Flexible Network Analytics in the Cloud

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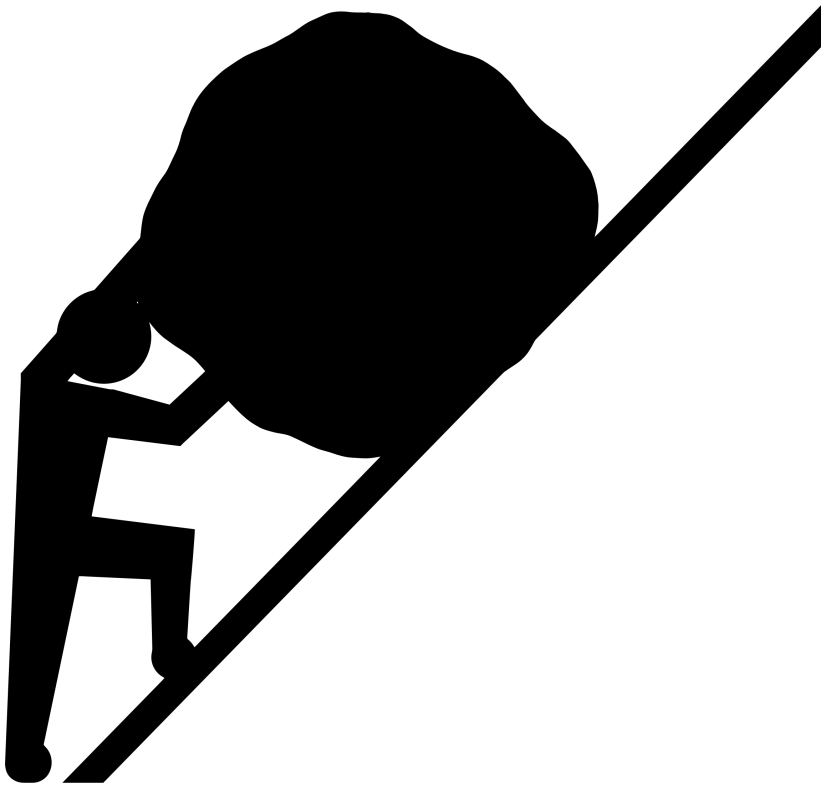
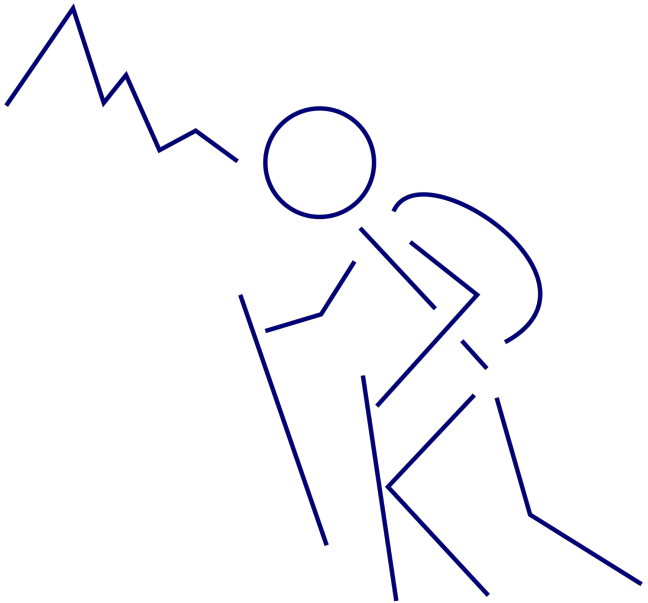
Sisyphus, Network Engineer



Crazy Happy Kid, Network Engineer

Rugged Adventurer, Network Engineer



Outline

Hard realities

Coping strategies

A programming model brings solace

Making the ascent with code

A scenic vista

Hard realities

Network measurement is harder than it seems.

Reality #1: It’s a mess

Everything is a struggle.

Ideal

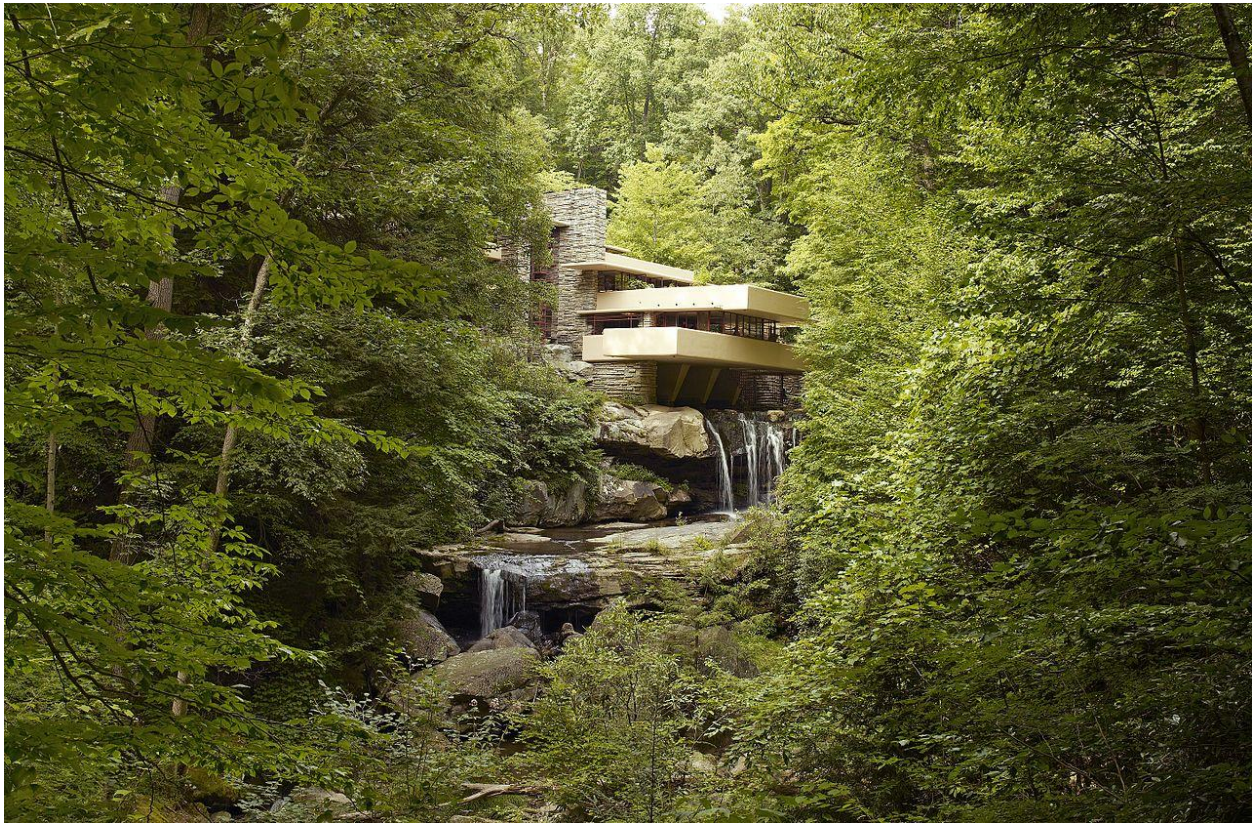


Photo: Fallingwater, Carol M. Highsmith via Wikimedia Commons

Reality

Photo: Shack, Oven Fresh via Wikimedia Commons

The world is not neat and tidy.

Your data is not neat and tidy.

Accept it, design for it, live with it.
Invite it over for dinner.

Reality #2: Things Change

I’m not kidding, everything *is* a struggle.

First Request

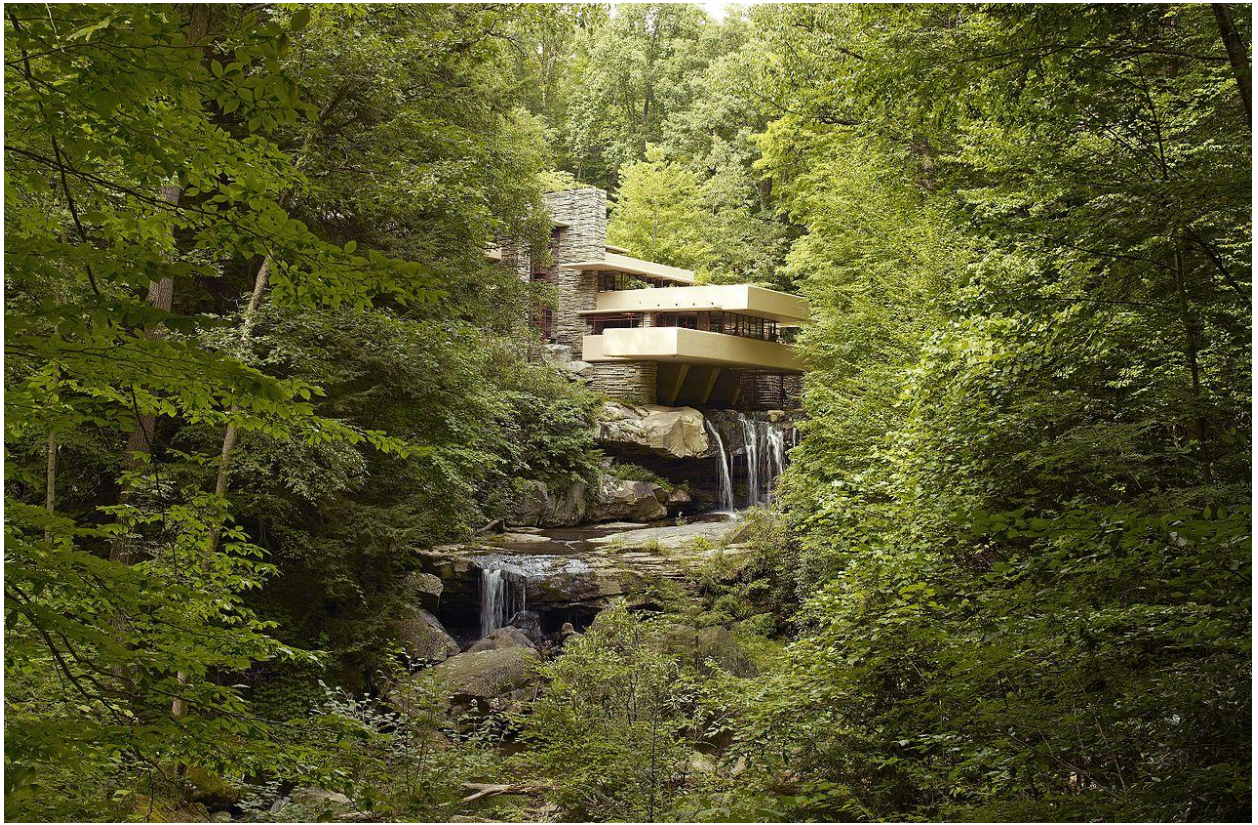


Photo: Fallingwater, Carol M. Highsmith via Wikimedia Commons

Second Request

Photo: Farnsworth House, Wikimedia Commons

What you needed yesterday probably isn’t what you’ll need tomorrow.

You have to build something today that will work tomorrow.

Don’t make decisions today that you can make tomorrow.
Save your raw data. All of it if possible.

Reality #3: There’s always more

I told you everything is a struggle, but I’m not sure you believe me.

Photo: Moscow. Standard buildings on Novokosinskaya street, аналоговый снимок via Wikimedia Commons.

There are always new devices coming online
and more telemetry you can collect.

Your storage and compute will be the same size
tomorrow as they are today.

Use the cloud to scale.
The cloud is elastic and (effectively) infinite.

Reality #4: It’s never really done

Nevermind. You’ll see for yourself, everything is a struggle.

Photo: © Saúl Briceño from Wikimedia Commons Exterior of Centro Financiero Confinanzas (Torre de David),

Nothing is ever really finished.

Time and money are limited.

Spend your time on the “what”: deriving insight from your data.
...not the “how”: building infrastructure.

Coping strategies

The reality of the situation

1. It’s a mess

- Design knowing things won’t be tidy

2. Things change

- Keep raw data to keep your options open

3. There’s always more

- Rely on the cloud for scaling

4. It’s never really done

- “What” not “How”

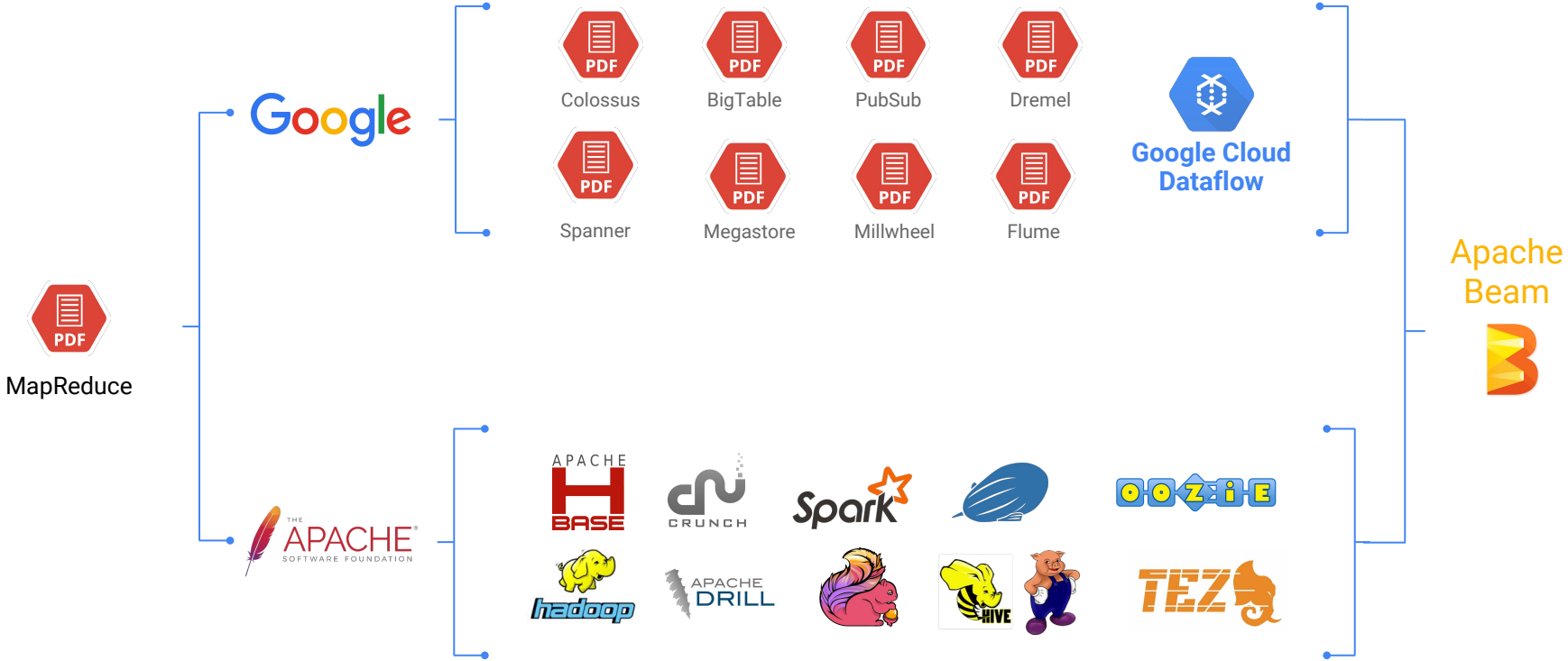
A programming model brings solace

What is Apache Beam?

1. The Beam Programming Model
2. SDKs for writing Beam pipelines
3. Runners for existing distributed processing backends
    - Apache Apex
    - Apache Flink
    - Apache Spark
    - Google Cloud Dataflow
    - Local runner for testing

Slide courtesy of the Apache Beam Project

The Evolution of Apache Beam



Slide courtesy of the Apache Beam Project

Why Apache Beam?

Unified - One model handles batch and streaming use cases.

Portable - Pipelines can be executed on multiple execution environments, avoiding lock-in.

Extensible - Supports user and community driven SDKs, Runners, transformation libraries, and IO connectors.

Slide courtesy of the Apache Beam Project

The Beam Model: Asking the Right Questions

What results are calculated?

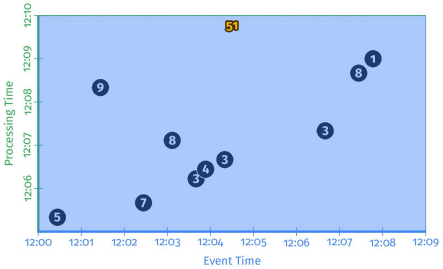
Where in event time are results calculated?

When in processing time are results materialized?

How do refinements of results relate?

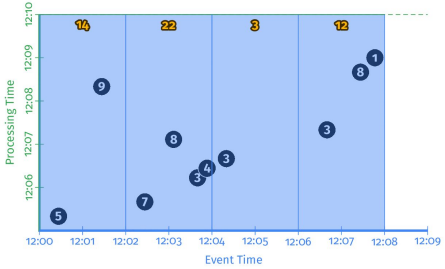
Slide courtesy of the Apache Beam Project

Customizing What Where When How



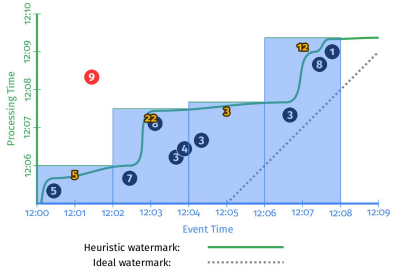
1

Classic Batch



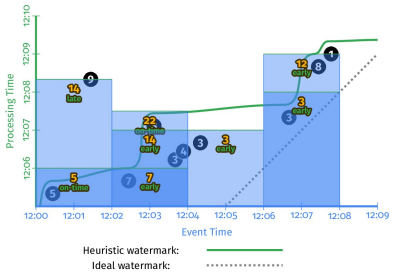
2

Windowed Batch



3

Streaming



4

Streaming + Accumulation

Slide courtesy of the Apache Beam Project

Making the ascent with code

Your immutable data store: raw data

Make an immutable (read-only) repository of raw data

- Minimize processing of the data
- Get it into the database as soon as possible
- Keep your raw data for as long as you can

Benefits

- You get to change your mind later
- If you make mistakes in later steps: recompute.

Views: how to turn raw data into usable data

Use Beam to transform your raw data into a “view” of the data

Examples:

- converting SNMP counters to rates
- grouping SNMP counters by customer or peer
- binning flows by attributes
- building network topologies from basic data

Views can be stacked, you can use one view as the input for a more refined view.

Core Beam Abstractions

PCollections
- Distributed, multi-element data set.

Transforms
- Some code to run on all the data
- Take PCollection in and produce a PCollection

Pipeline I/O
- Read data and produce a PCollection
- Take a PCollection and write data

Pipeline
- Input→PCollection→Transforms→PCollection→Output

f(allMyData): Focus on “what”, not “how”

Define the “what”

- I/O: What data to use and where it lives.
- PCollections: Grouping the data for each transformation step
- Transforms: allow you to define the “what”

Let Beam handle the “how”

- I/O: Reading and writing data at scale
- PCollections: distributing data across workers
- Transforms: applying your analysis to PCollections

Example: Computing Total Traffic

```
# Python Beam SDK
pipeline = beam.Pipeline('DirectRunner')

(pipeline
 | 'read'           >> ReadFromText('./example.csv')
 | 'csv'            >> beam.ParDo(FormatCSVDoFn())
 | 'ifName key'     >> beam.Map(group_by_device_interface)
 | 'group by iface' >> beam.GroupByKey()
 | 'compute rate'  >> beam.FlatMap(compute_rate)
 | 'timestamp key'  >> beam.Map(lambda row: (row['timestamp'], row['deltaIn']))
 | 'group by timestamp' >> beam.GroupByKey()
 | 'sum by timestamp'   >> beam.Map(lambda rates: (rates[0], sum(rates[1])))
 | 'format' >> beam.Map(lambda row: '{},{}'.format(row[0], row[1]))
 | 'save' >> beam.io.WriteToText('./total_by_timestamp'))

pipeline.run()
```

Data Processing Tradeoffs

1+1=2

Completeness

Latency

$$$

Cost

Slide courtesy of the Apache Beam Project

Stream or Batch?

Streaming for *realtime insight*

- Current network load
- Operational awareness
- Threat detection / Anomaly Detection
- Tend to be more expensive (VMs always running)
- Unbounded data sets

Batch for *precision* or *results that can wait*

- Billing
- Precise traffic reports
- Capacity planning
- Tend to be cheaper (VMs used in bursts)
- Bounded data sets

A scenic vista

What can we see from here?

- Define new views to get different perspectives on raw data
- Add new immutable data sets to gain more dimensions of data (SNMP, Flow/sFlow, syslog, …)
- Try out new ideas (running batch jobs is cheap and doesn’t impact system)
- Teach others to write their own analysis

Our experiences so far

1. There is a learning curve.
2. Docs aren’t amazing, but getting there.
3. You may have to adjust your thinking. Need to understand the model to know what will work at scale.
4. The cloud providers have a several choices when it comes to databases. It’s easy to spend a lot of time investigating.
5. Cost is manageable but it’s good to keep an eye on it.
6. In the interest of vendor neutrality details about our specific vendor haven’t been covered, but I’m happy to talk to you after the talk.

Thank you!

Questions?

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http://x1024.net/blog/2017-05-12-CHINOG/

More about Apache Beam:
https://beam.apache.org

The World Beyond Batch 101 & 102
https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-101
https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-102

More about ESnet:

Open source: http://software.es.net/
Visualization portal: https://my.es.net/