HDCoin: A Proof-of-Useful-Work Based Blockchain for Hyperdimensional Computing

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Abstract—Various blockchain systems and schemes have been proposed since Bitcoin was first introduced by Nakamoto Satoshi as a distributed ledger. However, blockchains usually face criticisms, particularly on environmental concerns as their “proof-of-work” based mining process usually consumes a considerable amount of energy which hardly makes any useful contributions to the real world. Therefore, the concept of “proof-of-useful-work” (PoUW) is proposed to connect blockchain with practical application domain problems so the computation power consumed in the mining process can be spent on useful activities, such as solving optimization problems or training machine learning models. This paper introduces HDCoin, a blockchain-based framework for an emerging machine learning scheme: the brain-inspired hyperdimensional computing (HDC). We formulate the model development of HDC as a problem that can be used in blockchain mining. Specifically, we define the PoUW under the HDC scenario and develop the entire mining process of HDCoin. During mining, miners are competing to obtain the highest test accuracy on a given dataset. The winner also has its model recorded in the blockchain and are available for the public as a trustworthy dataset. The winner also has its model recorded in the blockchain as the brain-inspired hyperdimensional computing (HDC). HDC is an emerging machine learning paradigm that utilize high dimensional patterns imitating brain activation functions to complete learning tasks. Recently, HDC has shown comparable capability with SOTA machine learning models under various application scenarios such as bio-informatics, natural language processing and robotics. Similar to other machine learning models, HDC also require significant amount of computation to train and fine-tune a model, which can serve as the computationally expensive task during the blockchain mining process. Compared with neural networks, HDC has an advantage that the HDC model architecture can be directly generated from a nonce, which does not require complicated architectural mapping like neural networks. HDC models also provide multiple knobs to tune the difficulty of mining problem, enabling capabilities of an adaptive and flexible difficulty configuration.

The debut of Bitcoin as a distributed ledger was almost 14 years ago to serve as a peer-to-peer electronic cash system [13]. Since then, many blockchain systems implemented such as Ethereum [18], have obtained great success for their advantages like decentralization, transparency and durability over the fiat currency. Despite of those advantages, blockchain also has its “pain-in-the-neck”. One of the biggest concern are from the “proof-of-work” (PoW) principle inside the competitive blockchain mining process [7], [5]. During mining, to determine a winner, different miners need to solve a cryptographic problem that is computationally expensive. For example, in bitcoin mining, the miner is required to find a random number referred to as “nonce” that could contribute to producing a hash with a certain number of zeros as prefix. Therefore, the energy consumed in finding the number can hardly yield any useful and practical outcomes beyond the blockchain.

To tackle this issue, frameworks with the principle of “proof-of-useful-work” (PoUW) are proposed, attempting to connect the mining process with real-world applications, i.e., to replace the problem of solving a cryptographic hash with a real world task that can yield useful outcomes. For example, miners are required to work with NP-hard optimization problems so that the computation power can be used to benefit transportation transactions [8]. Such concepts can be generalized applied to various optimization problems that are equivalent to solve the NP-hard travelling salesman problem [11]. In addition to optimization problems, the development of machine learning models such as the training of neural networks can also be elaborated as a computationally expensive problem for miners to solve using their computation power [2].

Inspired by those frameworks, we propose to introduce the concept of blockchain and PoUW into an emerging machine learning scheme: the brain-inspired hyperdimensional computing (HDC). HDC is an emerging machine learning paradigm that utilize high dimensional patterns imitating brain activation functions to complete learning tasks [9]. Recently, HDC has shown comparable capability with SOTA machine learning models under various application scenarios such as bio-informatics [12], [10], natural language processing [17], [15] and robotics [14]. Similar to other machine learning models, HDC also require significant amount of computation to train and fine-tune a model, which can serve as the computationally expensive task during the blockchain mining process.

The main contributions of this paper are listed as follows:

• We introduce the concept of blockchain into HDC and propose, HDCoin, for HDC model development. We define “proof-of-useful-work” principles under the HDC scenario and the mining cycle of HDCoin.
• During the mining cycle, miners compete against each other to train an HDC model based on the given training and inference set. The inference accuracy of the HDC model is used as the benchmark to determine which miner wins the competition. The nonce used in generating the winning HDC model, i.e., the outcome of the “useful-work” of HDCoin mining process is recorded into the blockchain as well for public reference.
• We evaluate the performance on mining using three datasets and illustrate the impact of HDC model hyperparameters, which can enable adaptive difficulty adjustment during the mining process.
II. HDCoin Preliminaries

A. HDC Notions

Hypervectors (HV) are numerical vectors that are high-dimensional, holographic vectors with i.i.d. elements \[ \theta \]. We can note a \( d \)-dimensional HV as \( \vec{H} = (h_1, h_2, \ldots, h_d) \), where \( h_i \) refers to the numerical elements inside the HV. In HDC, HVs are the fundamental component to represent information in different types, modalities and layers of features because of its high dimensionality.

To aggregate information from different HVs to establish new HVs, HDC uses different operations. The three mostly used operations in HDC are addition, multiplication, and permutation. Additions and multiplication are element-wise, taking two HVs as input operands and perform addition or multiplication with each element on the same index. Permutation, on the other hand, takes only one HV as the input and cyclically shifts the HV by a specific amount. Note that the dimension of the HVs are not modified, i.e., the dimension of the input HV and the output HV are identical.

To quantitatively measure the information likeness between two HVs, similarity metrics such as Euclidean distance, hamming distance (for binary vectors) and cosine similarity are usually used. A higher similarity suggests more overlap in the information the two HVs represent.

B. Developing HDC Model

To develop and HDC model for a classification task, there are three main steps: Encoding, Training, and Inference.

Encoding is the fundamental step to build an HDC model as it is used in both the other two steps. In encoding, the realistic features of an input sample is projected into their high-dimensional space representatives: the HVs. This is done by applying a set of application-specific HD operations. Without losing generality, we can assume a sample has a feature vector that contains \( m \) dimensions. For each dimension of feature there is a corresponding item memory \( R \). Suppose the application-specific set of HD operations is \( \Theta \), the corresponding encoded HV can then be denoted as \( \vec{H} = \Theta(R, \vec{F}) \).

Training is the step of establishing the associative memory. This is done by adding up all the encoded HVs that shares the same label into a HV which is referred to as class HV. Associative memory stores the class HVs at the number of classes in the learning task. Assume there are \( k \) classes in the classification task and the encoded the HVs \( \vec{H}^l \) for each training sample where \( l \) refers to the label of the sample. Training process in HDC is to build the associative memory \( A \) is thus by: \( A = \{ \sum \vec{H}^1, \sum \vec{H}^2, \ldots, \sum \vec{H}^k \} \).

Inference is the step of predicting the label of a sample that is unseen, using the associative memory established during the training step. During inference, the unseen sample is first encoded into its representative HV referred to as query HV \( \vec{H}_q \), using the same set of HD operations applied in training. Then, the similarity metrics are calculated between the query HV and each of the class HVs in the associative memory. The class with highest similarity is then selected as the predicted label of the unseen sample, because this indicates that the information inside the unseen sample is the most similar to that class. The inference step can be described as \( l = \text{argmax}(\delta(\vec{H}_q, A)) \).

III. HDCoin Blockchain and Mining

An overview of HDCoin mining cycle is illustrated in Fig. 1. HDCoin has basically two main sections, the blockchain and the mechanisms inside each miner during the mining process.

A. HDCoin Blockchain

The blockchain section of HDCoin resembles a typical blockchain framework of verifying transactions and adding it to the blocks. Assume there are \( k \) blocks already on the blockchain, to create the \( k+1 \) block, there requires to be the following content to be hashed into the block: 1). hash of the the previous block, 2). hash of the (confirmed) transactions in the block (based on Merkle root \( \delta(\vec{H}_q, A) \)), 3). the 32-bit nonce from the winning miner that is used to generate the highest competitive HDC model. There are also other information hashed into the block, including the timestamp, and the difficulty of this block (which is an adaptive parameter), etc.

B. HDCoin Mining

The miner section consists of the training and inference of an HDC model. During the mining process, the miner first picks the transactions they wish to verify from a pool of unconfirmed transactions. At the same time, the miner obtains the training and inference set of a specific learning task which can be distributed by the blockchain or appointed from open source datasets that are publicly available. The integrity of the dataset can be verified via existing hashing protocols like SHA-256.

Once the dataset is prepared, the miner starts to randomly choose a nonce which is a 32-bit integer number. Setting the nonce as a seed, the miner subsequently generates the item memories for the learning task. The miner uses the item memory to encode the samples from the training and inference set to obtain corresponding encoded HVs to each sample. According to Sec III-B, all the samples from the training set are aggregated together to establish the associative memory. After training, the associative memory is then evaluated by the inference HVs to obtain the inference accuracy. Until here, we obtain a mapping from the nonce to the accuracy of the inference set. The miner can repeat the process and perform trials on different nonces to achieve higher accuracy as possible.

C. Proof-of-Useful-Work

From the mining process we can understand that, in HDCoin, rather than solving a cryptographic hash function problem as the “proof-of-work”, miners train an HDC model, which is the “proof-of-useful-work”. The trained HDC model becomes a “useful” outcome from the process of confirming the transactions which is one of the objective by a traditional blockchain.
The nonce used to generate the HDC model is to be recorded into the blockchain with the consensus of miners on the network. This is to validate that the nonce genuinely has the highest accuracy out of all miners. Therefore, all the miners on the network takes the nonce and repeat the process of training and inference to verify if the nonce can reach the declared accuracy. Other format-wise validations during the verification process such as the data structure, timestamp, size checks are also applied here. Once the verification succeeds, the nonce is recorded onto the blockchain the the network is proceeding to the next block. The recorded nonce can act as an authentic HDC model distribution to the public.

D. Adaptive Mining Difficulty

Similar to other blockchain frameworks, the difficulty of mining in HDCoin needs to be adaptive. In neural network, quality threshold like the accuracy is usually used to control the difficulty of mining, i.e., when the bar of accuracy increases, it becomes more difficult to train the neural network. However, we think it is not enough, or rather, not optimal to use accuracy as the difficulty adjustment knob because the accuracy of different application can vary at very large scales.

For example, for simple and benchmark-level datasets like MNIST handwritten digits, a simple LeNet-like architecture can achieve a very high accuracy within a short time period even for a commodity desktop to train from scratch while for more challenging datasets like ImageNet, to obtain SOTA accuracy requires significantly larger model and days of GPU training time [5]. Particularly when there is a relatively new application and/or dataset, it is not straightforward to know what accuracy threshold to set as the bar for the mining competition.

HDC however, has the advantage over neural networks because apart from the accuracy, there is also another hyper-parameter that can be used to tune the difficulty of the mining task: the HV dimension. With a higher dimension of HV in the HDC model, there requires more computations for encoding, training and inference, as well as a larger vector space for HV to represent information, thus adding difficulty for the overall mining competition. The dimension as the difficulty parameter is also required to be hashed into the blockchain since this is the necessary information for generating the HDC model together with the nonce.

IV. Evaluation on Mining Performance

A. Setup

As a case study on the evaluation of mining performance, we choose three applications from different domains: 1). CARDIO: Cardiotocography dataset aiming at classifying measurements of fetal heart rate (FHR) and uterine contraction (UC) features into 10 classes [4]; 2). UCIHAR: Human activity recognition dataset aiming at recognizing 12 types of human activities [1]; and 3). ISOLET: Speech recognition dataset aiming at recognizing voice audio of the 26 letters of the English alphabet [3].

We choose the hyper-parameter HV dimension and sweep from 3,000 to 15,000 for evaluating mining performance under adaptive difficulty settings. All the experiments are conducted using a commodity laptop with Intel Core i7-10700F (2.90 GHz) CPU and 32 GB memory.

B. Experimental Results

We first present the results on the maximum accuracy a miner can reach when generating HDC models with different number of nonces during each mining cycle of all the three applications. We can observe that, when the number of nonces increases, the maximum achieved accuracy also increases. This is reasonable as the miner invests more computation resources in training by attempting to achieve higher accuracy. For CARDIO, the accuracy grows more than 3% from 83.5% to 87.0% when the number of nonces increases, while for ISOLET and UCIHAR, the accuracy increases only within 1%. This indicates that
there is inconsistency across applications on the sensitivity against nonce changes.

Moreover, the accuracy can also saturate, i.e., reaching a cap of accuracy increase after a certain time of generating and training the HDC model with different nonces. For example, accuracy of UCIHAR stops significantly increase after trying 10 nonces. For CARDIO, the slope of accuracy increase also lessens after 12 nonces. This is because when the accuracy reaching the ceiling, the dominating factor affecting accuracy is not the nonce for generating and training the HDC model, but the capability limit of the specific machine learning algorithm itself.

In addition to the relationship between accuracy and the number of nonces, we also evaluate the nonce time under different HV dimensions. The nonce time is defined by the total CPU time spent on using one nonce to generate the item memory, encoding, training and inference. From Table I, we can observe that when HV dimension becomes higher, the nonce time also increases as more operations are required with higher dimensionality of the HVs.

For different applications, the nonce time also drastically varies as the encoding mechanism, the size of the dataset and the number of classes can change. For example, CARDIO usually only requires less than 10 second for a nonce however, the execution of ISOLET and UCIHAR needs more than one minute of runtime. This provides a flexible knob in addition to accuracy threshold to enable HDC as a flexible and easy-to-configure mining task which can target at different scenarios particularly according to the computation resources allocated in the blockchain.

### TABLE I

| HV dimension | 3000 | 5000 | 7000 | 10000 | 15000 |
|--------------|------|------|------|-------|-------|
| nonce time CARDIO | 2.88 | 4.27 | 5.17 | 6.89  | 10.16 |
| (sec) UCIHAR  | 70.68| 98.11| 125.59| 161.58| 231.47|

V. CONCLUSION

This paper introduces HDCoin, a blockchain framework for the emerging brain inspired hyperdimensional computing scheme. Specifically, we use the training of HDC model as the “proof-of-useful-work” (PoUF) as an alternative to the traditional “proof-of-work” schemes of solving a cryptographic hash. We also elucidate the HDCoin mining process from the distribution of dataset and the verification of the winner. The model from the winning miner is also recorded into the blockchain as an authentic way of accommodating and publicly sharing an HDC model. HDCoin enables adaptive difficult on mining by two aspects: the accuracy as well as the hyper-parameter of HDC. We evaluate the mining performance of HDCoin using three datasets from diverse application domains. To the best of our knowledge, this is the first attempt to introduce blockchain into hyperdimensional computing and shed light for potential future research in this direction.

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