Accuracy: 0.4946
0.10
0.05
0.00
−0.05
−0.10

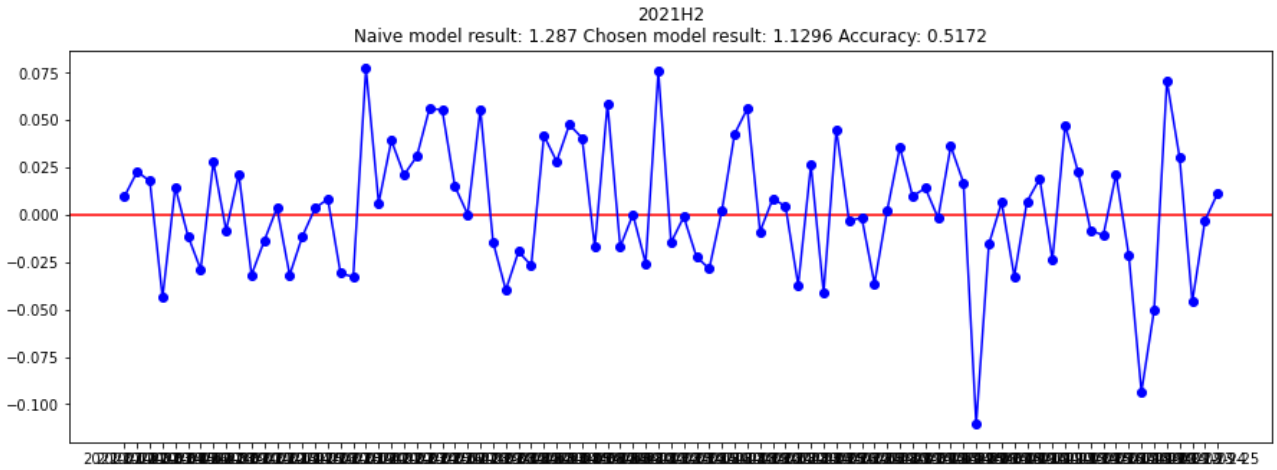

2019H1
Naive model result: 2.7535 Chosen model result: 2.6112 Accuracy: 0.5856
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15


2019H2
Naive model result: 0.6803 Chosen model result: 0.7593 Accuracy: 0.4783
0.15
0.10
0.05
0.00
−0.05
−0.10


2020H1
Naive model result: 1.2817 Chosen model result: 1.8028 Accuracy: 0.522
0.2
0.1
0.0
−0.1
−0.2
−0.3


2020H2
Naive model result: 3.183 Chosen model result: 2.5349 Accuracy: 0.5272
0.10
0.05
0.00
−0.05
−0.10


2021H1
Naive model result: 1.1429 Chosen model result: 1.3607 Accuracy: 0.5138
0.20
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15



The following table presents the accumulated results for every half-year:

Year	Naive model	Chosen model
2018H1	-53%	-34%
2018H2	-40%	-5%
2019H1	+175%	+161%
2019H2	-32%	-24%
2020H1	+28%	+80%
2020H2	+218%	+153%
2021H1	+14%	+36%
2021H2	+29%	+13%

5. Conclusions

It seems that, up until now, Bitcoin evolution can be predicted well enough for beating the market using the assumptions indicated in 3.I.

The model chosen in this project performs specially well during bear markets and loses to the market during bull runs (see the graphic above for 2019H1 and, specially, 2020H2), but over an extended period of time it seems to be able to better the Bitcoin performance. This may change as more professional investors start trading bitcoin (see Bitcoin moves in lockstep with US stocks as big traders enter market).

An investor that had bought Bitcoin at the beginning of 2018 and held it until the september 2021 would have gotten a **216%** return. The same investor following the presented model's advice would have achieved a **775%** return.

6. User manual of the frontend