Chapter 8: Breaking Up With Your Relational Database

“I call it the law of the instrument, and it may be formulated as follows: Give a small boy a hammer, and he will find that everything he encounters needs pounding.”

Abraham Kaplan, The conduct of inquiry: methodology for behavioral science

It’s an all-too-familiar story. You’ve been faithful companions for years. You knew everything about your partner and came to depend and rely on it for many of your core needs. But, times have changed. Your needs are more nuanced and complex, and you’re starting to have doubts about your relational structure. Your thoughts and queries begin to stray; you survey and index the field and find new, vibrant and exotic options that you never knew of before. And, then, you realize the hard truth: it’s time to break up with your relational database.

Relational databases (RDBMS) have been around since the 1970s when Edgar Codd proposed1 “*a relational model of data for large shared data banks*” (so much for ‘big data’ being a 21st century concept) as an alternative to the network models—heavily inter-linked, on-disk structures—prevalent at that time. Despite the hype surrounding newer database technologies, relational databases still have quite a bit to offer but should not be the only tool you look to when trying to solve a problem, find “badness” or organize your security data. In this chapter, we’ll explore these newer technologies through security use-cases but also show you how to breathe life into your existing RDBMS relationship.

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A Primer on SQL/RDMBS Databases

Due to the regular attention given to infosec’s “most wanted”—SQL Injection (SQLi) vulnerabilities—this chapter assumes the reader has some familiarity with traditional RDBMS systems such as MySQL (http://www.mysql.com/downloads/), MariaDB (https://mariadb.org/), Oracle (http://www.oracle.com/technetwork/database/enterprise-edition/downloads/index.html) or PostgreSQL (http://www.postgresql.org/).

If you are coming at this chapter without prior experience in relational databases you will have an edge up on many readers that have a predisposition towards them, but some of the topics and references could be a bit confusing. This short primer on RDBMS systems should help introduce you to the basic concepts.

Most RDBMS systems have the following core attributes:

**Data is organized by *tables*,** **with *attributes* (*fields*) in *columns* and individual *records* stored in *rows***. For example, an RDBMS table to hold firewall log entries could have a structure that looks like Figure 8.1a with each log entry being a row and the individual data elements broken down into:

* A unique identifier for the firewall (*fwid*)
* A timestamp (*ts*)
* Source IP address (*src\_ip*)
* Source port (*src\_port*)
* Destination IP address (*dst\_ip*)
* Destination port (*dst\_port*)
* Accept/Deny (*action*)
* Number of bytes transferred (*num\_bytes*)

The complete structure of a table or set of tables is called a *schema*.

**Data in tables is referenced by *rows* and *fields*.** Individual fields or combinations of fields called *keys* ensure each record within a table can be uniquely identified and help distinguish the relationships between tables. The firewall and proxy (8.1b) tables in Figure 8.1 are “linked” together by source IP address (*src\_ip*) and both of them are “linked” to the asset database (8.1c) by their *id* fields.

Figure 8.1 [793725c08f01.eps]

Fields can also be part of one or more *indexes,* which are separate data structures that provide optimized ways to organize data in those fields and can dramatically speed up operations that lookup data (*queries*).

**Data is accessed and manipulated through a structured query language** **(*SQL*)**. SQL was designed to be both a human readable- and platform-independent way to perform insert, update and delete actions, plus run queries against the data. For the example database in Figure 8.1, we can query the destination information (timestamp and IP) for a source IP address in both the proxy and firewall tables with the following SQL statement

**SELECT** ts, dst\_ip

**FROM** proxy\_log\_entry

**WHERE** src\_ip = "10.20.30.40"

**UNION**

**SELECT** ts, dst\_ip

**FROM** fw\_log\_entry

**WHERE** src\_ip = "10.20.30.40";

**Application programs should not rely on the physical structure of the data**. There are a host of options when it comes to deciding how to physically store data in a database and indicating how indexes are organized. All of these choices should be fully abstracted from the application or user who should be able to execute the same high-level query and have it work regardless of changes to physical representation.

The relational structure, mostly uniform query language and physical abstraction properties were major contributors to the popularity of SQL databases, especially since mapping problems like customer records and sales orders into fields and rows is fairly straightforward and just “makes sense”. Yet, as we’ll see later in the chapter, the relational structure is not well suited for all types of data or problems.

Realizing The Container Has Constraints

Compared to Codd’s era, we are awash in computing resources. Memory, storage, CPU and network capacity are all relatively cheap and the need to accommodate the underlying architecture of physical storage when designing, building and using databases is (for the most part) no longer present. Becoming an amateur DBA is now as simple as executing “sudo apt-get install mariadb-server” on any Debian-ish Linux box (with similar, easy installation options for Windows and MacOS). In some ways, it is this simplicity and ubiquity that has contributed to the fallacy that traditional SQL/RDBMS databases are destined for extinction due to “lack of scalability and functionality”.

The reality is that modern SQL databases are comparable to web servers, proxy servers, firewalls and mail servers in that their “out of the box” configuration is going to be in “jack of all trades” mode. The default features and capabilities will be enough to get you off and running, and may even perform moderately well as your record counts and schema complexities increase. But, when the types or amounts of data begin to push the boundaries of the default configuration you *will* run into problems. It’s important to understand the most common types of constraints you will face as your SQL needs grow and where to turn when you begin to encounter them.

Constrained By Schema

It may not be obvious at first glance, but there are significant differences between the following two, simple SQL table structures:

**CREATE** **TABLE** fw1 (

src **varchar**(15) **NOT** **NULL**,

dst **varchar**(15) **NOT** **NULL**,

dpt **int** **NOT** **NULL**,

d **int**(11) **NOT** **NULL**)

**CREATE** **TABLE** fw2 (

src **int**(10) **unsigned** **NOT** **NULL**,

dst **int**(10) **unsigned** **NOT** **NULL**,

dpt **smallint**(5) **unsigned** **NOT** **NULL**,

d **date** **NOT** **NULL**)

When creating a table to store “network” information, it’s tempting to use character storage for IP addresses since that’s how we humans interact with them. It’s also tempting to just handle a UNIX timestamp (as seen in the ‘*ts*’ field in Figure 8.1) as a big integer value since, well, that’s what it is. Also, destination TCP/UDP ports (*dpt*) *technically* are integers. There are, however, potentially significant issues at play with these choices.

If the *src* and *dst* fields are indexed you may not notice any issues at first if all you’re doing is issuing queries for individual IP addresses, like this:

**SELECT** \* **FROM** fw1 **WHERE** src = "10.35.14.16"

The index will speedily find the rows containing the value for *src* and the database engine will return the results as quickly as it can transfer data from disk to your query client. If you do not have an index on those fields, then the same query will have to perform **a full table sequential scan**, which could be a fairly long operation when you have millions of rows.

If you needed to find all matching rows for portions of a subnet, you may be faced with creating complex regular expressions (regex) or carving up the IP space into multiple slices to get the benefit of intelligent query prefix optimization for SQL’s “LIKE” operator or split out the subnet into individual IP addresses to ensure you gain the benefit of full speed queries. Non-optimized wildcard searches—especially ones without a common prefix—will, again, result in a full table scan, performing regex string comparisons for every field value.

By switching to the numeric representation of IP addresses (as discussed in Chapter 4), you can gain disk space, memory size and query time efficiency since many index types are optimized for numeric range selections. Converting to/from integers is usually as simple as using built-in INET\_ATON or INET\_NTOA functions. Similarly, moving from a straight integer timestamp to a *date* field brings with it more straightforward query composition and increased query execution speed. Finally, switching *dpt* from an integer to a smallint will save you two bytes per record which can be important if you plan on using in-memory tables or start racking up billions of records.

If you regularly work with specialized field types (e.g. IP addresses, geo-location data) you could even consider using different database platforms—such as PostgreSQL—that have direct support for a diverse array of custom fields.

RDBMS schemas also tend to be somewhat fixed structures. While it’s possible to add or remove columns to existing tables, there are real penalties for doing so, both at creation time and beyond. You will immediately incur a space penalty as the new field is added to each row with that operation (whether necessary or not) also occupying a decent amount of time on large, established table structures. Some RDBMS systems are able to compensate for these issues, but you may need to leave your “amateur DBA” status at the door as you start to become a professional database administrator in order to solve these issues.

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You got some ‘EXPLAINin’ to do!

To become a true database wizard requires delving into the dark arts of the subject matter. SQL queries are a bit like magic spells in that the wrong inflection can drastically change the results (usually for the worse). You can get an idea of how to tweak your schemas and optimize your queries with the EXPLAIN statement, available in most RDBMS systems.

EXPLAIN will, well, *explain* what the query engine will do with the SQL you’ve given it without executing it. For example, if we were to load the AlienVault database mentioned in Chapter 4 into a simple SQL database, it might look like this:

MariaDB> **DESCRIBE** avrep;

+--------+---------------------+------+-----+---------+-------+

| Field | Type | Null | Key | Default | Extra |

+--------+---------------------+------+-----+---------+-------+

| ipn | int(10) | YES | MUL | NULL | |

| bad | tinyint(3) unsigned | YES | | NULL | |

| con | tinyint(3) unsigned | YES | | NULL | |

| type | varchar(50) | YES | | NULL | |

| cc | varchar(2) | YES | | NULL | |

| city | varchar(30) | YES | | NULL | |

| latlon | varchar(30) | YES | | NULL | |

+--------+---------------------+------+-----+---------+-------+

To get a count of all IP addresses coming from China (CN), you might issue the following query:

MariaDB> **SELECT** **COUNT**(ipn) **FROM** avrep **WHERE** cc="CN";

You can see how optimal that query is (or isn’t) by prefixing it with EXPLAIN (we’ve added the EXTENDED and \G to make the output clearer for the book’s printed format):

**EXPLAIN** **EXTENDED**

-> **SELECT** **COUNT**(ipn) **FROM** avrep **WHERE** cc="CN"\G

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* 1. row \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

id: 1

select\_type: SIMPLE

table: avrep

type: ref

possible\_keys: NULL

key: NULL

key\_len: NULL

ref: NULL

rows: 265597

Extra: Using where

For this query, no keys are being used, so this will require a table scan. You can optimize it by adding an index on the *cc* field:

**CREATE** **INDEX** cc\_idx **ON** avrep (cc);

and, re-run EXPLAIN:

**EXPLAIN** **EXTENDED**

-> **SELECT** **COUNT**(ipn) **FROM** avrep **WHERE** cc="CN"\G

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* 1. row \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

id: 1

select\_type: SIMPLE

table: avrep

type: ref

possible\_keys: **cc\_idx**

key: **cc\_idx**

key\_len: **5**

ref: **const**

rows: **132798**

filtered: **100.00**

Extra: Using where

to see if there are any changes. In this case, the EXPLAIN output shows that the SQL query engine identified the index for the CC field and that using it will reduce the number of rows scanned.

It’s a good idea to use EXPLAIN on more complex queries, especially ones that may be run often. You may be able to identify bottlenecks that you are attributing to “those darn old school SQL databases” when it’s really your schema or SQL composition that needs work.

Constrained By Storage

When this book hits the shelves in 2014, consumers will have access to 5TB hard drives. With that type of capacity being a general user commodity it’s difficult to contemplate how a database could be constrained by storage given that enterprise-class disks have even more options through larger and faster disks and disk arrays. Open source SQL databases such as MySQL or MariaDB can have individual tables as large as 256TB, which will fit comfortably on, say, a BTRFS (https://btrfs.wiki.kernel.org/index.php/Main\_Page) filesystem capable of holding 16EiB of data. What, then, are these storage “constraints”?

* **Speed**. If your analytics needs are modest, it’s tempting to stick with consumer-grade equipment for both cost and ease of deployment. However, that 5400RPM USB 2.0 disk may get quite long-in-the-tooth for even modestly sized projects given the way consumer drives are designed (since they aren’t expecting to serve database workloads). You *could* use consumer disks in a consumer storage array, but you’re only temporarily masking the problem. If your analytics workflow performance starts to degrade, consider investing in faster disks with increased cache. Plus, if the impacts are severe enough, it may be time to switch to true commodity *server* hardware with faster enterprise-class storage—or even solid-state disks (SSD)—and a proper industrial-class storage array.
* **Caching**. Databases use both disk and RAM in concert when performing most of their operations. Delving into RAM and cache discussions can stir up as much debate in the DBA community as sparking a similar conversation about desktop signature anti-virus in the defender community. Increasing the amount of RAM *will* help your database perform faster, especially when you need to issue the same query more than once (think a nested SELECT query used in multiple, but diverse main SELECT statements). RAM and disk caching will also help when inserting data into a database since write-caching can be employed to mask I/O bottlenecks.
* **Capability.** Just because you *can* store alottabytes in a table doesn’t mean you *should*. For example, storing three years of enterprise firewall log data in a single RDBMS table *is* possible, but it’s truly a bad idea. By optimizing the underlying storage configuration and using table partitioning techniques available in most modern RDBMS systems, you can turn what may have been a marathon of a query into a sprint and probably still keep everything on one system.

Constrained By RAM

Lack of sufficient active RAM or using a traditional RDBMS with a configuration that cannot take advantage of large amounts of RAM is the harbinger of doom for any project that needs to scale. As indicated in the previous section, databases use RAM to (among other things) cache portions of tables that are on disk and also to cache query results. More advanced SQL databases can also use RAM for **in-memory tables**. If you know you’re going to have regular use of referential data (e.g. asset metadata, non-frequently changing IP lists), loading that information into an in-memory SQL table can reap huge rewards as you perform JOINs, UNIONs and sub-SELECTs, and it’s usually as simple as just identifying the query—which can be the full set of rows and fields from an existing table—you want to populate in an in-memory configuration. For example, if you wanted to store all the IP addresses contained in the AlienVault table in an in-memory table (to guarantee it stays there versus rely on the cache keeping it there) you could do the following:

**CREATE** **TABLE** avrep\_mem **ENGINE**=**MEMORY**

-> **SELECT** ipn **AS** ip

-> **FROM** avrep;

It’s also best to avoid consumer-grade RAM and opt for high quality ECC (error-correcting code) memory to avoid the perils of data corruption.

Constrained By Data

There are definitely examples of “security data” that fit well into the relational model including firewall logs, web server logs, anti-malware logs and asset information. Each of those example sources easily maps into interconnected rows and columns. But, what about the JSON structure of an incident recorded in VERIS format as seen in Chapter 6? While it’s *possible* to develop a relational structure for this data, it’s hardly an optimal solution.

To optimize database table structures and query efficiency, Codd came up with the notion of **normalization**, which is just a way of describing a method to organize fields and tables to eliminate as many redundancies as is feasible and make it easier to modify or extend the database schema with as little impact as possible. “Over-normalizing” a database can make working with the underlying data awkward and complex. “Under-normalizing” a database can increase the complexity of the application code or database stored procedures and will—most likely—needlessly expand the size of your data store.

Normalizing tabular data that is designed to fit into tables is generally a straightforward task. Mapping and normalizing hierarchical data (like the JSON VERIS data) means converting the hierarchies into graph adjacency lists, materialized paths or nested sets that definitely increase query complexity. You could always go halfway and limit the nesting by storing large chunks of the JSON tree as BLOBs (binary large objects) in special fields, but that also makes queries complex **and** slow, since you’ll likely be performing full text searches of those fields.

RDBMS systems are great for a wide variety of problem sets and data types, but they should not be the only tool in your toolbox since there are so many custom options available, as we’ll see in the next section.

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Who/what is this ‘Maria’?

Many readers may have used or come into contact with the MySQL RDBMS. For many years, it was a foundational element of the initial “LAMP” (Linux/Apache/MySQL/PHP) stack of components one would use to build websites. After Oracle acquired MySQL, there was a community-developed fork of the code created under the name “MariaDB”. MariaDB is a drop-in replacement for MySQL. You can uninstall MySQL (preserving data, of course) and install MariaDB and everything will “just work”.

MariaDB versioning and features have been on par with counterpart MySQL releases, but significant divergence is occurring with newer iterations, including support for cutting-edge storage engines, dynamic columns and interfacing with NoSQL environments (Cassandra).

Choosing MariaDB over MySQL, PostgreSQL or traditional commercial RDBMS offerings is a decision you and your security and analytics team members must make and may be highly dependent on corporate requirements, if you’re constrained by them. Even if you “can’t” use MariaDB, it’s definitely a project that should be on your watch-list.

Exploring Alternative Data Stores

There are many longstanding and new database storage and database management systems that have shunned the conventions and conformity of straight-laced SQL. These technologies are usually grouped under the term **NoSQL** (Not only SQL), which makes it easier to classify them, but also adds confusion since the features and functionality each provides can be radically different from each other. By “not being SQL” they all offer alternate ways of designing solutions and storing information that can be of huge benefit when incorporating data analysis into your security strategy. We’ll take a look at some of the more prominent ones and sneak in a security use case or two along the way to give you an idea of where you might want to pick one over the other.

BerkeleyDB

Perl wonks will no doubt be familiar with Berkeley DB (BDB) (http://www.oracle.com/technetwork/products/berkeleydb/overview/index.html) and you can find support for it in R (RBerkeley), Python (pybsddb) and most other scripting/programming languages. BDB is a local (i.e. embedded) **key/value** store that does what the description suggests: lets you identify a *key* and store arbitrary data associated with it, then perform highly efficient lookups with the *key*. By it’s own definition, it’s neither a relational database, object-oriented database, network database or database sever. Unlike keys and fields in RDBMS sysstems, BDB is completely value-agnostic.

If you’ve ever worked with the default configuration of SpamAssassin (http://spamassassin.apache.org/) or postfix (http://www.postfix.org/) or dealt with open source LDAP servers such as OpenLDAP (http://www.openldap.org/), you’ve encountered BDB.

Key/value stores perform well in situations where data writes are infrequent but reads are potentially plentiful: i.e. *caches*. Consider, once again, the IPv4 address space. If you only needed to cache certain attributes of an IP address (e.g. geolocation data, reputation data) and only needed local resources, choosing BDB as your platform has some serious merit. It doesn’t have the overhead that comes with traditional RDBMS databases (though modern versions of BDB “speak” SQL) and can be optimized for the key and value data structures. Plus, the keys and values can also be language independent (i.e. you can populate BDB stores with R and read them with Python, or vice-versa). Here’s a very basic example of storing IP geolocation data with R:

*# R code to interface with BDB*

library(RBerkeley)

*# create and open BDB database*

dbh <- db\_create()

db <- db\_open(dbh, txnid = NULL, file = "av.db", type = "BTREE", flags = mkFlags(DB\_CREATE, DB\_EXCL))

*# store geolocation data*

db\_put(dbh, key = charToRaw("24.62.253.107"), data = charToRaw("43.2555,-70.8829"))

*# read it back to show it works*

coords <- rawToChar(db\_get(dbh, key = charToRaw("24.62.253.107")))

db\_close(dbh) *# close BDB db*

print(coords)

# [1] "43.2555,-70.8829"

and, reading the same data back with Python:

*// Python code to interface with BDB*

from bsddb3 import db

import struct

import socket

*// initialize and open BDB database*

av\_db = db.DB()

av\_db.open('av.db',None,db.DB\_BTREE, db.DB\_DIRTY\_READ)

*// get first key/value pair*

cursor = av\_db.cursor()

av\_rec = cursor.first()

*// print it out to show it worked*

print av\_rec

// ('24.62.253.107', '43.2555,-70.8829')

av\_db.close() *// close BDB file*

It would be very straightforward to expand this example to store the entire AlienVault database, indexed by IP address and with the other associated fields stored in the value component.

Berkeley DB also has solid thread support and scales as large as 256TB. If your workloads can deal with disk-seek times, you do not want the hassle of maintaining a server process or multi-node infrastructure for your caches and there’s a chance you need multi-platform and multi-programming language support, it’s definitely a good choice.

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BDB Alternatives

Oracle is now the proprietor of Berkeley DB. While it’s still provided under a GNU AGPL v3 license, Oracle also offers a commercial version with fairly steep licensing options. If you are concerned that this may become fully commercial in the future, there are alternatives that provide the same feature set, including:

* Kyoto Cabinet (http://fallabs.com/kyotocabinet/)
* MapDB (http://www.mapdb.org/faq-general.html)

Redis

It’s tempting to think of Redis () as just a server-version of a key/value store since that’s what it looks like on the surface with it’s most basic commands, GET and SET and it’s basic data type being a *binary safe string* (so you can store virtually any type of data in the key or value components). What Redis *really* is, however, is more of an in-memory **data structure** **server** that is also persisted on disk (that also has many other useful features). The in-RAM requirement should not be glossed over lightly since every data structure and element **must** fit into RAM for Redis to work. This constraint should help prevent you from trying to shoehorn large relational or hierarchical structures into Redis (since that’s definitely not what it’s designed for).

Redis operates as a data structure server by providing a framework of operations for four fundamental data storage types: **lists**, **hashes**, **sets** and **sorted sets**.

**Lists** store single binary safe strings that are either pushed on to the front (LPUSH) or back (RPUSH) of the list. Lists make superb message queue structures and excel at keeping the “last *n*” number of items available.

**Hashes** expand the key/value NoSQL model by providing a way to identify and manipulate fields within the value component in a very space-efficient manner. We can replicate the geolocation Berkeley DB geolocation example quite easily with Redis hashes straight from the Redis command line interface:

redis> HMSET ip:24.62.253.107 lon 43.2555 lat -70.8829 zip 03878

redis> HMGET ip:24.62.253.107 lon lat

1) "43.2555"

2) "-70.8829"

The main differences here are that you can query this database server from any client on the network versus be constrained by just local file access and that everything is in memory, so lookups will be almost instantaneous.

**Sets** store non-repeating collections of binary safe strings. This makes them ideal for associating elements together for quick membership determination. For example, creating a “workstations” set and populating the members with IP addresses makes it trivial to determine whether an IP address you’ve seen in a packet is coming from a workstation node:

redis> SADD workstations "10.23.34.45"

redis> SADD workstations "10.32.43.54"

redis> SADD workstations "10.45.34.32"

redis> SADD workstations "10.34.23.45"

redis 127.0.0.1:6379> SISMEMBER workstations "10.10.10.10"

(integer) 0 *// not in set*

redis 127.0.0.1:6379> SISMEMBER workstations "10.23.34.45"

(integer) 1 *// in set*

**Sorted sets** provide a means to associate a raked value with a member of a set. You could, then create risk or reliability sets for each of the malicious host types in the AlienVault database, using the values from those fields or keep a running count of times you’ve seen those known-bad hosts attempt to access your resources (or when *your* resources have attempted to access those bad ones).

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Advanced Redis Features

Redis supports **partitioning** which lets you use memory on other systems to hold portions of Redis data structures. This is similar to the way you can partition tables in MariaDB, MySQL and Oracle and helps you get around single-system RAM constraints.

Redis also has a built-in **publish-subscribe** service. With it, you can create a number of clients that subscribe to a channel that is publishing log entries or just new, individual IP addresses that make their way on to your internal “suspicious” list. When any new value is pushed, each client will get the message and can take some type of action, like running a set of analytics routines or parsing and storing the information into multiple SQL and NoSQL data stores for later processing.

There is robust Redis support in Python (redis-py) and R (rredis) and the API is very straightforward to work with. Say you want a centralized and efficient way to know whether you’ve seen an IP address in an indicator of compromise (IoC) you’ve received from some external source. Rather than rely on a query to return from your clunky centralized log management system, setup a workload that takes IP addresses from the log streams and stores them in a centralized Redis simple key/value or hash data structure with as much metadata as you need. Here’s a Python example of how to “watch” a log file (in this case, a web server log) and store the data in Redis:

*# log watcher/Redis importer*

import time

import re

import redis

import pickle

*# setup regex to parse web log entries*

logparts = r'(\S+) (\S+) (\S+) \[(.\*?)\] \

"(\S+) (\S+) (\S+)" (\S+) (\S+)'

logpart = re.compile(logparts)

*# map field names to extracted regex values*

def field\_map(dictseq,name,func):

for d in dictseq:

d[name] = func(d[name])

yield d

*# extract data from weblog*

def web\_log(lines):

groups = (logpart.match(line) for line in lines)

tuples = (g.groups() for g in groups if g)

colnames = ('host','referrer','user',

'datetime','method', 'request',

'proto','status','bytes')

log = (dict(zip(colnames,t)) for t in tuples)

log = field\_map(log,"bytes",

lambda s: int(s) if s != '-' else 0)

log = field\_map(log,"status",int)

return log

*# "tail" for python*

def follow(thefile):

thefile.seek(0,2)

while True:

line = thefile.readline()

if not line:

time.sleep(0.1)

continue

yield line

*# setup log watching*

logfile = open("/var/log/nginx/web.access.log")

loglines = follow(logfile)

log = web\_log(loglines)

*# setup Redis connection*

red = redis.StrictRedis(host='redhost.example.com',

port=6379, db=0)

*# for each entry, store pythonic-data structure in*

*# associated with a key (could also use Redis hash*

*# for more language-independence)*

for line in log:

l = line['host']

a = red.get("ip:%s" % l)

if (a == None):

a = {}

a['ls'] = time.time()

a['ct'] = 1

red.set("ip:%s" % l,pickle.dumps(a))

else:

a = pickle.loads(a)

a['ls'] = time.time()

a['ct'] += 1

red.set("ip:%s" % l,pickle.dumps(a))

And, here’s the query component:

*# query script*

from datetime import datetime

import redis

import pickle

import sys

*# setup Redis connection*

red = redis.StrictRedis(host='localhost', port=6379, db=0)

*# get IP address from the command line & query Redis*

ipaddr = sys.argv[1]

ioc = red.get("ip:%s" % ipaddr)

*# if found*

if (ioc != None):

b = pickle.loads(ioc)

print("IP [%s] was last seen on [%s].\nTotal times seen ")

print("since we started counting: [%d]." %

(ipaddr, datetime.fromtimestamp(b['ls']),b['ct']))

else:

print("%s has not been seen, yet." % ipaddr)

Now, it’s quick work from the command line to know whether you’ve seen an IP address:

dds$ lastseen 24.62.253.107

IP [24.62.253.107] was last seen on [2013-10-13 18:57:59.875430].

Total times seen since we started counting: [80787].

If you’re thinking, “I could just use grep”, remember that this is a constantly streaming, online activity from potentially hundreds or thousands of sources spanning weeks or months. If you architect it properly, Redis will always beat “grep”.

Hive

It’s virtually impossible to write a book about data analysis without mentioning “Hadoop” (http://wiki.apache.org/hadoop), and if you’re already investigating or using Hadoop then you may have come across Hive (http://wiki.apache.org/hadoop/Hive/LanguageManual). Hive sits on top of the Hadoop Distributed file System (HDFS) (http://hadoop.apache.org/docs/stable/hdfs\_user\_guide.html) that partitions data across—potentially—*thousands* of nodes. Hadoop *MapReduce* jobs execute across these nodes using this data. The *map* component takes a set of data elements, breaks them into key/value pairs and performs a comparison and/or computation on them. The *reduce* component takes these results and combines them to come up with a final result set (which may involve another comparison and/or computation).

Hive provides a SQL-like interface to this HDFS data. Rather then becoming an expert Java coder to compose and execute MapReduce jobs, Hive abstracts this complexity and converts SQL into MapReduce jobs for you. This is a very important point to remember: in the Hadoop ecosystem, *everything* boils down to a MapReduce job across very large amounts of data. The complexities of setting up a Hadoop environment and *keeping* it running are mixed into the cost/benefit analysis when choosing this as part of your analytics platform.

While Hive provides the comfort of SQL, some key features of SQL do not come along for the ride. For example, the Hive query language (HiveQL) provides only limited support for SQL JOINs. If your needs go beyond combining tables on equality conditions, you cannot use Hive due to the limitations of the Hadoop MapReduce paradigm. You also need to use caution when ordering result sets with SQL’s ORDER BY, since Hive currently only uses a single reduce engine to perform that sorting task, creating potential bottlenecks. There are many other subtleties to Hive and HiveQL as well. While you may not need to become a Java expert, you will have to thoroughly understand how HiveQL queries translate to MapReduce jobs and learn how to optimize queries to take advantage of this platform.

If you have the time, space, personnel, budget *and* use-cases to setup Hadoop/HDFS/Hive, then it may be well worth the investment. Imagine being able to keep a full year’s online archive of every log file from every system, network device, firewall and mail server in a massively efficient data warehouse and perform basic inquiries across all of those components. *That’s* where the real power of Hive+Hadoop lies.

type="tip"

What about HBase, Cassandra, Pig, …?

The full Hadoop ecosystem continues to expand at a relentless pace. Advancements within the environment itself (e.g. Hadoop 2.0) as well as integration with the environment (e.g. Cassandra, MongoDB) and unique vendor-specific offerings are introducing nascent new alternatives that have their own strengths, tradeoffs and idiosyncrasies.

You will need to spend some effort looking at all the options you have available and mapping them to your perceived needs, then choosing a direction and sticking with it. A Hadoop analytics environment—much like Rome—cannot be built in a day. Despite the continuing advancements, this ecosystem is far from mature and you will be forging new ground over a long period of time with each step you take.

MongoDB

MongoDB (http://www.mongodb.org/) could be called the “MySQL of NoSQL” databases as it has a large and active community, is easy to deploy in development and scales fairly well in production. At its core, Mongo provides a way to do extremely quick prototyping given the schema-less nature of the platform. Unlike traditional SQL databases where you need to define the fields you will be using up-front, Mongo let’s you start with a basic pseudo-schema and refine your needs along the way. For example, it’s very straightforward to start storing IP geolocation info from the AlienVault reputation database for an IP address:

> db.av.insert ( { ip:"193.147.49.42",

geo:"40.4085,-3.6921" })

> db.av.find({ ip:"193.147.49.42" })

{ "\_id" : ObjectId("525bfbe02074bfa7aaad8316"),

"ip" : "193.147.49.42",

"geo" : "40.4085998535,-3.69219994545" }

then, choose to add other information later, like the type of malicious activity the host is engaged in:

> db.av.update ( { ip:"193.147.49.42" },

{ $set : { maltype:"Scanning Host" } } )

> db.av.find({ ip:"193.147.49.42" })

{ "\_id" : ObjectId("525bfbe02074bfa7aaad8316"),

"geo" : "40.4085998535,-3.69219994545",

"ip" : "193.147.49.42",

"maltype" : "Scanning Host" }

You do pay a price for these incremental field updates given the way Mongo stores the data and manages the on-the-fly schema changes, and you may need to dump and reload the database to regain storage and query efficiency if you perform these types of changes in production versus just experiment during development.

Mongo breathes JSON and uses binary JSON (BJSON) in API calls. This means you need to be comfortable with JavaScript notation and will definitely want to keep the JSONLint (http://jsonlint.com/) URL handy to assist you when errors crop up in your input data. The use of JSON provides the capability of storing deeply nested or hierarchical records and structures, which will require you to re-think any notions you may have on normalization. If you’re used to performing RDBMS normalization, then you’ll need to take a step back, ignore most of what you’ve been taught or learned and embrace the verbosity of this side of the NoSQL universe.

For example, malicious nodes in the AlienVault database can have multiple malicious activities associated with them. In traditional, normalized SQL, you would likely setup a separate table with host key and malicious node type field and have a row for each entry:

+-------------+-------------+

|193.147.49.42|Scanning Host|

|193.147.49.42|Spamming |

+-------------+-------------+

then, perform a JOIN when retrieving results. With Mongo, you would store those components as a JSON array within the record:

> db.av.update ( { ip:"193.147.49.42" },

{ $set : { maltype:[ "Scanning Host", "Spamming" ] } } )

It may be difficult to see the value of this additional complexity with such a trivial example, but the power this holds starts to become much clearer if you take a look back at the VERIS JSON data in Chapter 6. Creating a normalized table structure to store all the fields in an incident is possible, but not necessary given Mongo’s ability to efficiently store, process and query complex field structures. If you have Mongo and git installed, you can download and import the complex incident data in the entire VERIS Community Database in about five minutes without the need to create a database or table schema ahead of time:

*# clone the VCDB github repository*

dds$ git clone https://github.com/vz-risk/VCDB.git

*# import all the incdients*

dds$ cd VCDB/incidents

dds$ ls | head -5

0012CC25-9167-40D8-8FE3-3D0DFD8FB6BB.json

002599D4-A872-433B-9980-BD9F257B283F.json

005C42A3-3FE8-47B5-866B-AFBB5E3F5B95.json

0096EF99-D9CB-4869-9F3D-F4E0D84F419B.json

00CC39F6-D2E0-4FF4-9383-AE3E28922015.json

dds$ for f in \*.json ; do \

mongoimport -d veris -c public --jsonArray $f \

done

*# find all financial firms with security incident in the VCDB*

*# 52 is NAICS code for financial firms*

dds$ mongo veris

> db.public.find({"victim.industry": { $regex : "^52" } },

... { "victim.victim\_id" : 1, \_id : 0 } )

{ "victim" : [

{ "victim\_id" : "Blue Cross & Blue Shield of Rhode Island" } ] }

{ "victim" : [

{ "victim\_id" : "Group Health Incorporated" } ] }

{ "victim" : [

**{ "victim\_id" : "Delta Dental of Pennsylvania" },**

**{ "victim\_id" : "ZDI" } ] }**

{ "victim" : [

{ "victim\_id" : "UK National Health Service" } ] }

{ "victim" : [

**{ "victim\_id" : "Mundo.com" },**

**{ "victim\_id" : "Public Defender of Venezula" },**

**{ "victim\_id" : "Caroni Seguros SA" } ] }**

…

(We’ve highlighted instances where Mongo has understood some incidents have multiple victims.)

If your record count is large enough to span multiple Mongo nodes, these simple queries will work un-altered. Mongo can also perform data aggregation or even run map-reduce jobs across a whole cluster, mimicking some of the functionality of both Hadoop and more traditional SQL databases.

Mongo can also be used as a tool in your data acquisition and cleanup processes, where you may have traditionally used built-in structures in your programming or scripting languages. For example, log processing is one of the less glamorous activities of security data analysis. They come in all shapes and sizes and some, like Cisco’s IronPort e-mail logs, require extra processing to get into a form useful for analytics. Take a look at the following sample:

Fri Oct 18 11:05:01 2011 Info: Start MID 346564 ICID 1042862

Fri Oct 18 11:05:01 2011 Info: MID 346564 ICID 1042862 From:

<dave@example.com>

Fri Oct 18 11:05:01 2011 Info: MID 346564 ICID 1042862 RID 0 To:

<steve@test.com>

Fri Oct 18 11:05:01 2011 Info: MID 346564 Message-ID

‘<112067.438985349-em02@steel>’

Fri Oct 18 11:05:01 2011 Info: MID 346564 Subject ‘TPS Reports Due'

Fri Oct 18 11:05:02 2011 Info: MID 346564 ready 864 bytes from

<dave@example.com>

Fri Oct 18 11:05:02 2011 Info: MID 346564 matched all recipients for

per-recipient policy local domains in the outbound table

Fri Oct 18 11:05:03 2011 Info: MID 346564 interim AV verdict using

Sophos CLEAN

Fri Oct 18 11:05:03 2011 Info: MID 346564 antivirus negative

Fri Oct 18 11:05:03 2011 Info: MID 346564 DLP no violation

Fri Oct 18 11:05:03 2011 Info: MID 346564 queued for delivery

Fri Oct 18 11:05:03 2011 Info: Delivery start DCID 178987 MID 346564

to RID [0]

Fri Oct 18 11:05:04 2011 Info: Message done DCID 178987 MID 346564

to RID [0]

Fri Oct 18 11:05:04 2011 Info: MID 346564 RID [0] Response ‘ok:

Message 10569973 accepted’

Fri Oct 18 11:05:04 2011 Info: Message finished MID 346564 done

Because Mongo allows incremental schema build out, you can use that feature to create records for each message (MID) as you parse the log file then add fields as you go, ending up with a final, complete database and an idea of what a complete per-record schema might look like. The Mongo entry for the above record could look like:

{

mid : "346564",

icid : "1042862",

from : "dave@example.com",

to : "steve@test.com",

messageID : "112067.438985349-em02@steel",

subj: "TPS Reports Due",

bytes: "864"

matchStatus : 1,

delivered : 1,

av : { engine : "Sophos", verdict: "CLEAN" },

dlp : { violation : "none" },

start : "Fri Oct 18 11:05:01",

finish : "Fri Oct 18 11:05:01"

}

Once all the records have been created, you can then use Mongo and Python or R to perform time series analysis, z-scaled anomaly detection, clustering or a host of other analyses.

type="tip"

Why not use Mongo for everything?

It’s possible to fall into the trap of trying to use Mongo for everything, especially since it allows you to be a bit lazy up front. While it’s great for some tasks, the platform still has some rough edges at the time this chapter was written that you might want to take into account when deciding on Mongo for a project. Here are just a few:

* Record counting operations are improving but are still slower than other database platforms due to the way Mongo uses the underlying b-tree database file structures.
* Field names are not compressed and take up real space *per-record*. This leads to practices such as using “sip” instead of “src\_ip” or “sourceIP” and “u” for “username”, making queries somewhat unreadable unless you’re extremely familiar with the data.
* Maintenance operations are still required and can impair operations. You *will* need to compact the database regularly and this can be a time-consuming, blocking operation across a whole cluster. While this is, most likely, not a problem for your analytics environment be careful if you’re using Mongo to present an interactive data interface to other users.
* By default, writes to a Mongo database work a bit like UDP packets in that it’s “send, and pray it’s received”. You need to explicitly set options for enabling “write concern” to get more TCP-like behavior. This can have a serious impact on performance such as the need to guarantee writes of log entries you are aggregating into Mongo.

Special Purpose Databases

It’s far too easy to get snarled on what truly constitutes a “database”. For those still entrenched in the SQL world, NoSQL is a serious affront to their sensibilities. For those who’ve adjusted to the NoSQL paradigm, tools such as ElasticSearch (http://www.elasticsearch.org/) and Neo4j (http://www.neo4j.org/) may be equally as world jarring.

When databases become part of an analytics workflow, one of the primary use case scenarios may look like:

* Identify the data sources (e.g. logs, traditional databases, alerts)
* Collect, transform (if needed) and store the data
* Query the data store
* Provide analytics on the results

When working with raw SQL or NoSQL databases, you have to perform most of the setup and cleanup tasks on your own which requires, as seen in the previous sections, DBA-like intimacy with the underlying database platforms.

ElasticSearch For Logs

If you’re focused on the goal of analytics more than the journey of how to get your data there, you may be interested in tools like ElasticSearch that abstract the complexities of the back-end and give you an input, query and analytics interface to work with on the front end.

ElasticSearch consumes practically anything you give it and provides straightforward ways to ask it questions and get data out of it. You just need to feed it semi- or unstructured data and fold in some domain intelligence to enable smart indexing. It works its multi-node NoSQL magic in conjunction with a layer of full-text searching to give you almost instantaneous query results even for large amounts of data. It’s *highly* geared towards log data and supports an aggregation framework similar to that of Mongo.

If you are analyzing a wide variety of logs in your security work, ElasticSearch may be something you should consider investigating.

Neo4j For “Connections”

As indicated in a few previous chapters, many areas of information security analytics involve looking at connections between nodes. You’ve also seen how network graph structures can make working with these connections a bit easier. While it’s possible to model graph structures in SQL databases or Mongo, Redis, etc. it’s easier to use a something like Neo4j that provides direct support for network graph models and operations.

If the igraph operations in Chapter 4 intrigued you, then you’ll be even more impressed with the feature set in Neo4j since it essentially scales similar computations and analytics across millions or billions of nodes. You can import high level vertex + edge connection data into Neo4j from netflow sources, firewall, proxy, e-mail and DNS logs and augment the connection and node information with detail data from each of those sources.

You still need to have a graph model in mind when you’re designing for Neo4j and will need to learn a new graph-specific query language—Cypher—to get work done. Many fine-grained tasks will either roll up your sleeves and code a bit in Java or Python or interface with Neo4j’s REST interface to funnel query output into your analytics platform of choice.

In Summary

Becoming a truly effective as a security data scientist will require a shift in mindset from any monolithic relational database fidelity you may have. Solving real problems will require you to keep your options open, recognizing each database technology has unique benefits for specific tasks.

This chapter has presented a survey of various technologies combined with small examples in many different types of SQL and NoSQL database environments. We’ve outlined strengths and weaknesses in the choices you have and even provided some counseling on how to enhance interactions with your traditional SQL stores.

We’ve focused on some core database offerings, but have not provided an exhaustive reference since that would be a book on it’s own. You will need to keep abreast of developments in the database space—both SQL and NoSQL—to see where you may need to make adjustments in the future. If you are working with larger and larger amounts of data, it may be time to wade a bit deeper into the Hadoop ecosystem, provided you understand the level of commitment required and the constraints you will be facing.

Finally, you’ve seen that databases can take many forms that they can be used as a means to an end (e.g. log parsing) as well as an end in and of themselves.

For Further Reading

Relational Database Design Clearly Explained, Second Edition (The Morgan Kaufmann Series in Data Management Systems) ISBN-13: 978-1558608207 Jan L. Harrington. One of the most complete and accessible resources available, and is especially helpful to nascent arrivals to the world of RDBMS systems.

Lublinsky, Boris, Kevin T. Smith, and Alexey Yakubovich. Professional Hadoop Solutions. John Wiley & Sons, 2013. An excellent and thorough introduction to the Hadoop ecosystem with modern, real-world examples and advice on how to secure your Hadoop analytics environments.

Tiwari, Shashank. Professional NoSQL. John Wiley & Sons, 2011. Far more comprehensive reference on NoSQL database technologies that digs in a bit deeper on many of the options we’ve described in this chapter.

References

1Codd, Edgar Frank. "A relational model of data for large shared data banks." Communications of the ACM 26, no. 1 (1983): 64-69.