

Tracking Network Events with Write Optimized Data Structures

The Design and Implementation of TWIAD: The Write-Optimized IP Address Database

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Abstract—Access to network traffic records is an integral part of recognizing and addressing network security breaches. Even with the increasing sophistication of network attacks, basic network events such as connections between two IP addresses play an important role in any network defense. Given the duration of current attacks, long-term data archival is critical but typically very little of the data is ever accessed. Previous work has provided tools and identified the need to trace connections. However, traditional databases raise performance concerns as they are optimized for querying rather than ingestion.

The study of write-optimized data structures (WODS) is a new and growing field that provides a novel approach to traditional storage structures (e.g., B-trees). WODS trade minor degradations in query performance for significant gains in the ability to quickly insert more data elements, typically on the order of 10 to 100 times more inserts per second. These efficient, out-of-memory data structures can play a critical role in enabling robust, long-term tracking of network events.

In this paper, we present TWIAD, the Write-optimized IP Address Database. TWIAD uses a write-optimized B-tree known as a B^f tree to track all IP address connections in a network traffic stream. Our initial implementation focuses on utilizing lower cost hardware, demonstrating that basic long-term tracking can be done without advanced equipment. We tested TWIAD on a modest desktop system and showed a sustained ingestion rate of about 20,000 inserts per second.

I. INTRODUCTION

The recent hack of the US government’s Office of Personnel Management (OPM) exposed the personal information of millions of federal employees. The OPM breach illustrates the critical role that network monitoring systems have and will continue to play in cybersecurity. According to the Department of Homeland Security (DHS), an intrusion-detection program called Einstein was involved in the response to the breach [1]. DHS’s Computer Emergency Readiness Team used the Einstein system to discover the recent hack at OPM. After OPM suffered a breach in March 2014, the agency beefed up its cybersecurity via a “comprehensive network monitoring plan, through which OPM detected new malicious activity.”

Tracking network events continues to play an integral part of securing data and communication networks. This includes being able to store all of the connections occurring over a network, enabling applications such as intrusion detection

and post-event forensics. Effective network event tracking requires data structures that can consistently provide strong ingestion performance guarantees over long periods of time. Furthermore, recent public compromises such as the OPM breach have highlighted the need for maintaining records that cover years worth of traffic.

Many institutions use common data stores such as Hadoop [2] in server clusters on advanced hardware for network situational awareness. Although this solution may be performant, it is costly because of the hardware and maintenance involved. We wanted a lightweight solution with a smaller start-up cost that maintained high performance guarantees.

Other situational awareness solutions use large databases based on Bloom filters, a probabilistic data structure for approximate membership queries [3]. Bloom filters are placed in front of data structures such as B-trees and improve query performance by providing constant-time, negative answers to point queries. Since our solution must be efficient for point and range queries, Bloom filters alone are insufficient because they do not improve range query performance. Moreover, Bloom filters are only viable when they can be contained within RAM, limiting their ability to keep long-term data that grows without bound.

Finally, it might seem that solid state drives (SSDs) solve many of the issues associated with network traffic ingestion since they have random I/O performance and latency orders of magnitude better than traditional spinning hard-disk drives (HDDs). However, SSDs are substantially more expensive per gigabyte than HDDs, which can be a prohibitive barrier to widespread use of SSDs for network monitoring.

Furthermore, the issue of write amplification occurs uniquely in SSDs because the actual physical size of the data written to disk may be a multiple of the logical size of the data intended to be written [4]. Flash memory uses relocate-on-write, which erases memory before it is rewritten and requires garbage-collection because the erase operation is much less precise than the write operation. Therefore, writing to a SSD requires accessing and moving user data and metadata more than once. Rewriting on the disk reads, updates, and rewrites existing physical data to a new location on the disk. Larger amounts of data must be erased and rewritten than the actual amount required by the new data. Flash memory disk blocks wear out as data is erased and rewritten, shortening the life of an SSD. As a result of cost and write amplification, SSDs alone

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are not a solution to the challenges of network monitoring on a large scale. Therefore, our solution must perform well on HDDs as well as SSDs.

We therefore propose the use of write-optimized data structures (WODS) [5]–[10] for I/O-efficient tracking of long-term network traffic. WODS are designed to resolve the bottleneck caused by writing to disk and can ingest data up to two orders of magnitude faster than traditional B-trees. Additionally, WODS mitigate write amplification in SSDs by writing larger blocks of data to disk at a time and reducing the amount of physical memory that needs to be deleted and rewritten.

Write-optimization has been successfully implemented in many commercial key-value stores and databases [11]–[17]. Additionally, previous research demonstrates the feasibility of write-optimization in indexing core system components such as file systems [18].

We present *TWIAD*, a write-optimized database tailored to IP address tracking. We use the mature B^ε -tree implementation from Tokutek’s Fractal Tree Index (ft-index) [16] as the index under *TWIAD*. While we initially focus on tracking IP addresses, our system is generic and can easily be adapted to track other network data such as domain names, complete URLs, and email addresses. Our initial results show that a B^ε -tree-based index provides a feasible, lightweight, and portable database for tracking network events. Our contributions include:

- the application of write-optimized data structures to network event tracking
- the design and implementation of a write-optimized IP address database (*TWIAD*) and associated query tools
- an initial performance analysis of *TWIAD* on basic hardware showing a high ingest rate of 20,000 entries per second.

The rest of the paper is organized as follows: we review related work and background information in Section II, describe the requirements and resulting design in Section III, present our results in Section IV, discuss future applications of *TWIAD* and write-optimized data structures as a whole in Section V, and conclude our work in Section VII.

II. BACKGROUND AND RELATED WORK

In this section, we describe write-optimized data structures, streaming databases, and existing network event tracking systems.

A. Write-Optimized Data Structures

Here, we cover write-optimized data structures and their performance bounds. Specifically, we describe the B^ε -tree and the reasons we have chosen it for network event tracking. The best WODS (including the B^ε -tree) subvert a trade-off between read and write performance and instead can outperform B-trees.

The B-tree is a data structure where internal nodes have variable numbers of children within a predefined range. The elements of the tree are maintained in sorted order at the leaves. Each internal node has keys directing searches to the subtree associated with the query value. B-trees support

insertions, deletions, sequential accesses, and point queries in $O(\log_B N)$ time.

1) B^ε trees: A B^ε -tree is a B-tree with buffers at each node. New insertions take place at the root buffer of the B^ε -tree. When a node’s buffer is filled, items are moved from that node’s buffer to the buffer of one of its children—this process is referred to as flushing. The algorithms for point and range queries are the same as those in a B-tree, but with a search through the buffer of each internal node on a root-to-leaf path.

B^ε -trees have asymptotically better performance than B-trees. For example, consider a B-tree of N elements where each node has B keys of constant size and where the size of keys is far larger than the size of the related data. Such a tree has fanout B and therefore has height $O(\log_B N)$. Therefore, inserts and searches will take $O(\log_B N)$ I/Os. A range query with k results then requires $O(\log_B N + \frac{k}{B})$ I/Os.

In contrast, a B^ε -tree has nodes of size B . Each internal node of the tree has B^ε children where $0 < \varepsilon \leq 1$. Each node has a “pivot key” for each child, so the keys take up B^ε space in each node. The remaining $B - B^\varepsilon$ space in each node is used to buffer inserted elements.

ε is a tunable parameter that determines the tree’s fanout. The tree’s fanout is B^ε and its height is $O(\log_{B^\varepsilon} N) = O(\frac{1}{\varepsilon} \log_B N)$. Therefore, searches in a B^ε -tree are slower than those in a B-tree by a factor of $\frac{1}{\varepsilon}$. However, whenever a node flushes elements to one of its children, it moves at least $\frac{B - B^\varepsilon}{B^\varepsilon} \approx B^{1-\varepsilon}$ elements. Each element must be flushed $O(\frac{1}{\varepsilon} \log_B N)$ (the height of the tree) times to reach a leaf. Therefore, the amortized cost of inserting N elements is $O(\frac{1}{\varepsilon B^{1-\varepsilon}} \log_B N)$. Furthermore, range queries cost $O(\frac{1}{\varepsilon} \log_B N + k/B)$ I/Os where k is the number of elements returned by the query.

We present an example: consider $\varepsilon = 1/2$. Point and range query costs are now $O(\log_B N)$ and $O(\log_B N + \frac{k}{B})$ respectively. Although these are the same asymptotically as query bounds for B-trees, the insert cost for the B^ε -tree is $O(\frac{\log_B N}{\sqrt{B}})$, an improvement by a factor of \sqrt{B} over traditional B-trees.

Additionally, B^ε trees have much larger nodes than B-trees. Larger nodes improve range query performance because the data is spread over fewer nodes and therefore requires fewer disk accesses to read it in. B-trees must use smaller nodes because every new addition to the database requires that a node be completely rewritten. In contrast, writes are batched in B^ε trees, allowing their nodes to be much larger than those of a B-tree — for example, nodes in a B-tree are generally around 4 or 6KB, while a typical node in Tokutek’s implementation of a B^ε -tree is 4MB. As a result, the height of a B^ε tree is not much greater than that of a B-tree on the same data. Therefore, point query performance in a B^ε tree is comparable to point query performance in a B-tree.

For example, consider a key-value store of 1TB of data, with keys of size 128B and records (key+value) of size 1KB — assume that data is logged and that all updates in the log are periodically applied to the main tree in batch. Assume that a common server has about 64GB of RAM.

First, we examine a B-tree with 4KB nodes given the above situation. The fanout of the tree is 4KB/128B = 32. Even if all of the internal nodes of the tree can fit into RAM, only a small fraction of the 1TB of leaf nodes can be held in cache. Given a sequence of random insertions, most updates will require 2 I/Os — 1 I/O to read in the target leaf and another to write it back to disk.

In contrast, consider a B^ϵ -tree with branching factor 10 and nodes with size 1MB. Again, all internal nodes can fit in cache, but the leaves must be held on disk. When items are inserted into the tree, they are stored in the tree’s root buffer. The root is cached, so this action requires no I/Os. When an internal node becomes full and flushes to a non-leaf child, the data structure requires two writes — one to update the parent and one to update the child. Since both nodes are cached, no reads are necessary. If an internal node flushes its buffer to a leaf, one read is required to load the leaf into memory. There will be 1TB/1MB= 2^{20} leaves. Furthermore, the tree has fanout 10, so its height will be $1 + \log_{10} 2^{20} \approx 7$. Therefore, each item is involved in 14 I/Os because it is written and read once at each level of the tree.

While it may seem that this performance is worse than that of a B-tree, each flush in the B^ϵ -tree moves $\sim 1\text{MB}/10 \approx 100\text{kB}$ of data, or around 100 items. The data moved in each flush is approximately proportional to the node size divided by the branching factor. Therefore, the amortized cost of flushing an item to a leaf is 14/100. A B-tree requires 2 I/Os for each item, so in our example the B^ϵ tree can insert data $2/(14/100) \approx 14$ times faster than the equivalent B-tree. Furthermore, this speedup grows as key-value pairs get smaller as in connection log storage.

Both the B-tree and the B^ϵ tree require a single I/O to read the corresponding leaf in a point query. However, range queries can be much faster in a B^ϵ -tree because the B^ϵ -tree seeks once for each leaf size. In our example, the B-tree would need to seek every 4KB whereas the B^ϵ tree would seek once every 1MB.

B^ϵ -trees can achieve further improved performance through upserts, an efficient method for updating key-value pairs. If an application wants to update a value associated with some key k in the tree, it inserts a message $(k, (f, \Delta))$ into the tree, where f is some function that can be used to apply the change denoted by Δ to the old value associated with k .

This message is inserted into the tree normally. However, when the message is flushed from a node to one of its children C , the tree checks whether C ’s buffer contained the old value v associated with the key k . If so, then the tree replaces v with $f(v, \Delta)$ and discards the upsert.

If the key k is queried before the function from the upsert message is applied, the B^ϵ -tree calculates $f(v, \Delta)$ while answering the query — this does not affect query performance because an upsert for a key k will always be on the path from the root to the leaf containing k . Therefore, upserts can improve update speed by orders of magnitude without reducing query performance.

2) *Log-structured Merge Trees*: The log-structured merge tree (LSM tree) [19], [20] is another write-optimized data

TABLE I
ASYMPTOTIC I/O COSTS OF VARIOUS WRITE-OPTIMIZED DATA STRUCTURES

Data Structure	Insert	Point Query w/o Upserts	Point Query w/ Upserts	Range Query
B-tree	$\log_B N$	$\log_B N$	$\log_B N$	$\log_B N + \frac{k}{B}$
LSM	$\frac{\log_B N}{\epsilon B^{1-\epsilon}}$	$\frac{\log_B^2 N}{\epsilon}$	$\frac{\log_B^2 N}{\epsilon}$	$\frac{\log_B^2 N}{\epsilon} + \frac{k}{B}$
LSM+BF	$\frac{\log_B N}{\epsilon B^{1-\epsilon}}$	$\log_B^2 N$	$\frac{\log_B^2 N}{\epsilon}$	$\frac{\log_B^2 N}{\epsilon} + \frac{k}{B}$
B^ϵ -tree	$\frac{\log_B N}{\epsilon B^{1-\epsilon}}$	$\frac{\log_B N}{\epsilon}$	$\frac{\log_B N}{\epsilon}$	$\frac{\log_B N}{\epsilon} + \frac{k}{B}$

structure. There are many variations on the LSM tree, but generally they have a logarithmic number of indices (data structures, e.g., B-trees) of exponentially increasing size. Once an index at one level fills up, it is flushed and merged into the index at the next largest level. Commercial write-optimized databases often use LSM trees.

Although LSM trees can have the same asymptotic complexity as a B^ϵ -tree, queries in a naïve implementation of a LSM tree can be slow, as shown in Table I. Steps have been taken to improve the query performance of LSM trees—of note, many implementations of LSM trees now use Bloom filters [3] at each index [11]–[15]. Point queries in LSMs with Bloom filters have been reported to improve to $O(\log_B N)$, therefore matching B-tree point query performance.

However, Bloom filters do not help with range queries, because the successor of any key may be at any level of the data structure. Furthermore, the viability of Bloom filters degrades with upserts. To compute the result of a query, all relevant upserts must be applied to the key-value pair. If there are many possible upserts at each level of the LSM tree, searches need to be performed at each of those levels. LSMs only match B-tree query performance in specific cases, while B^ϵ -trees match B-tree query times in general.

Since range queries are common in network event detection systems, we chose B^ϵ -trees as the underlying data structure for TWIAD because of LSM range query performance.

B. Streaming Databases

A great deal of progress has also been made in the related field of stream processing engines (SPE). While data stream managers have important applications in network event tracking, most of the literature is focused on developing query schemes and algorithms [21]–[24]. Some of the issues identified by the streaming community such as approximate query results, updating query results over time, and dynamic query modification are outside of the scope of this paper.

Our vision for TWIAD is that of a write-optimized streaming database for network event tracking. Connection logs are constantly fed into the database — the main goal is to process a large volume of data consistently over time while maintaining ingestion guarantees. Streaming research has important applications to network event tracking and write-optimization. We are currently focusing on optimizing ingestion and leave the integration of results from streaming research as future work to optimize queries.

C. Network Event Tracking Databases

Previous development has also been done on large databases for network traffic monitoring. Network traffic monitoring solutions differ from traditional relational database management systems (RDBMSs) in the following ways:

- 1) The data and storage must be stream-oriented. Fast ingestion and sequential access are important, while fast random access and concurrency control are not.
- 2) Since network traffic data is usually only used a few times (or even once), load time is a significant cost. Therefore, the database must maintain data integrity over long periods of time while still loading streams of data into the database.
- 3) Network connection logs are aggregations of many small records with fields a few bytes wide, so per-tuple overhead in RDBMSs can lead to a prohibitive cost in space.

Prior work on network event tracking databases has focused on developing query languages for streams. Systems like Gigascope [25] and Tribeca [26] propose query languages for complex analysis. The inventors of the existing systems note that performance for a stream database is measured by how high the input stream(s) rate can be before it begins dropping data, not how fast the database can answer queries. Specifically, Cranor et al. observe that “touching disk kills performance—not because it is slow but because it generates long and unpredictable delays throughout the system.” Our system, TWIAD is designed to specialize in ingesting data quickly and predictably.

D. Write-Optimized Intrusion Detection Systems

Some IDS companies are beginning to offer services that include write-optimized databases. For example, Countertack, an IDS software company, uses big data analytics from Cloudera, which is built on Hadoop and HBase [27]. Similarly, Google’s Stenographer does simple packet capture and uses LevelDB for storage [28]. It is designed to write packets to disk quickly and not well suited to reading back large amounts of packets. Finally, Hogzilla is another open source IDS supported by Snort, Apache Spark, and HBase [29].

While these systems are important steps towards using write optimization in network event tracking, we wanted to build a lighter-weight and simple tool that processes logs while still leaving the user freedom to determine what kind of analytics they want to do on the data.

III. REQUIREMENTS AND DESIGN

TWIAD is a write-optimized database built on Tokutek’s Fractal Tree index, an implementation of a B^ε-tree.

A. Requirements

We designed TWIAD to leverage the performance strengths of B^ε-trees. We focused primarily on ingestion performance—the database will answer queries, but most of the computation is spent on inserting events documented in connection logs into the database.

TABLE II
EXAMPLE ROW STRUCTURE OF BRO CONNECTION LOG

field type	ts time	uid string	id.orig_h addr	id.orig_p port
value	980997832.690939	Ch80yl33lQkOymHcab	209.11.146.100	111
field type	id.resp_h addr	id.resp_p port	proto enum	service string
value	0.254.205.104	36831	tcp	-
field type	duration interval	orig_bytes count	resp_bytes count	conn_state string
value	0.075242	0	0	RSTOS0
field type	local_orig bool	missed_bytes count	history string	orig_pkts count
value	-	0	HR	2
field type	orig_ip_bytes count	resp_pkts count	resp_ip_bytes count	tunnel_parents set[string]
value	84	0	0	(empty)

B. Software

We used the publicly available B^ε-tree implementation (ft-index) from Tokutek [30].

Our contribution is a system designed to mediate between network connection data and the underlying B^ε-tree while simultaneously answering queries. We chose to implement this layer in C because the original index was in C and we wanted to maximize performance without going through other languages.

One of our design goals for the database is for the index to be “loosely coupled” with the IDS. Therefore, we chose to implement it as a tool for processing logs from the IDS rather than integrating it with the IDS. That also means that the IDS can handle bursts, since it is always just logging. The indexer can run in the background at low priority, it can fall behind and then later catch up when the system is less busy.

C. Database Design

The database is designed specifically to store network connection logs — we used logs from the Bro IDS system, a sessionization and intrusion detection tool. Fields from a typical connection log and an example row are provided in Table II. The database can easily be extended to ingest other types of logs and inputs.

We want to access any connection information regarding an IP in a query, regardless of whether it was the origin or responder IP. Therefore, we insert every row in the connection logs twice — once with the the origin and responder IP address and port in the order of the original row as specified in Table III and again with the origin and responder IP addresses and ports switching order in the key as detailed in Table V. The value is the remaining fields not included in the key.

As a result, two database entries are created for each row in a connection log. To indicate which of the entries is “reversed” (i.e. the order of the origin and responder ports and addresses was switched), we set the byte isReversed to 1 if the entry was reversed and 0 otherwise.

The key and value formats are described in Table III and Table IV are based on Bro log format. We chose this format in order to query specific IP addresses as well as range over time for that IP address. Furthermore, we appended the other fields to the key to prevent the possibility of collisions.

TABLE III
KEY DESIGN

Byte Range	Length	Field
[0, 3]	4	Origin IP
[4, 11]	8	Timestamp (*10000 second since epoch)
[12, 14]	3	Origin Port
[15, 18]	4	Destination IP
[19, 21]	3	Destination Port

TABLE IV
VALUE DESIGN

Byte Range	Length	Field
[0, 3]	4	Protocol
[4, 11]	8	Duration
[12, 19]	8	Origin Bytes
[20, 27]	8	Response Bytes
[28, 32]	5	Connection State
[33, 36]	4	Origin Packets Bytes (sans header)
[37, 40]	4	Response Packets Bytes (sans header)
[41]	1	isReversed

D. Client Architecture

We designed a client-side CLI tool to relay queries from an authorized user to the server and to receive and display results. The goals of the CLI tool were to easily integrate into users' workflows and respond to queries. Results of the queries are given in some value-separated format for easy user processing.

Common queries include searching for connections with a specific IP address or subnet or over some time range.

We provide a few examples of usage:

```
/twiad:twiad-client --ip 18.281.23.9
```

The first query requests all connections involving a specific IP address over all time stored in the database.

```
/twiad:twiad-client --subnet  
13.48.133.201/8 --year
```

The second query requests all connections involving the specified subnet over the past year. There are flags available to query the past week, month, quarter, and year.

```
/twiad:twiad-client --subnet  
13.48.133.201/16 --start 2010:1:2:10:30:5
```

The third query requests all connections involving the specified subnet starting from the beginning of the time period after the start flag. Times are entered in the format yyyy:mm:dd:hh:mm:ss. For example, the above time is January 2 10:30:05 0700 MST 2010.

The tool also allows the user to specify the end of a requested time period with `--end`.

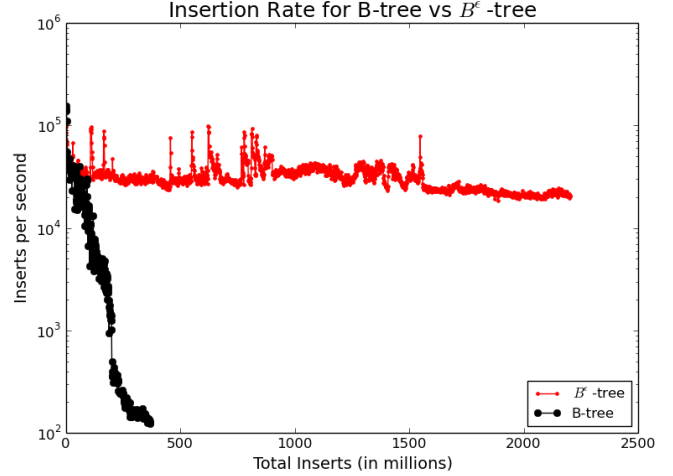
IV. RESULTS

To benchmark TWIAD we used the publicly available backscatter dataset from the Center for Applied Internet Data

TABLE V
REVERSED KEY DESIGN

Byte Range	Length	Field
[0, 3]	4	Destination IP
[4, 11]	8	Timestamp (*10000 seconds since epoch)
[12, 14]	3	Destination port
[15, 18]	4	Origin IP
[19, 21]	3	Origin Port

Fig. 1. Insertion rate vs. number of inserts



Analysis (CAIDA) [31]. We ran tests on several basic PCs and measured the number of inserts completed every minute as well as tracking the duration of insert transactions. While our systems initially saw high insertion rates as the size of our database grew we stabilize to a steady state of approximately 20,000 inserts per second. We benchmarked both the fractal tree index (B^ϵ -tree) and Berkeley DB (B -tree).

To provide a test data set, we generated Bro connection logs from the backscatter dataset. The dataset consists of collections of responses to spoofed traffic sent by denial-of-service attack victims and received by the UC San Diego (UCSD) Network Telescope. Data was collected between 2001 and 2008. While not perfectly representative of normal network traffic it certainly represents actual network traffic and presents a challenging data set.

We ran our tests on a basic desktop PC with 32 gigabytes of RAM and Intel i7-2600 CPU at 3.40GHz. This system is representative of a typical older desktop that an organization could repurpose as an IP address database system.

A. Ingestion Performance

As a basic metric to monitor our systems ingestion rate, we recorded the amount of time it takes to insert a constant number of rows (e.g., 100,000). That is, we keep track of the time that it takes to insert *each* 100,000 rows.

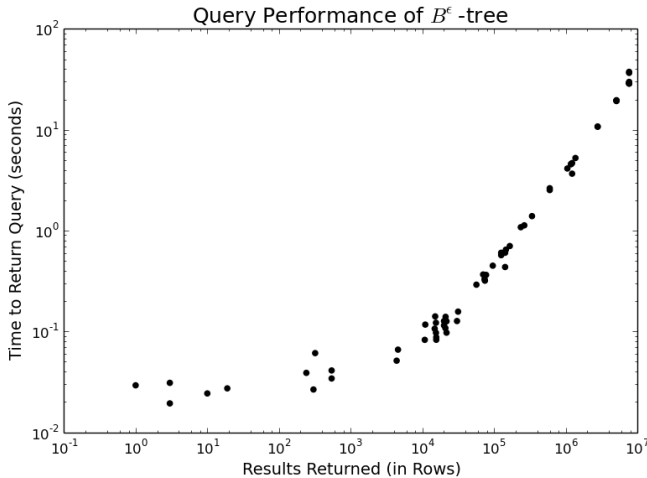
From this we calculate the average number of inserts per second over that period. Figure 1 shows the average insertion rate plotted against total number of database entries inserted for both the fractal tree and traditional B tree.

We can see that the database built on the fractal tree index (B^ϵ -tree) has a sustained insertion rate of 20,000 rows per second for over 1 billion rows. In contrast, the ingestion rate for the database built on BerkeleyDB (B -tree) is similar to that of the fractal tree index in the beginning but quickly and severely drops off to about 100 inserts per second.

B. Query Response Time

We tested a few queries around the size range that a typical user might execute. In our experience, a simple point query

Fig. 2. Query Performance Measurements (121.5 M entries in DB)



came back in well under one second on a database with around 121.5 million entries. Figure 2 shows the time that it took a database using a fractal tree index with about 121.5 million entries to answer range and point queries. We observe that reasonably sized queries that network analysts generally expect return in well under a second. Queries are fast because write-optimization makes indexing more efficient.

As shown in table VI, queries for IP addresses in our database generally return in under a second, while the same search using `grep` takes multiple seconds or even minutes. Query times on the order of tenths of a second will allow network analysts to more quickly discover and respond to network events. This is a significant improvement over a common strategy of searching through connection logs.

TABLE VI
FRACTAL TREE QUERY VS GREP PERFORMANCE (121.5 M DATABASE ENTRIES)

IP Queried	Rows Returned	Time (grep, s)	Time (twiad, s)
0.183.158.39	3	6.242	0.030878
202.178.243.254	7697311	796.276	37.528948
61.132.23.66	600328	160.858	2.630128
210.117.64.88	15513	10.386	0.096910
210.117.64.222	20106	10.833	0.114642
210.117.64.16	21005	35.084	0.126801
210.117.64.84	21785	11.350	0.126013
208.149.123.22	543	7.605	0.040972
195.158.245.52	126186	16.253	0.570452
200.42.64.226	15661	7.372	0.082603

V. APPLICATIONS

A. Intrusion Detection

A great deal of progress has been made on network intrusion detection systems that monitor network traffic for predefined patterns and alert system administrators when potentially problematic network traffic is detected. Previous work focuses on machine learning algorithms and frameworks for intrusion detection [32]–[34]. Additionally, systems like Bro and Snort [35], [36] are lightweight intrusion-detection tools that

take steps toward resolving issues with complex deployment and high cost.

TWIAD has important applications in network intrusion detection. It allows queries over long time periods and can efficiently store large amounts of data while maintaining insertion performance guarantees. Users can ask for all instances of an IP or subnet over a time range and analyze the connections related to a potentially suspicious or adversarial IP. Efficiently storing and having access to previous connection logs allows network analysis to examine threats and take steps towards recovery.

B. Data Visualization

Write-optimized databases for network event tracking can also be used in data visualization efforts on network traffic. Previous work with visualization focuses on the graphical representation of network flows [37]. Combining previous work on pattern detection and visualization with faster packet storage will improve the scope and utility of the representations.

VI. FUTURE WORK

While TWIAD has seen success in processing long-term large-scale network traffic events, there is still much to be done.

For example, we would like to include applications of write-optimization to sessionization tools such as Bro. The power of upserts would be especially beneficial because the row corresponding to a connection could be efficiently updated as packets arrive. Although our implementation did not take advantage of upserts because we did not need to update rows, we can leverage the performance gains resulting from upserts in future work in updating the database or deleting from it.

In order to learn more about our system’s performance, we would like to continue testing against other large-scale database systems such as Hadoop, Accumulo, and Cassandra to determine the relative performance of TWIAD against currently popular solutions for analysis of large datasets. Future experiments will also include tests on more robust hardware to determine the performance of write-optimized data structures on a variety of test systems and where they provide the greatest speedup.

As discussed in Section II, previous related work explores the development of query languages for network event tracking. Although our current work focuses on ingestion performance, we will use other results to improve query performance and allow more specific requests to the database. Thus, we leave a comparison of TWIAD against other network event and stream tracking databases such as Gigascope, Borealis, and Tribeca as future work.

Additionally, we will perform experiments to analyze possible adversarial attacks on the data structure. The amortized cost of inserting new elements in the database is at least an order of magnitude faster than traditional structures such as B-trees. As the B^ϵ -tree grows large, the time to flush down a root-to-leaf path grows because the height of the tree increases. The flushing mechanism may trigger a cascade

effect that requires multiple flushes lower in the tree when the root node is flushed. Future experiments will analyze data loss on a stream of network connections over time. We will explore whether there is a data pattern or speed of arrival that triggers a catastrophic sequence of buffer flushes and I/Os that impact database performance. For example, the database will experience a burst in connections during a denial-of-service attack and has to keep up by ingesting the connection data.

VII. CONCLUSIONS

TWIAD demonstrates the potential of write-optimized data structures for network event tracking. We have created a lightweight, portable system that can be installed on a simple server and monitor network traffic. Furthermore, we were able to track connections with a generic server and modest hardware. For smaller institutions with moderate resources, TWIAD can easily be installed on a spare machine, store information about connections, and maintain situational awareness of the network. We have seen sustained ingestion rates of around 20,000 inserts per second that support the feasibility of TWIAD as a real-time network event tracking system.

Future work will focus on additional testing against other systems and improvements to make the database more amenable to data analysis. Our work indicates that future applications of write-optimization in network security are likely to improve performance.

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