Look Ahead ORAM: Obfuscating Addresses in Recommendation Model Training

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Abstract— In the cloud computing era, data privacy is a critical concern. Memory accesses patterns can leak private information. This data leak is particularly challenging for deep learning recommendation models, where data associated with a user is used to train a model. Recommendation models use embedding tables to map categorical data (embedding table indices) to large vector spaces, which is easier for recommendation systems to learn. Categorical data is directly linked to a user’s private interaction with a social media platform, such as the news articles read, ads clicked. Thus, just knowing the embedding indices accessed can compromise users’ privacy. Oblivious RAM (ORAM) [4] and its enhancements [15], [18] are proposed solutions to prevent memory accesses patterns from leaking information. ORAM solutions hide access patterns by fetching multiple data blocks per each demand fetch and then shuffling the location of blocks after each access.

In this paper, we propose a new PathORAM architecture designed to protect users’ input privacy when training recommendation models. Look Ahead ORAM exploits the fact that during training, embedding table indices that are going to be accessed in a future batch are known beforehand. Look Ahead ORAM preprocesses future training samples to identify indices that will co-occur and groups these accesses into a large superblock. Look Ahead ORAM performs the ”same-path” assignment by grouping multiple data blocks into superblocks. Accessing a superblock will require fewer fetched data blocks than accessing all data blocks without grouping them as superblocks. Effectively, Look Ahead ORAM reduces the number of reads/writes per access. Look Ahead ORAM also introduces a fat-tree structure for PathORAM, i.e. a tree with variable bucket size. Look Ahead ORAM achieves 2x speedup compared to PathORAM and reduces the bandwidth requirement by 3.15x while providing the same security as PathORAM.

I. INTRODUCTION

In this age of cloud computing, data privacy is becoming critical. Users want to keep their data private while using cloud based vendors like Microsoft Azure and Amazon AWS. While computations and content of a memory location may be protected through trusted execution environments (TEEs) [5], [7], [9], [10], [16] and encryption, the address access patterns cannot be protected. In particular access patterns in recommendation systems reveal user data. Recommendation systems are used extensively in social media platforms [6], [12], [17]. Recommendation systems provide recommendations based on the categorical data associated with users’ past choices. This categorical data leaks information about the user’s prior behaviors such as articles browsed, advertisement clicked etc. This categorical data is stored in the form of huge embedding tables containing millions of entries. The embedding table access indices thus can leak information about the user behavior.

The most popular memory access pattern obfuscation technique is Oblivious RAM (ORAM) [4]. Instead of accessing a single data block per memory access, ORAM accesses multiple data blocks per access. Furthermore, ORAM changes the data accesses to the same data blocks would be sent to different addresses. ORAM guarantees memory access pattern obfuscation. Among the recent ORAM frameworks, PathORAM [15] is the most popular. PathORAM stores the data blocks in the form of a tree and assigns them a path (leaf node). Instead of reading a single data block, the entire path from the root of the tree to the leaf node is read for each access. Unfortunately, the security provided by all ORAMs [2], [4], [13], [15] comes at the cost of significant performance and bandwidth overhead. Theorem 1.2.2 in [4] indicates that when accessing $t$ data blocks of a RAM which contains $N$ data blocks, additional $\max\{N, (t-1)\cdot \log(N)\} - t$ data blocks need fetching. Even the optimized PathORAM [15] needs to access $t\cdot [\log(N) - 1]$ data blocks for each block accessed. These additional accesses cause memory access delays and bandwidth contention.

Some work have been done to reduce the overheads of PathORAM by using superblocks as mentioned in PrORAM [18]. In PrORAM superblocks are formed based on past memory access patterns i.e. blocks accessed together in the past are grouped together into superblocks. PrORAM is based on the fact that past predicts future. Memory accesses to huge embedding tables follow a highly random behaviour and hence making predictions based on past history is not viable. Due to this PrORAM performs similar to PathORAM.

When training recommendation models, and for that matter most machine learning modes, the future memory access patterns are known beforehand. So, even though predicting future based on past is difficult due to random memory accesses, looking into the future to find data locality is quite feasible. Look Ahead ORAM exploits this behavior where the future memory access patterns are known beforehand.

This paper proposes Look Ahead ORAM, a dynamic superblock technique that takes the data locality in the future memory access patterns into consideration. The data blocks that will be accessed together in the future in Look Ahead
II. EMBEDDING TABLE

Embedding tables are commonly used in recommendation systems [12], [17] to handle categorical data. Categorical data can represent recent clicked ads or watched movies, and categorical data is typically sparse. During recommendation model training, embedding tables will learn to place semantically similar inputs closer in the embedding space. Embedding table lookups are defined as $R = A^T W$, where $W$ is the embedding table, $A = [e_1, e_2, ..., e_l]$ where $e_i$ is a one-hot vector [11]. By the definite, a embedding table lookup is fetching entries from embedding tables.

III. THREAT MODEL

Look Ahead ORAM has three main parts: the server_storage, the trainer_GPU, and the preprocessor. The preprocessor is not on the cloud computing node and is considered secure. Similar to the server in the ORAM setting, the server_storage’s access patterns are insecure. However, the content of memory blocks is secured by a standard encryption algorithm. The trainer_GPU has tightly integrated HBM memory, where the stash is stored, and training takes place. Trainer_GPU’s accesses to HBM are assumed secured. Communication channels among those components are secured by a standard encryption algorithm.

IV. LOOK AHEAD ORAM

We can analyze memory access patterns of future batches/epochs when training models. Look Ahead ORAM exploits these future access patterns to form superblocks. A superblock is multiple blocks that are assigned the same path.

Look Ahead ORAM forms superblocks based on embedding table entries which will be accessed in future batches/epochs. When using superblocks, Look Ahead ORAM’s reads/writes happen at the granularity of superblocks. When a superblock size of four is accessed, all four blocks are brought to the stash. Look Ahead ORAM will assign a new path for each block in the superblock based on their future localities.

The following subsections will discuss the general architecture and detailed design of Look Ahead ORAM. Look Ahead ORAM mainly consists of two operations: The first one is preprocessing. The preprocessor will read future batches/epochs of embedding table accesses to assign future paths for each embedding table entry. The second one is training recommendation systems using the future path assignment information generated from the first operation.

A. LOOK AHEAD ORAM ARCHITECTURE

Figure 1 shows Look Ahead ORAM’s general architecture. In addition to the traditional ORAM client-server model, Look Ahead ORAM has a preprocessor node, and the ORAM client uses a GPU for training recommendation models.

ORAM Server(Server_storage): The CPU and DRAM in the cloud server are equivalent to a traditional ORAM server. DRAM in the cloud server is where the binary tree structure is stored. Server_storage will send requested embedding table entries to the ORAM client. Access patterns to the ORAM server are insecure and can be observed. Thus, Look Ahead ORAM must obfuscate accesses to the server_storage.

ORAM Client(Trainer_GPU): The trainer_GPU and its HBM are equivalent to a traditional ORAM client. The recommendation training takes place in the trainer_GPU. Huge embedding tables cannot fit into HBM. Look Ahead ORAM stores embedding tables in the binary tree format in the server_storage, where memory is cheaper and more abundant. The trainer_GPU only contains embedding table entries required to train with the current batch of inputs. Trainer_GPU will ask server_storage for embedding table
entries. Trainer_GPU will request paths corresponds to indices it needs to provide memory obliviousness.

Additionally, trainer_GPU stores the position map and the stash in the HBM. The position map contains the exact location where each embedding table index is stored, and the stash is the local storage that contains the fetched or overflowed embedding table entries. When assigning new paths to accessed blocks, trainer_GPU uses metadata provided by the preprocessor. Details about the preprocessor’s metadata will be discussed in the next subsection. Besides acting like an ORAM client, the trainer_GPU also computes MLP [3] and other operations required during training.

Preprocessor node: The third component is the preprocessor shown in figure [1]. This component is not present in the traditional PathORAM design. The preprocessor will read future training samples to form superblocks and assign a new path independently to each individual block in every superblock. Its algorithm is discussed in the section below.

B. Preprocessing Algorithm

1) Algorithm overview: The preprocessor is responsible for reading future accesses and assigning future paths to all accessed embedding table entries. This algorithm consists of dataset scan and superblock path generation.

2) Dataset scan: Assume superblock size is \( S \). The preprocessor reads future training batches/epochs and places \( S \) adjacent embedding table accesses to the same superblock bin. The binning process continues until the preprocessor reaches its memory limit. The preprocessor can scan epochs of training samples if memory space permits.

3) Superblock path generation: After binning, the preprocessor will assign a path to each superblock. Paths are sampled from a uniform random variable. Then, the preprocessor will produce a (superblock, future path numbers) tuple. Future path numbers in the tuple are future paths assigned to data blocks in the associated superblock. This final mapping is encrypted and sent to trainer_GPU. Trainer_GPU uses this metadata to assign new paths to accessed data blocks. Note that this mapping can be either stored in HBM in the plaintext or server_storage in the ciphertext. Trainer_GPU’s access to this metadata is independent of embedding table entries accessed.

Note that the preprocessing must run ahead of trainer_GPU so that trainer_GPU never has to wait for preprocessing. Luckily, in practice, preprocessing is much faster than actual training operations in the trainer_GPU.

C. Fat Tree

We observe that using big superblocks increases stash significantly. We proposed a fat-tree structure, where nodes closer to the root have a bigger bucket size because when assigning a new path to a data block, the block is more likely to be written back to nodes close to the root. Fat-tree structure shows reduced stash usage compared to a normal tree.

D. Security Analysis

The preprocessor is not a part of the cloud GPU server and is assumed to be secure and hence adversary cannot access it. Trainer_GPU’s accesses to HBM are secure because HBM is closely placed with GPU’s logical core using interposers [1], making HBM access tracing impractical. Accesses to the server_storage are oblivious because those access patterns are identical to the patterns generated by PathORAM. A proof of security of superblocks can be found in [18] and a proof of PathORAM security can be found in [15]. Communication channels in Look Ahead ORAM are secured by a standard encryption algorithm.

V. Evaluation

A. Methodology

We evaluate the performance of normal tree and fat-tree implementations of Look Ahead ORAM using different superblocks sizes compared to baseline PathORAM. We use two types of datasets 1) a permutation of 0-N addresses where none of the addresses are repeated till all the addresses are accessed at least once (referred as permutation dataset), and 2) an address pattern with Gaussian distribution made to emulate DLRM embedding table indices. The first type of dataset is the worst case access pattern for PathORAM proven in [15]. For both dataset types we conduct experiments on 10 million unique address blocks.

System configuration: We conducted our experiments on a server consists of a Intel Xeon E-2174G, and a RTX 1080 Ti. This server has 64 GB DDR4 memory and 11GB GPU memory.
B. Performance improvements

Permutation dataset: In this section, we measured the time required by the processor to access a given block. This time includes sending the path to be fetched to server_Storage, the server_Storage accessing the ORAM tree, the subsequent fetching of all blocks in that path, and the sending of all the data blocks in the path back to the trainer_GPU’s stash. The performance of a normal tree while using a superblock size of 1 is equivalent to the baseline PathORAM design. As shown in figure 2 with 10M permutation data set, using Look Ahead ORAM with normal tree structure and a superblock size of 2 and 4, gives us a speedup of 1.59X and 1.84X improvement over baseline, respectively. This shows that forming superblocks by looking into the future memory accesses gives us considerable speedup. Though when the superblock size is increased to 8, the speedup goes down to 1.3X. This is because, in our experiments, we fixed the size of buckets for each superblock size to 6. For a fixed size bucket, when the superblock size exceeds the bucket size, forming superblocks puts a lot more pressure on the tree as this requires more blocks to be located on the same path. This results in significant stash usage, which in turn leads to many background evictions.

The yellow colored last four bars in figure 2 show the performance of Look Ahead ORAM with fat-tree. With a superblock size of 1 in fat-tree, we are not taking advantage of our ability to look into the future and forming superblocks, but still paying the penalty of fetching extra blocks from memory due to the fat-tree’s large bucket size at the root level. So for a superblock size of 1, we are paying the penalty of the added bandwidth requirement without the added advantage of superblocks. The performance compared to baseline is 0.65X. When the superblock size is increased to 2 and 4, the performance improves to 1.09X and 1.62X.

When the superblock size is increased to 8, the advantage of the fat-tree is most visible. As mentioned previously, the fat-tree structure is best suited in case of heavy stash contention. Fat-tree is designed to handle large superblocks more efficiently. Hence the fat-tree outperforms normal tree implementation when the superblock size is 8. We see this result in figure 2 where a fat-tree with superblock size 8 gives a speedup of 1.81X, but a normal tree with superblock size 8 only gives 1.3X improvement.

Gaussian dataset: Figure 3 show the results for Gaussian data set for 10M data inputs. Permutation data set is proven to be the worst case access pattern for PathORAM like implementations. Because of this Gaussian data set does not suffer from the same pressure on the stash due to excessive background evictions and hence performs better than the permutation set. The results of superblock size of 1-4 show a similar pattern to the permutation dataset. But for a superblock size of 8, the Gaussian dataset does not experience enough pressure on the stash to justify fat-tree structure. The normal tree structure performs better than the fat-tree structure for superblock size 8 due to the lack of pressure on stash, the disadvantages of the fat-tree outweigh the advantages. On top of performance improvement, we get a bandwidth reduction of 3.15X while using Gaussian dataset because of the reduction in the number of background evictions and the number of actual memory accesses.

C. Stash and Background Eviction

Stash Usage: Figure 4 shows the stash usage of Look Ahead ORAM for both fat-trees and normal trees for two different superblock size configurations. For Normal-4 and Fat-4, the superblock size is 4 for a normal tree but is 8-to-4 for a fat-tree. Normal-8 and Fat-8 have a superblock size of 8 for a normal tree and 16-to-8 for a fat-tree. After around 12500 accesses, the fat-tree structure grows much more slowly than a normal tree for larger superblock sizes. Note that this decrease in stash usage comes at the cost of extra bandwidth required for the fat-tree per memory access.

VI. RELATED WORK

Static Superblocks: The idea of superblocks for PathORAM is originated in [14]. They are created statically at the system configuration. No superblocks are created or destroyed afterward. However, Prefetch-PathORAM dynamically creates and destroys superblocks every time some data blocks are accessed. PrORAM: PrORAM [18] dynamically creates and destroys superblocks using counter based history capture scheme. Prefetch-PathORAM relies on future access knowledge as opposed to history based predictions.
Fig. 4: Fat-tree vs normal binary tree. Fat-tree incurs less blocks in the stash when superblock size is large

VII. CONCLUSION

In this paper, we propose Look Ahead ORAM, a novel ORAM architecture that utilizes future memory access patterns to reduce overheads of privacy when training recommendation systems. Look Ahead ORAM preprocesses future memory accesses to form large superblocks. This allows Look Ahead ORAM always to utilize localities and improve memory access efficiency. Look Ahead ORAM’s novel three-component architecture also incorporates GPUs for training. The fat-tree structure allows Look Ahead ORAM to reduce the number of background evictions when the stash is full. With those novel changes, Look Ahead ORAM achieves nearly 2X speedups and 3.15x bandwidth reductions compared to the original PathORAM.

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