
PRIVACY-PRESERVING BLOCKCHAIN MINING

SYBIL-RESISTANCE BY PROOF-OF-USEFUL-WORK

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ABSTRACT

Blockchains rely on a consensus among participants to achieve decentralization and security. However, reaching consensus in an online, digital world where identities are not tied to physical users is a challenging problem. Proof-of-work provides a solution by linking representation to a valuable, physical resource. While this has worked well, it uses a tremendous amount of specialized hardware and energy, with no utility beyond blockchain security. Here, we propose an alternative consensus scheme that directs the computational resources to the optimization of machine learning (ML) models – a task with more general utility. This is achieved by a hybrid consensus scheme relying on three parties: data providers, miners, and a committee. The data provider makes data available and provides payment in return for the best model, miners compete about the payment and access to the committee by producing ML optimized models, and the committee controls the ML competition.

Keywords Machine Intelligence · Useful Proof-of-work · Blockchain Mining · Distributed Systems · Predictive Analytics

1 Introduction

1.1 Proof-of-Work

Bitcoin[1] presented a workable solution to the problem of double-spending of electronic cash (without a controlling central entity such as a bank). Launched in 2009, the Bitcoin network implements a peer-to-peer network of computers that maintains a distributed ledger tracking all the network participants' balances of the so-called cryptocurrency enabled by this system. In an open network of pseudonymous participants, reaching consensus about what transactions to include in the ledger is challenging – a simple voting scheme won't work since an individual can get an unfair influence by pretending to be an arbitrarily large number of individuals, a so-called Sybil attack[2]. For Bitcoin, Sybil-resistance was achieved by requiring participants to expend real-world resources for a chance to append new transactions to the ledger, a scheme known as Proof-of-Work (PoW)[3, 1, 4].

1.2 Proof-of-Useful-Work

Since PoW serves no useful purpose beyond providing Sybil-resistance, it follows that the vast amounts of energy that went into its creation are, for all other intents and purposes, wasted[5, 6, 7]. There have been some attempts at ameliorating this shortcoming, by instead securing the blockchain with useful work, that is, Proof-of-Useful-Work (PoUW). Early examples were Primecoin[8], where the work required was to search for chains of prime numbers, and Permacoin[9], intended to direct mining resources to distributed storage of archival data. However, these efforts have failed to reach wide adoption, possibly, due to the limited utility of the work performed. More recent efforts have attempted to find PoUWs relying on work of general utility[10, 11], the former based on the orthogonal vectors problem (useful to obtain graph properties), and the latter, allowing for fully generalized tasks via a reliance on Intel’s SGX.

Here we take a different approach and focus on a specific, but common, task: privacy-preserving data mining.

1.3 Privacy-preserving data mining

The application of machine learning (ML) to important problems, such as medical, personal or financial, often results in an apparent contradiction: training the models require access to large and varied data sets, while, at the same time, security and privacy need to be preserved. Recent news reports have highlighted the repeated failures to achieve the latter[12, 13]. In order to maintain data privacy and not leak information about the input-target mappings, the raw data has to undergo some form of obfuscation, that while both preserving privacy and data utility (i.e. modelling accuracy). This is known as privacy-preserving data mining.

The ML problem has to be structured in a way that makes it suitable for mining in a permissionless online environment. Given a data set of numerical features and a categorical or continuous target associated with each example, the task can be set up as an ML competition, where miners compete to predict the targets given some inputs. The miner that best predicts the test targets wins. A standard ML competition relies on a trusted party, the organizer, who has full access to the data set and withholds a subset of the targets from the competitors. The organizer releases two sets of data to the competitors, a complete set of input-targets pairs for model training, hereafter the training data, and a partial set consisting of only inputs, the test data inputs. During an initial training phase, the competitors train their ML models and submit their predictions of the test data. Once this phase is over and submission can no longer be made, the organizer compares the submissions to the test targets and assigns the competitor with the best predictions the winner. However, without the trusted organizer, the correct input-target mapping would be publicly available and, no training required for a perfect score. Thus, for the purposes of a permissionless blockchain, the trusted organizer has to be replaced by a secure and trustless mechanism. We demonstrate that this can be accomplished using a hybrid consensus scheme.

A second challenge when using ML as a PoW is that the difficulty cannot be set in advance. In most PoW blockchains, the average block interval is adjusted via an adaptive parameter, the difficulty[14]. This acts as a threshold where the first miner to exceed it wins. Should the mining power increase or decrease over time, the difficulty threshold is adjusted accordingly so as to maintain the average time it takes to cross it. Thus, the difficulty provides an, on average, known relationship to the amount of computation required, and thus, the rate of block generation[15]. In contrast, for the PoUW proposed here, the amount of work depends on unknown factors. How much computation is needed to train a model to reach some set level of performance depends crucially on the data set. On the one hand, given a simple, low-dimensional training set good performance can be reached with a trivial amount of computation, while on the other hand, training a model on high-dimensional image or audio data may take weeks on high-end hardware, and on random data, it is impossible to ever do better than chance. Thus, without advance knowledge of the dimensionality and probability distributions in the data, there is no way of reliably estimating how much computation is required, and as a consequence, the block interval cannot be controlled by the ML equivalent of a difficulty parameter.

A number of proposals for hybrid consensus where the scheme is combined with a classic consensus scheme[16, 17] have been made. In these, PoW is used to select members of a consensus group privileged to write blocks[18, 19, 20, 21, 22], resulting in a permissionless blockchain capable of greater block rates than blockchains based on Nakamoto consensus (i.e. Bitcoin-style consensus)[23, 21].

1.4 Our Contributions

We propose a novel Sybil-resistance scheme based on a PoW useful for privacy-preserving machine learning, that is, a PoUW. It builds on ByzCoin[20], bitcoinNG[23] and ML competitions. Data privacy is achieved with a geometric data perturbation, a perturbation method that preserves privacy while still allowing for efficient model learning by several common ML algorithms. This work addresses two key challenges for blockchain consensus schemes and

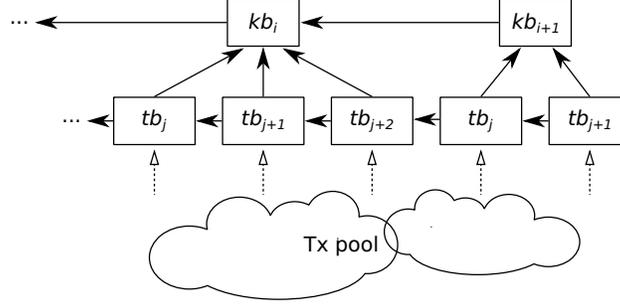


Figure 1: Hybrid blockchain. kb_i is keyblock i , tb_j is transaction block j and Tx pool is the transaction pool. Full arrows indicate block linkage by hashes.

privacy-preserving data mining. First, it provides a way of decreasing the energy waste inherent to blockchains based on Nakamoto consensus, and second, lays the groundwork for a decentralized two-sided market for machine learning models.

The advantages of this strategy are threefold (1) it decreases the energy waste, (2) it provides a decentralized market for machine learning models, and (3) it harnesses the full computational potential of blockchain networks.

2 Our Framework

2.1 Overview

Here, we focus in not on the consensus scheme *per se*, but on a Sybil-resistance mechanism that can be used with some version of a classical consensus protocol for a permissionless blockchain. Classical consensus protocols require a fixed size committee of known members that together, collect transactions from users, append them block-wise to the blockchain, and ensure that the chain will have only one history that cannot be deleted or rewritten[17, 24]. Thus, we describe a scheme by which miners can perform useful work that allows them to join a fixed size committee of members participating in the consensus protocol. With this goal, we follow the hybrid consensus protocols[21, 20, 22, 18, 19] where PoW is utilized to dynamically select committee members. The resulting blockchain is composed of two parallel chains, one made up of long-interval PoW-mined keyblocks and the second made up of short interval transaction blocks produced by a fixed size committee executing a classical consensus protocol (see Figure 1). However, different from previous protocols, here, the work performed is training ML models which require the committee to, in addition to agreeing upon transaction blocks, also to time the generation of keyblocks.

Once a fixed-size committee is in place several consensus protocols could serve the purpose of producing the transaction blocks[21, 22, 18, 19, 17].

Our scheme rests on the actions of four parties: (1) data providers, (2) miners, (3) the committee and (4) non-committee nodes. In short, the data provider provides data, pre-processes and makes it publicly available. Critical to the pre-processing is splitting the data set into a test set and a training set, where the test targets are kept secret during the competition period. The miners train ML models on the training data and submit their predictions of the test data. The winning miner writes a keyblock and gets to join the committee. The committee generates transaction blocks, signs miner submissions and thereby controls the timing of key blocks. Finally, the non-committee nodes accept transaction blocks signed by the committee, and the keyblock with the winning proof made up of the test targets and the best predictions.

2.2 Cryptography

We shall rely on four cryptographic tools: digital signatures, a hash function H , an encryption-decryption function E and a threshold-cryptosystem.

In a threshold cryptosystem, n parties share a secret key, out of which a subset of size t is required for its use. Specifically, in a (t, n) -threshold cryptosystem, n parties set up a group public key, and each party retains an individual share of the secret key. With this setup, t of the n parties are required for creating a signature that validates against the group public key or decrypting a ciphertext encrypted by that key[25, 26]. A signature that validates against the public

key thus represents a cryptographic proof of agreement by at least t committee members. The group keys are set up at the beginning of each round by running a distributed key generation protocol[27].

2.3 The blockchain

The blockchain is composed of two parallel chains of keyblocks and transaction blocks (see Figure 1). Keyblocks are mined and they provide access to the committee. By winning a keyblock, a miner becomes a committee member for a fixed number m of keyblocks. As a new member enters the committee another member is selected to leave (based on some pre-determined criteria), keeping m constant. The committee members public keys are recorded in the keyblocks from $kb_{h-\lambda-m}$ to $kb_{h-\lambda}$, where kb is a keyblock, h is the current blockheight, and λ , a non-negative integer, is a security parameter. New keyblocks are mined with a fixed time interval which is controlled by the committee. To ensure that all miners compete on the same data set, each keyblock is tied to a specific data set by the inclusion of a hash of the test targets in the previous keyblock (see Figure 2). This data set is being mined by the miners, who submit their hashed test target predictions included in proposals for the next keyblock. The winning miner gets to append the next keyblock and to join the committee once the keyblock has become part of the stable chain, that is after λ blocks. The accepted block needs to be signed by the committee, and have the best predictions of the test targets. Thus, the keyblock contains five parts.

1. A hash of the test set predictions
2. Test targets
3. A committee signature proving a timely submission
4. A hash of the test targets for the next keyblock
5. A hash of the previous block

2.4 The data provider

The data provider’s goal is to buy a good ML model of a data set to which it has access. In preparation for a future keyblock round, the data provider releases the data set that it wants modeled. To this end, the data provider has to perform two tasks. First the data have to be pre-processed and released on the network, and second, the data provider has to commit to payment in exchange for the winning model.

In order to maintain data privacy and not leak information about the input-target mappings, the raw data has to be obfuscated. There are multiple approaches to this and among them homomorphic encryption of the data. However, although promising, this is currently not viable for practical ML on relatively large data sets[28, 29]. Instead, we opt for a geometric data perturbation (GDP) that allows for ML on cleartext data, while still maintaining data privacy and mitigating information leakage[30]. Many ML algorithms rely on multidimensional geometric relationships to learn a model of the data. GDP preserves this information, and thus, allow for several common ML algorithms to learn well on the perturbed data, while not losing privacy when the data is made publicly available. GDP achieves this by a sequence of random geometric transformations, including multiplicative transformation by R , translation transformation by ψ , and a distance perturbation by Δ [30].

$G(X) = RX + \psi + \Delta$, where G is the geometric perturbation function, and X is the input data array.

The requirements on the data are that it is a numerical data set, X , with examples (records) in rows and attributes (features) in columns, and that each row belongs to a predefined class, indicated by the class labels, y .

Importantly, knowledge about the input-target mapping in the original data set is not informative when learning a model of the perturbed data set. Beyond maintaining privacy, this also ensures that a model trained on the perturbed data is only useful to a party with access to the perturbation matrices ($PM = [R, \psi, \Delta]$). However, up until the end of the submission period, the perturbation matrices need inaccessible to the data provider. If the data provider has full insight into the input-target mapping of the test set then it can take advantage of this itself proposing a keyblock with perfect predictions in order to join the committee.

To keep the perturbation matrices secret to all parties during the submission period, they are twice encrypted ($EPM \leftarrow E(E(PM, pk_{dp}), pk_C)$), first by the data provider’s public key and second by the committee’s public key. This ensures that the perturbation matrices are ultimately only accessible to the data provider but first after they are released by the committee. Similarly, the test targets are also encrypted by the committee’s public key in order to keep them secret until the committee has stopped signing the submissions, thus giving the committee control the release of the test targets.

The intermediate steps of the pre-processing have to be kept secret from all parties including the data provider. For this reason, the pre-processing has to be executed by verifiable computation, a way of having an untrusted party execute some code with a trusted (verifiable) result.

There are multiple proof-based verifiable computation schemes, all with different strengths and weaknesses, but their basic structure is common. A worker performs a computation, and along with the results returns a proof that the client (or verifier) can use to quickly verify that the computation was executed correctly. If the proof checks then the client accepts the results, and if not, the client can reject with a high probability that the computations were incorrectly executed. Verifiable computation schemes are much slower than native execution, and generally, too slow for practical use[31]. However, this computation is only performed for the keyblocks (not transaction blocks) (see Figure 1). Keyblocks are generated at a rate much slower than execution time of verifiable computation algorithms, providing us with the the freedom to select among multiple schemes. Thus, the requirements that need to be fulfilled are the following. (1) Non-interactive, publicly verifiable proof that the pre-processing was correctly executed, (2) the proof needs to be zero-knowledge, that is, it can be verified without access to the pre-processing arguments, thus maintaining data privacy, and (3) a relatively small proof that can be included in a key block. In addition, the same pre-processing function will be used repeatedly (but with new arguments) for all data sets, favouring schemes with a relatively high, initial, setup cost, but which can be amortized across repeated use.

The pre-processing function F takes as arguments the original data $Data$ and u , the concatenation of the data provider’s public key pk_{dp} and the committee’s public keys pk_C ($u \leftarrow pk_{dp} || pk_C$). The original data is kept private by the data provider. The function F perturbs, shuffles and splits the data, and encrypts and hashes the test targets y_{test} . It returns the perturbed training inputs X_{train}^p , training targets y_{train} , perturbed test inputs X_{test}^p , a hash of the test targets $Hy_{test} \leftarrow H(y_{test})$, the test targets encrypted by the committee’s public key $Ey_{test} \leftarrow E(y_{test}, pk_C)$, and EPM .

$$(X_{train}^p, y_{train}, X_{test}^p, Hy_{test}, Ey_{test}, EPM) \leftarrow F(Data, u)$$

For brevity, we give the complete output of F the label F_{out} .

A key generation algorithm, $KeyGen$, takes as arguments the function F and security parameter k , and returns a public evaluation key pk_E and a public verification key pk_V . [31, 32]

$$(pk_E, pk_V) \leftarrow KeyGen(F, k)$$

The two keys, pk_E and pk_V , are included in the blockchain’s genesis block.

The worker algorithm executed by the data provider takes as arguments the public evaluation key pk_E , the data $Data$, and the concatenation of data provider’s and committee’s public keys u . It returns F_{out} and π_F , a proof of F_{out} ’s correctness.

$$(F_{out}, \pi_{out}) \leftarrow Compute(pk_E, Data, u)$$

Give the verification key pk_V , the deterministic verification algorithm returns 1 if the computation was correctly executed, and 0 otherwise.

$$\{0, 1\} \leftarrow Verify(pk_V, u, F_{out}, \pi_{out})$$

Provided these constraints, we have found that Pinocchio[32] provides the best fit. Pinocchio provides a small proof (288 bytes), relatively quick verification, and it allows for the inclusion of private inputs while still proving that the computation was executed correctly. Further, it provides an end-to-end toolchain, that compiles a subset of the C programming language into verifiable computing programs.

To make the data set available to the miners it can be uploaded to IPFS[33] from where miners can individually access it.

2.5 The miners

In contrast to most hashing-based PoWs where miners work on different instances of the same computational challenge, that is, a partial inversion of a hash function, the PoUW proposed here provides an essentially new challenge with each keyblock round.

In each keyblock round, the miners train ML models and commit to proposals for the next keyblock that includes their test target predictions. Instead of submitting the cleartext predictions, miners commit to the predictions by submitting a hash of the predictions plus a nonce. This mitigates the risk that a miner’s predictions are resubmitted (i.e. stolen) by someone else. Submissions are signed by the committee up until a deadline after which the committee decrypts the encrypted test targets, enabling the verifiers to evaluate a prediction score (e.g. F1-score) by comparing the test targets

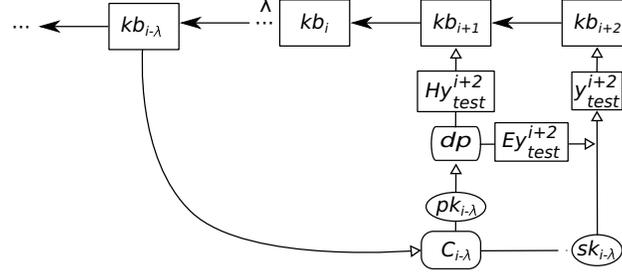


Figure 2: Keyblocks. kb_i is keyblock i , λ is a security parameter, Hy_{test}^{i+2} is the hash of the test targets for data set $i + 2$, dp is the data provider, Ey_{test}^{i+2} is the encrypted test targets for keyblock $i + 2$, $pk_{i-\lambda}$ and $sk_{i-\lambda}$ are the public and secret keys for committee $C_{i-\lambda}$, respectively.

to the submitted predictions. The keyblock with the highest prediction score is accepted and the miner producing it joins the committee after an additional λ keyblocks.

It is conceivable that, for a given keyblock, multiple miners submit the same prediction score. This risk cannot be satisfyingly mitigated by simply requiring the test set to be sufficiently big for such a tie not to occur by chance. There are two reasons for this. First, assuming binary classification, multiple miners with a prediction accuracy around 95% and a test set of size 1000, then the probability of any two miners submitting the same predictions is $0.95^{1000} < 5.3 \cdot 10^{-23}$. Although the probability for identical predictions is small, the probability of two identical prediction scores is much higher ($> 0.99^1$). Second, by chance or malicious intent the data set might be very easy and multiple miners reach 100% and thus, identical prediction scores. This necessitates a, preferably random, mechanism to break ties. For example, when a tie occurs the hashed predictions (see above) can be compared and the rewards goes to the miner with the smallest (or largest) hash.

Multiple data providers may simultaneously release data sets. Based on their payment commitments, the miner winning a round selects the next round’s data set by including a hash of the test targets y_{test}^H from the selected data set the proposed keyblock. This ties the next keyblock to the dataset (see Figure 2). Data providers that expect a greater value from a model would thus commit to a greater payment. This creates a long-term incentive for miners, to not only win the keyblocks, but to produce models useful to the data providers.

2.6 The committee

The committee is made up of m committee members, who all gained membership by winning at least one keyblock. The committee has two tasks: (1) generate transaction blocks, and (2) control the period over which the miners can submit predictions. Transaction blocks are generated according to a classical consensus protocol (not described here). To control the mining period, the committee members have to do two things. First, sign the miners’ keyblock proposal, and then end the submission period, stopping the signing and decrypting the test targets (see Figure 2). Committee members perform these tasks with a key pair derived from threshold cryptography, where each member has a share of the secret key sk_C , and a signature validates against to public key pk_C once t of m committee members have signed.

2.7 Verifiers

Finally, nodes external to the committee, that is, verifiers, accept and propagate the block with the best prediction score.

3 Related Works

There are a handful of projects working on different ideas involving blockchain and privacy-preserving computation and data mining.

Enigma Enigma is a peer-to-peer project aiming to become a decentralized platform for general privacy-preserving computation and data storage. The Enigma project relies on an external blockchain, like Ethereum, to record, organize and reimburse certain events while storage and computation are done in a privacy-preserving manner off-chain

¹From a simulation of 1000 000 runs.

with the help of encryption, distributed hash tables and secure multi-party computation. The Enigma project differs from our proposal in that it aims to support general privacy-preserving computation through multi-party computation (MPC)[34], not specifically privacy-preserving ML. MPC provided high security guarantees but, similarly to homomorphic encryption, doesn't scale well for big ML tasks[35].

OpenMined OpenMined is an open-source community directly aimed at developing a platform for secure, privacy-preserving ML. They are building a toolset allowing ML models to be trained anonymously and in insecure environments, where the model is private to the ML practitioner, and the data stays private to the individuals from whom it originates. They rely on homomorphic encryption and multi-party computation for model privacy and federated learning for data privacy[36].

The scheme starts with an ML practitioner creating a model, specifying which type of data to train it on and committing to a bounty for the trained model. This model is then encrypted/shared and submitted to a network where the members, provided they have the correct type of data, anonymously download and locally train the model. The updated models are uploaded to the network, and members get compensated in proportion to how much they contributed to improving the performance of the final model. Upon reaching a performance criterium, training stops and the original model creator can decrypt and use the model. With this scheme, the data scientist maintains full ownership of the model while still getting it trained without having access to the training data, and the data holders get paid for their contribution while maintaining full ownership over their data[36]. This strategy is similar to that of the Enigma project but uniquely focused on privacy-preserving ML. It does differ from our proposal in we instead propose a plaintext model trained on plaintext, but transformed data. This also, but indirectly, guarantees model privacy since the model outputs will be useless to anyone without the decryption key.

TrueBit TrueBit is a protocol designed to bring scalable, but not necessarily privacy-preserving, computation to smart contract platforms. It is being developed for Ethereum, but should in principle be adaptable to any smart-contract platform. It works by setting up opposing financial incentives for both performing the actual computations and for checking those computations. A verification game is run in order to settle disputes between the two parties. Similar to above-mentioned projects, scalability is achieved by outsourcing the computation to off-chain parties, and only performing small tasks in a contract[37].

However, the verification game is still rather inefficient which means that the security of TrueBit computations degrades with increasing complexity and data. Thus, for tasks relying on great amounts of data, for example, ML tasks, TrueBit as currently proposed is probably not sufficient[37], requiring either successful optimization or another strategy altogether.

The Golem Project The Golem project is also aiming to create a market for computation where parties can pay for, and be paid for computation. Similar to the other projects, computation should be done off-chain, and only book-keeping tasks and reimbursement will be handled on-chain. Their goal is for a great variety of tasks to run on the Golem network, but currently, it is only possible to run video rendering and some proof of concept ML tasks[38]. The exact scheme by which security will be ensured has not been specified, but TrueBit provides a possible mechanism by which to implement Golem[37, 38]. The Golem project differs from our proposal in that it is not privacy oriented.

The DanKu contract Algorithmia has developed a smart-contract for the Ethereum blockchain with the goal of establishing an automated marketplace for machine learning models.

The scheme is structured like an ML competition, where a data provider commits to pay for a trained model and makes training data available via a smart contract. Miners submit trained models to the same contract and after some period of time the test data is released and an evaluation function (in the contract) evaluates the submissions. The best submission receives the payment[39].

While the proposal is interesting and relatively uncomplicated, it results in quite a lot of on-chain data storage and computation. For example, to secure against manipulation by the data provider, sha3 hashes data groups must be uploaded to the contract, and thus, stored on-chain[39]. Assuming a dataset of 10 000 exemplars and data group size of five exemplars, then this corresponds to 2 000 256-bit sha3 hashes, totalling 64 kB. Given 625 000 gas per 1 kB² and block gas limit around 8 million³, then this is five times above the limit. Similarly, the evaluation function requires a forward pass of the trained models to be run in the contract, also resulting in a severe limit to the complexity of the model. This will likely lead block miners to reject large datasets and complex models, limiting the usefulness of

²<https://ethgasstation.info/index.php>

³<https://ethstats.net/>

the DanKu contract. Additional complications arise from the fact that the Ethereum Virtual Machine doesn't have a complete maths library, and that it does not support floating point numbers.

The project differs from our proposal in that privacy oriented but relies on transmission of data and models in the clear.

Numer.ai Numer.ai is an open ML competition on obfuscated financial data, and winners are rewarded with an ERC20 token. The data set is in plaintext, but obfuscated in order to protect it and make it useful only to Numer.ai. The submitted predictions are used to guide a hedge fund. However, apart from payout with an ERC20-token, this is not a decentralized blockchain project, but a normal hedge fund with outsourced management[40].

4 Concluding remarks

4.1 Incentives

Our proposal does not rely on a block reward to incentivize miners. Instead, it is fully reliant of fees. Miners and committee members receive payments for the services they perform. Committee members receive fees for the transactions they add to the blockchain, whereas miners train ML models for data providers and are paid via an on-chain contract. How much depends on the value of the model to the data provider. Thus, beyond simply winning the block, it is in the miners' long-term interest to provide good models to data providers. It is worth noting, that after the block is won, the resulting model is valuable only to the party with access to the perturbation matrices PM , that is, the data provider. Thus, there is no incentive to steal or withhold the model from the data provider, since the model is useless to everyone else.

For the timing of the submission deadline the data provider, the miners and the committee have opposing incentives. It is in the data provider's interest that the submission deadline is as late as possible since then more work will be performed for the reward it pays. The miners, on the other hand, are motivated to perform as little work as possible (i.e. short deadline) for the same reward, whereas the committee reaps transaction fees up until the deadline and are thus interested in a long deadline. However, only the committee controls when the deadline falls allowing for the other parties to be ignored. The committee's incentive to extend the deadline can be curtailed by fixing the number of transaction blocks that can be produced between two keyblocks. This removes the possibility for committee members to earn more transaction fees by a delaying the deadline and processing more transaction blocks.

4.2 Attacks

Committee members could collude in order to stay in the committee. Together, t of m colluding members could decrypt Ey_{test} and thus make perfect predictions without training any model. For comparison, miners in a PoW blockchain have a similar incentive to collude in order to execute a majority attack. However, the combination two factors help to mitigate this attack. First, miners depend on the cryptocurrency to not lose value (i.e. they hold and expect to win more cryptocurrency), and second, any such an attack is detectable since the resulting blockchain fork can be observed. The value of the cryptocurrency would likely be negatively impacted if a majority attack was detected. Thus, security is provided by transparency and the long-term economic incentives of miners.

Our proposal depends on data providers finding trained models sufficiently valuable to pay for them. Should they not, then they will stop providing payments and data and the network will grind to a halt. In this respect, the committee members long-term economic incentives are similar to those of PoW miners, that is, they are incentivized to not negatively impact the value of the cryptocurrency. However, for the analogy to be complete, it is important to consider whether collusion would be detectable. The data provider is the only party who can directly detect whether a model has actually been trained or not by assessing how well it generalizes to new data. A data provider receiving a model that doesn't generalize to new data is unlikely to pay for yet another model. Similarly, a putative data provider that doesn't believe it will receive a useful model in return for payment is also unlikely to provide data. Thus, in spite of committee collusion not being publicly observable (e.g. in the form of a fork), it is still indirectly observable via the data providers. The result of committee collusion would negatively impact the value of the native cryptocurrency and for this reason, go against the incentives of the committee members.

4.3 Future directions

A difficult problem is that should t of m committee members be Byzantine (i.e. not following protocol), they can completely control the committee, and can maintain that control for an indefinite number of keyblocks without much effort. This is in contrast to a PoW blockchain where a majority attack requires constant effort. However, the risk of collusion decreases with the number of committee members m and the size of t . Thus, it is of greatest importance to

identify the compatible classical consensus protocol that allows for the greatest number of committee members, that is, highest possible node decentralization. While of critical importance, this task falls outside of the scope of this work and is deferred to later studies.

Another concern is denial-of-service (DoS) attacks by miners. A miner can cheaply submit a large number of keyblock proposals since proposals that do not reflect any model optimization are cheap to produce, and until the submission period is over and the test targets y_{test} are released, the committee cannot evaluate the quality of a given submission. This makes it possible for a miner to perform a DoS attack overwhelming the committee’s capacity to sign keyblock proposals. This attack vector might be mitigated by requiring miners to deposit cryptocurrency and returning it only to well-behaving miners. However, further consideration of this is deferred to future work.

Finally, the committee selection suffers from a cold start problem. The selection of the first committee poses a problem since the proposed scheme requires an existing committee in order to update the committee. There are alternative ways to select the initial committee, and we will briefly outline two here. First, the initial committee could simply be made up of a group of participants that in random order exit the committee as new members enter by winning the mining competition. This requires a benevolent group, but is otherwise not too different from how Bitcoin started with Satoshi as the sole miner during the first year. Another approach, could be to begin with a standard PoW, adding one member for each keyblock until the committee is full, and thereafter switching to PoUW. This circumvents the reliance on the benevolence of the initial members, but somewhat delays the initialization of the PoUW and creates a few additional complications.

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