HDLock: Exploiting Privileged Encoding to Protect Hyperdimensional Computing Models against IP Stealing

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ABSTRACT

Hyperdimensional Computing (HDC) is facing infringement issues due to straightforward computations. This work, for the first time, raises a critical vulnerability of HDC — an attacker can reverse engineer the entire model, only requiring the unindexed hypervector memory. To mitigate this attack, we propose a defense strategy, namely HDLock, which significantly increases the reasoning cost of encoding. Specifically, HDLock adds extra feature hypervector combination and permutation in the encoding module. Compared to the standard HDC model, a two-layer-key HDLock can increase the adversarial reasoning complexity by 10 order of magnitudes without inference accuracy loss, with only 21% latency overhead.

1 INTRODUCTION

As an alternative to the deep neural networks (DNNs), brain-inspired hyperdimensional computing (HDC) is proposed as a promising solution to classification tasks with higher efficiency and less storage footprint [6]. For example, the recent quantized HDC [4] inference can be 10x faster than that of a binary neural network at the same model size and accuracy. Although not designed for complex learning tasks, HDC is particularly suitable for real-time classification on resource-limited devices, such as lightweight Internet of Things (IoT) devices and wearables.

The ultra efficiency and lightweight nature of HDC has attracted many research interests. As a result, HDC implementations have been explored for different hardware platforms, such as FPGA [4], GPU [9], and in-memory-computing systems [7]. Unfortunately, compared to the emerging studies on the performance improvement of HDC algorithm, its security is significantly under-explored. Few existing works have explored the attack [17] and defense [8] of the HDC inference with a focus on input, leaving the HDC model security under-explored. Similar as other machine learning methods, for which the model intellectual property (IP) is of high confidentiality [13], the HDC models should also be well preserved against IP stealing or model extraction attacks. Building a high-performance HDC model involves multiple stages, including expensive training data collection as well as careful hyperparameter tuning for class hypervector construction (e.g., the number of retraining rounds and “learning rate” [4]). As a result, it is very costly to produce a well-performing HDC model, which could become an target of IP stealing or model extraction attacks.

This work, for the first time, explores the IP security of HDC models and raises one critical vulnerability of the current HDC encoding module, which could leak the entire HDC model. This vulnerability is associated with the unique summation and multiplication structure in the encoding phase of HDC models. Leveraging such vulnerability, the attacker could extract the entire encoding module, even without the knowledge of the mapping information of hypervectors. As a result, the attacker can steal the HDC model or even reason the training dataset. Further, we propose a novel defense framework, namely HDLock, to mitigate such vulnerability. HDLock constructively applies combination and permutation to the HDC encoding module to protect its model IP. Specifically, the feature hypervectors are derived from several selected and permuted base hypervectors, making it significantly challenging for the attacker to reason the feature hypervectors. The base hypervector selection and permutation rules are regulated by a key, which can be stored in a tamper-proof memory as many circuit locking schemes [15]. HDLock can efficiently mitigate the HDC IP stealing attacks, disabling the attacker from acquiring the encoding details without correct guess on the feature hypervectors.

The main contributions of this work are as follows:

- To the best of our knowledge, this is the first work investigating the IP security of the HDC model. Leveraging the raised vulnerability, attackers can craft specific adversarial inputs and quickly reason the mapping information by observing the encoding outputs.

- As mitigation, we propose a defense framework, HDLock, to significantly increase the adversarial reasoning cost (complexity). HDLock constructively uses combination and permutation to protect the HDC model, which effectively eliminates reasoning attack while still being hardware-friendly.

- We thoroughly evaluate the vulnerability and the proposed framework. Experimental results demonstrate that HDLock can significantly harden the adversarial reasoning. For example, the reasoning complexity can be enlarged by 10 order of magnitudes compared to the original model with only 21% time overhead, without the inference accuracy loss.

The remainder of this paper is organized as follows. Sec. 2 briefly reviews the preliminaries of HDC. Sec. 3 presents the discovered vulnerability of HDC models in detail. Sec. 4 illustrates the proposed defense framework HDLock, the evaluations and results on the vulnerability and countermeasure are presented in Sec. 5. Sec. 6 concludes this paper.

2 PRELIMINARIES OF HDC

Hyperdimensional Computing (HDC) is a paradigm that represents object feature indices and values using hyperdimensional vectors (HV), \( HV \in \{1, \ldots, D\} \) [6]. Specially, the hypervectors representing feature indices (FeaHV) are supposed to be orthogonal to each other, while the hypervectors representing feature values (ValHV) are usually linearly correlated, corresponding to the feature value...
A non-binary HDC model can be trained as

\[ \text{sign}(\sum_{i=1}^{N} \text{ValHV}_{j,i} \times \text{FeaHV}_{i}) = \text{sign}(\mathcal{H}_{nb}) \]

where \( \Omega_j \) represents the hypervectors of the \( j \)-th object class assuming there are \( C \) classes in total. Similarly, the result can also be binarized in the binary HDC model.

**Inference:** For inference, a query sample is firstly encoded to a hypervector \( \text{QueryHV} \), using the same feature and value hypervectors. Then, the similarity between \( \text{QueryHV} \) and the \( \text{ClassHV} \)s is calculated, and the most similar \( \text{ClassHV} \) indicates the inference label. The similarity between the \( \text{QueryHV} \) and \( \text{ClassHV} \) is quantified using cosine function for non-binary model, which calculates the angle between these two hypervectors. In binary model, Hamming distance is used as all hypervectors are binary [10].

## 3 HDC MODEL IP VULNERABILITY

Considering the intellectual property (IP) value of the HDC model, its base hypervectors (e.g. feature and value hypervectors in Fig. 1) should be well-protected. Otherwise, once the attacker learns the base hypervectors, s/he can easily duplicate a similar HDC model for malicious attacks, such as reverse engineering the inputs [8] or generating adversarial inputs [17]. Moreover, due to the simple composition in an HDC model, it is very easy to be reverse engineered, as detailed below.

### 3.1 Threat Model

To enable efficient inference, HDC models are typically run on resource-constrained in-memory computing platforms or FPGAs. Unfortunately, most existing security solutions could not properly used for protect the HDC models on these platforms. For example, the physical isolation techniques [2] proposed for FPGA security have been tampered with practical attacks [18], while the security consideration on in-memory computing is under-explored.

As the first work exploring HDC model IP security, we use a strong threat model, in which the HDC model owner protects the model IP by keeping users from directly accessing the encoding module details. For example, the IP owner stores the index mapping\(^1\) of the base hypervectors in a secure environment, such as a tamper-proof memory preventing from probing internal signals, as suggested in [15]. Considering the limited computing resources in lightweight IoT devices, we assume that there are insufficient secure memory to store the entire HDC model (usually of MegaBytes) for IP protection purpose. Therefore, protecting the index mapping is an adequate solution for IP protection, which is much more memory-efficient than protecting all the hypervectors in the presence of tiny secure memory space.

Consequently, our threat model assumes that the raw data of base hypervectors are vulnerable while the mapping information is preserved from attacker access. As a result, the attacker can only access the unindexed hypervectors stored in the non-secured memory, and craft his/her own inputs and observe the encoding outputs. Note that our threat model is more strict than the white-box assumption in [8], since the hypervectors are stored publicly while the mapping information (as a "key") can be stored in secure memory to lock the encoding module.

\(^1\) Index mapping represents the mapping information between features/values and corresponding hypervectors.
3.2 Reasoning HDC Model with Divide-And-Conquer Strategy

This section presents the vulnerability of the HDC models, which can be utilized by the adversary to deduce the mapping information even on the base hypervectors (i.e., the unindexed \( \text{FeaHV} \)s and \( \text{ValHV} \)s). We use the same notations presented in Sec. 2, that the encoding input has \( N \) features and \( M \) discretized value levels, corresponding to \( N \) orthogonal \( \text{FeaHV} \)s and \( M \) consecutively distributed \( \text{ValHV} \)s, where \( \text{ValHV}_1 \perp \text{ValHV}_M \).

Since the encoding entangles the \( \text{FeaHV} \)s and \( \text{ValHV} \)s with multiplication, the hypervisor mapping information cannot be directly derived from the encoding output. Although protecting the mapping information can resist brute force attack, we demonstrate that it is still vulnerable to our proposed attack flow, as shown in Fig. 2. Since the non-binary HDC model is vulnerable as it has no obfuscation operation (i.e., the binarization in binary HDC) to compress the information in hypervectors, thus we use the more-secure binary HDC model as a case-study. The proposed attack strategy can be conducted in the following two steps:

**Value Hypervisor Extraction:** The inherent weakness of \( \text{ValHV} \)s lies in the consecutive distribution, which means only \( \text{ValHV}_1 \) and \( \text{ValHV}_M \) are orthogonal while all the other \( \text{ValHV} \)s are uniformly distributed in between, as shown in Eq. 1b. Hence, the two farthest hypervectors, \( \text{ValHV}_1 \) and \( \text{ValHV}_M \), can be determined by observing the Hamming distances between all value hypervectors. To identify these two \( \text{ValHV} \)s, the attacker can craft an adversarial sample, of which all the features have the minimum value (i.e., corresponding to \( \text{ValHV}_1 \)), so the encoding output is:

\[
\mathcal{H}_{b, \text{min\_value}} = \text{sign} \left( \sum_{i=1}^{N} \text{FeaHV}_i \times \text{ValHV}_1 \right)
\]

One property for the single-value input is that the \( \text{ValHV} \) can be moved out, so the summation of \( \text{FeaHV} \)s is treated as a whole without consideration of the inner arrangement. Therefore, the attacker can simply estimate the \( \text{ValHV}_1 \)

\[
\text{ValHV}'_1 = \mathcal{H}_{b, \text{min\_value}} \times \text{sign} \left( \sum_{i=1}^{N} \text{FeaHV}_i \right)
\]

By comparing the similarity between the estimated \( \text{ValHV}'_1 \) and the two \( \text{ValHV} \) candidates, the attacker can determine the correct \( \text{ValHV}_1 \). The mapping information of \( \text{ValHV}_M \) and other \( \text{ValHV} \)s can also be determined subsequently.

**Feature Hypervisor Extraction:** With the mapping of value hypervectors, the adversary can deduce the \( \text{FeaHV} \) mapping using specific inputs. Taking the first feature hypervisor \( \text{FeaHV}_1 \) as an example, the attacker can craft an adversarial input, in which the first feature value is the maximum (\( \text{ValHV}_M \)) and other feature values are the minimum (\( \text{ValHV}_1 \)). Hence, the output \( \mathcal{H}_{b,1} \) can be denoted as:

\[
\mathcal{H}_{b,1} = \text{sign} \left( \text{FeaHV}_1 \times \text{ValHV}_M + \sum_{i=1}^{N} \text{FeaHV}_i \times \text{ValHV}_1 \right)
\]

Using such crafted inputs, the attacker can separate and analyze the feature of interest from the summation individually. Since all the value hypervectors are determined, the mapping information of \( \text{FeaHV} \)s can be deduced with the divide-and-conquer strategy, i.e., the attacker assumes the \( n \)-th feature hypervisor in the candidate pool corresponds to the real \( \text{FeaHV}_n \), and denotes it as \( \text{FeaHV}_n \). The result in Fig. 3 shows that the correct guess generates an \( \mathcal{H}_{b,1} \) with much lower Hamming distance to the golden \( \mathcal{H}_{b,1} \) than other wrong guesses.

By iterating all candidates in the feature hypervectors pool, the attacker finds one feature hypervisor with which the derived \( \mathcal{H}'_{b,1} \) is closest (i.e., smallest Hamming distance) to the \( \mathcal{H}_{b,1} \). Following this strategy, the attacker can determine the mapping information for the feature hypervectors. The computing complexity is \( O(N^2) \), since the divide-and-conquer method divides the permutation into \( N \) independent tasks and solves them one by one.

To explicitly demonstrate the feasibility of the proposed attack strategy, we use the HDC model of MNIST as an example. To reason the feature hypervectors, we craft an adversarial input image to attack the first pixel, in which the first pixel is set as white (255) and all other pixels are set as black (0). As proof-of-concept, we set the 400-th feature hypervisor \( \text{FeaHV}_{400} \) as the one corresponding to the first pixel, i.e., the correct guess. The result in Fig. 3 shows that the correct guess generates an \( \mathcal{H}'_{b,1} \) with much lower Hamming distance to the golden \( \mathcal{H}_{b,1} \) than other wrong guesses.
4 HDC MODEL LOCKING AS A DEFENSE

In this section, we present a resource-friendly model locking framework for the encoding modules, namely HDLock, for both binary and non-binary HDC models. HDLock significantly increases the searching cost of the raised attacks, making it infeasible for the attacker to reason the mapping information within an acceptable time duration. Meanwhile, we avoid complicated locking designs that suffer in efficiency and performance.

4.1 HDLock Framework Overview

To significantly enlarge the search space for the attacker, HDLock modifies the calculation of encoding module, and still keeps the mapping information as a key to lock the HDC model. Fig. 4 presents the HDLock framework on the encoding module.

In HDLock, the feature hypervector is represented as the product of $L$ permuted base hypervectors:

$$FeaHV_i = \prod_{l=1}^{L} \rho^{k_{i,l}}(B_{i,l})$$

where $L$ stands for the layers of representation, and $\rho^{k_{i,l}}(\cdot)$ is the permutation that rotates the $l$-th base hypervector on the $i$-th feature by $k_{i,l}$ bits. Here, the base hypervectors ($B$s) are randomly generated and orthogonal to each other. We assume the generated pool has $P$ base hypervectors stored in the public memor, and the indices and permutation value is stored in the secure memory as the key of the $FeaHV$s generation in Eq. 9. Regarding to the generated $FeaHV$s, the encoding output with HDLock framework $\mathcal{H}_{Lock}$ is

$$\mathcal{H}_{Lock} = \sum_{i=1}^{N} FeaHV_i \times ValHV_{f_i}$$

$$= \sum_{i=1}^{N} \left( ValHV_{f_i} \times \prod_{l=1}^{L} \rho^{k_{i,l}}(B_{i,l}) \right)$$

The key will store $N \times L$ base hypervector mapping information. Specifically, the key is composed of $N$ sub-keys, where $key_{fi}$ is applied to the $i$-th feature constructed by $L$ permuted base hypervectors. $k_{i,l}$ and $index(B_{i,l})$ show the rotated bits and the base hypervector index for the $l$-th hypervector on the $i$-th feature. Given a wrong guess of the key, the encoding output $\mathcal{H}_{lock}$ will also be wrong. Even using the proposed divide-and-conquer attacking strategy, the complexity of figuring out all the $FeaHV$s is $O\left(N \cdot (DP)^L\right)$.

Why Not Represent the Value Hypervectors? In the proposed HDLock framework, only the feature hypervectors are represented with combination and permutation on base hypervectors, while the value hypervectors are still open to access. If $ValHV$s are constructed by base hypervector combination, the base hypervectors must be correlated due to the correlation of $ValHV$s, which greatly weakens the resistance against the reasoning attacks. Further, the design of base hypervectors for $ValHV$s is complicated, in order to retain the linear correlation. Therefore, jointly considering the security, effectiveness, and resource/time overhead, we find that only protecting $FeaHV$s is sufficient if the required reasoning time is already unaffordable to the attackers.

4.2 Security Validation

In this section, we validate the security of $FeaHV$s represented with combination and permutation. Since $ValHV$s are not protected, we assume a strong attack model in which the attacker already obtained the entire $ValHV$s mapping information, i.e., only the mapping of $FeaHV$s needs to be reasoned.

By attacking one $FeaHV$, more tricky strategies are required to reason the correct mapping. Taking the first feature $FeaHV_1$ as an example, where two adversarial inputs can be generated: the first one has all features of the minimum value ($ValHV_{1}$), while the other is the same except that its first feature has the maximum value ($ValHV_{M}$). Hence, these two encoding outputs $\mathcal{H}^1_{Lock}$ and $\mathcal{H}^M_{Lock}$ are

$$\mathcal{H}^1_{Lock} = \text{sign} \left( ValHV_1 \times \prod_{l=1}^{L} \rho^{k_{1,l}}(B_{1,l}) + \mathcal{H}_0 \right)$$

$$\mathcal{H}^M_{Lock} = \text{sign} \left( ValHV_M \times \prod_{l=1}^{L} \rho^{k_{i,l}}(B_{i,l}) + \mathcal{H}_0 \right)$$

where

$$\mathcal{H}_0 = \sum_{i=1}^{N} \left( ValHV_i \times \prod_{l=1}^{L} \rho^{k_{i,l}}(B_{i,l}) \right)$$

is the constant part. Therefore, the difference between $\mathcal{H}^1_{Lock}$ and $\mathcal{H}^M_{Lock}$ is totally resulted in by the difference on the first term. Although $\mathcal{H}_0$ dominates the output, there are still a few different elements caused by the first term. Leveraging this information, the attacker can determine which guess is correct.

To create a criterion judging the guesses, the attacker does subtraction on the two outputs in Eq. 11, and select the indices $I$ whose elements are non-zero. Afterwards, s/he generates a guess $\prod_{l=1}^{L} \rho^{k_{g,l}}(B_{g,l})$, and calculate

$$\mathcal{H}_{attack} = \text{sign} \left( ValHV_1 - ValHV_M \times \prod_{l=1}^{L} \rho^{k_{g,l}}(B_{g,l}) \right)$$

where $k_{g,l}$ and $index(B_{g,l})$ denote the guesses on the permutation and index of base hypervector, respectively. The attacker can calculate Hamming distance of the subtraction result and $\mathcal{H}_{attack}$ on indices $I$. The correct guess of the key on the first feature has the lowest Hamming distance. To reason one feature mapping, the attack needs $(DP)^L$ guesses.

To explicitly show the robustness of HDLock, we again attack the first pixel of MNIST binary HDC model, where $N = 784$ and $D = 10,000$. We set $P = N = 784$ and $L = 2$ for the validation\(^\dagger\), so there are 4 parameters ($k_{1,1}, index(B_{1,1}), k_{1,2}, index(B_{1,2})$) defining

\(^\dagger\)With $P = N$, these base hypervectors can directly serve as the feature hypervectors for the normal unprotected HDC model.
As the validation result shows, even if the attacker already correctly guessed most parameters, the mapping information will be useless as long as there is still one parameter incorrectly reasoned. The attacker has to apply \(4.81 \times 10^{16}\) tries to get the correct mapping information for the encoding module of the MNIST dataset. The validation on the non-binary HDC is shown in Fig. 6, where cosine value is calculated to indicate the similarity between the guess and the golden reference. Similar to the HDLock on binary HDC model, even if most parameters are correctly guessed, the derived mapping information will be useless as long as one of them is wrong. Hence, The number of needed tries is still \(4.81 \times 10^{16}\), which makes the reasoning on HDLock significantly expensive.

5 EXPERIMENTAL EVALUATION

In this section, we comprehensively evaluate the discovered vulnerability and the proposed locking strategy on several popular benchmarks, ranging from small to large dataset: MNIST (handwritten classification) [12], UCIHAR (human activity) [1], FACE (face recognition), ISOLET (voice recognition) [3], PAMAP (physical activity) [14]. These datasets are commonly used for HDC performance analysis in previous works [4, 5]. For the FACE dataset, we collect 623 face images in the open-source CMU Face Images dataset [3], while 623 non-face images are randomly selected from the CIFAR-100 dataset [11] as a small-scale benchmark. All the experiments are evaluated with Python on an 3.60GHz Intel i7 processor with 16GB memory.

5.1 Attacks on Different Benchmarks

The experimental results shown in Tab. 1 compare the original (correct) HDC model and the reconstructed (estimated) HDC model by the reasoned hypervectors. For all the benchmarks, the reconstructed model can still achieve the same good accuracy as the original one, which means the mapping information of feature and value hypervectors are unfortunately leaked. Moreover, all the reasoning attacks can be completed in 3 hours, demonstrating the practical feasibility and efficiency of the reasoning attack for the normal HDC models.

5.2 HDLock Performance Evaluation

Compared to the normal HDC models, the permutation and combination schemes in the encoding phase by HDLock can significantly increase the attacking complexity, from \(O(N^2)\) to \(O(N \cdot (DP)^L)\). We show the number of needed reasoning guesses in theory in Fig. 7, which aligns with the time consumption if each guess costs approximately equal time. The number of guesses increases monotonically with the power of \(L (L = 2\) in our case), along with the \(D\) and \(P\) increments. Further, the number of guesses increases exponentially along with the key layers \(L\), as shown in Fig. 7(b). Also, we demonstrate that \(P\) and \(L\) are mutually enhanced, i.e., increment on \(P\) can introduce more complexity on the locking framework when \(L\) is larger.

Note that there exists trade-off while choosing the number of layers \(L\), as more layers will lead to longer encoding time, while less
layers might not ensure the security against powerful computing resources. To analyze such trade-off on practical hardware setup, we deploy the HDLock framework on a Xilinx Zynq UltraScale+ FPGA [16]. The HDC computing is segmented, pipelined and paralleled as tree structure, as discussed in [4].

Fig. 8 shows the accuracy comparison between the baseline (non-binary) HDC model and the HDLock framework with different number of layers. The result demonstrates that there is no observable negative impact on the accuracy while applying HDLock. This is because the encoding module of HDLock does not change the orthogonality of feature hypervectors or the correspondence between the encoding input and output.

Then we evaluate the time overhead caused by the introduced combination and permutation in HDLock. Since only the encoding procedure is different between HDLock and the baseline HDC model, we compare the encoding time overhead to provide objective and representative comparison. Also, we combine the non-binary and binary HDC model comparison, since they have identical encoding except for the binarization. The experimental results in Fig. 9 show that the encoding time increases relative to the baseline HDC models. Besides, an important observation is that the increasing growth is independent of the dataset scale, as long as the hardware resources to steal the IP of an HDC model.

6 CONCLUSION

In this paper, we raise an urgent vulnerability of the emerging HDC models, which could be utilized by the adversary to steal the IP of the critical encoding module. To mitigate this vulnerability, we present a defense framework, HDLock, to protect the encoding module. With HDLock, the combination and permutation of multiple base hypervectors are used to generate hypervectors representing features. Experimental evaluations demonstrate that, the security of the encoding module protected by HDLock is exponentially increased without incurring inference accuracy loss, while the time overhead is only linearly increased. With a two-layer key protection, HDLock can increase the security by 10 order of magnitudes, while only consumes 21% extra latency.

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Figure 8: The accuracy changing for benchmarks on (a) non-binary and (b) binary record-based encodings. Here $L = 0$ means the baseline HDC model without protection.

Figure 9: The encoding time changing of HDLock framework relative to baseline HDC model. To give objective comparison, clock cycles are utilized as the encoding time, so the relative encoding time is the ratio of two clock-cycle measurements.
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