Machine Learning in/for Blockchain: Future and Challenges

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Abstract

Machine learning (including deep and reinforcement learning) and blockchain are two of the most noticeable technologies in recent years. The first one is the foundation of artificial intelligence and big data, and the second one has significantly disrupted the financial industry. Both technologies are data-driven, and thus there are rapidly growing interests in integrating them for more secure and efficient data sharing and analysis. In this paper, we review the research on combining blockchain and machine learning technologies and demonstrate that they can collaborate efficiently and effectively. In the end, we point out some future directions and expect more researches on deeper integration of the two promising technologies.

Keywords: blockchain, machine learning, deep learning, Bitcoin.

1 Introduction

A blockchain is a shared, distributed public ledger that stores transaction data in a chain of sequential blocks [1]. The data (block) are time-stamped and validated before adding to the chain. Each block contains information from the previous one. The mathematical structure for storing data makes

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it nearly impossible to fake [2]. Thanks to the legacy of cryptocurrency, the term "blockchain" has transformed from a cryptography terminology to a buzz word. Many people believe that cryptocurrency IS blockchain. This is incorrect. While blockchain is the foundation of cryptocurrency, the applications of the blockchain technology are much wider. Scenarios involving data validating, auditing, and sharing can all consider applying blockchains.

In this paper, we review the research on combining blockchain and machine learning technologies and demonstrate that they can collaborate efficiently and effectively. Machine learning is a general terminology that includes variety of methods, machine learning, deep learning and reinforcement learning. These methods are the core technology for big data analysis [3]. As a distributed and append-only ledger system, the blockchain is a natural tool for sharing and handling big data from various sources through the incorporation of smart contracts (i.e., a piece of code that will execute automatically in certain conditions). More specifically, blockchain can preserve data security and encourage data sharing when training and testing machine learning models. Also, it allows us to utilize distributed computing powers (for example, IOT), for developing on-time prediction models with various sources of data. This is especially important for deep learning procedures which require a tremendous amount of computational power. On the other hand, blockchain systems will generate huge amount of data from different sources, and the distributed systems are harder to monitor and control than the centralized ones. Efficient data analysis and forecasting of the system behaviors are critical for optimal blockchain mechanism designs. In addition, machine learning can facilitate the data verification process and identifying malicious attack and dishonest transactions in the blockchain. The interdisciplinary research on combining the two technologies is of great potential.

In this paper, we review articles that either using machine learning techniques to study the blockchain system/structure itself or implementing blockchain techniques to improve machine learning, e.g., collaborative/distributed learning. The reviewed papers are summarized in Table 1 below. For papers that apply machine learning and blockchain techniques separately to various areas, we do not include them in our review but list some of them in Table 2 below. In the rest of this paper, we first review basic idea and terminology of blockchain in Section 2. The review is by no means exhaustive, but sufficient for Sections 3, 4, and 5 that introduce how machine learning, deep learning and reinforcement learning can be incorporated into or improve blockchain system. Our work is concluded by Section 6 that discusses possible research

Method	Application	Paper
Machine Learning	Transaction Entity Classification	Yin et al. (2017), Akcora et al. (2019), Jourdan et al. (2018)
Macinile Learning	Bitcoin Price Prediction	Jourdan et al. (2018), Akcora et al. (2019)
	Biccom 1 rice 1 rediction	Abay et al. (2019), Shah et al. (2014)
	Privacy and Security Preserving	Harris and Waggoner (2019), Chen et al. (2018), Zhu et al. (2019)
Deep Learning	Computation Power Allocation	Loung et al. (2018)
	Cryptocurrency Price Prediction	Mcnally et al. (2018), Lahmiri et al. (2019)
	**	Alessandretti et al. (2018)
Reinforcement Learning	IoT, Resource Allocation, Cryptocurrency Portfolio Management	Liu et al. (2018), Nguyen et al. (2019), Wang et al. (2019), Jiang et al. (2017)

Table 1: Summary of Reviewed Papers

Area	Exemplary Sources
Healthcare	[4], [5], [6], [7], [8]
Data Trading	[9]
IoT Related	[10], [11], [12], [13], [14], [15]
Manufacturing	[16]

Table 2: Summary of Some Less Relevant Papers

directions and challenges arising from ongoing and future fusion of machine learning and blockchain.

2 Review on Blockchain

A blockchain, literally speaking, is just a chain of digital blocks. Each block contains a certain amount of data; and the chain connects these data to form a distributed database. A newly created block includes multiple transactions collected from nodes and broadcasts to every node on the network. It can be accepted and added to the blockchain by nodes that have the same consensus protocol. Each added block includes information of the previous block in the chain. Hence, if the block is changed, all blocks before this block will be invalid as well. The strategies to reach agreement of the new block (consensus) vary in different types of blockchain. The mathematical structure of the blockchain implies two essential properties: (i) the data (in block) is immutable [2]; (ii) the distributed network with consensus allows users to communicate directly with each other and download a copy of the current ledger, which means that there is continuous monitoring and redundancy of the data in the network. Therefore, the blockchain is more robust to individual outrages and attacks.

Depending on who can access to the blockchain and who can validate data, blockchains can be categorized into public chains, private chains, and consortium chains. Most cryptocurrencies are based on public chains. Al-

though a fully distributed public blockchain, which allows everyone to participate in the network, is nearly impossible to be forged, shortcomings include high power consumption on transaction validation and low efficiency for recording transactions that may occur at the same time. In the use of enterprise level, private and consortium chains are developed for higher efficiency. A private chain is controlled and operated by one organization or a founder who takes responsibilities for validating and processing transactions. New users need to apply for permissions from the organization in order to participate in the network. Besides transactions that are visible to the organization, an user is able to determine who can access to its transaction rather than every user on the network. An example of a private blockchain is the IBM Hyperledger Fabric ¹. It is a blockchain platform to provide decentralized data storage solutions using smart contracts, called Chaincode, for enterprises that enroll in the network through a trusted membership service provider. Consortium chain is similar to the private chain except that it is managed by multiple users or organizations. Transactions are usually validated and processed by all or a subset of users. Hyperledger Fabric also allows consortium chain. An example of the consortium blockchain is Quorum², which is an open-source blockchain platform for companies to collaborate. A selected group of users are assigned voting rights. Private and consortium blockchains process transactions much faster than public blockchains, but they are less secure.

In what follows, we use the bitcoin system, which is the most known blockchain application, as an example to demonstrate how blockchain works in detail [17, 18, 19, 20]. At the end, we also briefly discuss how Ethereum [21, 22], another popular public chain system, is different from the bitcoin system and introduce the concept of smart contract.

The bitcoin transaction is defined as transferring the cryptocurrency from one node (input address) to the other node (output address) without a third party being involved. Here nodes are devices connected to the blockchain network, being responsible for storing, verifying, and broadcasting blocks of transactions constantly in order to keep all data up to date. In the traditional centralized banking system, the transaction will be handled by a person or machine of the bank. In the bitcoin system, the transaction will be broadcast to all users in the network for validation and bookkeeping. Every transaction has a unique hash serving as a transaction identifier. Hash is generated by the hash function, which converts any string or number

¹Hyperledger Fabric: https://www.ibm.com/blockchain/hyperledger

²https://www.goquorum.com/

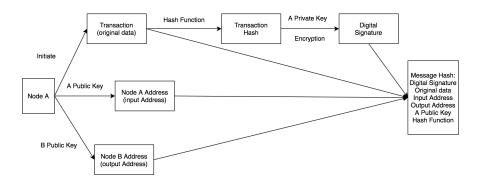


Figure 1a: How Bitcoin Blockchain Works between Nodes

to a unique fixed-length output. A small change in the input leads to a significant difference in output. Bitcoin uses the SHA-256 Hashing Algorithm to generate transaction hashes that always start with many zeroes. Under the SHA-256 Algorithm, any length of the input is transferred to a fixed 256-bits output.

The transaction between two nodes is completed in two stages, the node stage and the block stage. Figure 1 below illustrates how blockchain works at the node's level. Both A and B obtain a unique pair of keys (strings of characters), the private key used for encryption, the public key used for decryption and addresses generation. Suppose a transaction T_{AB} is initiated by Node A who wants to send digital coins to Node B. Original transaction data is first transferred to a transaction hash through a hash function. Then a digital signature is generated by encrypting the transaction hash. Next, the digital signature along with the input transaction address (Node A address) generated by the public key of Node A, the output transaction address (Node B address) generated by the public key of Node B, and the original transaction data with corresponding the hash function are hashed and sent to Node B. After receiving the transaction T_{AB} from Node A, Node B verifies it by comparing two hash values generated by the digital signature and the original transaction data. After the transaction got verified, it is uploaded to a transaction pool to be added to the blocks. The process of transaction creation is illustrated in Figure 1b.

In the second stage, the active participants of the network will aggregate transactions to form blocks, and they will compete to append their own block to the blockchain network. The process is also known as mining. The mechanism to determine whether a block can be added to the chain is called

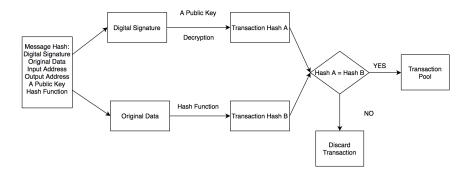


Figure 1b: How Bitcoin Blockchain Works between Nodes

consensus. Bitcoin blockchain applies proof-of-work (PoW) as its consensus protocol. Intuitively, mining nodes compete with each others to solve a hard math problem, i.e., to find a specific hash value that is lower than the target hash. The node broadcasts its block to the whole network when it finds the required hash. Once information on the new block is validated by a majority of nodes, the new block is appended to the blockchain and the node that first creates the block is awarded a certain number of Bitcoin.

The Bitcoin belongs to the type of unspent transaction output (UTXOs) based blockchain. Each node can only input entire (not fractional) unspent transaction outputs (UTXOs) in a transaction. The cumulative UTXOs serve as the balance of each node. For instance, suppose a Node A has two UTXOs that record 10 Bitcoins and 20 Bitcoins respectively, and plans to send 25 Bitcoins to Node B. Node A needs to spend both UTXOs as its input transaction. At the end of the transaction, two input UTXOs are spent and removed from the UTXO set of Node A. A new UTXO that records 5 Bitcoins is returned to Node A while another new UTXO recording 25 Bitcoins is sent to Node B. The process is shown in Figure 2. The address that Node A uses to receive its change is called Bitcoin change address.

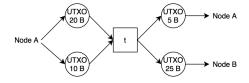


Figure 2: UTXOs Involved in Transaction

Another type of public blockchain is account based blockchain, e.g., Ethereum. Compared to the bitcoin transactions, Ethereum transactions include not only digital coins (Ether), but also *smart contracts*. A smart contract is a piece of automatically executed code that allows the execution of a transaction automatically. More specifically, the smart contract is uploaded to a node address. Other nodes can call a function of this smart contract in order to create a transaction. Ethereum is currently using PoW as its consensus protocol but plans to adopt proof-of-stake (PoS) in the future. Miners are replaced by validators, and they vote on which block will be added next to the chain. The more stakes (usually the cryptocurrency) a node have, the more voting power it will have. Therefore, in PoW, the probability of generating a new block relies on how much computing power every node utilizes. In PoS, the probability of creating a new block depends on how many coins each node has. The node obtaining a larger number of coins has a larger probability of creating a new block.

3 Machine Learning for Blockchain

In this section, we review several applications of machine learning for the blockchain. Specifically, Section 3.1 reviews three studies regarding transaction entities classification [23, 24, 25] with different purposes. One focuses on the recognition of cybercriminal entities using supervised learning [23] as well as topological data analytics (TDA) method [25], while another on the recognition of common categories of entities that inleude most transactions [24]. Section 3.2 reviews Bitcoin price prediction from different perspectives such as probabilistic graphic models [24], Bayesian regression [26] and feature selection using TDA [27, 28].

3.1 Transaction Entity Classification

In the Bitcoin network, it is crucial to recognize entities behind those potentially illegal ones. The study of identifying entities behind addresses is called address clustering [29]. Yin et al. (2017) apply supervised learning to classify entities of transactions that may involve in cybercriminal activities. The classification model is trained based on 854 observations with categorical identifiers and then applied to study 10000 uncategorized observations that take 31.62% of unique addresses and 28.99% of total coins in the overall Bitcoin blockchain. The categorical identifiers represent 12 classes of entities, five of which are related to cybercriminal activities. Thirteen classifiers from the Python machine learning package "scikit-learn" are applied.

By comparing accuracy scores of all classifiers, it is found that Random Forests (77.38%), Extremely Randomised Forests (76.47%), Bagging (78.46%) and Gradient Boosting (80.76%) stand out as the best four classifiers. After further comparing precision, recall, and f1 score of these classifiers, bagging and gradient boosting stand out, which are then applied to analyze the 10000 observations. The classification outcome shows that 5.79% (3.16%) addresses and 10.02% (1.45%) coins are from cybercriminal entities according to the bagging method (gradient boosting method).

Bitcoins are found to be a common way to make the ransomware payment. In order to detect addresses related to ransomware payment, Akcora et al. (2019) apply a topological data analysis (TDA) approach to generate the bitcoin address graph by first grouping similar addresses into nodes and then putting common addresses between two nodes into the set of edges. The TDA is an approach commonly used for dimension reduction. It represents the data set in a graph by first dividing data to sub-samples based on different filtration criteria and then clustering similar points in each subsample. The Bitcoin transaction graph model is a directed graph, denoted as G = (V, E, B), where V is the set of vertices, E is a set of edges and $B = \{Address, Transaction\}$ is a set of node types. By using six graph features extracted for each address, a TDA Mapper method is applied to create six filtered cluster tree graphs. After calculating the number of ransomware addresses in each cluster, denoted as V, a suspicion score is assigned to a new address. The suspicion scores of addresses in the cluster are set to be 0 initially. It increments by one if inclusion and size thresholds are satisfied as follow: (1) the inclusion threshold, denoted as ϵ_1 , times the total amount of labeled ransomware addresses is less than V; (2) the size threshold, denoted as ϵ_2 , times the number of labeled ransomware addresses in the cluster is greater than the number of all addresses in the cluster. Suspicious addresses are then filtered by a quantile threshold, denoted as q, when their suspicious scores are higher than the quantile threshold. The result indicates that the best TDA model with $\epsilon_1 = 0.05, \epsilon_2 = 0.35, q = 0.7$ outperforms random forest (RF), and XGBoost in new ransomware addresses prediction.

Jourdan et al. (2018) are interested in classifying entities of transactions into four most common categories: Exchange, Service, Gambling, Mining Pool, based on data collected from 97 sources [30]. The goal of classification is to assist in selecting an appropriate prediction model that is built according to categories of transactions [24]. The applied classification method is a gradient boosted decision tree algorithm along with a Gaussian process based optimization procedure that determines optimal hyperparameters. Figure 3 concludes that accuracies in Exchange, Gambling, and Service

categories are high. However, the accuracy in the Mining Pool category is poor. This may indicate that mining activities may not be appropriate as an independent label.

Category	Accuracy	F_1	Precision
Exchange	0.94	0.92	0.91
Gambling	0.95	0.97	1.00
Mining	0.50	0.67	1.00
Service	0.95	0.88	0.83
Overall	0.92	0.91	0.92

Figure 3: Classification Performance [24]

3.2 Bitcoin Price Prediction

UTXOs record the number of Bitcoins in transactions, which enables us to track buying and selling information to predict the Bitcoin price. Another contribution of Jourdan et al. (2018) is to forecast the value of UTXOs by creating probabilistic graphical models. The first model is called the Block-transaction address model (BT-A) that is a stationary graphic model of a Bitcoin block with conditional dependency structures. As an extension of BT-A, a Block-transaction entity-address model (BT-EA) is further developed by adding a categorical entity to each address. In terms of MSE, RMSE, MAE, RMAE³, simulation results in Figure 4 show that this extension significantly outperforms the BT-A model in all categories except for Exchange.

Metric	BT-EA				BT-A
	Е	S	G	M	All
MSE	1.22	-0.30	-0.02	0.06	1.12
RMSE	125	53.3	1.15	5.19	90.5
MAE	15.6	0.94	0.20	2.42	7.47
RMAE	1.82	1.74	1.86	1.93	1.69
NRMSE	1.34	1.28	1.42	1.22	1.29

Figure 4: BT-A and BT-EA Performance [24]

The dependence structure of the BT-A model to obtain the output UTXOs values, denoted as $V_{o,u}$, is illustrated in Fig 5. Here is some ex-

 $^{^3}$ MSE is mean squared error; RMSE is the root mean squared error; MAE is mean absolute error; RMAE is the root mean absolute error

planation. The BT-A model starts with computing the number of available UTXOs for the i^{th} input address A_i , denoted as $k_{A_i}^{UTXO}$. For each input address, the number of UTXOs used in a transaction is uniformly drawn from 1 to $k_{A_i}^{UTXO}$ with the corresponding UTXO value, denoted as $V_{i,u}$. The total input value of a transaction is calculated by summing the input UTXOs value of each input address, denoted as $V_t = \sum V_{i,u}$, and the value of an output UTXO is uniformly drawn from 1 to total transaction value minus validation fee.

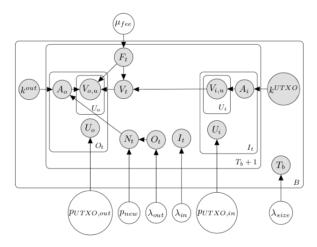


Figure 5: Block-transaction Address Model [24]

Another more direct way to predict Bitcoin price is to use Bayesian regression for "latent source model" [31] as firstly done by Shah et al. (2014). The latent source model aims to model the underlying pattern of price variation. Specifically, the Bitcoin price, denoted as y, is predicted given the feature x, and the latent source model refers to (3.1) below.

$$P(y|x) = \sum_{k=1}^{T} P_k(y) \exp\left(-\frac{1}{2}||x - s_k||_2^2\right) \mu_k$$
 (3.1)

where $s_1, ..., s_k$ are K distinct unknown latent sources⁴ (time series) that are never estimated, P_k is a latent distribution associated with probability μ_k , denoted as $P_k(T=k) = \mu_k$. The expectation of P(y|x) can be estimated as follows:

⁴An example of latent sources is Twitter activity of a news topic that becomes a trend following one of a finite number of patterns [31]

$$E[y|x] = \frac{\sum_{i=1}^{n} y_i \exp(-\frac{1}{4}||x - x_i||_2^2)}{\sum_{i=1}^{n} \exp(-\frac{1}{4}||x - x_i||_2^2)}$$
(3.2)

The future average price change is determined by price changes over three periods of historical data: previous 30 minutes sample, 60 minutes sample and 120 minutes sample, denoted as Δp^j , j=1,2,3. Each Δp^j is calculated by (3.2). Then Δp over a 10-second period is formulated as

$$\Delta p = w_0 + \sum_{j=1}^{3} w_j \Delta p^j + w_4 r \tag{3.3}$$

- w_0, w_1, w_2, w_3, w_4 are weights to be estimated.
- $r = (v_b v_a)/(v_b + v_a)$, where v_b, v_a are the top 60 orders of total buying and selling volume.

We would like to point out that in order to apply formula (3.3), it is crucial to verify the stationarity of the price data, which was unfortunately not done in the referenced paper. The trading strategy for each user is designed as "buy one bitcoin when $\Delta p > t$; sell one bitcoin when $\Delta p < -t$; otherwise holding the current number of bitcoin when $-t \leq \Delta p \leq t$." Here, t is a pre-specified threshold. The designed prediction model is trained by data gathered from Okcoin before May 2014 and is tested by data after that. It is found that increasing t leads to an increase of the average profit per trade.

To better characterize input features, Akcora et al. (2019) introduce a concept of graphic chainlet, which describes the local topological features of Bitcoin blockchain, to explore impacts of the Bitcoin blockchain structure on Bitcoin price formation and dynamics. A transaction-address graph representation of the Bitcoin blockchain is shown in Figure 6. Circle vertices represent input and output addresses. A square vertex indicates the transactions and edges stand for UTXOs (a transfer of Bitcoins). A chainlet model represents x input UTXOs and y output UTXOs involving in a transaction, denoted as $C_{x\to y}$. All chainlet and chainlet clusters clustered by various criteria are evaluated by the Granger causality test. The result concludes that the split chainlet cluster defined as when y < x < 20, individual chainlet (e.g., $C_{1\to 7}$, $C_{6\to 1}$, $C_{3\to 3}$), extreme chainlets (e.g., $C_{20\to 2,3,12,17}$), clusters according to Cosine Similarity (e.g., $C_{9\to 11}$, $C_{3\to 17}$, $C_{8\to 14}$, $C_{1\to 1}$) are significant to Bitcoin price dynamics. A price prediction model is further developed using significant chainlets.

Chainlet model studies topological features from a single transaction aspect and only takes the number of input and output UTXOs into account.

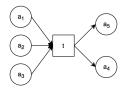


Figure 6: A Transaction-Address Graph

Abay et al. (2019) extend the chainlet model to a new graphic model "Chain-Net" that further assesses topological features from all or multiple transactions and take the amount of transferred Bitcoin into consideration. More specifically, from the perspective of all transactions, an occurrence matrix is created to count the number of distinct chainlets among all transactions. An amount matrix records the sum of Bitcoins transferred for distinct chainlets. By considering both occurrence and the amount bitcoins transferred in a transaction, an occurrence matrix with a threshold⁵, denoted as O^{ϵ} , is created to count the number of distinct $C_{i\to j}$ that is larger than ϵ . Different thresholds result in different values of O^{ϵ} , which are considered as Filtration Features (FL) input in the prediction model. Betti sequences and Betti derivatives for the blockchain network are also considered as features in the model. A sliding prediction approach associated with parameters of prediction horizon, window length and training length is applied to train the time series prediction model. According to simulation results, ChainNet adopts Betti model features and FL features for short and long term prediction, respectively, to obtain a better performance.

Although there are other studies related to Bitcoin price prediction using machine learning methods, e.g., [32, 33], it is hard to include all papers in the review. As a result, we will move on to review more articles in prediction of cryptocurrency price using deep learning and reinforcement learning in Section 4 and Section 5.

4 Deep Learning

In this section, we turn to the application of deep learning. In Section 4.1, three privacy-preserving collaborative learning frameworks [34, 35, 36] are reviewed. In Section 4.2, we review a deep learning work [37] that allocates computation resource to assist mobile blockchain mining. In Section 4.3,

⁵threshold, denoted as $\epsilon, \epsilon \in \{0, 10, 20, 30, 40, 50\}$

we focus on cryptocurrency price prediction [38, 39] and digital portfolio management [40] using Recurrent Neural Network (RNN) and Long-Short Term Memory (LSTM) models.

4.1 Decentralized Privacy-Preserving Collaborative Learning

Harris and Waggoner (2019) build a decentralized collaborative learning framework with blockchain. The new designed framework extended by the previous two frameworks [41, 42] is designed to collaboratively build a dataset and train a predictive model. The framework starts with letting the provider define a loss function and upload 10 out of 100 partial dataset with corresponding hashes. By using the smart contract that initially contains a model, other participants add their own data or uploading an update along with a deposit of 1 unit of currency until the end condition set by the provider is met. The provider uploads the rest of 90 partial datasets to evaluate participants' models. The better model tends to receive more rewards in the end.

Chen et al. (2018) propose a framework called "Learning Chain" to preserve user's privacy by applying a decentralized version of the Stochastic Gradient Descent (SGD) algorithm and a differential privacy mechanism. The proposed framework contains three phases: blockchain initialization; local gradient computation; global gradient aggregation. In the first phase, a peer-to-peer network is set up with computing nodes and data holders. The second phase involves each data holder P_k retrieving the current model from the block t, denoted as w_t , and computing its own local gradient. A differential privacy mechanism is then applied to generate a hidden local gradient, denoted as $\nabla g_k(w_t)^*$, by adding a noise factor to the local gradient. The message broadcasts a pseudo-identity of P_k , normalized hidden local gradient, denoted as $\nabla \widehat{g}_k(w_t)^*$, together with the norm of its un-normalized version to computing nodes on the network. In the final phase, after solving Proof-of-Work (PoW), the winner node selects top l-nearest local normalized gradients according to the cosine distance between each normalized local gradient and the sum vector of $\nabla g_k(w_t)^*$ to update the global gradient. The predictive model is updated by $w_{t+1} = w_t + \eta \nabla J(w_t)$, where $\nabla J(w_t)$ is the updated global gradient.

"Learning Chain" is trained and tested in three different data sets: synthetic data set; Wisconsin breast cancer data set; MNIST data set; using the Ethereum blockchain framework. There exists a trade-off between privacy and accuracy in the sense that decreasing the privacy budget leads to

an increase of test errors on all data sets. This proposed model is further compared with the "Learning ChainEX", which is implemented with higher differential privacy and has similar test error.

Zhu et al. (2019) develop a blockchain-based privacy-preserving framework to secure the share of updates in federated learning. The Federated Learning algorithm is developed by [43], which allows each mobile device to compute and upload updates to the global predictive model based on their local data sets. A security issue arises when there exist Byzantine devices in the network. In this case, the blockchain transaction mechanism is adopted to ensure the security of sharing and updating changes. Specifically, model updates are written in a blockchain transaction by nodes. Along with the digital signature of a node, a transaction broadcasts to other nodes information, including changes of hyperparameters and weights, public keys (participants' addresses). Other nodes validate the transaction and test updates according to their local data sets. If most nodes confirm that the performance score of the updated model is higher than the existing model under their local data sets, the updates are implemented into the current model.

4.2 Computing Power Allocation

Luong et al. (2018) develop a deep learning-based auction algorithm for edge computing resources allocation to support mobile mining activities. The designed framework enables mobile device miners to submit their bid valuation profiles to one Edge Computing Service Provider (ECSP) for buying additional computing power. The valuation profile for miner i, denoted as v_i , is drawn from a distribution that assigns a higher value v_i when its block size divided by initial computing capacity is larger. The ECSP evaluates all valuation profiles and maximizes its revenue in the following steps.

An allocation rule is applied to map transformed valuation profiles, denoted as $\overline{v}_i := \phi_i(v_i)$, to assignment probabilities using a Softmax function. The winner miner i will pay the price $p_i := \phi_i^{-1}(\text{ReLU}(\max_{i \neq j} \overline{v}_j))$. In the end, the loss function of ECSP is defined as

$$\widehat{R}(\mathbf{w}, \beta) = -\sum_{i=1}^{N} g_i^{(\mathbf{w}, \beta)}(\mathbf{v}^s) p_i^{(\mathbf{w}, \beta)}(\mathbf{v}^s)$$
(4.1)

where stochastic gradient descent (SGD) is applied. Here, g_i is the assignment probability and N is the number of miners. The above designed deep learning (DL) based auction mechanism is empirically compared to a regu-

lar auction mechanism. It is found that DL-based auction achieves higher revenue and converges to the optimal value faster than other mechanisms.

4.3 Cryptocurrency Price Prediction

For forecasting Bitcoin price, McNally et al. (2018) compare performances of two deep learning algorithms, i.e., Recurrent Neural Network (RNN) and Long-Short Term Memory (LSTM). It is interesting to note that two hidden layers with 20 nodes per layer are sufficient in both models. Specifically, the RNN model adopts the tanh fcuntion as its activation function while LSTM applies tanh and sigmoid functions for different gates, which result in longer training time. The data set used to train and test LSTM and RNN models is the bitcoin price from Aug 19th, 2013 to July 19th, 2016. Features including the opening price, daily high, daily low, the closing price, hash rate, and mining difficulty are used in the model. The importance of features is evaluated by the Boruta algorithm, which is a wrapper built around the random forest classification algorithm. The traditional time series model, AutoRegression Integrated Moving Average (ARIMA), is empirically compared with these deep learning models. The simulation results show that LSTM, RNN, and ARIMA have similar accuracy, which are 52.78%, 50.25%, and 50.05%. However, deep learning models have much lower RMSE values. In addition, the LSTM model is capable of recognizing long-term dependencies in contrast to the RNN model.

In contrast with other studies mainly for predictive models, Lahmiri et al. (2019) instead conduct a chaotic time series analysis before building deep learning models. Hence, their first step is to calculate the largest Lyapunov exponent (LLE) and then apply detrended fluctuation analysis (DFA) to detect chaos characteristics of cryptocurrency price data without having the assumption of stationarity. Then a deep neural network (DLNN) model with LSTM implementation [44] and a generalized regression neural network (GRNN) model [45] are built to predict three types of cryptocurrency: Bitcoin, Digital Cash, and Ripple price. The number of data samples obtained for the model is 3006 Bitcoin, 1704 Digital Cash ,and 1357 Ripples. The authors create a many-to-many sequence prediction, which utilizes the first 90% observations for training and the last 10% observations for testing and out-of-sample forecasting. According to Figure 7 whose x-axis represents the time horizon and the y-axis represents the price, positive Hurst exponent (HE) value indicates long-memory features of data, and negative LLE value indicates training data is chaos. As a result, a short-term prediction model would be suitable for data. The simulation results claim that the LSTM model outperforms the GRNN model in all three cryptocurrencies' price predictions. Although the RMSE of the LSTM model is still high, the model demonstrates a similar trend to real price changes for all three cryptocurrencies.

	LLE		HE	
	Training sub-sample	Testing sub-sample	Training sub-sample	Testing sub-sample
Bitcoin	0.1250	-7.8711	1.0087	0.9776
Digital Cash Ripple	0.3205 0.8181	-10.7333 -0.0065	0.9559 1.0741	1.0901 0.8715

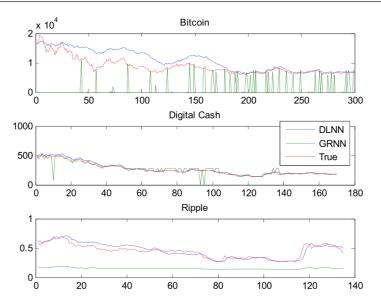


Figure 7: Chaotic Analysis and Prediction Result [39]

Besides cryptocurrency price prediction, Alessandertti et al. (2018) explore a portfolio analysis by forecasting daily prices of 1681 types of cryptocurrencies. Three models are developed to predict the prices of every kind of cryptocurrency. For each type c, the target is the return of investment (ROI) at each time $t_i \in \{0, ..., 895\}$, which is expressed as:

$$ROI(c, t_i) = \frac{\operatorname{price}(c, t_i) - \operatorname{price}(c, t_i - 1)}{\operatorname{price}(c, t_i - 1)}$$
(4.2)

Features considered are price, market capitalization, market share, rank, and volume. The first model is an ensemble of regression trees using XGboost, which features of each type of cryptocurrency are paring with prices of each type of cryptocurrency. The second model is a regression model by considering features of all kinds of cryptocurrency as a whole paired with prices

of each type of cryptocurrency. The third model adopts RNN with LSTM implementation with the second model's features and target paring strategy. All models are one-step ahead forecasting. A portfolio is constructed based on the predicted prices. Model hyperparameters are optimized by maximizing either sharp ratio or geometric mean of the total return. The result concludes that all three models generate profits, and the optimization of parameters using the sharp ratio metric achieves a higher return. Another conclusion is that the first two models implementing gradient boosting with decision trees have higher accuracy for the short-term (5-10 days), while the third model adopting LSTM has a better prediction performance in the long term (around 50 days).

5 Reinforcement Learning

In this section, we first review the work [46] that incorporates reinforcement learning into blockchain in order to ensure the security of data collection, storage and processing in the IoT. Secondly, we review studies that applies reinforcement learning and deep reinforcement learning to assist mobile mining activities [47, 48]. The last study [49] we will review is regarding cryptocurrency portfolio management using reinforcement learning.

Liu et al. (2018) propose a framework to secure data collection and sharing among mobile terminals (MTs) on the IoT network. The framework consists of two phases: data collection and data sharing. In the first phase, each MT, denoted as m, adopts multi-agent deep reinforcement learning (DRL) to maximize efficacy of data collection. The state space is defined as $S = \{S_1, S_2, S_3\}$. Here, $S_1 = \{(x^k, y^k), (x^c, y^c)\}$ is a set of state which represents coordinates of k Point-of-Interest (PoIs) and c obstacles in the environment, denoted as $E_x \times E_y$, where $x \in [0, E_x], y \in [0, E_y]$; S_2 stands for MTs' coordinates and S_3 represents sensing time $h_t(k) \in [0, t]$ for the i-th POI. Action space consists of moving direction, denoted as θ_t^m , and moving distance, denoted as l_t^m . Thus, it is written as $A = \{(\theta_t^m, l_t^m) \mid \theta_t^m \in [0, 2\pi), l_t^m \in [0, l_{max})\}$. The reward r_t^m is given as

$$r_t^m = \frac{w_t b_t^m}{\alpha b_t^m + \kappa l_t^m} \tag{5.1}$$

where b_t^m is the amount of collected data, α , κ are the energy consumption per collected data and per travelled distance; w_t is the achieved geographical fairness, calculated by

$$w_t = \frac{(\sum_{k=1}^K h_t(k))^2}{k \sum_{k=1}^K h_t(k)^2}$$

Each MT is implemented by four deep neural networks and actor-critic algorithm is applied to maximize the reward.

After MTs finish the data collection, they share data through an Ethereum blockchain network. However, the first step would be to send data to the certificate authority (CA) for verification. Once CA verifies the ownership of MTs' data and checks the consistence of received data and original data stored in the terminal, a digital signature is generated and sent back to the MT. As a result, the MT is able to broadcast its transaction request consisting of digital signature of CA, original data and its public key to other nodes on blockchain network to be further validated. By comparing to randomly moving MTs, MTs implemented DRL collect much more data but consume more energy. The blockchain-based data sharing framework can still store all data sent by MTs even under Dos attack.

Nguyen et al. (2019) propose a mobile edge computing (MEC) based blockchain network to assist mobile users (MUs) mining activities. Specifically, at each time step, MUs make a selection between two actions, offloading the mining task to MEC or solving the mining problem itself. Objectives considered for the joint optimization problem are minimizing offloading cost of time and energy while maximizing the privacy level. The immediate reward is defined as $r^t(s,a) = P^t(s,a) - C^t(s,a)$, where P(s,a) is the privacy level and C(s,a) is the cost. Reinforcement learning and deep reinforcement learning are applied to train MUs and update the Q network. The result concludes that although the convergence speed for RL and DRL are almost the same, agents trained by DRL models receive higher total rewards.

Wang et al. (2019) apply a single-agent RL to find the optimal mining strategy. Honest mining indicates that miners always continue mining the last block of the longest chain and publish a new block immediately after the newly mined block. On the contrary, adversary mines new blocks starting from intermediate blocks and construct a private chain of blocks. They aim to publish a series of new blocks later in order to be the longest chain and replace the current chain. The blockchain mining model is designed as a single agent MDP model, denoted as M = (S, A, P, R), shown in Figure 8 below.

The reward is given by $(r^{(a)}, r^{(h)})$, where $r^{(a)}$ denotes the number of new blocks mined and accepted by the adversary and $r^{(h)}$ represents the number of new blocks mined and accepted by the honest network. The action space, denoted as A = (Adopt, Override, Match, Wait) contains four actions that each adversary may take. The adversary takes Adopt action if he accepts the honest chain and mines the last block of the honest chain just like honest miners do. The action Override involves the adversary publishing one more

block than the current chain. The new chain becomes the longest chain and the old chain is now replaced. Adversary takes action Match to publish the same number of blocks as the honest chain. It creates two branches of blocks for miners to mine. The last action is Wait that the adversary does not publish any blocks to the network. The state space, denoted as $S = (l^{(a)}, l^{(h)}, fork)$, consists of the length of the honest chain, denoted as $l^{(h)}$, the length of the adversary chain, denoted as $l^{(a)}$, and fork = (relevant, irrelevant, active), where relevant stands for the latest block mined by the honest network, irrelevant means the latest block mined by the adversary, and active represents the adversary takes Match action from the previous state, and now the chain splits into two branches that have the same length. The RL algorithm is applied to find the optimal mining strategy by updating the expected cumulative rewards. Specifically, two Q functions are updated in (5.2) below.

$$q^{(i)}(s_t, a_t) \leftarrow (1 - \beta)q^{(i)}(s_t, a_t) + \beta[(r_{t+1}^{(i)} + \lambda q^{(i)}(s_{t+1}, a')]$$
(5.2)

where $i \in \{a, h\}$, λ is a number close to 1, $a' = argmax_a f(s_{t+1}, a)$. The current best action is chosen by the ϵ greedy strategy to maximize the objective function (5.3).

$$f(s,a) = \frac{q^a(s,a)}{q^a(s,a) + q^h(s,a)}$$
 (5.3)

Sensitivity analysis is applied to evaluate the designed optimal strategy and the simulation result is shown in Figure 9. After setting the discounted factor as 1, the paper concludes that the optimal mining strategy outperforms current mining strategies presented in [50, 51].

Current State, Action	Next State	Transition Probability	Reward
$(l^{(a)}, l^{(h)}, \bullet)$, $adopt$	(1, 0, irrelevant)	α	$(0, l^{(h)})$
$(t \cdot \cdot \cdot, t \cdot \cdot \cdot, \bullet)$, and $(t \cdot \cdot \cdot, t \cdot \cdot \cdot, \bullet)$	(0, 1, irrelevant)	$1-\alpha$	$(0,t,\gamma)$
$\left(l^{(a)}, l^{(h)}, \bullet\right), adopt$	(1, 0, irrelevant)	α	$(l^{(h)}+1,0)$
	(0, 1, irrelevant)	$1-\alpha$	$(\iota \cdot \wedge + 1, 0)$
$(l^{(a)}, l^{(h)}, irrelevant), wait$	$(l^{(a)}+1,l^{(h)},irrelevant)$	α	(0,0)
$(l^{(a)}, l^{(h)}, relevant), wait$	$(l^{(a)}, l^{(h)} + 1, relevant)$	$1-\alpha$	(0,0)
$(l^{(a)}, l^{(h)}, active)$, wait	$(l^{(a)}+1,l^{(h)},active)$	α	(0,0)
$(l^{(a)}, l^{(h)}, relevant), match$	$(l^{(a)}-l^{(h)},1,relevant)$	$\gamma (1 - \alpha)$	$(l^{(h)},0)$
	$(l^{(a)}, l^{(h)} + 1, relevant)$	$(1-\gamma)(1-\alpha)$	(0,0)

Figure 8: MDP for Blockchain Mining [47]

Jiang et al. (2017) conduct a study for cryptocurrency portfolio management using deep reinforcement learning. In contrast to other studies whose prediction models output cryptocurrency prices, their CNN model produces

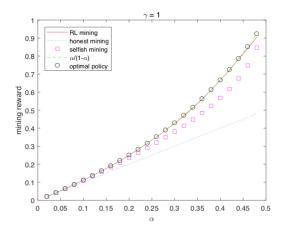


Figure 9: Simulation Result for Different Mining Strategies [47]

a portfolio weight vector instead. The state space is a history price matrix that records all asset prices in each time period. The corresponding action would be to change portfolio weights, denoted as $\vec{w_t}$, at each time period t. Instead of estimating Q function, a deterministic gradient policy is implemented using a direct reward function. The reward function through n periods is to calculate the average logarithmic return as follows.

$$R = \frac{1}{n} \sum_{t=0}^{n} \ln(\vec{w_t} \cdot \vec{y_t})$$
 (5.4)

where each $\vec{y_t}$ is the price change vector of t^{th} trading period. A Softmax function is applied to the output layer to ensure $\sum_i w_{t,i} = 1$. The model is trained by gradient based methods. Adam Optimization is used to find the optimal hyperparameters and l_2 regularization is applied to avoid overfitting.

Backtesting experiment is conducted to evaluate the performance of the trained CNN model. Three benchmark strategies and three algorithms summarized by [52] are compared to the designed CNN model. The optimal hyperparameters and model settings are found via cross-validation. All models are evaluated by the backtesting method using the testing data set. The result concludes that the CNN model with two hidden layers has the best performance. More specifically, the CNN model is only inferior to the Passive Aggressive Mean Reversion model in terms of accumulative return. However, the CNN model achieves a significantly lower risk after comparing Shape Ratios. One issue that the paper should have clarified is Whether the portfolio is self-financing or not.

6 Conclusion and Future Challenges

The research we review either applies blockchain in a database to improve users' privacy in learning process; or uses machine learning to optimize computer resource allocation or cryptocurrency investment decisions. The majority can be categorized as applying one technique to another; few is the actual integration of the two technologies. Hence, it is fair to say the current research is still very preliminary from an interdisciplinary perspective.

However, we expect new research lines to emerge in the following areas:

- Design "smart agents" with learning abilities to regulate the blockchain and detect abnormal behaviors. The former is especially important for consortium chain and private chain that require coordination among users, while the latter is critical for public chain;
- The learning-based analysis of blockchain-based system is rare. From financial systems to supply chains, there is an enormous amount of data available to evaluate the performance of the decentralized structure of blockchain compared with the traditional centralized one. Learning-based analysis can shed insights on the mechanism design of the blockchain structures and provide on-time forecasting models;
- Blockchain to allow anonymously data sharing. With the development of IOT and wearable device, the privacy issue catches more and more attention of users. Combining with data fusion, we can design multiple-layer blockchain structures that allow sophisticated authorization of data for different users.
- The blockchain mining activity could be considered as an MDP process. Although there exist a few works related to finding the optimal mining strategy using single-agent reinforcement learning, individual mining is not as popular as pool mining in reality. Specifically, miners collaborate and compete with each other to mine blocks. A multi-agent reinforcement learning (MARL) with a mixed setting of collaborative and competitive agents is more suitable to model the complex pool mining activity and helps miners find the optimal mining strategies in the future.
- Cryptocurrency plays an important role, especially in the public chain.
 Different chains have their unique cryptocurrency. Now cryptocurrency or cryptocurrency portfolio is an investment option similar to other financial products. Some works have studied cryptocurrency

price prediction using supervised learning techniques, but only a few of them explore potentials of RL or deep RL. In many cases, RL and deep RL have a better in financial forecasts, e.g., stock price prediction, since historical data cannot reflect the current market, which further results in poor prediction performance of future price changes. We expect that more works adopting RL, deep RL, or inverse RL to study the investment return of cryptocurrencies emerge soon.

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