BlueVoyant: Detecting Security Dumpster Fires on the Internet

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Who is BlueVoyant?
Who Are We?
Third Party Risk Detection
What is it and Why is it Hard?
What is Third Party Risk?

First Party Risk – hack the bank’s central servers

Third Party Risk – Don't attack the bank directly; go after one of their suppliers or a smaller company they are buying (target the weakest link)

https://xkcd.com/2347/
What is Third Party Risk?

Your Organization

Certification Bodies
Inventory Planning
Shipping
Tier 1-N Suppliers
Brokers/Agents
Fourth Parties
Contract Manufacturing
Infrastructure & Application Support
Hosted Vendor Solutions
Disaster Recovery
Licensed Vendor Solutions

Licensing
Franchise
Joint Ventures
Distribution & Sales
Customers
Facilities
Human Resources
Legal
Marketing
Insurance
Technology
Sourcing
Logistics
R&D

Distributors
Loyalty Partners
Warranty Processing
Call Center
Office Products
Waste Disposal
Cleaning
Contractors
Benefits Providers
Payroll Processing
Media and Sales

Advising Agency

Contract Manufacturing

Payroll Processing
What is our product?

“One of your vendors has a remote office that didn’t patch the latest VPN server vulnerability and has remote access exposed. We opened a case, and worked with them to patch the issue and close the port.”
Big Moving Targets

- **Lots of data**
  - Some streaming, some batch
  - Up to 11M events per second incoming

- **Disparate data**
  - Different formats, semantics, delivery
  - Data arrives late, changes schema/semantics, changes in volume

- **Dynamic footprints**
  - Shared assets, cloud-hosted assets
  - Mergers/acquisitions, growth, reduction, adoption of third-party services/resources

- **Dynamic threat landscape**
  - Emerging vulnerabilities
    - (or knowledge of them)
  - Emerging attack vectors
Important Needles, Big Haystack

- Data points processed per second: 11M
- Number of findings generated by pipeline: ~100
- Number of findings that meet notification threshold: ~5-8
- Number of findings that are communicated to vendor (after removal of false positives, footprint or mitigating control): ~4

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Solution: Prophet
Any analytic we derive today may be wrong tomorrow, all we know is what was observed
Why Beam?
Why not <insert your favorite buzzword>?

- **Batch and strEAM data sources ;-)***

- **Why not SQL on some backend?**
  - We tried it!
    - SQL is limiting, and quickly gets hard to maintain
    - Latency XOR throughput
  - Real code (not just SQL), high-level types, caches, hit APIs
    - Workflows (not just reading/writing)

- **Adds high throughput to a low-latency backend***
  - *With some effort (see: rest of this talk)*

- **Manage business logic, not virtual machines + tuning params (sorry spark)**
  - Beam + Google Dataflow :chefs-kiss:
Beam as a Data Model Layer

CyberDatum

- Schema validation
- Semantic validation
- Normalize datatypes
- High-level datatypes
- Column relations
- Trigger collection jobs or API requests

Pushed Data
Kafka
BQ

Pulled Data
APIs
s3/GCS

Collected Data

Asset(s)
(ip or domain)

Event or observation timestamp(s)
Beam as an Analytic Engine

Every day, pull... data for the latest footprints...

...to identify nuggets of risk!

...and apply our latest analytics...

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*HealthCareCompany* uses *DataManagementCompany*, which has a bunch of their personal health data (HIPAA) in a publicly readable bucket!

*SaasCompany* uses *HRCompany* that runs a mail server with known remote code vulnerabilities!

*BigCompany* recently acquired *SmallCompany*, who was actively targeted by known malicious botnet servers yesterday!

Like having a billion human analysts running daily queries and analysis on the results
Beam Challenges

- Pushed Data
- Pulled Data
- Collected Data

CyberDatum

Data Warehouse

Footprints

Analytics

Risk

Austin, 2022
Beam Challenges

1. Ingesting and indexing up to 11M records/second
2. Running billions of queries every day in ~1 hour
3. Running analytic processing on billions of results

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Ingesting and indexing up to 11M records/second
Beam Challenges

1. Ingesting and indexing up to 11M records/second

Pushed Data
Pulled Data
Collected Data

Data Warehouse (BigTable)

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A Typical Datasource

- Manageable data volume for Dataflow and BigTable
- Batch jobs (mostly)
- Single index (one BigTable row per record)

Record:

- server_ip: 1.2.3.4
- date: 2022-07-18
- port: 3389
- banner: “Windows 2000, RDP 4.0 …”

Beam

BigTable row:

(1.2.3.4, 2022-07-18)
-> { port: 3389, ... }

- Dataflow + BigTable is an efficient and cost effective solution 🎉
The Problem Datasource

- High-volume
  - p50: 2M records/s, p95: 11 M records/s
- Continuous stream
- Multiple indexable fields (many BigTable rows per record)

Record:

```
client_ip: 1.2.3.4
qname: badguyz.net
answer_ip: 5.6.7.8
timestamp: 2020-12-09
```

Queryable as:

```
(1.2.3.4, 2020-12-09)
(badguyz.net, 2020-12-09)
(5.6.7.8, 2020-12-09)
```

We’d need to write at least ~25 M rows/s to BigTable
- Would need a very large BT cluster, too expensive
How do we reduce costs?

Bottleneck: BigTable key creation.
- Goal: reduce the number of keys we write to BigTable.
- group records into timestamp bins, and write each bin to an individual row:

\[
\begin{align*}
(1.2.3.4, 2020-12-09T01:00:01) & \rightarrow [\text{record-A}] \\
(1.2.3.4, 2020-12-09T01:00:59) & \rightarrow [\text{record-B}] \\
= & \quad (1.2.3.4, 2020-12-09T01:00) \rightarrow [\text{record-A}, \text{record-B}]
\end{align*}
\]

- Improves BigTable write throughput
- But shuffle is expensive, need many dataflow workers to finish in time
Any problem in computer science can be solved with another level of indirection.

(attributed to David Wheeler).
Records on Google Cloud Storage, indices in BigTable

 gs://data-sponge/records1.avro

Record 0 ===
client_ip: 1.2.3.4
qname: badguyz.net
timestamp: 2022-07-18
...

Record 1 ===
client_ip: 3.4.5.6
qname: zombo.com
timestamp: 1999-11-02
....

Record 2 ===
....

BigTable rows:

(1.2.3.4, 2022-07-18)
  -> [records1.avro, record 0, bit_qr: 1, ...]

(badguyz.net, 2022-07-18)
  -> [records1.avro, record 0, bit_qr: 1, ...]

(zombo.com, 1999-11-02)
  -> [records1.avro, record 1, bit_qr: 0, ...]
**Writes**

- **Data stream**
  - Spark Streaming (writes records)
    - ~1.5 - 15 M records/s
  - Avro on GCS (stores full records)

- **Dataflow Batch Jobs** (create indices)
  - Runs hourly, indexing previous hour’s data
  - 50-150 nodes (depending on demand)

- **BigTable** (stores GCS urls and offsets)
Reads

Client

"badguyz.net" on 2022-07-18 ?

[(gs://bkt/1.avro, lines 2,3, qr:1),
 (gs://bkt/2.avro, lines 5,8, qr: 0), …]

Filter files to fetch

gs://bkt/1.avro … ?

[ (client_ip: 1.2.3.4, qname: badguyz.net, timestamp: 2022-07-18), …]

Scan through files to relevant records

BigTable (stores GCS urls, offsets, …)

Avro on GCS (stores full records)
“Local Group-By”
“Local Group-By”

Classic map-reduce shuffle:

1
(a: 1), (a: 2),
(b: 1), (b: 2)

2
(a: 3), (a: 4),
(b: 3), (c: 1)

1
(a: [1, 2, 3, 4])

2
(b: [1, 2, 3]),
(c: [1])

All-to-all communication :(
We don’t care about getting all the “a”s on one worker, we just want fewer key-value pairs. Avoids expensive ($ and time) shuffles.
Local Group-By as a Beam DoFn

// Each DoFn gets its own local set of groups.
HashMap<String, List<RecordT>> groups;
public void startBundle() {
    groups = new HashMap<>();
}
public void processElement(@Element KV<String, RecordT> element, ...) {
    groups.compute(element.getKey(), (key, group) -> {
        if (group == null) group = new ArrayList<RecordT>();
        group.append(element.getValue());
        return group;
    });
}
public void finishBundle(FinishBundleContext c) {
    for (KV<String, List<RecordT>> group : groups) {
        c.output(group);
    }
}
Local Group-By as Beam DoFs

// Simple way to get better grouping: Lather, rinse, repeat
PCollection<KV<String, List<RecordT>>> locallyGroupedRecords = records
    .apply("Locally group 1", ParDo.of(new LocalGroupBy()))
    .apply("Locally group 2", ParDo.of(new LocalGroupBy()))
    .apply("Locally group 3", ParDo.of(new LocalGroupBy()));

Gives more complete grouping per worker at the cost of more CPU time
- still better than a broad shuffle.

Can we group across DoFn threads as well?
Local Group-By as a Beam DoFn

// All DoFs on a worker share a single groups map; here lie concurrency headaches...
static ConcurrentHashMap<String, List<RecordT>> groups = new ConcurrentHashMap();
static final Object mutex = new Object();
static int numActiveBundles = 0;

public void startBundle() {
    synchronized (mutex) {
        numActiveBundles++;
    }
}

public void processElement(@Element KV<String, RecordT> element, ...)
    // Same as before, add our element to the map.
}{

public void finishBundle(FinishBundleContext c) {
    synchronized (mutex) {
        if (numActiveBundles-- > 0) {
            mutex.wait(); // DANGER ZONE: what if we never make progress here?
        } else {
            for (KV<String, List<RecordT>> group : groups) {
                c.output(group);
            }
            groups = new ConcurrentHashMap();
            mutex.notifyAll();
        }
    }
}

Better grouping, but much trickier code and dubious benefits
Local Group-By as a Spark Transform

Spark provides an API for processing all of the elements of a single partition as a single iterable:

```scala
val groupedRecords = myRecords.mapPartitions(partitionIt: Iterator[(String, RecordT)] => {
  val groups: HashMap[String, ArrayList[RecordT]] = new HashMap()
  partitionIt.forEach {
    case (key, record) => {
      val curGroup = groups.getOrElseUpdate(key, new ArrayList())
      curGroup.add(record)
    }
  }
  groups.toIterable
})

Can/should we add this API to Beam? Pros/Cons?
Local Group-By as a Spark Transform

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```

Can/should we add this API to Beam? Pros/Cons?
Running billions of queries every day in ~1 hour
Beam Challenges

Pushed Data

Pulled Data

Collected Data

2

Running billions of queries every day in ~1 hour

Data Warehouse (BigTable)

Risk

Analytics

CyberDatum

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Amdahl’s Law

Amdahl’s Law

![Graph showing Amdahl’s Law with different parallel portions: 50%, 75%, 90%, 95%.

Number of processors on the x-axis ranging from 1 to 65536.

Speedup on the y-axis ranging from 0 to 20.

Figure 2: Two workers process the two bundles in parallel.
Inputs (1)

What’s a CIDR?

8.8.8.8/32 -> [8.8.8.8]

1.2.3.4/16 -> [1.2.0.0, 1.2.0.1, 1.2.0.2, ..., 1.2.255.255]

Inputs are compressed - don’t want long tails on large ranges.

FanOut / Reshuffle at each of 8, 16, 24, 32 to distribute this “decompression”. We furthermore need to convolute wrt time.
Naive Approach (2)

After exploding our CIDRs, we’re left with:

~6.3 Billion Queries and hope for the best?

Translates to:

2048 Cores

~4-6 Hours of Runtime

Lots of OOMs / retries / vacuous queries (no results)
Wait a Minute… (3)

~6.3 Billion IPv4 addresses!?

There’s only ~3.7 Billion publicly addressable IP addresses

Pigeonhole Principle?

GBK Confirms this… But that’s still a lot of queries!

OK - queries are cut in half, but what about our OOMs/Retries/Vacuous Queries?
Problem Queries (4)

Vacuous Queries:

\( \exists ? \rightarrow \text{Nope} \)

Still costs time to answer that question

OOMs:

\( \exists ? \rightarrow \text{Very Much Yes} \)

Opposite problem - too much data per worker
Secondary Index (5)

SELECT ip, COUNT(*) FROM secondary_index
WHERE start_time <= timestamp
AND timestamp <= end_time GROUP BY ip

Now we know what IPs we have data for and how much data we have for each.

Secondary Index is built by utilizing DAG structure of Beam - just tack on an additional operation to write IP/Timestamp to your favorite RDBMS as a side-effect of otherwise running your pipeline.
Do You Exist? (6)

Bitmaps

Naive: $2^{32} - 1 = \sim 536$MB

RoaringBitmap: $\sim 222$ MB

Computed via custom CombineFn

Broadcast via Side Input and do an In-memory Filter

$\sim 6.3$ Billion $\rightarrow \sim 1.5$ Billion

This is pre-GBK/Dedupe
Solving OOMs (7)

Not only do we have proof of existence, but we have <IP, Count>

Assume Uniform Distribution of IP over time range

We can now partition/split keyspace of a range accordingly

(1.2.3.4, [2022-04-01, 2022-05-01], 30)

-> ~30 of (1.2.3.4, [2022-04-01, 2022-04-02], 1),

(1.2.3.4, [2022-04-02, 2022-04-03], 1), ...

(1.2.3.4, [2022-04-30, 2022-05-01], 1)
Further split the queries according to Bigtable’s sampleRowKeys()

Ensure queries are sympathetic to the underlying storage layer.

Same process as before, but takes tablet-boundaries into account

BT RowKeys are 4096 bytes, lexicographically ordered.

We store IPv4 as Hex, to enable scanning not just single IPs, but CIDR ranges too.

After Bitmap/Split/Dedupe/GBK: $6.3\text{B}\rightarrow 1.5\text{B}\rightarrow \sim 450\text{MM}$ Scans
Running the Queries (9)

Batch ~450MM Scans into collections of 256 each

~1.8MM “Scan Groups”

What happens when steps fused to scans fail part way through?

Entire step needs to be retried. Ouch!

Shuffle is your friend: “Fusion Break”

Reshuffle.viaRandomKey() will checkpoint you data preventing rescanning of Bigtable/External Service and recalculating scans.
MultiThreading! (10)

Beam model says you “don’t have to think about this multithreading” but you may want to anyway.

- Scio has some great examples if you speak Scala

Think of DoFn’s as individual Microservices

- Beam handles networking/statefulset/message passing

What it doesn’t do is benchmarking - you’ll be spending a lot of time here.

Tip: Start with a fixed number of threads
End Results (11)

Cores:

2048 -> 348 cores (could go lower but we like the headroom)

Runtime:

~4-6 hours -> ~1.5 hours (end-to-end)

MGMT:

-> 😱💰
Running analytic processing on billions of results
Beam Challenges

- Pushed Data
- Pulled Data
- Collected Data

CyberDatum

Data Warehouse (BigTable)

Footprints

Risk

Running analytic processing on billions of results

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Processing the Records

- Pull out observations that are attributed to our footprints
- Enrich observations with whatever the current threat landscape looks like
- Determine what these observations and enrichments are telling us
  - Do we even care about every single observation?
  - Can we determine who/what may be vulnerable? Who is running out of date code?

Bigtable

Text Records

700M+ Daily

Enrichments

- Fingerprints
- Regexes
- Analytic Workflows

Analysis

How to interpret the records?

Beam

- Bigquery
- Postgres
- /dev/null

20B+ Daily
Enrichment

- Need to detect Software types and versions
  - Typical solution is plain regex - but that's too slow for this amount of data
  - Running a database of regexes against a database of outputs is an N^2 shuffle
  - Instead, we can run a compiled regex database scanner against each element (no shuffle!)
    - Maintained and curated to keep up with the changing landscape

- Problem
  - High amount of data overlap = lots of unnecessary cpu-heavy processing
  - GroupByKey to the rescue! We only need to process “unique records” once
    - 270M -> 6M records actually require processing
Analysis

- How to determine what to actually output? What is important?
  - Could use Side Input queries from BQ
    - Inefficient/Expensive to join records against large regex sets
    - Difficult to handle multi-CPE CVEs (Firefox.101 OR Firefox.102) AND (Ubuntu-20.04 OR Ubuntu-20.10)
  - Static prebuilt CVE mapping dictionaries
    - Combination of analyst fingerprinting and processed NIST CVE rulesets
    - Determine which CVEs apply to found CPEs
    - Determine how old the detected versions are
    - Very fast lookups in memory

Vulnerable? Up to date?

14 CVEs
Version 7.4 from 2016 Newer versions exist

...
Output

- Finally we have output... **too much output**
  - 1 record => multiple software ids => potentially 100+ CVEs each
    - Extrapolated across millions of assets and footprints
  - Lots of redundant and costly output data!
    - Daily 20B records/6TB of highly redundant data
    - $$$ and downstream sadness
  - GroupByKey to the rescue again
Let’s group by the record text, emit “normalized” records, and dedupe what we can. This record… but billions more…

Using GBK and Beam Distinct transforms: 20B records (6TB) realized data => 3 datasets at 30GB total

- Also! The normalized data can be used as “ground truth” datasets now, all as a side effect of trying to save time and money
Wrap up

- **Before-Beam**: many disparate processes with different stacks
  - Anywhere from 1-10 hours to process individually
  - Complexity of maintenance
  - Limited to SQL or cross-platform chaos

- **The Beam Way**: all data processed within a single integrated codebase
  - 1hr process to generate the same outputs (and in cheaper/efficient ways)
  - Only one code base and architecture now :D
  - Ad-hoc analysis, end-to-end A/B testing
Beam Questions and Feature Requests

- Controlling bundle sizes? (GroupIntoBatches incurs shuffle)
- Operations on a bundle or all bundles local to a single worker?
- Splittable DoFn for querying BigTable where results may have long tails?
- Fusion break – can we do it without a shuffle?
Always looking for good data engineers

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