Cloud-Based Data Pipelines and Interfaces for Batch Data

DAREDATA ENGINEERING

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Main Points

- How you end up deciding to use batch processing technologies.
- An example architecture that uses Snowflake and AWS batch processing technologies to satisfy some real life business requirements.

General Advice

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You shouldn’t select your technologies based upon the type of data that you’re working with.

Rather, you should use some combination of data and business requirements to select a final data interface and work backward from there.

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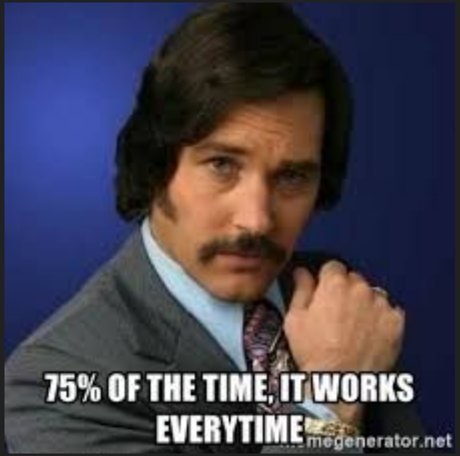
Try to future-proof if possible. If you have two choices that serve your current use cases equally well and one is more open than the other, go with the more open one.

If you follow these guidelines...

75% of the time, it works every time

So, if you follow these guidelines, you’ll usually end up choosing SQL as your main data interface.



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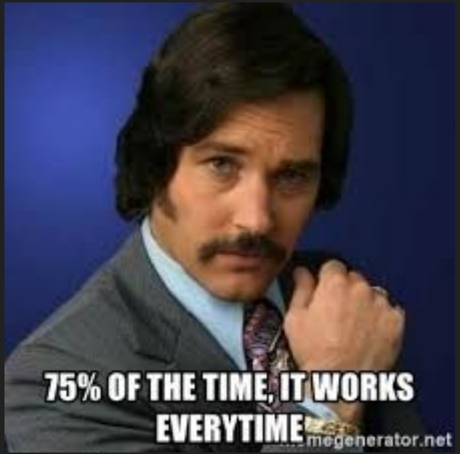
It's not a protocol per-se but the implementations typically share enough in common that SQL knowledge gained using one implementation is largely transferable to another.



Batch or Streaming Data

How do you know which one you’ve got?

Batch or Streaming Data?

Let’s first take a flawed (but still useful) look at the types of data that you would use streaming or batch technologies to process.

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Quite often, measures a low number of dimensions (temperature, humidity) or (x, y coordinates of a mouse click) or (page element that was clicked).

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When processing it, you need access to large portions of the dataset to compute aggregate statistics

Batch or Streaming Tech

Which one should you use?

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If the answer is “no”, you can use batch processing technologies.

Some Useful Exercises

Question

I need to raise an alarm within 30 seconds if the temperature in my brewery goes above 25 degrees

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Streaming

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I need to know how much we sold yesterday before the manager’s meeting at 9am every morning.

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What was the average price of a product over the last 2 years.

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This one could be more tricky… might depend on how quickly you need that data deduplicated and for what use case!

Fact

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Most use cases can be satisfied with SQL as the interface and with pipelines (ETLs) implemented using batch processing technologies.

Implementing Batch Data Pipelines

Use Case

Let’s pick a real live use-case from a previous client called Daltix that provides price analytics via web scraping.

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They sell data, sometimes via a service or an app but the end product is always tabular data.

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It would be nice if they could be given the same interface that is used internally so we could leverage internal knowledge in providing support.

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The clients know SQL.

SQL brings much joy to the world.

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It turns out that the clients don't need real-time data.

The most stringent requirements for delivery are that once per day, the data needs to be in delivered around mid-morning.

Sooooo Batch

Given that the raw data has typically been scraped before 7am, we are clearly in batch territory as we have several hours to process something on the order of millions of json structures.

Raw Input / Output

The raw output of the scrapers is json which is super nice and the business cases are mostly satisfied by taking the json data structures and flattening them into tabular ones.

Extra Requirements

However, we have one extra fun little requirement which is that some very non-trivial code needs to do some NLP on a few of the unstructured fields to turn un-structured promo strings into structured data.

Architecture v1

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Tangent Time!

Airflow (Quick Note)

All of these operations are scheduled and coordinated using Airflow.

More Tangent Time!

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A Data Mart’s main job is to ensure that specific business requirements can be met.

You want it to be AS EASY AS POSSIBLE to create Data Marts (because this is where the business value is directly generated) which means that you really do want your Data Warehouse and your Data Marts to be implemented in the same technology / network in order to avoid expensive export / import operations typically involved in ETLs.

Back On Track

Going through the components

scrapers -> AWS s3 (scraper output data lake)

-> Spark (Partitioning the data) -> AWS s3 (partitioned data lake)

-> AWS Lambdas (promo extraction) -> AWS s3 (promo output data lake)

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The scrapers write out to an S3 data lake in a way that is just segmented by the date that it was crawled. This is the very beginning of the pipeline.

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Every hour, there is a spark job that reads in all of the data from the past hour and writes it out to another s3 bucket in a more organized way (i.e. more partitions).

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It also does a few relatively simple transformations and deduplications. The output is JSON.

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This type of processing requirement is significant because it requires code and is not something that can be expressed in simple set-theory based transformations that you might do in SQL.

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Remember: Data Warehouses main job is to be complete, not necessarily optimized or easy to use.

Data Transformation in Snowflake

Now that we have a data warehouse in an SQL format that supports a DDL, we can subset and transform the data into use-case-specific tables that are derived from our data warehouses.

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Compare this to using a proprietary interface like SAS or SPSS and you are light years ahead in terms of flexibility, speed, and cost.

Architecture V3

(yes, we skipped V2)

Learnings and Changes Since I Was At Daltix

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There aren’t enough use cases for Lambdas to justify introducing a new technology into the stack.

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Batch processing covers the vast majority of use cases.

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Questions?