

Towards Characterizing Blockchain-based Cryptocurrencies for Highly-Accurate Predictions

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Abstract—In 2017, the Blockchain-based cryptocurrency market witnessed enormous growth. Bitcoin, the leading cryptocurrency, reached all-time highs many times over the year leading to speculations to explain the trend in its growth. In this paper, we study Bitcoin and explore features in its network that explain its price hikes. We gather data and analyze user and network activity that highly impact Bitcoin price. We monitor the change in the activities over time and relate them to economic theories. We identify key network features that determine the demand and supply dynamics of a cryptocurrency. Finally, we use machine learning methods to construct models that predict Bitcoin price. Our regression model predicts Bitcoin price with 99.4% accuracy and 0.0113 root mean squared error (RMSE).

Index Terms—Bitcoin; Blockchain; modeling; prediction

I. INTRODUCTION

Blockchain-based digital currencies have experienced exponential growth in the last year [1]. Bitcoin, the most popular cryptocurrency, was launched in 2009, and stayed as the only Blockchain-based cryptocurrency for more than two years. However, today, the cryptocurrency world has more than 5000 cryptocurrencies [2] and more than 5.8 million active users [1]. Bitcoin leads the cryptocurrency market with 58% market share; corresponding to \$4.9 Billion USD trade volume and over 12,000 transactions per hour [3]. In December 2016, the price of 1BTC was under \$1000 USD, compared to about \$19,000 USD in late 2017 [4]. Such exponential growth in price led to a lot of interest in cryptocurrency in general and Bitcoin in particular. Researchers in technological and financial sectors are trying to find the reasons behind changing paradigms in cryptocurrency market. In this paper, we carry out an extensive study on Bitcoin to analyze the features that have correlate significantly with the change in the price.

The underlying technology of every cryptocurrency is the Blockchain. Blockchain acts as a decentralized public database that preserves anonymity and augments trust between users. Trust in an anonymous peer-to-peer model is achieved by consensus protocols such as Proof-of-Work (PoW), Proof-of-Stake (PoS), Proof-of-Knowledge (PoK), and distributed consensus [5]. The decentralized environment and the append-only model prevent Blockchains failure and data tampering, and such features lay ideal foundations for cryptocurrency applications to be built on top of Blockchain.

Cryptocurrencies involve the exchange of digital assets (tokens), and have evolved from virtual currency to smart

contracts and applications beyond currency. This transformation of cryptocurrencies is categorized as Blockchain 1.0, 2.0 and 3.0 [6]. Blockchain 1.0 solely involves transfer of digital currency between parties. Bitcoin is an example of Blockchain 1.0, since it only allows transfer of digital tokens (bitcoins). Blockchain 2.0 is an extension of Blockchain 1.0 that allows transfer of many other assets, offering more flexible protocols for the users to design their transactions, such as smart contracts [7] and decentralized autonomous organizations (DAOs) [8], which are among many useful applications of Blockchain 2.0 [9]. Blockchain 3.0 is yet another extension of this technology that envisions the use of Blockchain beyond digital currencies, with applications for distributed censorship resistant organization models [10], digital identity verification [11] and decentralized domain name system [12].

New cryptocurrencies address shortcomings of older ones, with better throughput, scalability, and programmability. Although this gives a general idea why cryptocurrency markets have grown, many factors contributing to the rise in cryptocurrency prices are not well-understood. In this paper, we look at the dynamics of various variables in a cryptocurrency, namely Bitcoin, which can shed light on its growing price. We use Bitcoin as an example and perform an in-depth analysis and experiments using the public data available on its Blockchain. Towards understanding the various attributes of the system, we find strong correlation between various network features and the price. As a result, we construct machine learning-based regression models that learn from the highly correlated features and predict the price with a very high accuracy.

Contributions. First, we outline how various features in the Bitcoin system affect the price through a correlation study. Among them, we identify the highly correlated features that contribute most to the price. Next, we show how these features are influenced by user and network activity, and provide a rationale behind the recent increase in price. Next, we use regression analysis and deep learning to construct price prediction models. Our prediction models estimate Bitcoin's price with high accuracy, and outperform the state-of-the-art.

Organization. In section II, we review the related work. In section III, we highlight the preliminaries of this work involving the trends in major cryptocurrencies over the year and the correlation among them. In section IV, we outline our methodology and characteristics of dataset. In section V we perform data analysis to extract the most significant

features that impact the price. In section VII we carry out our experiments and report the results. Discussion and concluding remarks are made in section VIII.

II. RELATED WORK

In this section, we review the notable related work. We focus on analyses dedicated to understand how Bitcoin and cryptocurrency influence the financial and other systems, general analysis of Bitcoin, and Bitcoin price prediction.

Vigna *et al.* [13] analyzed how Blockchain based applications are challenging the global economic order by exploring the impact of Blockchain based applications on the future of the financial system. Swan [6] proposed a possibility of cheaper, efficient and secure economical models based on Blockchain. The use of Blockchain 3.0 is estimated to create new possibilities in Internet of Things (IoT) [14], privacy management [15] and voting systems [16].

Blockchain 2.0 transformed cryptocurrency from mere exchange of tokens to smart contracts. Rose [17] analyzed the evolution of digital currencies and Omohundro [18] explored recent developments in cryptocurrency and smart contracts. Kosba *et al.* [7], Zhang *et al.* [19] and Juels *et al.* [20] explored different dimensions of smart contracts, including criminal smart contracts. Peters *et al.* [21] analyzed the future of banking system ledgers with Blockchain technology, transaction processing and smart contracts.

For better applications, the security attack surface of Blockchain is also explored, including the 51% attack, selfish mining, double-spending, block withholding, block forks and distributed denial-of-service (DDoS) attacks [22]; arguably the most prevalent attack [23].

Limited research is done on the feature-based price analysis. Indera *et al.* [24] developed a non-linear autoregressive Bitcoin price prediction model using the opening and closing past prices to predict future price. Almeida *et al.* [25] used past prices and trading volume of Bitcoin to train an artificial neural network to predict the next-day price. McNally [26] explored various machine learning approaches to predict Bitcoin price using Bitcoin price index, achieving a maximum accuracy of 52% with Long Short Term Memory (LSTM) networks. Concurrent to our work, Jang and Lee [27] performed a time series analysis of Bitcoin to improve predictive performance. They use Bayesian neural network with other linear and non-linear benchmark models to explain volatility in Bitcoin price.

In this paper, we explore other features, besides past prices, to establish patterns in price. We investigate various network features and identify the highly correlated ones that determine the price. Using those features, we train and test our model, which achieves a near-perfect prediction accuracy.

III. PRELIMINARIES AND MOTIVATION

The main goal of this work is broad, and aims to provide the initial step towards characterizing Blockchain-based cryptocurrencies for predictions. However, limited by space and time, in the following we argue that our work, although limited

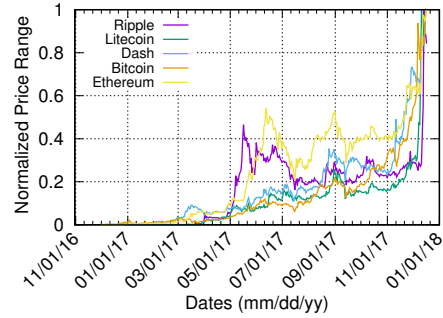


Fig. 1. Cryptocurrency price change in 2017. Notice that the growth rate has ranged from more than 5x (Litecoin) to about 2.5x (Ethereum) over the past two months (early November 2017 to late December 2017).

to Bitcoin, can perhaps shed light on characteristics of other systems. We leave exploring them as a future work.

In Figure 1, we plot the price change trend of five major cryptocurrencies over time. The difference in the actual price value of each currency is high, and cannot be plotted in one graph. As such, we use the min-max normalization to scale the data in the range $[0, 1]$ and plot the normalized price. The min-max scaling is conducted as $z = \frac{x_i - \min(x)}{\max(x) - \min(x)}$.

In Figure 1 we observe an exponential increase in the price of every cryptocurrency over the year, and particularly in the recent months. The growing trend started around April 2017, and kept on increasing. Towards the end of 2017, the rise in the price has been very steep. It is commonly conceived that these cryptocurrencies are competitors in the market and price hikes in one leads to a price fall in another. However, from the plots we observed that there is an almost monotonic change in the price of all the currencies simultaneously. They all followed similar trends of rise and fall over time.

To further analyze the similarity in their trends, we use the Pearson correlation coefficient between the price in all currencies over time, defined as $\rho(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}}$. We report our results in Table I. While the pair-wise correlation is high across all currencies, supporting the initial premise of this work, we observe significant correlation between Bitcoin, Dash and Litecoin price growth. Furthermore, we found a significant correlation between the price trend of Ethereum and Ripple. This correlation pattern can be explained by the underlying protocols: while Ripple and Ethereum use similar protocols, the underlying protocol of Bitcoin and Litecoin is almost identical, and except that Litecoin provides four times the total number of producible coins [28]. As such, the growth in one major cryptocurrency, derives the growth in another similar currency, highlighting the speculative nature of the interdependent interactions between the currencies' prices, and hinting on the potential generality of findings to other systems.

IV. METHODOLOGY

In this section, we outline the the data acquisition and overall characteristics. We then outline the high-level theme of our analysis, including price change prediction.

Dataset acquisition and attributes. For this study, we acquired data from the public Blockchain of Bitcoin [29]

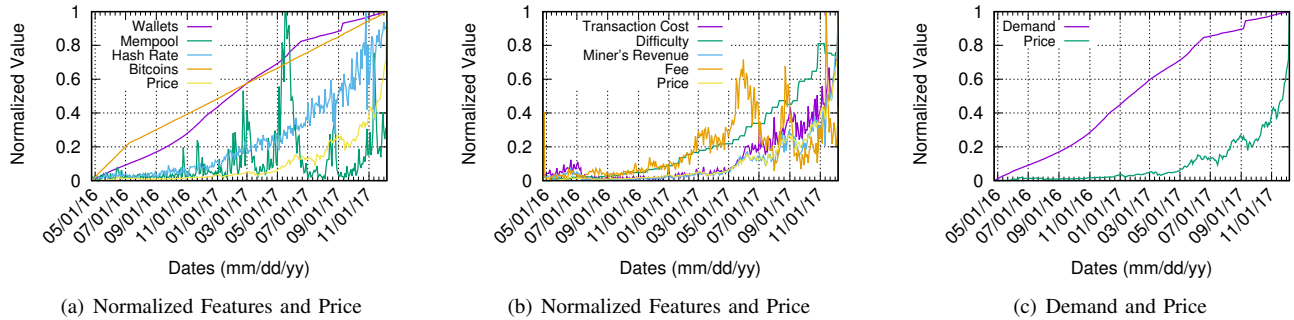


Fig. 2. Trends in Bitcoin features captured over the year (April 2016 to December 2017). Notice that the hash rate, the difficulty, and the transaction cost are highly correlated with the price. Also the increase in demand (Total Wallets / Total Bitcoins) has led to an increase in the price.

TABLE I
CORRELATION MATRIX OF FIVE CRYPTOCURRENCIES

	Ripple	Litecoin	Dash	Bitcoin	Ethereum
Ripple	1.00	0.77	0.72	0.69	0.87
Litecoin	0.77	1.00	0.91	0.92	0.84
Dash	0.73	0.91	1.00	0.96	0.90
Bitcoin	0.69	0.92	0.96	1.00	0.86
Ethereum	0.87	0.84	0.90	0.86	1.00

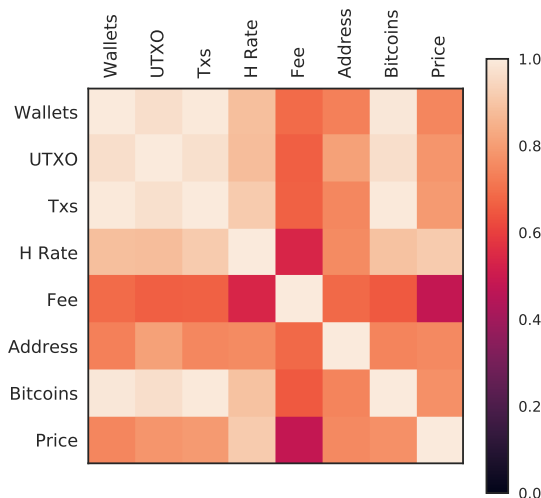


Fig. 3. Correlation matrix of significant feature

and API's of online resources [4], [30], [31]. We collected data from 04/2016 to 12/2017. The dataset included features such as the number of wallets, unspent transaction outputs (UTXO's), mempool size, block size, mean confirmation time, miner's income, transactions per day, transactions per block, unique Bitcoin addresses, cumulative network's hashing rate, network's difficulty, fee, fee per transaction, system-wide total bitcoins, trade volume and the market price of Bitcoin.

Data characteristics. The number of wallets and unique addresses give an estimate of how many new users join the network everyday. We collected data of 16,320,980 wallets and 869,100 unique addresses in total. In Bitcoin, memory pool (mempool) is a repository where unconfirmed transactions are stored before being mined. The size of mempool varies depending on the rate of the incoming transactions, the transaction backlog, and the rate of transaction mining. In our dataset, we observed that the mempool reached a maximum size of over 220,000 unconfirmed transactions in December 2017. The hashing rate determines the aggregate processing

power that miners possess in order to solve a new block.

In Bitcoin, the size of blocks is fixed at 1MB and the average block computation time is 10 minutes. As the hashing power of the network increases, the difficulty of solving a block increases to keep block computation time within 10 minutes. We observed a maximum hashing rate of Bitcoin equal to 11,941,671 Terahashes per second (TH/second) and a difficulty parameter of 1,590,896,927,258. The cost per transaction increased from \$8 to \$91 USD/transaction. The total coins in Bitcoin at the time of our data collection were 16,722,625. When a new block is computed, it adds 12.5 coins to the network, and the total number of transactions in the dataset were 279,342,431. The price of Bitcoin increased from \$459 USD to \$16,700 USD over our data collection period.

Analysis metrics and price change prediction. In this paper, we analyze the attributes of the cryptocurrency system, exemplified by Bitcoin, that are most correlated with the hikes in its price. First, to determine the contributing features towards price hike, we found the most highly correlated features in the data. Those features gave us general insights about trends in Bitcoin. From that, we estimated the change in user behavior (characterized by various Bitcoin attributes associated with users) that led to increase in price. For example, if the number of wallets is increasing then more users are joining the network, which leads to (possibly) more demand to the (almost) fixed number of coins in the system. With the limited bitcoins and high collective purchase power, the price (naturally) goes up. Using the highly correlated features, we train a regression model to predict Bitcoin's price over time. For that, we divide our data into a training dataset and a test dataset, and cross validate the predicted outcome. With good accuracy, we were able to construct the real life changes in Bitcoin network that might affect the price in the future.

V. DATA ANALYSIS AND TRENDS

General trends. We analyze the trends in features of our dataset. In order to do that, we normalize the data using the min-max normalization and plot various normalized features over time in Figure 2. In Figure 2(a) and Figure 2(b) we observe that the number of wallets, the hash rate, the number of bitcoins, the cost per transaction, the difficulty, and the miner's revenue all increased along with the price. The mempool size and the fee varied over time, although had an identical

trend to one another; the correlation between the fee and the mempool size was 0.82. When the mempool size grows, for sudden high demands, or while the Bitcoin network is under flood attacks [32], users naturally pay more to prioritize their transactions, which explains the high correlation between the mempool size and the transaction fee.

Supply-and-demand trends. In Bitcoin, the average block computation time is 10 minutes and each block generates 12.5 bitcoins. Therefore, the supply of new currency in the system is deterministic and linear. When new users join Bitcoin, new wallets are created. In Figure 2(a), we observe that the number of wallets have increased non-uniformly, raising the demand for the limited number of bitcoins. Since the number of wallets grew at a higher rate than new coins, we can consider this as a demand and supply model: a growing rate of wallets denotes that more users are joining Bitcoin, which leads to an increase in demand for the coins. Since the increase rate of coins is (a small) constant, the new coin supply to system is less than the demand, which explains the primary cause of price rise (under the increasing number of wallets). We plot the min-max normalized number of wallets per available bitcoins in Figure 2(c). We first calculated the number of wallets per bitcoin, and then normalized the number using the min-max normalization. We observe that there is an increase in the demand, which contributes to the price hike.

Features for price prediction. To determine the most useful features in our dataset for price estimation, we calculated the correlation matrix of all data attributes. We report a subset of correlation matrix in Figure 3, where “Tx’s”, “Address” and “Bitcoins” correspond to the total number of transactions, the number of unique addresses, and the total number of bitcoins. For our regression model and prediction, we selected features with correlation coefficient greater than 0.6.

VI. EFFECTS OF USER ACTIVITY ON PRICE

In this section, we try to explain the user activity, determined by highly correlated features, affects the price. Among them the features such as the number of wallets, the hash rate, and the UTXO’s, determine the number of new users coming into Bitcoin, new miners joining the mining pools, and the aggregate spendable balance of all the users.

Wallets and Unique Addresses. As mentioned earlier, the increase in the number of wallets corresponds to greater demand of the limited coins in the system, which results in a price hike. This reasoning can also be extended to the number of unique addresses and the number of transactions per day. The growth in these two features indicate more users coming into the system and making more transactions. As such, the increase in the number of users and user activity (transactions) corresponds to (possibly) more cash is flowing into the system. Since cash flow in Bitcoin increase, the (collective) purchase power of users also increases. This implies that for fixed assets (bitcoins) owned by a user A in the system, there is some user B in the system who is willing to pay more for the same set of assets. In economics, the trend above is captured by a theory known as the “greater fool theory” [33], which states that the

price of a commodity is determined by the expectations of users rather than by the commodity’s intrinsic value.

Difficulty and Hash Rate. Computing a block generates new coins in the system, which are given to the miner as a coinbase reward. Miners earn bitcoins from the coinbase rewards and fee paid by the users for transaction processing. As the price grows, the corresponding value of miner’s income (in USD) also grows. In Figure 4(a), we plot the miner’s income from our dataset. We observed that the coinbase rewards and fee have increased over time. With the growing incentive of income, more miners are joining the mining pools hoping to capitalize on the increasing monetary reward, which explains why the hashing power grows with the price.

In Bitcoin, the difficulty is a measure of how long it takes to compute a block, which is defined by a target value set by the network [34]. Based on the hashing power, the *target* is adjusted every two weeks (the time it takes to create 2016 blocks) to keep block mining time within 10 minutes. The difficulty is recomputed based on the hashing power: if hashing power increases, the probability of finding a block within under 10 minutes increases. To adjust the probability, the difficulty is raised by increasing the target. In Figure 4(b), we plot the difficulty along with the network’s hashing rate. In (1) and (2), we show how the block computation time, $T(B)$, is affected by the hashing rate, H_r , the *target*, $Target$, the probability of finding a block, $P_r(B)$, and the average number of hashes required to solve the target, H .

$$P_r(B) = \frac{Target}{2^{256}}, H = \frac{1}{P_r(B)} \quad (1)$$

$$T(B) = \frac{H}{H_r} = \frac{1}{P_r(B) \times H_r} \quad (2)$$

Since the difficulty remains constant for 2016 blocks, we analyze how the mining pool size affects the price and the average block computation time. From our dataset we found a window of time where the difficulty was constant and the hashing rate was reduced. At the same time interval, we found the mean confirmation time for transactions and the price. From (2) we inferred that, with constant $P_r(B)$, the block time $T(B)$ increases if H_r is reduced, leading to a higher confirmation time for transactions and less coin base rewards per time unit, therefore leading to a fall in the price. In Figure 4(c), we plot one such case that happened in October 2017, whereby some miners left the pool while the target remained unchanged. We observed the price fell as the hashing power decreased and the confirmation time increased.

UTXO’s. Another important feature that contributes towards the price is the set of unspent transaction outputs (UTXO’s). UTXO’s are the spendable transactions in wallets that are confirmed in Blockchain. UTXO’s determine the number of sellers in Bitcoin. Just as the increase in the number of wallets indicates more buyers in the system, more UTXO’s indicate more sellers. UTXO’s depend on the number of coins produced and the nature of the ongoing transaction. There are two types of transactions, the fan-in and fan-out

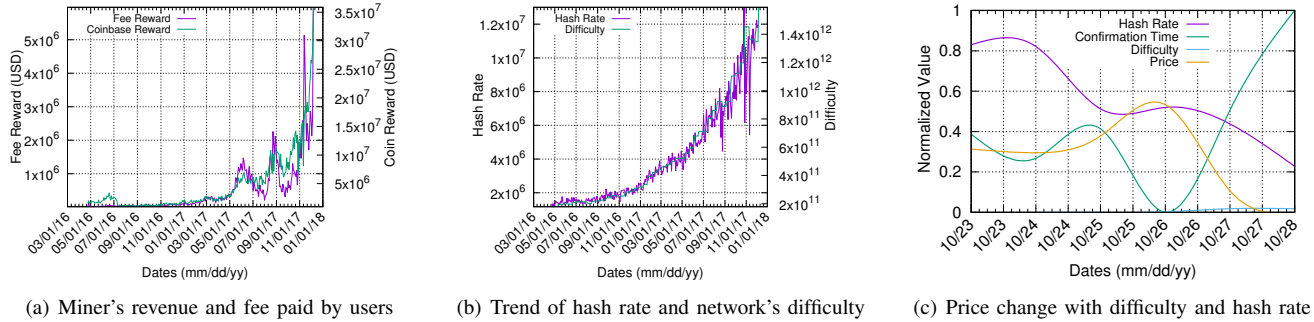


Fig. 4. In 4(a) miner's revenue is indicated by the coinbase reward. 4(b), shows the increasing hash rate and the network's difficulty. Notice in 4(c), when the network's difficulty is constant and the hash rate decreases, the price also decreases.

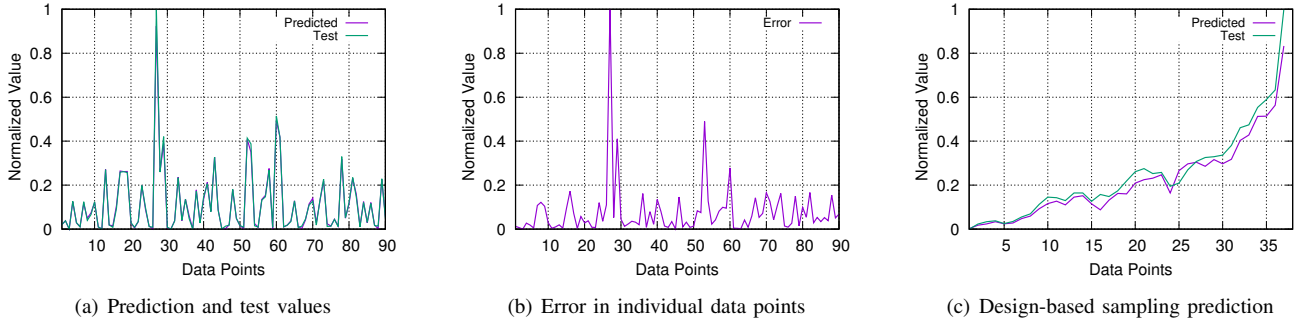


Fig. 5. Results obtained from regression model. Notice in 5(a), high similarity in prediction and test values indicate high accuracy.

transactions. The fan-in transactions include large inputs of previous UTXO's and create less number of outputs, thereby reducing the total UTXO's in Bitcoin. The fan-out work conversely, and increase the set of UTXO's. In our dataset, we observed that from August 1, 2017 to August 9, 2017, the UTXO set decreased considerably. As a result, the number of sellers in the system decreased, increasing demand and decreasing supply, thus increasing the price.

VII. PREDICTIONS: EXPERIMENT AND RESULTS

In this section we build a Bitcoin price prediction model using both regression and deep learning methods.

A. Regression Approach

For our first experiment, we formulated our problem as a multiple regression model based on highly correlated features in the dataset. We selected features that have a correlation factor greater than 0.6 with the price. We normalized the data using the min-max normalization, and divided the data into 80% training 20% testing datasets. We applied the random sampling method for data division and trained the model on linear regression, random forest regression and gradient boosting. We evaluated the performance of each model using accuracy, the root mean squared error ($RMSE$), and the mean absolute error (MAE), we are defined as:

$$\bar{y}_t = \frac{1}{N} \sum_{i=1}^N y_{t_i}, \quad A = \frac{\sum_{i=1}^N (y_{t_i} - y_{p_i})^2}{\sum_{i=1}^N (y_{t_i} - \bar{y}_t)^2},$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_{t_i} - y_{p_i})^2}, \quad MAE = \frac{1}{N} \sum_{i=1}^N |y_{t_i} - y_{p_i}|$$

where y_{t_i} is the test sample, y_{p_i} is the predicted sample, A is the accuracy, and \bar{y}_t is the mean test sample.

We report our results in Table II. While all results produce a high accuracy and a low error (measured by both the $RMSE$ and MAE), the linear regression model, although simple, provides the highest accuracy. In particular, using this model, we achieve an accuracy of 0.9944.

TABLE II
RESULTS OF THE THREE REGRESSION MODELS USED IN EXPERIMENT

	Accuracy	RMSE	MAE
Linear Regression	0.9944	0.0113	0.0060
Random Forrest	0.9272	0.0407	0.0115
Gradient Decent	0.9401	0.0369	0.0113

We plot the results of the linear regression in Figure 5. In Figure 5(a), we plot the predicted and test prices, where the prediction greatly matches the test observations (visually). In this experiment, we use the standard approach, where the regression model randomly selects data points from the dataset for both training and test data, irrespective of their temporal ordering. In Figure 5(b), we plot the error in each data point of the predicted and test price (note that the error here is individual error values; i.e., $y_t - y_p$ for all t and p).

To represent the temporal structure of the dataset, in Figure 5(c) we show visually the result of the prediction of our linear regression model where the training and test data is divided manually. In particular, instead of random sampling, we applied design-based regression analysis [35] in which we split the data in a deterministic pattern: we trained our model with data from April 2016 until September 2017, and used September to December 2017 data as test data, and validated it against our prediction. As a result, we obtained a prediction

accuracy of 0.9504. Compared to the state-of-the-art [26], which uses time series of the previous price for predicting future price of bitcoin, 0.9504 is significantly higher.

B. Deep Learning Approach

We also built a neural network and used conjugate gradient algorithm with linear search for price prediction. We normalize and split the data into 20% test and 80% training subsets. We train our network on 100 epochs and compute the training and validation errors. For this model evaluation, if the training and validation errors are high, the model is considered to be underfitting, and overfitting otherwise. In our model the training error was 0.00013, where the corresponding validation error was 0.00089. From this experiment, we notice that the error, while small, is slightly higher than the training error. Such a model is considered to be a good fit. We also observe that the error rate reduced steeply within first 30 epochs. For comparison, we also used the hessian gradient decent optimization for our analysis. The Hessian algorithm reduces training and validation error at a faster rate in less epochs. It does that by choosing second derivative information for better gradient direction. However, the overall margin of error with hessian algorithm was more than the conjugate gradient's.

VIII. CONCLUSION AND FUTURE WORK

In this paper, look into analyzing cryptocurrency market price through a correlation analysis with various cryptocurrency attributes, exemplified by Bitcoin. We collect Bitcoin's data over more than 20 months and estimate the most significant features that influence the price. We computed the correlation between features such as hashrate, number of users, transaction rate, total bitcoins and price. We map the change in features on users and network activities to understand the dynamics of Bitcoin. We used our findings to construct a machine model that accurately predicts Bitcoin price with minimum error rate, based on other attributes than past price. Compared to the previous work that predicts Bitcoin price based on previous price observations, our approach is highly accurate. In the future we aim to build upon this work by developing a multivariate time series forecasting model with long short-term memory (LSTM) neural networks.

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