CF969-7-SP

Big-Data for Computational Finance

Assignment

Review Report - Short-term bitcoin market prediction via machine learning

22 April 2022

Submitted by,

Arjun Gopal Cheroor Gokuladasan

Word Count:1733

Table of Contents

List of Figures

List of Tables

Abstract

The Short-term Bitcoin Market Prediction via Machine Learning explains the predictability of the bitcoin market over time horizons ranging from 1 to 60 minutes. There is an elaboration of the multiple machine learning models tested and discovered. While all models outdo a random classifier, recurrent neural networks and gradient boosting classifiers are particularly well-suited for the investigated prediction tasks. The authors used a diverse feature set that included technical, blockchain-based, sentiment/interest-based, and asset-based features. Their findings show that technical features are still the most important for most methods, followed by blockchain-based and sentiment/interest-based features. It has also been discovered that predictability increases with longer prediction horizons. However, a quantile-based long-short trading strategy yields up to 39% monthly returns before transaction costs. Also, the brief holding periods result in negative returns after money transfer costs. [1]

Introduction

Bitcoin is a cryptocurrency invented by Satoshi Nakamoto in 2008. In this study, the author's look at the bitcoin market's short-term predictability. Machine learning methods are progressively being used in this domain. Bitcoin accounts for approximately 58 percent of the cryptocurrency market, with a market capitalization of roughly 170 billion US dollars (September 2020). This research paper answers whether machine learning models can predict short-term movements in the bitcoin market by comparing six well-established machine learning models trained on nine months of minutely bitcoin-related data against each other. The findings show that trained models outperform random classification.

Related work

Financial market prediction is a popular field of study in financial research. The evidence on the predictability and efficiency of financial markets is ambiguous. Machine learning is increasingly being used to forecast financial markets.

Theory on market efficiency

In weak form efficient markets, prices reflect all information about past prices. In semi-strong form efficient markets, prices reflect all publicly available information. In strong form efficient markets, prices additionally reflect all private information. While regulators aim to prevent investors from profiting from private information, it is generally agreed upon that major financial markets are semi-strong form efficient.

Bitcoin market efficiency

Several findings in the financial literature [2][3] indicate that bitcoin may constitute a new asset class. There is mixed evidence among scholars regarding the efficiency of the bitcoin market. Most researchers find that the bitcoin market has become more efficient. To summarise, there is conflicting evidence among academics about the efficiency of the bitcoin market. Most researchers, on the other hand, believe that the bitcoin market has become more efficient over time. Because the bitcoin market has grown in size and gotten more competitive since its beginning, a rising degree of market efficiency appears logical.

Bitcoin market prediction via machine learning

Jaquart et al., [4] analyze the literature on bitcoin market prediction via machine learning. They have examined the body of literature with regards to applied machine learning methods, return-predictive features, prediction horizons, and prediction types. The feature importance across different models has received little academic attention so far.

Only a few studies (e.g., Dutta et al.,[5] Poyser [6]) have used all of the established feature categories thus far. Furthermore, the relative relevance of distinct features across different models has received little academic attention to yet. Only a few scholars [7,8] compare alternative prediction horizons, while the great majority of academics build their models using daily prediction horizons. [4] As a result, the bitcoin market dynamics over prediction horizons of less than 1 hour are yet unknown.

Methodology

Data

The authors used data from Bloomberg, Twitter, and Blockchain.com. All data processing and analysis is done in Python 3.7, with the programmes pandas 40 and numpy. Figure 1 depicts the evolution of the bitcoin price over the time period under consideration.

Figure 1. **Bitcoin price overview**. Bitcoin price development between March 2019 and December 2019.

Features

Jaquart et al. [4] have calculated minutely updated feature values for all prediction models. Returns are given for technical and asset-based features. They have only saved Tweets that don't include images or URL’s are used to construct sentiment/interest-based characteristics.

Feature set for models with memory function

They have constructed time series for all features specified for machine learning models with a memory function (i.e., LSTM and GRU). Finally, the memory models' input consists of 15 separate time series and each of the time series have 120 minutely time steps.

Feature set for models without memory function

Without a memory function, prediction models require data in the form of a one-dimensional vector with one observation per feature. By aggregating the 120-min history of the feature classes, the authors can provide temporal information about the feature values to the no-memory models in use. Blockchain-based data, as well as sentiment/interest-based features, are totalled in the aggregation process. As a result, they have 14 x12 +1 =169 distinct features in our feature set for prediction models without memory function.

Targets

The authors have formulated a binary classification problem for four different prediction horizons. The prediction models are trained on evenly balanced proportions and are not biased towards one certain class when classes are created straight from the training set. A model returns the likelihood of an observation belonging to a given class during prediction. min prediction horizon.

Generation of training, validation, and test sets

For each prediction task, the authors have converted all timestamps to Coordinated Universal Time (UTC) and constructed a data set. Most bitcoin trading platforms allow for continuous bitcoin trading, although there is a gap in the time series for the minutely Bloomberg bitcoin price series.

Prediction models

The authors have compared neural networks, tree-based models, regression models, and ensemble models with and without memory components. To limit the impact of randomness on the outcomes, they trained the stochastic prediction models on 10 different random seeds.

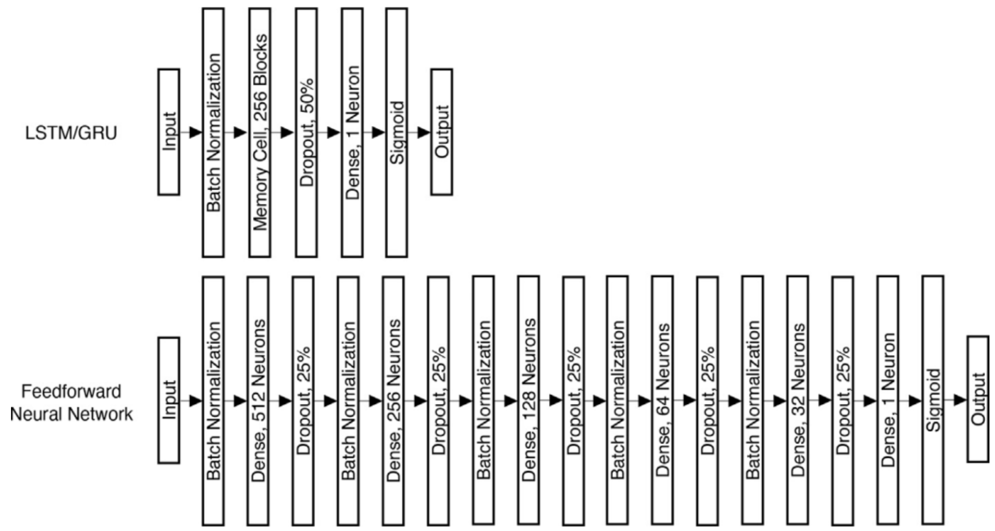

Figure. 2. **Neural network architecture**. Architecture of applied feedforward neural networks (bottom) and recurrent neural networks (top). Note: For the recurrent networks, the memory cell is either an LSTM cell or a GRU cell.

Neural networks

The structure and intended behaviour of artificial neural networks are based on the human brain's functions. All of the networks used were trained using the Adam optimizer 55 and a batch size of 5000. A basic type of neural network is feedforward neural networks (FNN).

Information is transmitted from the input layer to the hidden layers, where it is processed and modified before being classified in the output layer. Gated recurrent neural networks include long short-term memory (LSTM) and gated recurrent unit (GRU) networks. In several domains, LSTMs have been employed for a range of applications. Neural language processing and speech recognition [9,10], handwriting recognition and generation [11,12], music generation, [13] financial data analysis, and [14] are some of them.

Tree-based models

Tree-based models use a decision tree to learn attribute-class relationships. Single decision trees that have not been pruned are prone to overfitting to training data. Random forests use an ensemble strategy to address the tendency of tree-based models to overfit. Gradient boosting classifiers use several decision trees as input.

Ensemble models

Different model types can be integrated into a meta-model in an ensemble. The averaged prediction probability vector is the result of the meta-model.

Forecast evaluation

Based on the predictive accuracy on the test set, the authors have compared the forecasts of our prediction models. The effect of employing several random seeds on model accuracy and stability was investigated. The number of observations in the test sample is denoted by #test. They have also calculated the chances that a prediction model has a 50% true probability.

Feature importance

The measure of permutation feature importance determines the feature importance for all models. Every feature vector is randomly permuted using a random standard normally distributed vector. A significant reduction in prediction accuracy indicates that the model is heavily reliant on the feature.

Trading strategy

The authors have examined the economic ramifications of bitcoin market predictions by putting a simple trading technique to the test. They have assessed the return on this technique before and after transaction costs.

Results

Predictive accuracy

The accuracy scores, which are shown in Table 1, are used to compare the model predictions. The authors discovered that the prediction accuracy of all tested models is greater than 50%. Across all prediction horizons, RNNs or GBCs are the most effective approaches. Apart from the GRU, the LSTM model produces the most accurate predictions on the 60-min horizon, which are much better than the predictions of all other models.

	Accuracy			
Model	1-Min Predictions	5-Min Predictions	15-Min Predictions	60-Min Predictions
GRU	0.518411	0.524562	0.536490	0.556653
LSTM	0.519286	0.524931	0.531967	0.560067
FNN	0.509438	0.521988	0.520820	0.529587
LR	0.511272	0.517926	0.519595	0.538552
GBC	0.511093	0.529268	0.537282	0.557026
RF	0.511947	0.526662	0.534641	0.556356
E (All)	0.514626	0.526092	0.537863	0.557579

Table 1. **Accuracy overview**. Predictive accuracy of the machine learning models for the different prediction horizons.

Feature importance

The minutely precise return time series is the most prominent feature of both RNNs. For larger prediction horizons, the relative value of this trait declines. Less recent bitcoin returns become increasingly meaningful for longer forecast horizons. The most recent minutely return is most meaningful on the 1-min horizon. The probability that the prediction models will achieve a genuine accuracy is 50%. As a result, on the 15-min horizon, the bitcoin returns from 20 to 10 minutes before prediction are the most essential feature, while on the 60-min horizon, the bitcoin returns from 40 to 20 minutes before prediction are the most important feature.

Trading strategy

Three major insights emerge from the trading strategy's results. Firstly, there is a significant difference in trading results between the various prediction models. Higher predictive model accuracy may not always imply better trading outcomes. Second, with larger prediction horizons, the average return per transaction tends to rise. Third, with transaction costs of 30 basis points each round-trip, trading performance for all strategies becomes negative.

Conclusion

This research shows that machine learning algorithms can accurately forecast short-term bitcoin price changes. Clearly, the bitcoin market's predictability is limited, as seen by the forecasting accuracy of slightly more than 50%. The market predictability of bitcoin is comparable to that of other financial assets such as shares. The findings in the research paper suggests that the bitcoin market has gotten more efficient are consistent with their findings. The RNN and GBC models are especially well-suited to forecasting the short-term bitcoin market. The short-term predictability of the bitcoin market is examined in the empirical study by Jaquart, P et al [1]. They discovered that all the models they tested generate statistically sound predictions. Over the course of three months, a quantile-based trading strategy based on market predictions generates a return of up to 116 %. These profits, however, cannot compensate for transaction expenses due to the short holding periods and accompanying frequent trading activities.

References

[1] Jaquart, P., Dann, D., & Weinhardt, C. (2021). Short-term bitcoin market prediction via machine learning. *The Journal of Finance and Data Science*, *7*, 45–66. https://doi.org/10.1016/j.jfds.2021.03.001

[2] Glaser F, Zimmermann K, Haferkorn M, Weber MC, Siering M. Bitcoin-asset or currency? revealing users' hidden intentions. In: Proceedings of 22nd European Conference on Information Systems. 2014:1e15.

[3] Hu AS, Parlour CA, Rajan U. Cryptocurrencies: stylized facts on a new investible instrument. Financ Manag. 2019;48:1049e1068. https:// doi.org/10.1111/fima.12300.

[4] Jaquart P, Dann D, Martin C. Machine learning for bitcoin pricing - a structured literature review. In: WI 2020 Proceedings, GITO Verlag.2020:174e188. https://doi.org/10.30844/wi_2020_b4-jaquart.

[5] Dutta A, Kumar S, Basu M. A gated recurrent unit approach to bitcoin price prediction. J Risk Financ Manag. 2020;13. https://doi.org/10.3390/jrfm13020023. Article 23.

[6] Poyser O. Exploring the dynamics of Bitcoin's price: a Bayesian structural time series approach. Eurasian Econ Rev. 2019;9:29e60. https://doi.org/10.1007/s40822-018-0108-2.

[7] Madan I, Saluja S, Zhao A. Automated Bitcoin Trading via Machine Learning Algorithms. Working Paper; 2015.

[8] Smuts N. What drives cryptocurrency prices? An investigation of Google trends and telegram sentiment. ACM SIGMETRICS Perform Eval Rev. 2019;46:131e134. https://doi.org/10.1145/3308897.3308955.

[9] Graves A, Schmidhuber J. Framewise phoneme classification with bidirectional LSTM and other neural network architectures. Neural Networks. 2005;18:602e610. https://doi.org/10.1016/j.neunet.2005.06.042.

[10] Graves A, Jaitly N. Towards end-to-end speech recognition with recurrent neural networks. In: Proceedings of International Conference on Machine Learning. 2014:1764e1772.

[11] Graves A. Generating Sequences with Recurrent Neural Networks. Working Paper; 2013.

[12] Graves A, Liwicki M, Fernandez S, Bertolami R, Bunke H, Schmidhuber J. A novel connectionist system for unconstrained handwriting recognition. IEEE Trans Pattern Anal Mach Intell. 2009;31:855e868. https://doi.org/10.1109/TPAMI.2008.137.

[13] Eck D, Schmidhuber J. Finding temporal structure in music: blues improvisation with LSTM recurrent networks. In: Proceedings of the 12th IEEE Workshop on Neural Networks for Signal Processing. IEEE; 2002:747e756. https://doi.org/10.1109/NNSP.2002.1030094.

[14] M€akinen M, Iosifidis A, Gabbouj M, Kanniainen J. Predicting Jump Arrivals in Stock Prices Using Neural Networks with Limit Order Book Data. 2018. https://doi.org/10.2139/ssrn.3165408. Working Paper.