BigFoot: Exploiting and Mitigating Leakage in Encrypted Write-Ahead Logs

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ABSTRACT
Modern databases and data-warehousing systems separate query processing and durable storage. Storage systems have idiosyncratic bugs and security vulnerabilities, thus attacks that compromise only storage are a realistic threat. In this paper, we show that encryption alone is not sufficient to protect databases from compromised storage. Using MongoDB’s WiredTiger as a concrete example, we demonstrate that sizes of encrypted writes to a durable write-ahead log can reveal sensitive information about the inputs and activities of MongoDB applications. We then design, implement, and evaluate BigFoot, a WAL modification that mitigates size leakage.

1 INTRODUCTION
To take advantage of the elasticity of compute and storage resources in the cloud, many modern databases and data warehousing systems separate query processing and storage [1, 4, 19]. The two components are independently managed and connected over a network as shown in Figure 1. A coordinator receives clients’ requests and dispatches execution tasks to different query executors. Executors retrieve the data from either local memory or remote storage (e.g., a storage service such as Ceph [20] or S3 [2]), process queries, and write modified data back to remote storage for durability. This helps reduce operational costs since compute and storage can be provisioned and scaled independently.

![Figure 1: Separation between query processing and storage.](image)

Even databases that do not rely on cloud storage may use network-attached storage (NAS) in lieu of a disk attached to the query server. Persistent storage systems, whether cloud storage or NAS, have their own software stacks, including firmware, file system, OS, etc., distinct from the servers that process queries. Storage servers have their own bugs and security vulnerabilities. Consequently, storage should be viewed as a separate trust domain. Critically, persistent storage can be compromised independently of the query processor. A recent example of an attack that compromised storage without compromising query or application servers is the 2019 Capital One breach, where a former Amazon Web Services (AWS) engineer exploited a misconfiguration to obtain Capital One’s AWS credentials and used these credentials to gain unauthorized access to 106 million accounts [16].

Databases and data warehousing systems that disaggregate compute and storage should protect the secrets of the applications that use them (both data and queries) even if persistent storage is compromised. Encrypting data in persistent storage, i.e., “encryption-at-rest,” is not enough. Encryption hides the content but not the sizes of storage operations. Variable-sized reads and writes whose sizes are correlated with applications’ activities can reveal sensitive information, such as the values of inputs into these applications and the operations they are performing.

Our contributions. First, we identify write-ahead logging (WAL), a standard durability and concurrency control mechanism, as a source of fine-grained leaks about applications’ activities to compromised storage. We use MongoDB’s WiredTiger storage engine to demonstrate how an attacker in control of storage can infer secrets of a MongoDB-based application by analyzing the sizes of encrypted WAL writes that result from the application’s activities.

Second, we design, implement, and evaluate BigFoot, a segmentation and padding scheme that ensures all writes to the persistent storage are a realistic threat. We use MongoDB’s WiredTiger storage engine to demonstrate how an attacker in control of storage can infer secrets of a MongoDB-based application by analyzing the sizes of encrypted WAL writes that result from the application’s activities. We then design, implement, and evaluate BigFoot, a WAL modification that mitigates size leakage.

2 BACKGROUND
2.1 Write-ahead logging
Even databases that attempt to perform most operations in volatile memory must achieve durability. A popular technique is to checkpoint by flushing modified memory pages to disk at fixed time intervals. Crashes between checkpoints, however, may result in a loss of writes that have not yet been written to disk. Write-ahead logging (WAL) provides a way to make these writes durable [21].

In general, WAL is a family of techniques for providing atomicity and durability (two of the ACID properties) in database systems. WAL wraps information about the current write and stores it durably before the write is confirmed to the client application. Usually a log sequence number (LSN) is associated with each logged write to establish the happen-before relation [17] between logs. Log records are stored in a memory log buffer and later synchronously written to non-volatile storage by the WAL protocol. Upon failure, a data recovery scheme like ARIES [18] replays all logs in the LSN...
order to reconstruct the state of the database immediately prior to the crash.

### 2.2 Durability and recovery in MongoDB

We use MongoDB [9] as our case study and as the platform for our prototype of BigFoot. MongoDB is a popular, open-sourced, document-oriented database. WiredTiger isMongo’s storage engine.

**Checkpoints.** WiredTiger uses B-trees to store data in volatile memory. A snapshot is a consistent, durable view of these B-trees, written out to disk. Starting from version 3.6, MongoDB configures WiredTiger to create checkpoints (i.e., write the snapshot data to disk) every 60 seconds.

**Write-ahead logging.** To provide durability in the event of a failure between checkpoints, WiredTiger uses write-ahead logging to on-disk journal files [11]. WiredTiger creates one log record for each client-initiated write operation. A log record wraps all internal write operations to the WiredTiger’s in-memory data structures caused by the application-initiated write. A log record consists of a 16B header and data. Figure 2 shows the layout of headers. Note that (a) the first 4 bytes of the header of any log record are not all zeros because they contain the length of the record, and (b) this length is a multiple of 4 bytes.

![Figure 2: Header structure in log records.](image)

WiredTiger keeps track of the current checkpoint and the current starting point for WAL in the journal file. MongoDB configures WiredTiger to buffer all log records up to 128 KB in an in-memory data structure called the slot. Slots are synchronously flushed to non-volatile storage every 100 milliseconds or upon a full-sync write, whichever comes first. A full-sync write is a write operation that requires its journal record to be flushed to non-volatile storage before returning, thus ensuring that the written data survives a crash. A full-sync write provides the strictest durability, in contrast to non-sync writes where the data is recorded in a buffer in memory but there is no guarantee that it is immediately written to non-volatile storage. After a full-sync write is issued by the client to the query executor, all records in the slot buffer must be synchronized to non-volatile storage in order to commit the write.

Figure 3 shows an overview of how MongoDB achieves durability by periodically checkpointing memory data pages and appending slots of journal records to a disk file between checkpoints. After every checkpoint, all journal records whose writes “happened before” the checkpoint are automatically garbage-collected, freeing space for the future journal records. In this sense, the journal can be thought of as a circular buffer for write operations. WiredTiger keeps track of the current checkpoint and the current starting point for WAL in the journal file.

**Recovery.** When recovering from a crash, WiredTiger first looks in the data files for the identifier of the last checkpoint, then searches the journal files for the record that matches this identifier. WiredTiger then reads log records one by one from the journal file: First it scans through a 16B fixed size header to obtain meta information such as how large the whole record is. Second it reads through the data part of log record according to meta information. After reading each record, it immediately applies it and continues to the next record until all records are consumed.

![Figure 3: Checkpoints and WAL in WiredTiger.](image)

**Sharding.** MongoDB uses sharding [13] to support deployments with very large datasets and high-throughput operations that might exhaust the capacity of a single server. In the sharding mode, data is partitioned at the collection level. A collection is shared by all nodes in the cluster; each node runs a separate mongod [12] instance and stores a fraction of the collection. Each node maintains its own WAL/journal, thus a client-initiated write operation generates a journal record in the node that holds the corresponding data.

### 3 THREAT MODEL

We consider an adversary who completely controls the persistent storage but not the query processor (see Section 1). This adversary observes all durable reads and writes performed by the processor. Even if “at rest” encryption is deployed to hide the content, the adversary still observes the sizes of all reads and writes.

**Leakage in WiredTiger.** For concreteness, Figure 4 shows what an adversary in control of the disk (or any other persistent storage) observes in the case of MongoDB’s WiredTiger. We assume that the application running on top of MongoDB requires strong durability, thus every write operation is issued as a full-sync write and the corresponding WAL increment is immediately flushed to disk.

There are two types of writes in WiredTiger that can be observed by the storage adversary: checkpoint writes and WAL slot writes. Both writes are encrypted but, as we show in Section 4, their sizes...
Figure 4: Coarse- and fine-grained leakage in WiredTiger.

reveal information about the state of the application and even the data it is operating on.

A checkpoint write happens at fixed time intervals and commits to disk the result of multiple writes to the in-memory data structure. This is a coarse-grained leak. To achieve durability between checkpoints, a WAL slot write follows every application-initiated write to the in-memory slot buffer. If the application write is small (respectively, large), the corresponding incremental write to the on-disk journal is small (respectively, large). This is a fine-grained leak.

Another potential source of leakage is database logs which, in the case of MongoDB, are stored on disk in plaintext [10]. Depending on the configuration parameters controlling verbosity, logs may contain sensitive information about the MongoDB instance and applications running on top of it. The enterprise version of MongoDB uses log redaction to suppress messages associated with logged events, leaving only metadata, source file names, or line numbers related to the event. For example, if the logging message describes the tuple being inserted, log redaction modifies the log to remove the content of the tuple.

Out-of-scope threats. As explained above, we assume that the query processor is separate from storage. For the purposes of this paper, all attacks on the query processor are out of scope. In particular, we assume that the attacker does not have access to the query processor’s memory.

In the rest of this paper, we focus primarily on the encrypted, incremental WAL writes because their sizes reveal the most fine-grained information about applications’ activities. Leakage from checkpoint sizes may reveal coarse-grained information (such as relative changes in the overall memory footprint), but we do not investigate it in this paper. Attacks that exploit the relative timing of writes (e.g., how quickly writes follow each other) are also out of scope for the purposes of this paper.

4 INFERRING SECRETS OF MONGODB APPLICATIONS

In this section, we use MongoDB’s WiredTiger storage engine to demonstrate how the sizes of encrypted, incremental writes to the journal file can reveal applications’ secrets. We focus on two types of secrets: inputs into an application and operations performed by an application.

For the purposes of this section, we assume that the storage adversary knows which application is running on top of MongoDB. This information may be available from the logs and/or other leakage channels unrelated to the durability mechanisms.

4.1 Inputs into an e-commerce application

We simulate a very simple e-commerce application using the Brazilian E-Commerce Public Dataset posted on Kaggle. This dataset has information about 100K orders made at multiple marketplaces in Brazil from 2016 to 2018. Figure 5 shows the schema. Information about each order includes order status, price, payment, freight performance, customer location, product attributes, and customers reviews. We treat each table in the schema as a collection of documents in MongoDB.

In our simulated workload, the application simply inserts records from the olist_customers_dataset into MongoDB one by one. The attributes of these records are customer_id, customer_unique_id, customer_zip_code_prefix, customer_city, and customer_state.

Adversary’s objective. Each record insertion results in an incremental write to the WiredTiger’s journal file. Due to encryption at rest, the storage adversary observes only the sizes of these writes. The only source of variation in the size of the record is the “customer’s city” attribute. The adversary’s goal in this case is to use the size of the WAL write to infer the size of the original record written by the application and, from that, the value of the “customer’s city” attribute. This information can have commercial value. For example, it can help estimate where a company is expanding or seeing the biggest growth.

Directly inferring the value of the “customer’s city” attribute is not feasible for two reasons: (1) some city names have the same length, thus the corresponding records have the same size, and (2) there are only six distinct sizes of WAL writes that can be produced by records from the olist_customers_dataset because WAL write sizes are always multiples of 128 bytes. Figure 6 illustrates the latter: records with city names whose length is under 20 produce WAL writes of only 3 different sizes.

Therefore, our adversary has a coarser objective: given the size of a WAL write, infer the range of potential city names in the original list. 

![Figure 5: Brazilian E-Commerce Public Dataset Schema.](https://www.kaggle.com/olistbr/brazilian-ecommerce)
Figure 6: Records of different sizes may produce equally-sized WAL writes.

Table 1: Precision and recall for different WAL sizes.

| WAL Size (B) | City Name Range | # of City Names | Precision | Recall |
|--------------|-----------------|-----------------|-----------|--------|
| 128          | (0, 15)         | 3270            | 0.90      | 0.87   |
| 384          | (15, 18)        | 362             | 0.31      | 1.00   |
| 512          | (18, 21)        | 293             | 1.00      | 0.18   |
| 768          | (21, 24)        | 148             | 0.49      | 1.00   |
| 1152         | (24, 27)        | 41              | 1.00      | 0.13   |
| 1536         | (27, 30)        | 5               | 1.00      | 0.59   |

Table 1 shows the tradeoff between the accuracy of inference and the coarseness of inferred information: the bigger the interval, the higher the precision and recall. Bigger intervals contain more city names, thus the adversary infers less information about the true value of the city name in the record that generated a given WAL write. Smaller intervals offer lower precision or lower recall, but the adversary infers more information. Accuracy of inference is not uniform across intervals, e.g., longer city names are more vulnerable.

4.2 Resources of a medical application

To illustrate another type of adversarial inference, we show that a storage adversary can learn sensitive information by inferring the operations performed by medical applications running on MongoDB (as opposed to inputs into these applications).

Fast Healthcare Interoperability Resources (FHIR) [5] is the next-generation standards framework for health-care data exchange. FHIR-based data systems provide schemas and REST APIs specified in the standard to enable data exchange over HTTP between medical applications. FHIR-enabled applications include mobile and cloud-based health-care apps, EHR systems, server communication in institutional health-care providers, etc. FHIR solutions are built from modular components called "resources." A resource represents any health-care concept, e.g., patient, appointment, or medication, in a JSON form consisting of key-value pairs—see an example in Listing[1].

Listing 1: Schema for "Schedule" resource.

We simulate a very simple medical application that inserts instances of FHIR resources as documents into MongoDB.

**Adversary’s objective.** As before, the storage adversary only observes the sizes of WAL writes. In this case, the size of a WAL write is largely determined by the number of key-value pairs in the resource written by the application. The adversary’s objective is to infer the type of this resource and thus the operation performed by the application.

**Inferring resource type.** In our simulated workload, we create 10 instances for each resource type and randomly insert them one by one into the database in the full-sync mode. For each resource type, we record its schema and the average of WAL write sizes resulting from the insertion of resources of this type. We then construct a reverse mapping from WAL write sizes to resource schemas, shown in Figure 7. Two WAL write sizes map to 3 schemas each, twelve WAL write sizes map to 2 schemas each, and fifty-five WAL write sizes map to unique schemas. In the latter case, the adversary observing a particular WAL write size can infer the schema and resource type inserted by the application with 100% confidence. Figure 8 shows examples of sensitive schemas that can be inferred in this way.

5 MITIGATING WAL LEAKAGE

To mitigate leakage, we propose a modification to WiredTiger’s WAL mechanism. Our modification, BrGoOFP, ensures that every WAL write to persistent storage has the same size. This property ensures that the storage attacker cannot exploit the sizes of WAL writes to infer secrets of MongoDB applications.
Figure 7: Number of schemas corresponding to different WAL write sizes.

Figure 8: Examples of schemas that can be inferred from WAL write sizes.

5.1 Segmenting WAL slots

The naive solution to the problem of variable-sized slot writes is to pad every write to the full slot size. This solution is infeasible due to prohibitive space overhead (see Section 6.3).

Figure 9 shows how BigFoot works. It splits each slot write into fixed-size segments, pads the last segment with ‘0’ if necessary, then writes each segment to the on-disk journal file sequentially. Because the lengths of log records and segments are multiples of 4, the padding always consists of one or more 4-byte, all-zero blocks. Algorithm 1 shows the pseudocode of the segmentation algorithm, parameterized by the segment size \( S \).

Algorithm 1 Split slot into segments

\[
\begin{align*}
\text{Input: Slot SL, Segment Size } S \\
1: & \quad \text{function } \text{Segmentation(SL,} S) \\
2: & \quad \text{SSET = } \{\} \\
3: & \quad \text{while } \text{SL.size() } \geq S \text{ do} \\
4: & \quad \quad \text{seg, SL = truncate(SL, } S); \quad \text{// Split off a segment} \\
5: & \quad \quad \text{writeToJournal(seg);} \\
6: & \quad \quad \text{Pad remaining SL so that } \text{SL.size()} = S; \\
7: & \quad \text{writeToJournal(SL);} \\
\end{align*}
\]

Segment size is the key configuration parameter. Small segments reduce the space overhead caused by padding writes to the segment boundary, but they also increase the latency of big writes by increasing the total number of segments (since segments are written separately and sequentially). Big segments, on the other hand, increase the space overhead and reduce latency. In Section 6, we evaluate this tradeoff.

5.2 Recovery

When recovering from a crash, BigFoot reads from the last checkpoint in the journal file, same as the unmodified WiredTiger. The recovery process works the same as in the unmodified WiredTiger whenever it encounters a non-zero header. After reading a full log record whose length is known from the header, it skips all 4-byte, all-zero blocks (all such blocks must be padding—see above) until it encounters a 4-byte, non-zero block, which must be the beginning of the header of the next log record. The recovery process ends when all log records in the journal file have been consumed.

6 EVALUATION

Compared to the current WAL implementation in WiredTiger, BigFoot imposes a latency overhead due to segmenting each slot write into multiple segment writes and a space overhead due to padding all writes to the segment boundary. The latency overhead is most severe for large and/or concurrent writes when slots are mostly full. The space overhead is most severe for small, sequential writes when slots are mostly empty. Large segment sizes incur lower latency overhead but higher space overhead; small segment sizes have the opposite effect.

To evaluate the tradeoff between the segment size and these overheads, we use (a) micro-benchmarks to measure the latency of single writes, and (b) standard concurrent benchmarks to measure latency and throughput when slots are full. To measure space overhead, we use a sequential version of the standard benchmark that processes and persists write queries one by one. We also compare recovery time with the current implementation.

Experimental setup. We deployed a MongoDB instance in an AWS Virtual Private Cloud, configured with 16 cores, 128GB DRAM and 256GB Elastic Block Store (EBS) and running 64-bit Ubuntu 16.04 with Linux kernel 3.2.0-23.

For our Single Query micro-benchmark, we use insert queries of different sizes: small (128B), medium (512B) and large (1KB). Our macro-benchmarks are based on the Yahoo! Cloud Serving Benchmark (YCSB), designed for performance comparisons of key-value storage systems. The original YCSB contains Insert, Delete,
Update, and Read operations. Since BigFoot changes only the processing of writes, we created an all-insert version of YCSB. Each write operation inserts a tuple of 10 attributes; the size of each attribute is drawn from a certain distribution.

We experimented with several distributions, including uniform, Zipf, and constant. For Zipf distributions, the parameter controls the skewness of the distribution. For constant-size experiments, we experimented with $S = 200B$ and $S = 800B$ as the write size. In all cases, the size of each attribute is smaller than or equal to 100B, thus the maximum write size is $100*10 = 1000B$.

As explained above, we use the concurrent version of this benchmark to measure the latency and throughput overhead and the sequential version to measure the space overhead. Concurrent YCSB processes all writes concurrently. For this benchmark, the full-sync mode is disabled in MongoDB, therefore WAL writes are buffered in the slot and the entire slot is flushed to disk periodically. Sequential YCSB processes the same writes sequentially, with the full-sync mode enabled. Therefore, each WAL write is flushed to disk individually.

### 6.1 Latency overhead of a single write

Figure 10 shows how latency of a single write varies depending on the write size in the original WiredTiger and BigFoot with different segment sizes. As expected, latency increases with the segment size in all systems. BigFoot imposes $0.3 - 1\%$ extra latency because padding increases the amount of data to be written, more so when segments are large.

![Figure 10: Latency of a single write.](image)

### 6.2 Throughput and latency overhead of concurrent writes

Figure 11 shows throughput and latency under different concurrency levels. Writes for this experiment are generated from a uniform (0,1K) distribution, following YCSB. Latency increases as contention between threads becomes more intensive. Throughput starts declining when the system is saturated. The smaller the segments, the earlier BigFoot saturates (due to the increased number of writes for each slot flush). BigFoot with 4K segments saturates at almost the same point as the original WiredTiger. Depending on the segment size, BigFoot incurs $1 - 7\%$ overhead in throughput and $3 - 13\%$ overhead in latency.

The distribution of write sizes does not have a significant effect on the tradeoff shown in Fig. 11. Under the Zipf and constant distributions, the absolute values of latencies and throughputs, saturation points, and the differences between the original WiredTiger and BigFoot remain the same for all segment sizes as in Figure 11.

We conclude that BigFoot imposes a modest performance overhead vs. the original WiredTiger in the worst scenario for BigFoot, where all slots are full before they are flushed to disk.

### 6.3 Space overhead

We measure the space overhead of BigFoot by calculating Relative Cost (RC) as the ratio between the amount of data written to disk by BigFoot and that written to disk by the original WiredTiger for the same queries. For these experiments, we use the Sequential YCSB benchmark described above. This benchmark represents the worst-case scenario. In the original WiredTiger, it results in the biggest information leak to the storage adversary due to the highly variable sizes of individual WAL writes. In BigFoot, it results in the biggest space overhead due to the padding of each write.

![Figure 12: Relative space overhead for different distributions.](image)

Under the uniform write-size distribution in the YCSB benchmark, the original WiredTiger needs 25.5MB to persist WAL writes. Under a Zipf distribution, this amount varies from 2.58MB to 5.15MB depending on the skewness of the distribution. Under a constant distribution with 200B writes (respectively, 800B), this amount is 10MB (respectively, 40MB).
A naive padding solution which pads all writes to the full slot size would always require 640MB, regardless of the write-size distribution. This is equivalent to the 16x best-case or 248x worst-case relative space overhead.

Figure 12 shows the relative space overhead of BigFoot. This overhead is lowest under the uniform write-size distribution and when writes have large, constant size. When the distribution is highly skewed towards small WAL writes (Zipf with $\alpha = 1.3$), the space overhead is highest because small writes require a lot of padding. For a given distribution, larger segment sizes always result in larger space overhead.

6.4 Recovery time
For this experiment, we deliberately crash the system between checkpoints at times corresponding to different WAL sizes.

Figure 13 shows that the original WiredTiger needs between 1.18s and 1.43s to recover for all WAL sizes. BigFoot increases recovery time by 10 – 30% because it requires more I/O when reading WALs from disk during recovery.

7 LIMITATIONS
BigFoot aims to eliminate variable-sized WAL writes, which are the main source of fine-grained leakage to compromised storage in databases and data warehousing systems that separate query processing and storage. Eliminating variable-sized writes is important because, as we showed in Section 4, they reveal information even when encryption-at-rest is deployed.

BigFoot does not address coarse-grained leakage from the size of checkpoints. Checkpoints typically incorporate a large number of individual writes, and we are not aware of any method for inferring sensitive information from their sizes. Possible less-sensitive inferences include inferring the specific application operating on checkpoints, the size of its write activity, which is the topic of this paper.

Furthermore, we are not aware of any method to distinguish, say, two segment writes resulting from a slot filled by a large application write and two identically sized and timed segment writes resulting from a slot filled by multiple small, concurrent writes.

8 RELATED WORK
Prior work on information leakage from encrypted storage [3, 8, 14] focused on leakage-abuse attacks against “leaky” encryption schemes that permit keyword searches, comparisons, and other queries on encrypted data. In this paper, we focus on conventional at-rest encryption that does not permit any queries on the encrypted data and investigate leakage from the sizes of encrypted writes performed by the query processor.

There has also been work on leakage from access patterns [7, 15] and hiding these patterns by smoothing write frequencies [6]. Neither these attacks, nor defenses deal with leakage from the sizes of individual writes, which is the topic of this paper.

9 CONCLUSIONS
Storage-only attacks are a realistic threat to modern databases and data warehousing systems. We demonstrated that encryption alone is not enough to hide applications’ secrets from compromised storage. Fine-grained encrypted writes to the write-ahead log are correlated with applications’ inputs and activities and can thus reveal them to a storage attacker. We proposed BigFoot, a segmentation and padding scheme that equalizes the sizes of WAL writes. We implemented BigFoot as a modification to MongoDB’s WiredTiger storage engine and showed that it mitigates inference attacks at a modest performance cost.

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