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Eventually Consistent Data Operations

With Apache Airflow

By Nicolas Goll-Perrier
@ngollperrier

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Summary

28,1 million
unique visitors*

more than
27 million
classifield ads online

800 000
new ads every day

73
categories

*Source Médiamétrie Net Ratings, avril 2018

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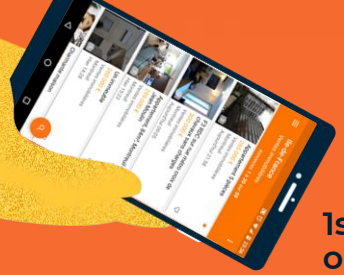


1st french website on the top 10 on audience

50,6 Google

45,9 facebook.

44,8 YouTube

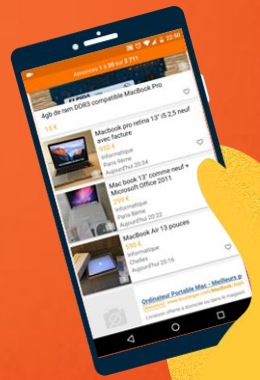
29,5 WIKIPÉDIA

28,2 leboncoin

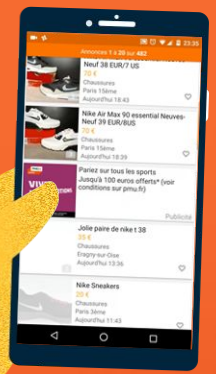
27,7 amazon

An app (iOS + Android)
downloaded 27 million times

70% of the audience
is on device mobile



The satisfaction rate of active users 85%**



*Source Médiamétrie Net Ratings, avril 2018
**Source Baromètre de satisfaction BVA novembre 2017

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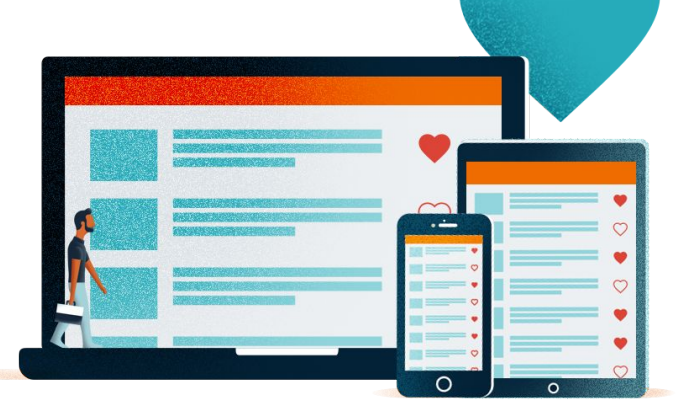

Technical stack

2
Datacenters
&
1
Cloud provider

2000
Virtual machines

15 Gbits/s
outflows & a database of
6 To

300M
images
36k
req/s on leboncoin

Tech team of more than
200
people

A strong « open-source » culture:
PostgreSQL, Spark, Kafka, Python, Go, Kubernetes
...

Summary

A typical (good) day of data operations

Recent Tasks	Last Run	DAG Runs
41	2019-01-28 00:00	43
114	2019-01-29 10:00	272
5	2019-01-28 00:00	344
26	2019-01-28 00:00	607
105	2019-01-29 10:10	274
6	2019-01-29 09:04	177
24	2019-01-29 05:32	72
9	2019-01-28 00:00	66
12	2019-01-28 00:00	607
24	2019-01-29 08:19	269
16	2019-01-28 00:00	113

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A typical (bad) day of data operations

Recent Tasks	Last Run	DAG Runs
41	2019-01-28 00:00	43
114	2019-01-29 10:00	272
5	2019-01-28 00:00	344
26	2019-01-28 00:00	607
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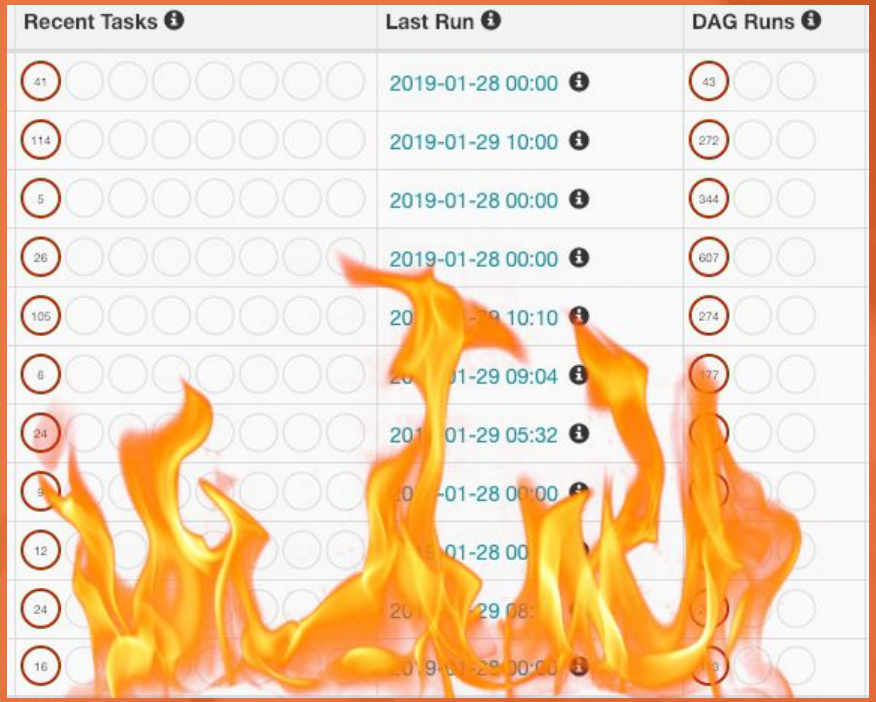
A typical (memorable) day of data operations



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What could possibly go wrong ?

Things that can fail loudly:

- **Access to source data**
  - Connectivity issue to a source database
  - Maintenance on source database
  - Missing log files, partitions
  - Rate limiting or parallelism quotas reached
  - Third party API down
- **Transformation and storage**
  - Resource allocation failure (memory, network, I/O, storage space)
  - Unplanned dataset size
  - Malformed/Unexpected fields in dataset
  - Incomplete test coverage leading to crashes
  - Inadequate capacity planning

Potential impacts:

- **Missed SLA**
- **Business Reactivity delay**
- **Cost of failure investigation**
- **Outdated ML models**
- **Catch-up period**
- **Lack of sleep**
- **...**

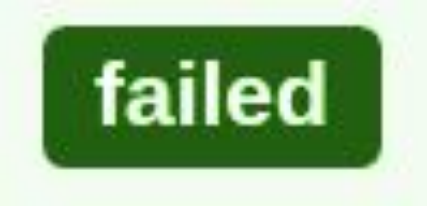
Everything is green, nothing to do ?

Things that can fail silently:

- **Product changes**
  - Unexpected business rule change
  - Changes in user behavior
- **Silent failures**
  - Success after several retries
  - Due to bugs in the code-base
  - Due to unhandled business rules
- **Inconsistent data**
  - Incomplete extraction range targeting
  - Late arriving events/facts

Potential impacts:

- **Erroneous Business Decisions**
- **Diminution of trust in KPIs**
- **Long investigations**
- **Patches will most likely be required**
- **Data re-processing**
- **...**

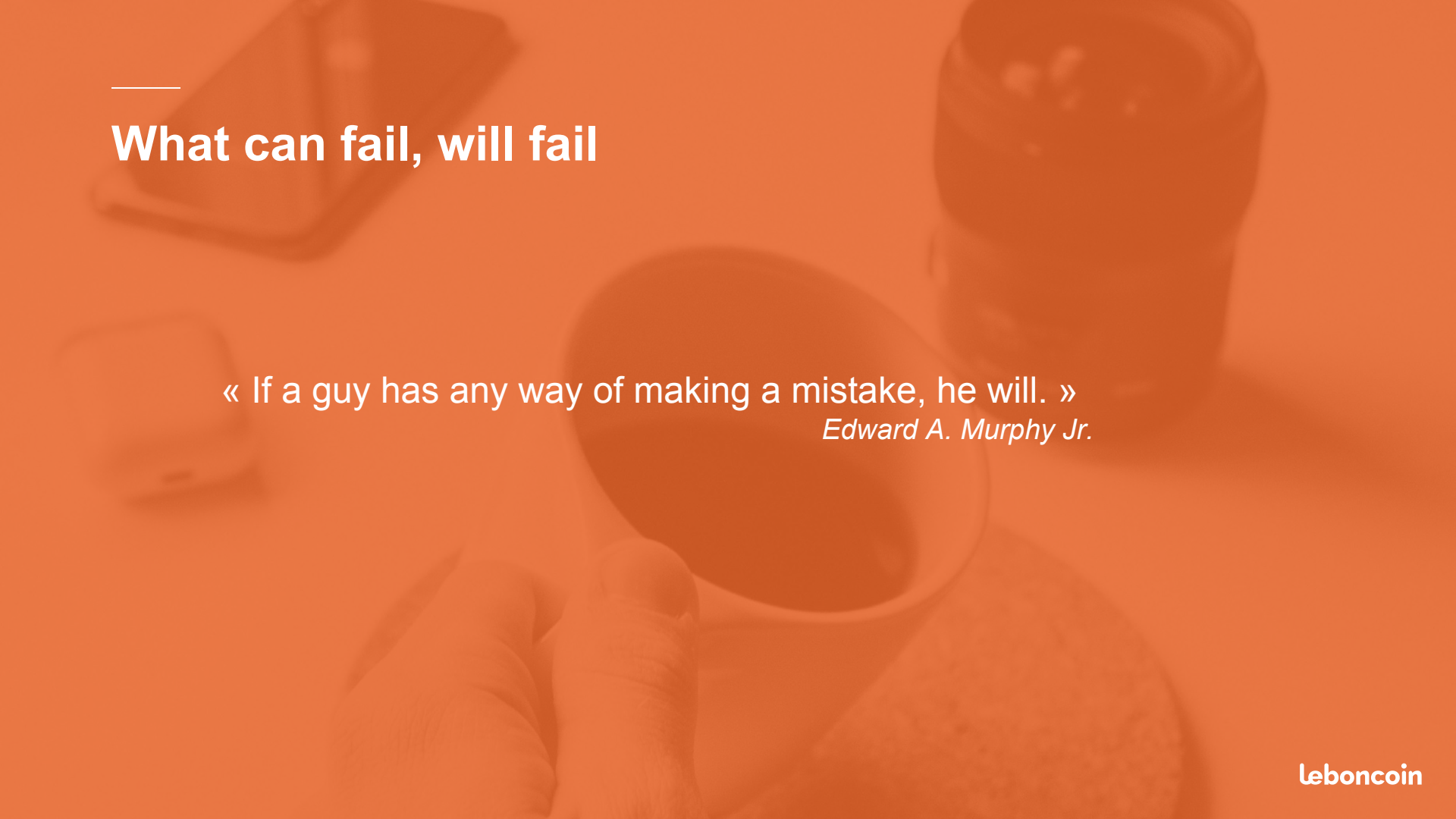


Summary

What can fail, will fail

« If a guy has any way of making a mistake, he will. »

Edward A. Murphy Jr.



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Preventing the fire

Adequate code quality and functionalities

- Unit testing, TDD
- Strong User Acceptance Testing
- Validation of Business Rules

Detecting failures

- Thresholds and Smoke Detection Tests
- Monitoring
- Communication

But…

- Not everything can be realistically planned for
- Data systems are downstream the information system
- Upstream errors may require time and full collaboration of many other teams

Hope for the best, plan for the worst

Recovery process should focus on:

- Identifying the origin of the issue (through airflow logs)
- Communicating on the impacts of the failure
- Fixing the cause of the issue
- Or waiting for an adequate fix
- Re-running the affected task instance after resolution
- Validate and communicate the availability and accuracy of the recovered data

Hope for the best, plan for the worst

Recovery process should NOT:

- Block independent or unaffected task instances
- Require large re-computation of unaffected dag runs
- Require Business specific knowledge
- Require manual data-cleanup or ninja patching of datasets
- Risk corrupting datasets/metrics

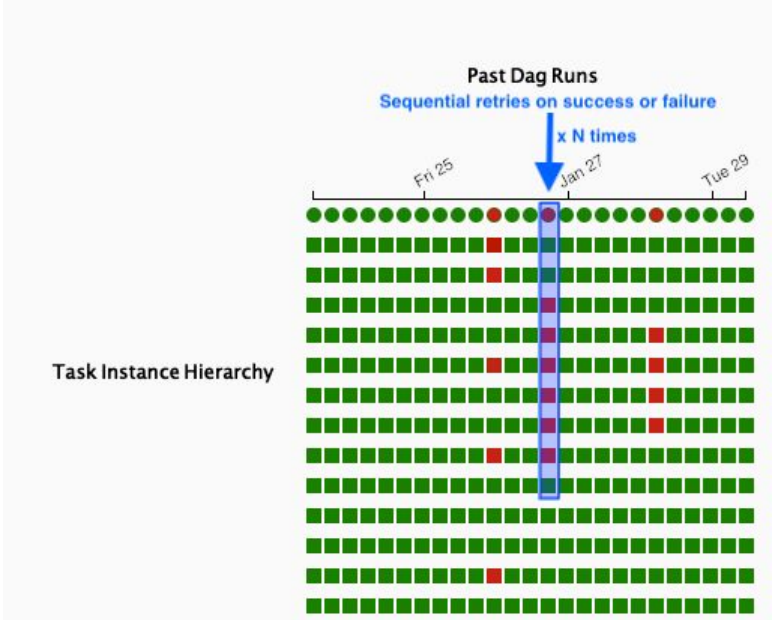
Summary

Providing replay agility

Idempotence

- Allows running of task instance any number of times
- Deterministic
- Typical use cases:
  - Re-running after patching source data
  - Re-running after fixing a bug
  - Re-running “just to be sure”

$$f(f(x)) = f(x)$$

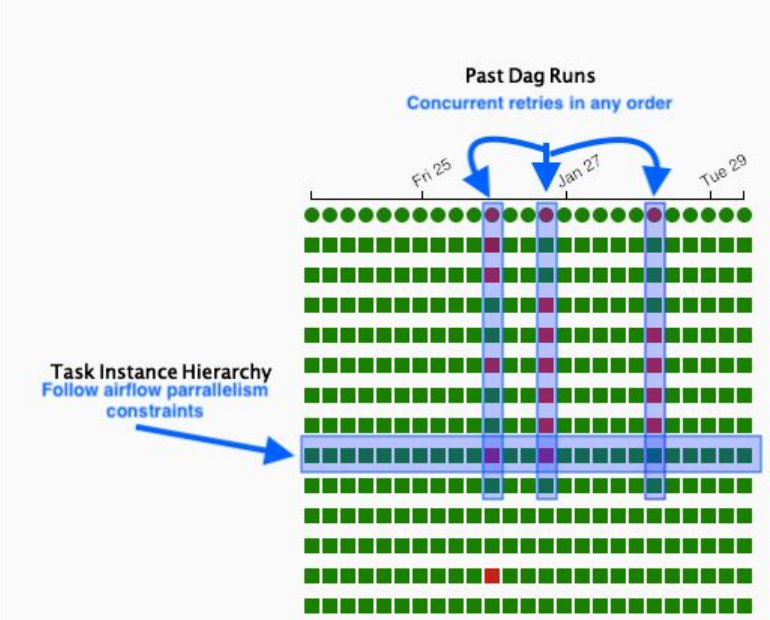


Providing replay agility (contd.)

Commutativity

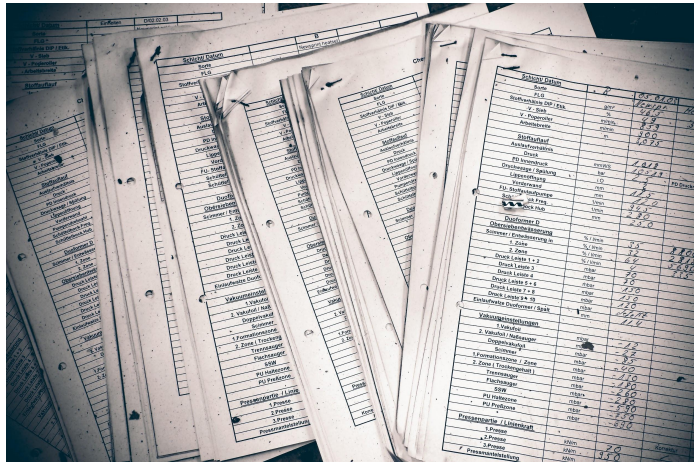
- Allows running of multiple instances of the same task in any order
- Typical use cases:
  - Non-blocking failures
  - Parallelizing re-run without a race condition

$$f(g(x)) = g(f(x))$$



Types of data objects

- **Fixed/Predictable objects**
  - Should never change during the lifetime of an application
  - Trivial, but very rare
  - Example: Time…
- **Immutable objects**
  - Once produced, cannot be altered
  - Low complexity
  - Availability depends on your information system
  - Examples: Stream of events, Logs, Business Facts (bills)
- **Mutable objects**
  - Have their own lifecycle, can change any number of time
  - Medium to High complexity (often nested)
  - Changes should be traced either by source application or change data capture
  - Examples: Domain objects (ads), Reference data (categories)…



Types of data objects (contd.)

Atomic datum

- As fine grained as can be
- Have their own life-cycle
- Can disappear over time (GDPR)

Aggregated data

- Often time-bound
- Inherit their properties from the underlying datum types
- Should converge towards the truth and be frozen

Identification and Versionning

- **Datum Identification**
  - Use natural keys whenever possible
  - Technical keys otherwise (sequence, event-id, UUID, …)
- **Dataset/batch Identification**
  - Depends on extraction mechanism
  - Generally the execution_date is a very good candidate
- **Datum Versioning**
  - Version input/output schemas for every unit of work
  - Include code version in processed output rows
  - Include actual processing date in each output rows

Atomic units of work

Atomic Individual Tasks

- Low coupling between tasks of different kind
- Single unit of work, don’t over-stretch your operations over multiple tasks
- Isolate business rule changes from technical changes
- Freeze outputs of all types of tasks on HDFS/Cloud Object Store
- Avoid past task instance/dag run dependency
- Stateless tasks if possible (don’t overuse XCOMs)

Summary

Replayable data extraction

Mostly outside of your scope...

- Bound by transactional system choices
- Many competing storage technologies
- Each comes with its own constraints and benefits
- Tuned for transactional performance
- Rarely exhaustive representation of the domain data

Or is it ?

- Be aware of the schema exposed (tables, events, APIs)
- Be aware of the objects life-cycle in your source system
- Communicate with your back-end engineering team to converge towards a mutually beneficial solution

Replayable data extraction

Detect changed objects in your source system

- Via application level mechanisms (preferably)
- Via Change Data Capture systems
- Via Snapshots (as a last resort, and not always possible)

Wait for completeness of your data-batches

- Identify key window bounds for your delta extracts
- Immutable can be incomplete too: plan for late arriving events

Avoid extraction replays as much as possible

- Store and freeze your unaltered extracts on HDFS/Cloud Object Store
- Following the guidelines above, you should rarely need to replay extractions
- Focus on resilience rather than replayability
- Most of the time, you won't be able to guarantee deterministic behavior anyway

Deterministic data transformations

Don’t couple extract and transform

- Extracted data should be persisted as closely to its original form as possible
- Extracted data should normally never be altered

The “easy” part, right ?

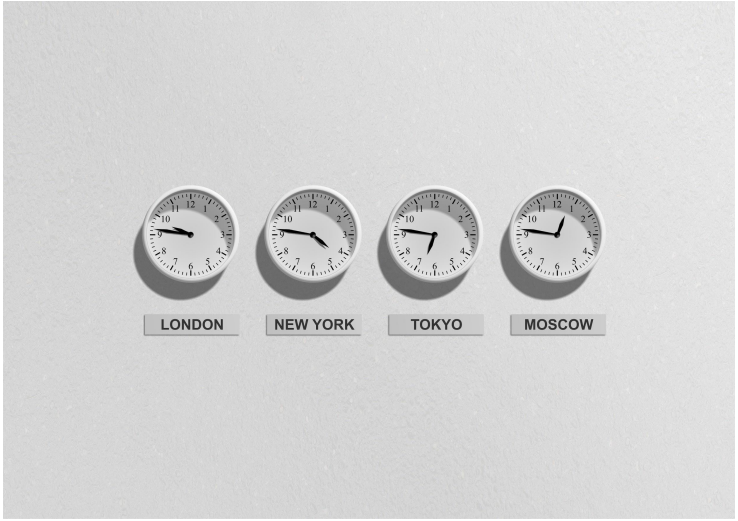
- Stateless: No external moving parts
- Can easily be isolated and tested in a sandbox
- Commutativity and Idempotence are inherently guaranteed

Single or Multiple Input => Single Output

Deterministic data transformations

Not quite as “easy” as it seems

- Identify whether business Rules are retro-active or not
- Ensure backward-compatibility for retro-active business rules
- Implement non retro-active business rules versioning either in code or in a separate configurable dataset



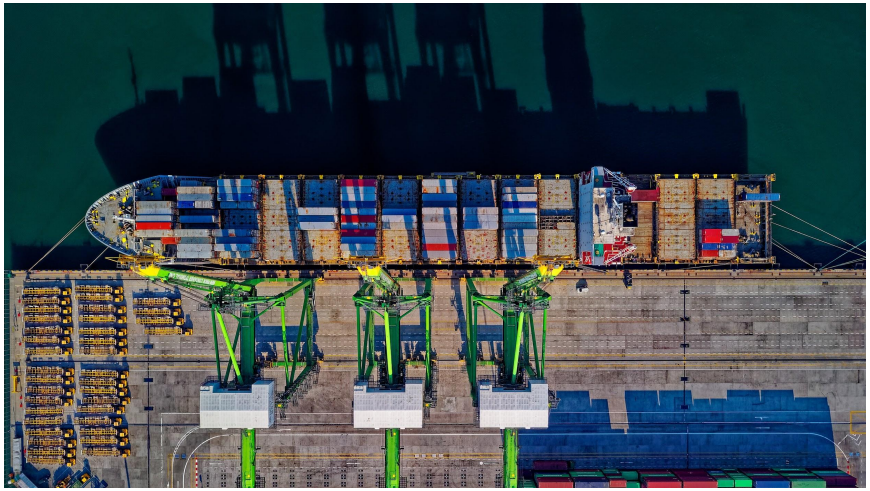
Eventually consistent data loading

Highly dependant on datastore engine

- Optimal choices may not be implementable with your storage engine
- Some might require more work than others
- Some might have degrade performance more than others

Ideally

- Overwrite, but also delete everything from the previous run (based on data version and dataset identification)
- Use fine-grained or coarse grained erasure depending on the underlying type of data objects
- Prefer ETL to ELT (whenever possible)
- Single Input => Single Output



Eventually consistent data loading

Adopt a dimension change policy:

- Reflecting your business requirements
- As consistent as need be, as simple as can be

For optimal consistency, prefer (in that order):

- Early Denormalization
- Dimension Snapshots
- Slowly Changing Dimension mechanisms
- Upsert Dimensions

Summary

Redshift Example #1

```
/* BULK DELETE AND REPLACE */
BEGIN;

DELETE FROM target_table
WHERE target_table.dataset_id = '{current_dataset}';

COPY target_table
FROM 's3://bucket/key/';

COMMIT;
```

Pros

- Idempotent
- Fast
- Simple
- Low additional I/O

Cons

- Non commutative

Ideal for

- Immutable data objects
- Order dependent tasks instances

Not suited for

- Mutable objects
- High parallelism of multiple task instances

Redshift Example #2

```sql
/* ATOMIC UPSERT */
BEGIN;

-- Insert input data in Temporary Table
COPY temp_table
FROM 's3://bucket/key';

-- Remove obsolete rows from target table
DELETE FROM target_table
USING temp_table
WHERE temp_table.primary_key_id = target_table.primary_key_id
    AND
    (
        target_table.data_version <= temp_table.data_version
        OR
        target_table.code_version <= temp_table.code_version
    )
;

-- Insert newer rows from temp table
INSERT INTO target_table
SELECT /*...*/
FROM temp_table
LEFT OUTER JOIN target_table USING (primary_key_id)
WHERE target_table.primary_key_id IS NULL;

COMMIT;
```

Pros

- Idempotent
- Commutative

Cons

- Complex
- Slower
- High additional I/O

Ideal for

- Mutable data objects, Snapshots
- Order independent, tasks instances

Not suited for

- High cardinality datasets
- Any parallelism of multiple task instances

Elasticsearch/Spark Example #1

Externally provided version

- Specify the column carrying the version
- Let ES index the new version separately

Pros

- Out of the box support in Hadoop ES
- Configuration only
- Detects version conflicts

Cons

- Fails on version conflict…
- Inadequate for retryable tasks

```
import org.apache.spark.SparkConf;
import org.apache.spark.sql.SparkSession;
import org.apache.spark.sql.Dataset;
import org.apache.spark.sql.Row;

import static org.elasticsearch.spark.sql.api.java.JavaEsSparkSQL.saveToEs;

SparkConf conf = new SparkConf(/*...*/)

conf.set("es.nodes", "elasticsearch")
    .set("es.port", "9200")
    .set("es.write.operation", "index")
    .set("es.mapping.version", "version")
    .set("es.mapping.version.type", "external");

SparkSession spark = SparkSession.builder().config(this.sparkConf).getOrCreate();
Dataset<Row> df = spark.read().format("parquet").load('s3://bucket/key');

saveToEs(df, index_mapping_name);
```

Elasticsearch/Spark Example #2

Externally provided version+conflict ignore

- Specify the column carrying the version
- Let ES index the new version separately
- Specify version conflict behavior

Pros

- Configuration only
- Detects version conflicts
- Safely discards obsolete data

Cons

- Not supported out of the box support in Hadoop ES
- Requires patch and re-compilation

```
import org.apache.spark.SparkConf;
import org.apache.spark.sql.SparkSession;
import org.apache.spark.sql.Dataset;
import org.apache.spark.sql.Row;

import static org.elasticsearch.spark.sql.api.java.JavaEsSparkSQL.saveToEs;

SparkConf conf = new SparkConf(/*...*/)

conf.set("es.nodes", "elasticsearch")
    .set("es.port", "9200")
    .set("es.write.operation", "index")
    .set("es.write.conflict.ignore", "true") // <= Will enable Commutativity and Idempotence
    .set("es.mapping.version", "data_version")
    .set("es.mapping.version.type", "external");

SparkSession spark = SparkSession.builder().config(this.sparkConf).getOrCreate();
Dataset<Row> df = spark.read().format("parquet").load('s3://bucket/key')

saveToEs(df, index_mapping_name);
```

Remaining difficulties

Cross DAG dependency tracking

- Requires manual check/awareness when replaying upstream DAGs
- Automation may become easier in the future thanks to improved data lineage?

Version aware DAG Run history

- Airflow does not persist the version of the DAG alongside the DAG Run
- A re-run will always use the most up-to date version
- Providing backward compatible DAGs is the prefered handling method for now

Conclusion

- *Know and understand your business processes*
- *Know your technological stack and its limitation*
- *Be pragmatic, not dogmatic*
- *Communicate efficiently with the information system and the business stakeholders*

Let’s keep in touch…

github.com/leboncoin

leboncoin Engineering blog

@leboncoinEng