



ANALYTICS

A Serverless Query Engine for Spare Parts

An open-source implementation of a Data Lake
DuckDB and AWS Lambdas

Ciro Greco

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A duck in the cloud. Photo by [László Glatz](#) on [Unsplash](#)

In this post we will show how to build a simple end-to-end application in the cloud on a serverless infrastructure. The purpose is simple: we want to show that we can develop directly against the cloud while minimizing the cognitive overhead of designing and building infrastructure. Plus, we will put together a design that minimizes costs compared to modern data warehouses, such as Big Query or Snowflake.

As data practitioners we want (and love) to build a top of our data as seamlessly as possible. Whether BI, Data Science or ML all that matters is the final answer how fast you can see it working end-to-end. The infrastructure often gets in the way though.

Imagine, as a practical example, that we need to build a customer-facing analytics application for our product. Because it's client-facing we have performance constraints that need to be respected, such as low latency.

We can start developing it directly in the cloud, but this immediately brings us to some infrastructure questions: where to host it? How big a machine do we need? Because of the low latency requirement, do we need to build a caching layer? How do we do it?

Alternatively, we can develop our app locally. It will be more intuitive from the developer experience point of view but only postpones the infrastructure questions, since in the end we still need to find a way to go from our local project to actual production. Moreover, the data will need to leave the cloud environment and be stored on a local machine, which is not exactly secure and auditable.

To make the cloud experience as smooth as possible, we have recently designed a data lake architecture where data are stored and processed in the cloud.

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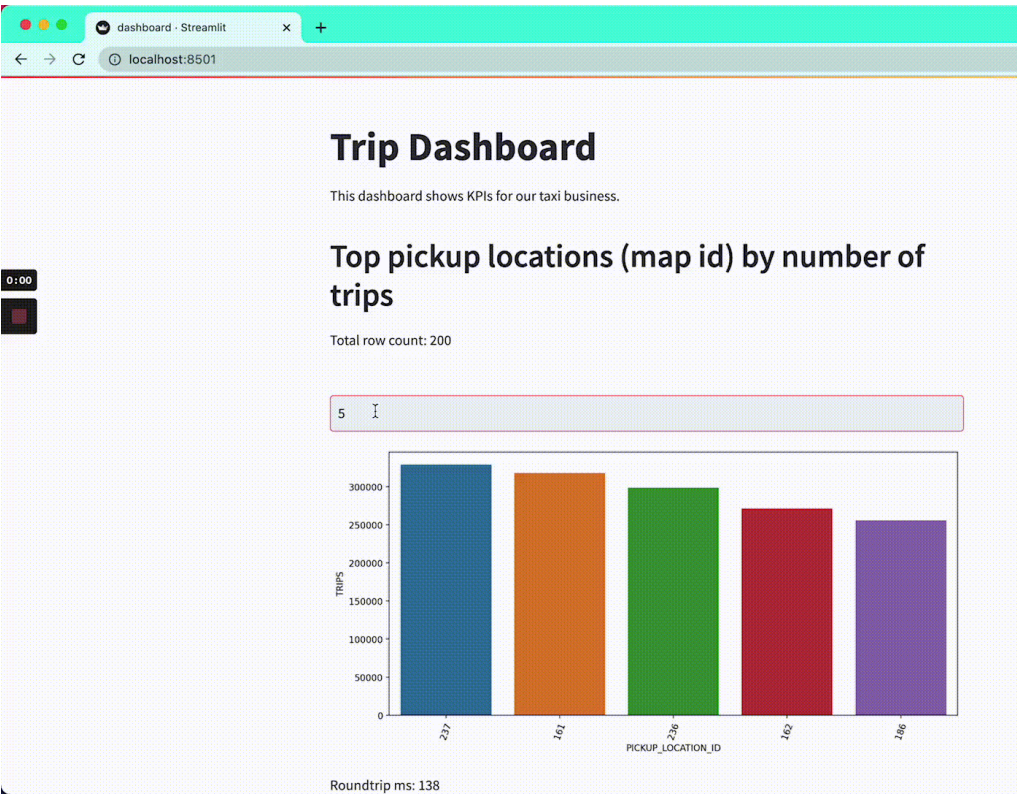
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simple cloud storage (AWS S3) and a serverless infrastructure that embeds DuckDB works as a query engine. At the end of the cycle, we will have an analytics app that can be used to both visualize and query the data in real time with virtually no infra costs.

Of course, this is a bit of a simplification, as some tweaks would be needed to run this project in real production scenarios. What we provide is a general blueprint to leverage the serverless storage and compute to build a data lake with a query engine in the cloud. We show how to power an interactive dashboard with an (almost) free cloud endpoint, no warehouse setup, and lightning fast performance. In our implementation, the application is a simple Streamlit app, but that's merely for explanatory purposes: you can easily think of plugging in your favorite BI tool.



A lightning fast analytics app built with our system. Image from the a

Ducks go serverless

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Y'all know DuckDB at this point. It is an open-source in-process SQL OLAP database built specifically for analytical queries. It is somewhat still unclear how much DuckDB is actually used in production, but for us today the killer feature is the possibility of querying parquet files directly in S3 with SQL syntax.

So most practitioners seem to be using it right now as a local engine for data exploration, *ad hoc* analysis, POCs and prototyping (with some creative ideas on how to extend its purpose to cover more surface). People create note small data apps with embedded DuckDB to prototype experiment with production data locally.

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The cloud is better. And if we often feel it isn't, it's because something is wrong with the tool chain we use, but there is a very big difference between a bad idea and a good executed.

If we combine a data lake architecture, a serverless DuckDB and a bit of ingenuity we can build a very fast data engine from spare parts: no warehouse setup, lightning fast and outrageously cheap costs – S3 most expensive pricing is \$0.023 per GB, AWS Lambda is very fast a

zero when not in use, so it is a no-fat computation bill, plus AWS gives you 1M calls for free.

Buckle up, [clone the repo](#), sing along and for more details, please refer to the [README](#).

Architecture

This project is pretty self-contained and requires only introductory-level familiarity with cloud services and

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The idea is to start from a Data Lake where our data is stored. Once the data is uploaded in our S3 in a parquet format, we then trigger the lambda with a SQL query. At that point, the lambda goes up, spins up a DuckDB instance in memory, computes the query and gets back to the user with the results which can be directly rendered as tables in the Terraform

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The architecture has a number of advantages mostly from the serverless design: speed, proximity to the data, and easy deployment are nice; plus, of course, the system is zero when not used, so we only pay per query.

General architecture of our system. Image from the authors

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Your first query engine + data lake from spare parts

We provide a simple script that will create an S3 bucket and populate it with a portion of the [NYC TLC Trip Records](#) (available under the [nyc.gov terms of use](#)), both as a Parquet dataset and as a hive-partitioned directory (you can run it with `python3 create_data_lake.py`). Once the data are in the data lake we can set up an Athena query engine on AWS lambda: if you have the Serverless CLI setup correctly, the lambda is [one command of Make again](#).

The lambda can be invoked in any of the usual ways, for example with a query as its main payload: when it runs, it uses DuckDB (using an instance if on a warm start) to execute the query against the data lake. DuckDB does not know anything about the data lake and after the execution, making the lambda purely stateless: as far as data semantics is concerned.

For instance, you can use the simple Python script in `examples/lambda/` to send this query to the lambda, and display the results:

```
SELECT
  pickup_at as pickup_time,
  dropoff_at as dropoff_location,
  trip_distance
FROM read_parquet(your_s3_bucket/dataset/taxi_2019_04.parquet')
WHERE pickup_at >= '2019-04-01' AND pickup_at < '2019-04-03'
LIMIT 10
```

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The results are visualized directly in your terminal. Image from the at

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Et voilà! You can now query your data lake, securely. This very simple design addresses directly two of the frictions for working in cloud data warehouses:

- The setup is significantly simplified since all the user has to do is to have her AWS credential. Once the setup is done, the user only needs access to the lambda (or a similar service): that is good, as it gives the user full query capabilities without access to the underlying storage.
- The performances are so good that it feels like working locally, even if we always go through the cloud. The cloud experience helps tame the too familiar frictions. The advantages of working on remote machines is paid by the coin of good developer experience.

(Almost) Free Analytics

It's all good and boujee, but let us say that we want to do a bit more than query data on the fly. Let's say that we want to build an application on top of a table. It's a very simple app, there is no orchestration and no need to calibrate the workload.

At the same time, let's say that this application needs to be responsive, it needs to be fast. Anyone who deals with data directly, for instance, knows how it is important to provide a fresh responsive experience to the clients who wait for data. The one thing nobody likes is a dashboard that takes minutes to load.

To see how this architecture can bridge the gap between data pipelines and real-time querying for analytics, we published a dbt DAG to simulate running some offline SQL transformations over the original dataset resulting in a new artifact in a data lake (the equivalent of a dashboard view).

To keep things as self contained as possible, we included a version that you can run locally on your machine (see [here](#) for more details – nor dbt nor the engine behind it matter, just the pattern to work). However, you can use a different runner for dbt and export the final artifact as a parquet file, write it to [S3](#) or [BigQuery](#).

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Architecture of our system paired with a dbt project. Image from the [dbt docs](#).

Architecture of our system paired with a dbt project. Image from the [dbt docs](#).

For the time being, we'll stick to our super simple `trips` table with two nodes. The first node takes the `pickup_location` data lake and order them by the number of trips:

```
SELECT
    pickup_location_id AS location_id,
    COUNT(*) AS counts
FROM read_parquet(['s3://{{ env_var('S3_BUCKET_NAME') }}trips.parquet'])
GROUP BY 1
```

The second that gives us the top 200 pick up location data set:

```
SELECT
    location_id,
    counts
FROM {{ ref('trips_by_pickup_location') }}
ORDER BY 2 DESC
LIMIT 200
```

We can visualize the DAG with dbt docs:

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Once our pipeline is done, the final artifact is uploaded to our data lake in:

```
s3://your_s3_bucket/dashboard/my_view.parquet
```

We can then reuse the query engine we built before the second (and final) node of our DAG to visualize the Streamlit app, simply by running in the terminal:

```
(venv) cirogreco@Ciros-MBP src % make dashboard
```

Every time we hit the dashboard, the dashboard hits the data lake behind the scenes. If you like this simple architectural pattern, it can be used in your own Streamlit app, or in a BI tool.

A few remarks on the "Reasonable Scale"

A while ago, we wrote a series of posts on what we call MLOps at Reasonable Scale where we talked about strategies to build reliable ML applications in companies that do not process data at internet scale and have a number

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constraints that truly Big-Data companies typically do not have. We mostly talked about it from the point of view of ML and MLOps because operationalizing successfully ML was a major problem for organizations at the time (maybe it still is, I am not sure), but one general observation remains: most data organizations are "Reasonable Scale" and they should design their systems around this assumption. Note that being a reasonable scale organization does not necessarily mean a small company. The enterprise world is full of data organizations that deal with a lot of complexity within large – sometimes – organizations and yet have many reasonable scale data systems often for internal stakeholders, ranging from a few thousand to a TB.

Recently, we happily witnessed a growing debate about whether companies need Big Data systems to deal with data problems,. The most important takeaway from this view remains that, if you are a Reasonable Scale organization dealing with unnecessary infrastructure can be a very heavy burden with plenty of nefarious ramifications in your processes. You could in principle build an entire data stack to support low latency dashboards – maybe you could use a Warehouse and a caching layer -, but since your resources are limited, wouldn't it be nice to have a simpler and cheaper solution?

In this post, we showed that the combination of data storage formats, on-demand compute and in-memory processing opens up for new possibilities at Reasonable Scale. The system is far from perfect and could use many improvements, but it shows that one can build an in-memory data app with no warehouse setup, lightning fast performance and virtually no costs. By removing the db from the equation and combine what is fundamentally right about local ("s

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processing is all you need") with what is fundamentally right about the cloud ("data is better processed elsewhere").

I am spending most of my time thinking about serverless data infra. If you are interested, you have feedback on this post or simply want to chat, drop me a line at ciro.greco@bauplanlabs.com

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