Machine learning for Bitcoin Price Prediction

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ABSTRACT_ This study aims to determine how accurately the direction of the price of bitcoin in US dollars can be anticipated. The Bitcoin Price Index is the source of the price information. Implementation results in varied degrees of success in completing the job. The Random Forest has the best accuracy in classifying data. The training time on the GPU outperformed the CPU implementation by 67.7% when both deep learning models were benchmarked on a GPU and a CPU.

KEYWORDS: Bitcoin, Deep Learning, Recurrent Neural Network, Random Forest

1.INTRODUCTION

Bitcoin is the universes' most importantdigital money and is exchanged on more than 40 trades overall tolerating north of 30 unique monetary standards. According to https://www.blockchain.info/, it currently has a market capitalization of 9 billion USD and sees over 250,000 transactions per day. As a cash, Bitcoinoffers a clever chance for cost expectation due its generally youthful age and coming about unpredictability, which is far more noteworthy than that of government issued types of money. It is likewise special corresponding to conventional governmentissued types of money concerning its open nature; no total information exists with respect to trade exchanges or cash out

dissemination for government issued types of money. Numerous studies have been conducted on the subject of stock market forecasting. Bitcoin presents a fascinating lined up with this as it is a period series expectation issue in a market still in itstransient stage. Customary time seriesforecast strategies, for example, Holt- Winters' remarkable smoothing modelsdepend on straight suspicions and require information that can be separated into pattern, occasional and commotion to be successful. For a task like forecasting saleswith seasonal effects, this kind of methodology is better. Because of the absence of irregularity in the Bitcoin market and its high unpredictability, these strategies are not exceptionally successful for this errand. Given the intricacy of the errand, profound learning makes for a fascinating mechanical arrangement in light of its presentation in comparable regions.

This paper compares parallelization techniques used in multi-core and GPU environments and investigates how accurately machine learning can predict Bitcoin's price. This paper contributes in the accompanying way: At the time of writing, only seven of the approximately 653 Bitcoin-related papers have a connection to machine learning for prediction. To work with a correlation withadditional customary methodologies in monetary estimating, an Irregular Woods is likewise produced for execution examination purposes

2.LITERATURE SURVEY

[1] S. Nakamoto, “Bitcoin: A peer-to-peer electronic cash system,” 2008

A purely peer-to-peer version of electroniccash would allow online payments to be sent directly from one party to another without going through a financial institution. Digital signatures provide part of the solution, but the main benefits are lost if a trusted third party is still required to prevent double-spending. We propose a solution to the double-spending problem using a peer-to-peer network. The network

timestamps transactions by hashing them into an ongoing chain of hash-based proof-of-work, forming a record that cannot be changed without redoing the proof-of- work. The longest chain not only serves as proof of the sequence of events witnessed, but proof that it came from the largest poolof CPU power. As long as a majority of CPU power is controlled by nodes that are not cooperating to attack the network, they'll generate the longest chain and outpace attackers. The network itself requires minimal structure. Messages are broadcast on a best effort basis, and nodes can leave and rejoin the network at will, accepting the longest proof-of-work chain as proof of what happened while they weregone.

[2] M. Briere, K. Oosterlinck, and A. Szafarz, “Virtual currency, tangible ` return: Portfolio diversification with bitcoins,” Tangible Return: Portfolio Diversification with Bitcoins (September12, 2013), 2013.

Bitcoin is a major virtual currency. Using weekly data over the 2010-2013 period,we analyze a Bitcoin investment from the standpoint of a U.S. investor with a diversified portfolio including both traditional assets (worldwide stocks, bonds, hard currencies) and alternative investments (commodities, hedge funds, real estate). Over the period under consideration, Bitcoin investment had highly distinctive features, including exceptionally high average return andvolatility. Its correlation with other assets was remarkably low. Spanning tests confirm that Bitcoin investment offers significant diversification benefits. We show that the inclusion of even a smallproportion of Bitcoins may dramaticallyimprove the risk-return trade-off of well- diversified portfolios. Results should however be taken with caution as the data may reflect early-stage behavior which may not last in the medium or long run.

[3] I. Kaastra and M. Boyd, "Designing a neural network for forecasting financial and economic time series," Neurocomputing, vol. 10, no. 3, pp. 215–236, 1996

Artificial neural networks are universal and highly flexible function approximators first used in the fields of cognitive science and engineering. In recent years, neural network applications in finance for such tasks as pattern recognition, classification, and time series forecasting have dramatically increased. However, the largenumber of parameters that must be selected to develop a neural network forecasting model have meant that the design process still involves much trial anderror. The objective of this paper is to provide a practical introductory guide in

the design of a neural network for forecasting economic time series data. An eight-step procedure to design a neural network forecasting model is explained including a discussion of tradeoffs in parameter selection, some common pitfalls, and points of disagreement among practitioners.

[4] H. White, "Economic predictionusing neural networks: The case of ibm daily stock returns," in Neural Networks, 1988., IEEE InternationalConference on. IEEE, 1988, pp. 451– 458.

A report is presented of some results of an ongoing project using neural-network modeling and learning techniques to search for and decode nonlinear regularities in asset price movements. The author focuses on the case of IBM common stock daily returns. Having to deal with the salient features of economic data highlights the role to be played bystatistical inference and requires modifications to standard learning techniques which may prove useful in other contexts.

3.PROPOSED SYSTEM

We suggest this programme, which can be seen as a valuable system because it aids in limiting the results of Random Forest. It can produce the best outcomes for attributes with no overlap by offering support through forecasting analysis.

IMPLEMENTATION

Random Forest:

A random forest is a machine learning method for tackling classification andregression issues. It makes use of ensemble learning, a method for solving complicated issues by combining a numberof classifiers.

In a random forest algorithm, there are many different decision trees. The random forest algorithm creates a "forest" that is trained via bagging or bootstrap aggregation. The accuracy of machine learning algorithms is increased by bagging, an ensemble meta-algorithm.

Based on the predictions of the decision trees, the (random forest) algorithmdetermines the result. It makes predictions by averaging or averaging out the results from different trees. The accuracy of the result grows as the number of trees increases.

The decision tree algorithm's shortcomings are eliminated with a random forest. It improves precision and decreases dataset overfitting. It produces predictions without needing numerous package configurations (unlike Scikit-learn).

Characteristics of a Random ForestAlgorithm:

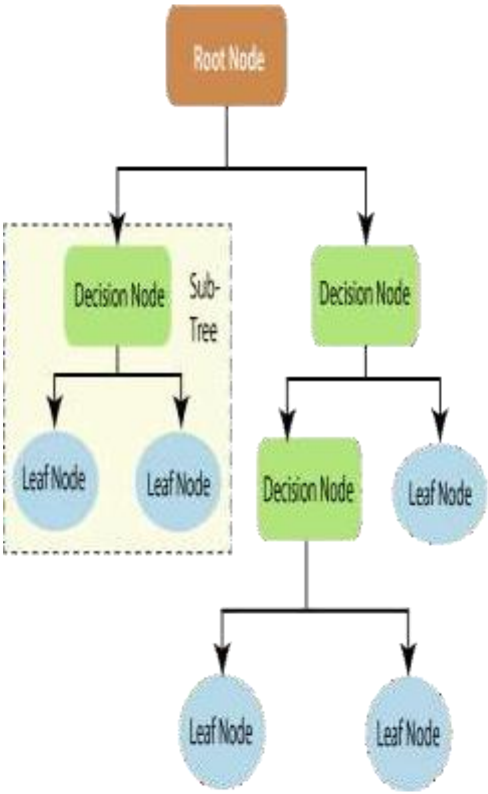
It's more accurate than the decisiontree algorithm.

- It provides an effective way of handling missing data.
- It can produce a reasonable prediction without hyper-parametertuning.
- It solves the issue of over fitting in decision trees.
- In every random forest tree, a subset of features is selected randomly at the node's splitting point.

A random forest algorithm's building components are decision trees. A decision support method that has a tree-like structure is called a decision tree. We will learn about decision trees and how randomforest methods function.

Decision nodes, leaf nodes, and a root node are the three parts of a decision tree. A training dataset is divided into branches by a decision tree algorithm, which then separates those branches further. This process keeps going until a leaf node is reached. It is impossible to further separatethe leaf node.

The attributes that are utilised to forecast the outcome are represented by the nodesin the decision tree. Links to the leaves are provided by decision nodes. The three different sorts of nodes in a decision tree are depicted in the diagram below.



Information theory can shed further light on decision trees' operation. The foundation of a decision tree is information gain and entropy. An review of these key ideas will help us better comprehend the construction of decision trees.

Uncertainty can be measured using entropy. Given a set of independent variables, information gain measures thedegree to which uncertainty in the target variable is minimised.

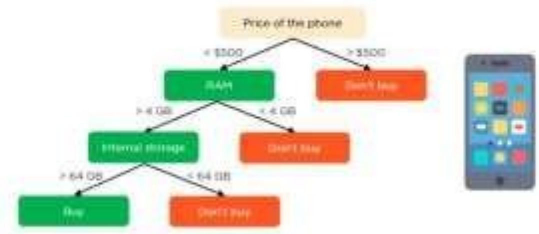
Using independent variables (features) to learn more about a target variable (class) isknown as the information gain idea. The information gain is calculated using the entropy of the target variable (Y) and the

conditional entropy of Y (given X). In this instance, the entropy of Y is reduced by the conditional entropy.

Information gain is used in the training of decision trees. It helps in reducing uncertainty in these trees. A high information gain means that a high degree of uncertainty (information entropy) hasbeen removed. Entropy and information gain are important in splitting branches, which is an important activity in the construction of decision trees.

Let’s take a simple example of how a decision tree works. Suppose we want to predict if a customer will purchase a mobile phone or not. The features of the phone form the basis of his decision. This analysis can be presented in a decision treediagram.

The root node and decision nodes of the decision represent the features of the phone mentioned above. The leaf node represents the final output, either *buying* or *not* *buying*. The main features that determine the choice include the price, internal storage, and Random Access Memory (RAM).



4.RESULTS AND DISCUSSION

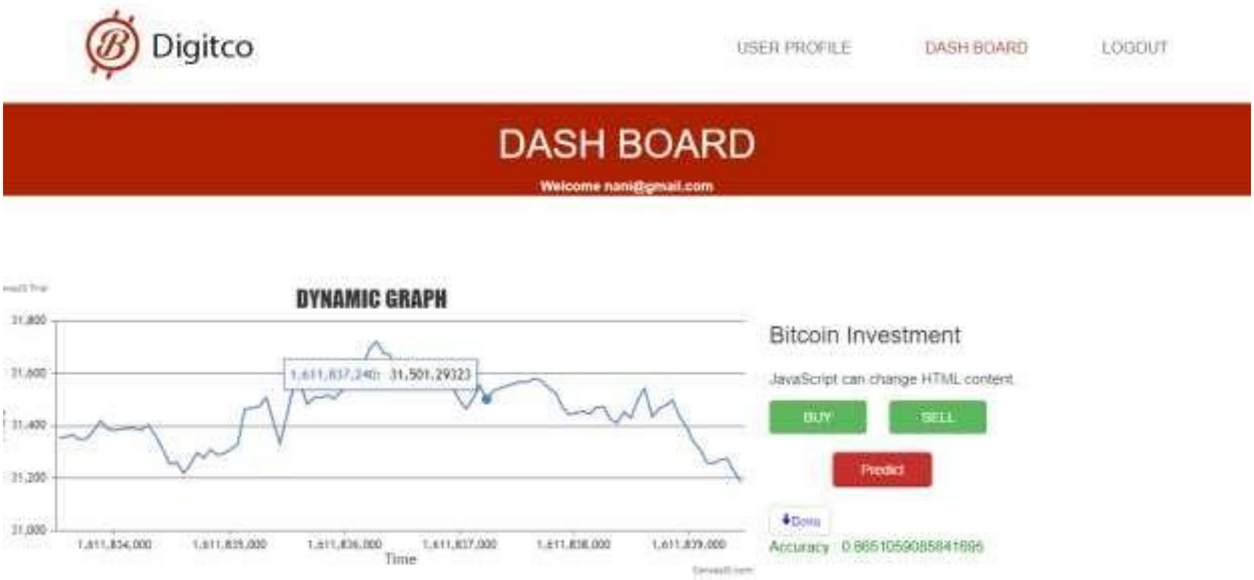


Fig 1:Prediction Graph

5.CONCLUSION

We have successfully developed a model to predict future outcomes for the Bitcoin cryptocurrency in this application. Python programming is used to develop this in a user-friendly environment.

FUTURE SCOPE

The capability to forecast future pricing can be added to this application. Using the revised dataset, we intend to investigatethe prediction process and employ the most precise and suitable forecasting techniques. We'll be concentrating a lot of our future effort on real-time live forecasting.

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