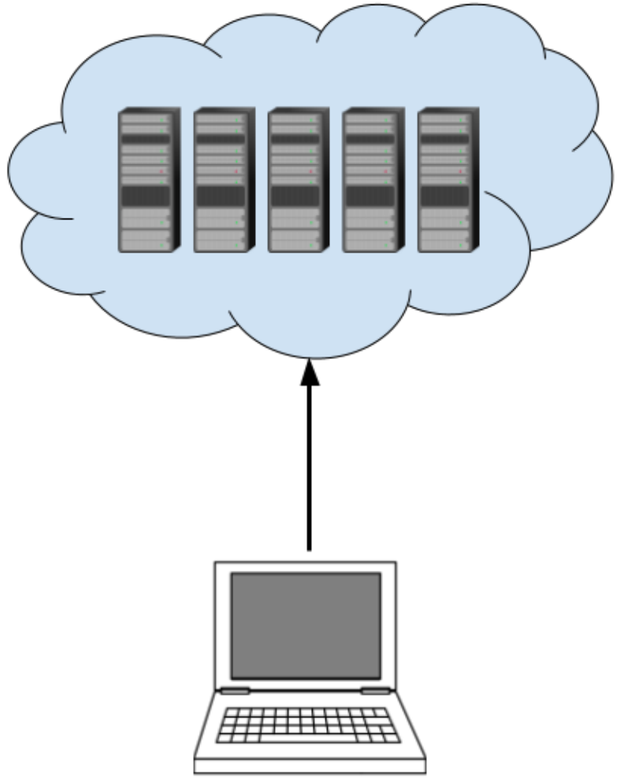
Getting started with Databricks

DATABRICKS CONCEPTS

Kevin Barlow
Data Practitioner

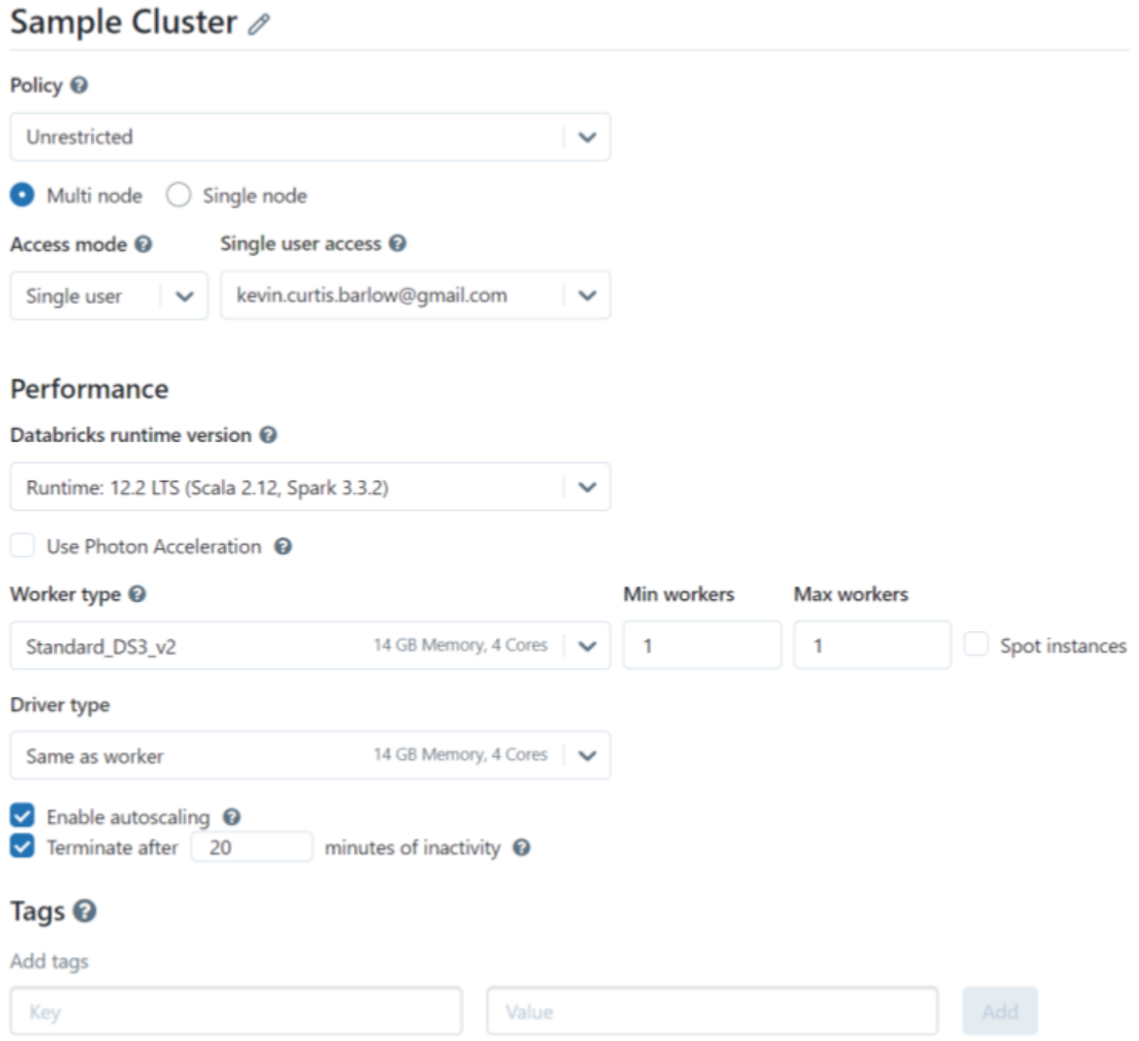
Compute cluster refresh



Create your first cluster

The first step is to create a cluster for your data processing!

Configuration options:

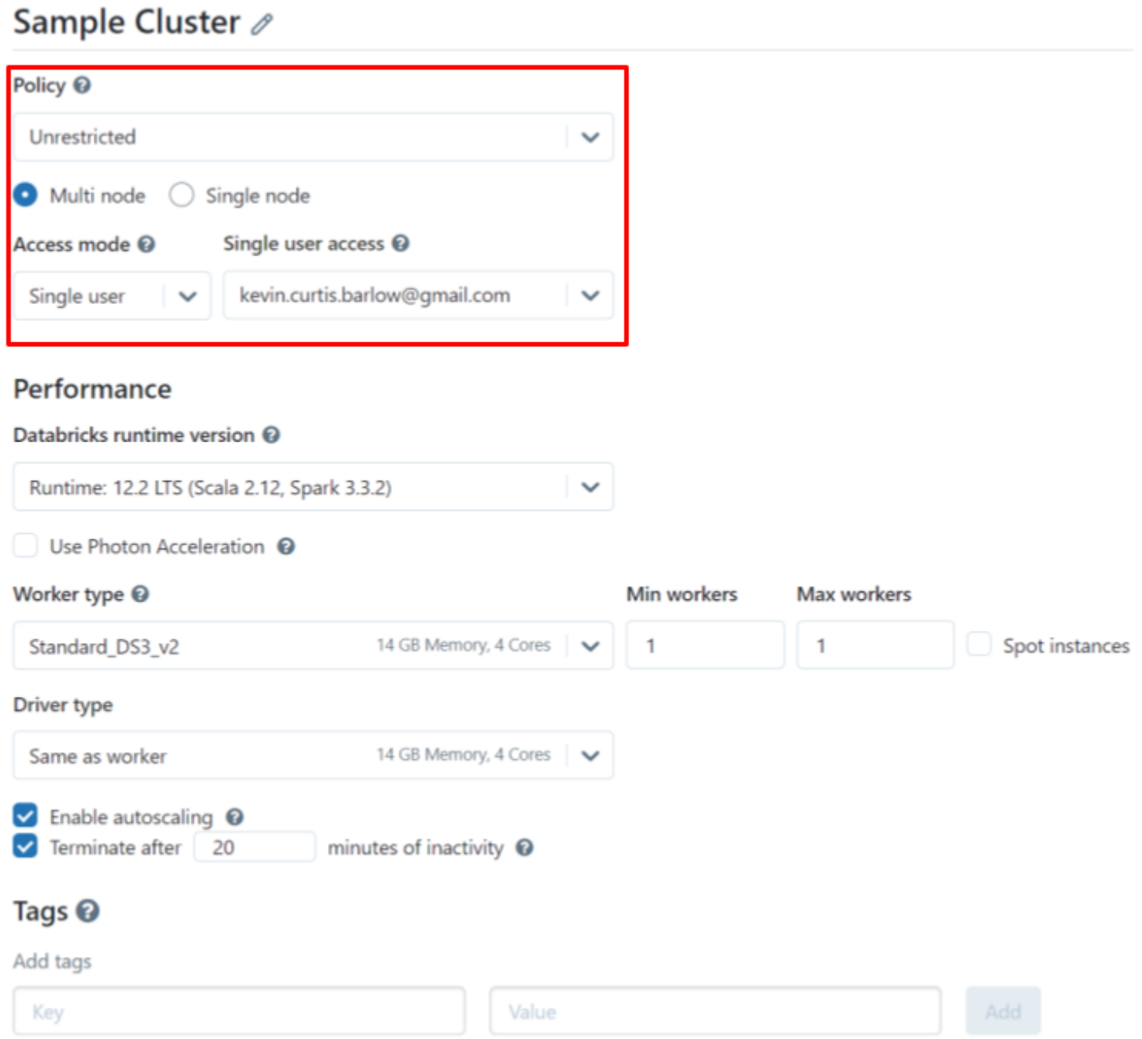


Create your first cluster

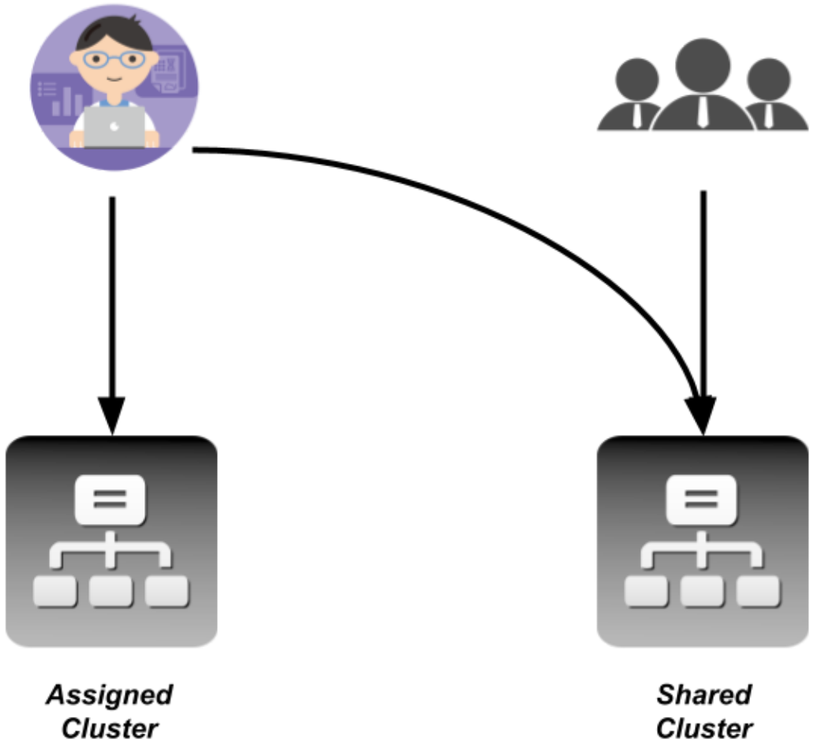
The first step is to create a cluster for your data processing!

Configuration options:

- Cluster policies and access



Cluster Access

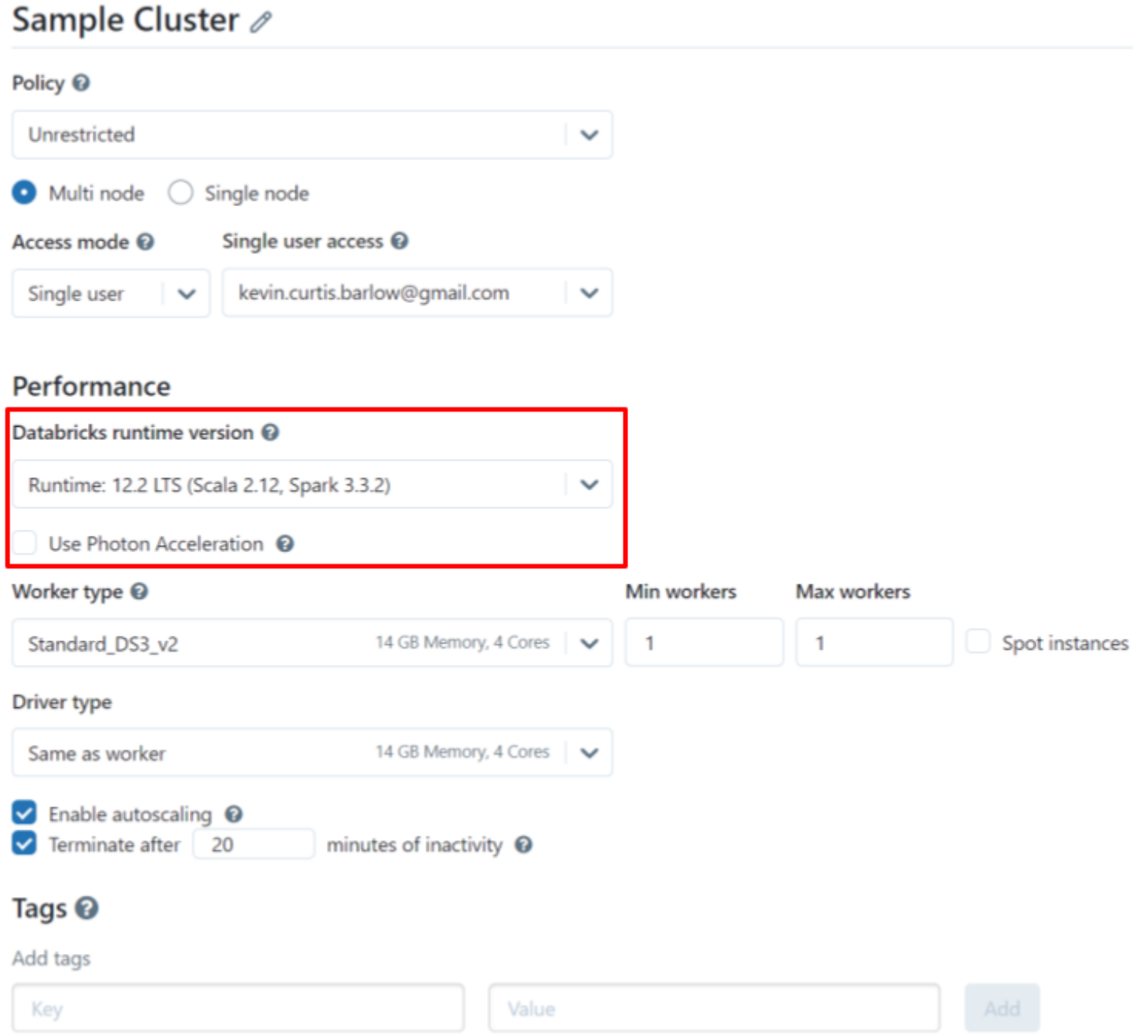


Create your first cluster

The first step is to create a cluster for your data processing!

Configuration options:

- Cluster policies and access
- Databricks Runtime
- Photon Acceleration

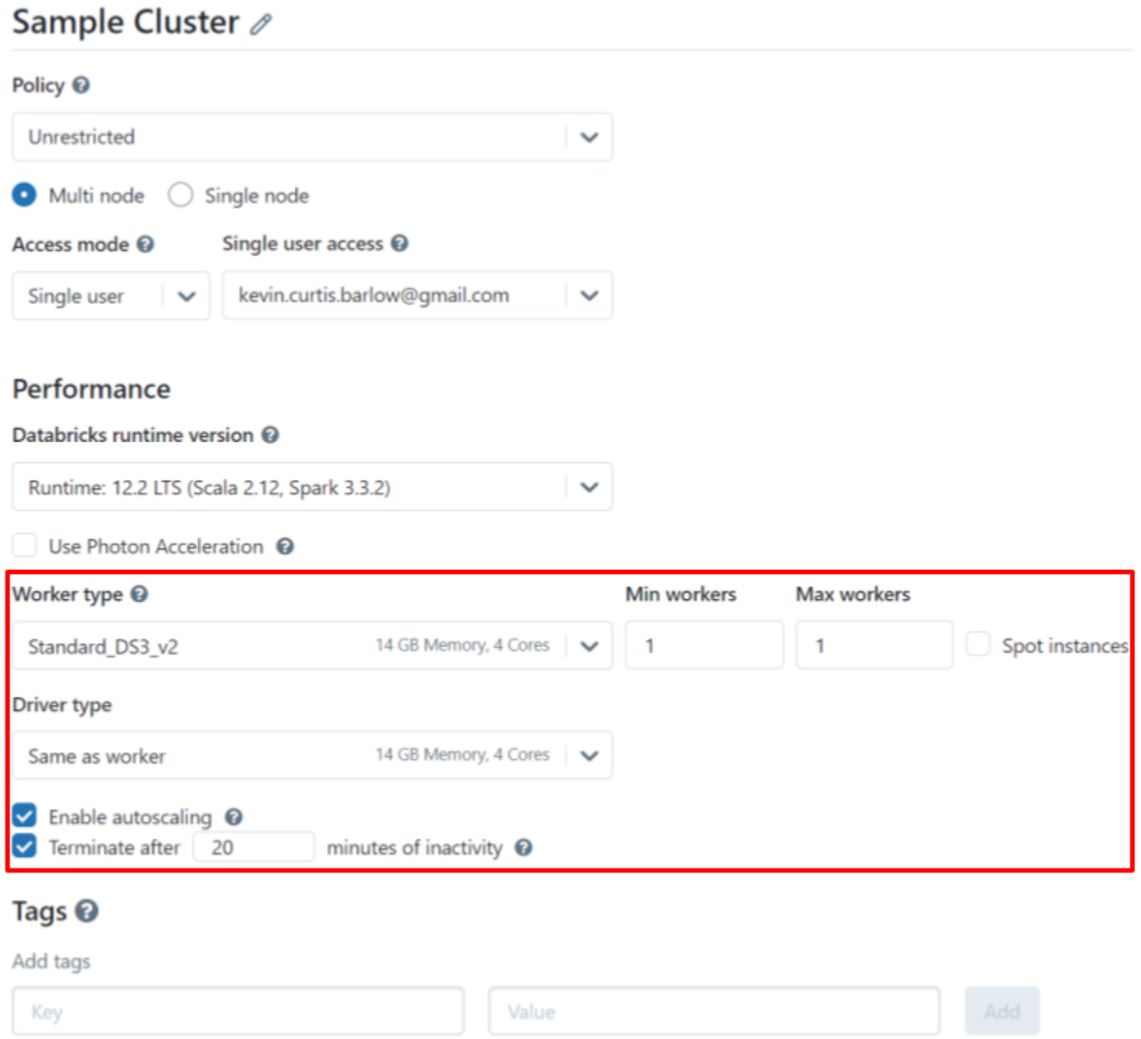


Create your first cluster

The first step is to create a cluster for your data processing!

Configuration options:

- Cluster policies and access
- Databricks Runtime
- Photon Acceleration
- Node instance types and number
- Auto-scaling / Auto-termination



Data Explorer

Get familiar with the Data Explorer! In this UI, you can:

1. Browse available catalogs/schemas/tables
2. Look at sample data and summary statistics
3. View data lineage and history

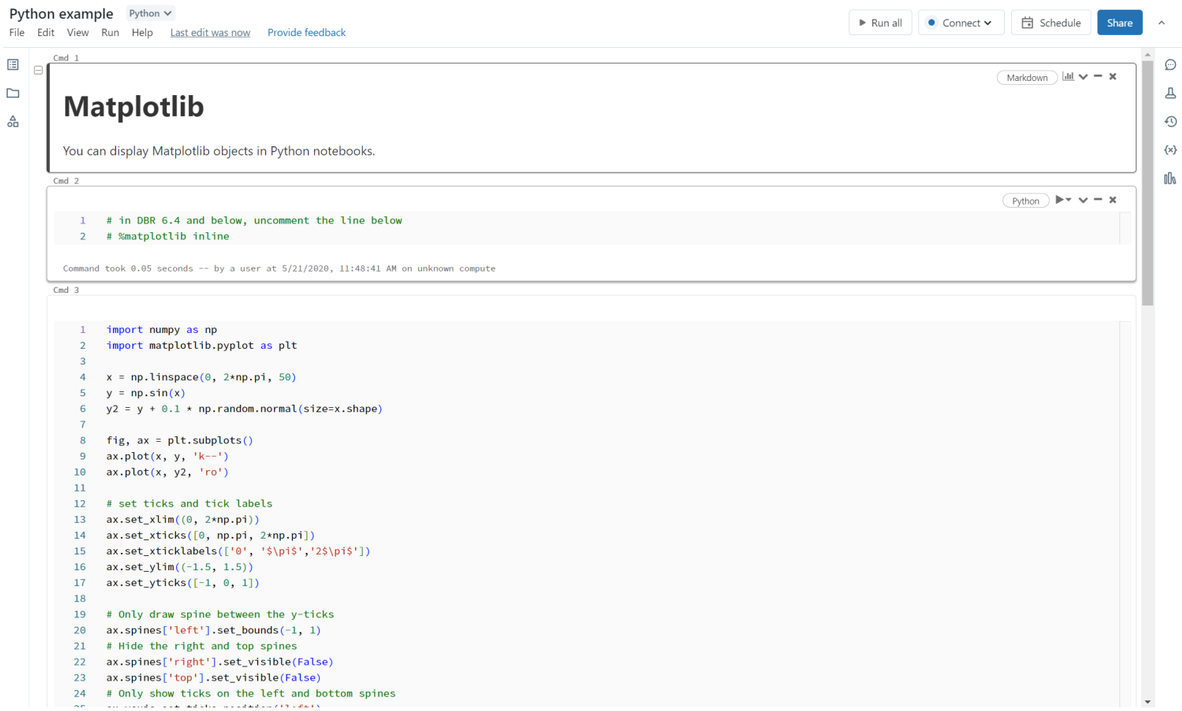
You can also upload new data by clicking the "plus" icon!

[1] Photo by Jakub Zerdzicki: https://www.pexels.com/photo/magnifier-loupe-17284804/

Create a notebook

Databricks notebooks:

- Standard interface for Databricks
- Improvements on open-source Jupyter
- Support for many languages
  - Python, R, Scala, SQL
  - Magic commands (%sql)
- Built-in visualizations
- Real-time commenting and collaboration



Let's practice!

DATABRICKS CONCEPTS

Data Engineering foundations in Databricks

DATABRICKS CONCEPTS

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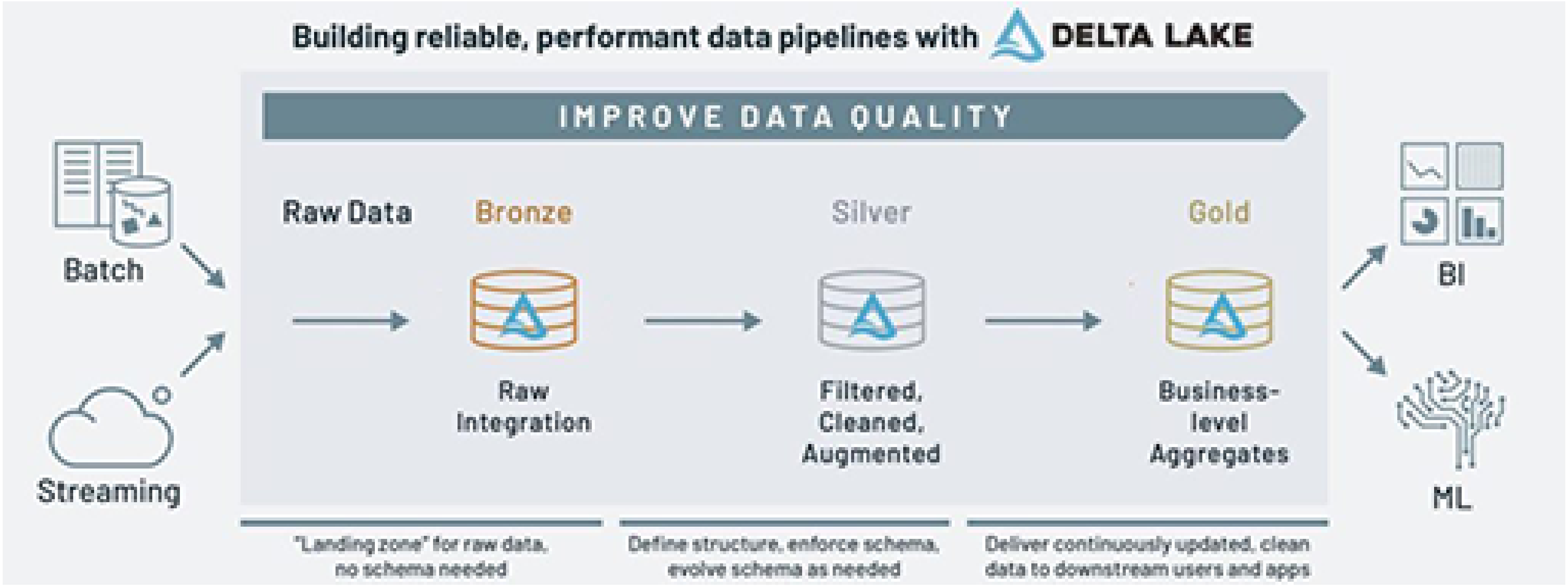
Data Practitioner

datacamp

Medallion architecture



Reading data

Spark is a highly flexible framework and can read from various data sources/types.

Common data sources and types:

- Delta tables
- File formats (CSV, JSON, Parquet, XML)
- Databases (MySQL, Postgres, EDW)
- Streaming data
- Images / Videos

Reading data

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Common data sources and types:

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- Databases (MySQL, Postgres, EDW)
- Streaming data
- Images / Videos

```
#Delta table
spark.read.table()
#CSV files
spark.read.format('csv').load('*.csv')
#Postgres table
spark.read.format("jdbc")
  .option("driver", driver)
  .option("url", url)
  .option("dbtable", table)
  .option("user", user)
  .option("password", password)
  .load()
```

Structure of a Delta table

A Delta table provides table-like qualities to an open file format.

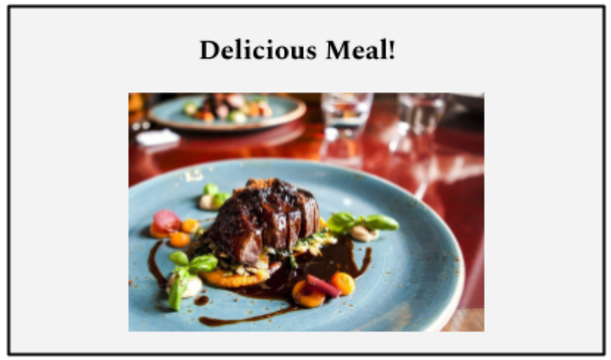
- Feels like a table when reading
- Access to underlying files (Parquet and JSON)

```
1  %fs ls /databricks-datasets/nyctaxi-with-zipcodes/subsampled
```

Table +

	path	name
1	dbfs:/databricks-datasets/nyctaxi-with-zipcodes/subsampled/_delta_log/	_delta_log/
2	dbfs:/databricks-datasets/nyctaxi-with-zipcodes/subsampled/nyc-zips-dataset-readme.txt	nyc-zips-dataset-readme.txt
3	dbfs:/databricks-datasets/nyctaxi-with-zipcodes/subsampled/part-00000-80b68cae-ce6a-41cf-87cd-2573d91b4c07-c000.snappy.parquet	part-00000-80b68cae-ce6a-41cf-87cd-2573d91b4c07-c000.snappy.parquet
4	dbfs:/databricks-datasets/nyctaxi-with-zipcodes/subsampled/part-00001-c883942d-366f-478a-be3b-f13fd4bee0ab-c000.snappy.parquet	part-00001-c883942d-366f-478a-be3b-f13fd4bee0ab-c000.snappy.parquet
5	dbfs:/databricks-datasets/nyctaxi-with-zipcodes/subsampled/part-00002-bbf9fd81-4b3a-46f3-943e-841b48ae743e-c000.snappy.parquet	part-00002-bbf9fd81-4b3a-46f3-943e-841b48ae743e-c000.snappy.parquet
6	dbfs:/databricks-datasets/nyctaxi-with-zipcodes/subsampled/part-00003-3d80435e-15f8-4154-92c7-515307e41c1b-c000.snappy.parquet	part-00003-3d80435e-15f8-4154-92c7-515307e41c1b-c000.snappy.parquet

Explaining the Delta Lake structure



Ingredients	Steps
• Ribeye Steak • Carrots • Red Wine •	1. Preheat oven 2. Mise en place 3. Sear meat 4. .....

DataFrames

DataFrames are two-dimensional representations of data.

- Look and feel similar to tables
- Similar concept for many different data tools
  - Spark (default), pandas, dplyr, SQL queries
- Underlying construct for most data processes

id	customerName	bookTitle
1	John Data	Guide to Spark
2	Sally Bricks	SQL for Data Engineering
3	Adam Delta	Keeping Data Clean

```
df = (spark.read
  .format("csv")
  .option("header", "true")
  .option("inferSchema", "true")
  .load("/data.csv"))
```

Writing data

Kinds of tables in Databricks

1. Managed tables
   - Default type
   - Stored with Unity Catalog
   - Databricks managed
2. External tables
   - Stored in another location
   - Set LOCATION
   - Customer managed

```
df.write.saveAsTable(table_name)


CREATE TABLE table_name
USING delta
AS ...
```

```
df.write
  .location('').saveAsTable(table_name)


CREATE TABLE table_name
USING delta
LOCATION "<path>"
AS ...
```

Let's practice!

DATABRICKS CONCEPTS

Data transformations in Databricks

DATABRICKS CONCEPTS

Kevin Barlow
Data Practitioner

datacamp

SQL for data engineering

SQL

- Familiar for Database Administrators (DBAs)
- Great for standard manipulations
- Execute pre-defined UDFs

```
-- Creating a new table in SQL

CREATE TABLE table_name
USING delta
AS (
  SELECT *
  FROM source_table
  WHERE date >= '2023-01-01'
)
```

Other languages for data engineering

Python, R, Scala

- Familiar for software engineers
- Standard and complex transformations
- Use and define custom functions

```
#Creating a new table in Pyspark


spark
  .read
  .table('source_table')
  .filter(col('date') >= '2023-01-01')
  .write
  .saveAsTable('table_name')
```

Common transformations

Schema manipulation

- Add and remove columns
- Redefine columns

#Pyspark

```
df
  .withColumn(col('newCol'), ...)
  .drop(col('oldCol'))
```

Filtering

- Reduce DataFrame to subset of data
- Pass multiple criteria

#Pyspark

```
df
  .filter(col('date') >= target_date)
  .filter(col('id') IS NOT NULL)
```

Common transformations (continued)

Nested data

- Arrays or Struct data
- Expand or contract

```
df
  .explode(col('arrayCol')) #wide to long
  .flatten(col('items')) #long to wide
```

Aggregation

- Group data based on columns
- Calculate data summarizations

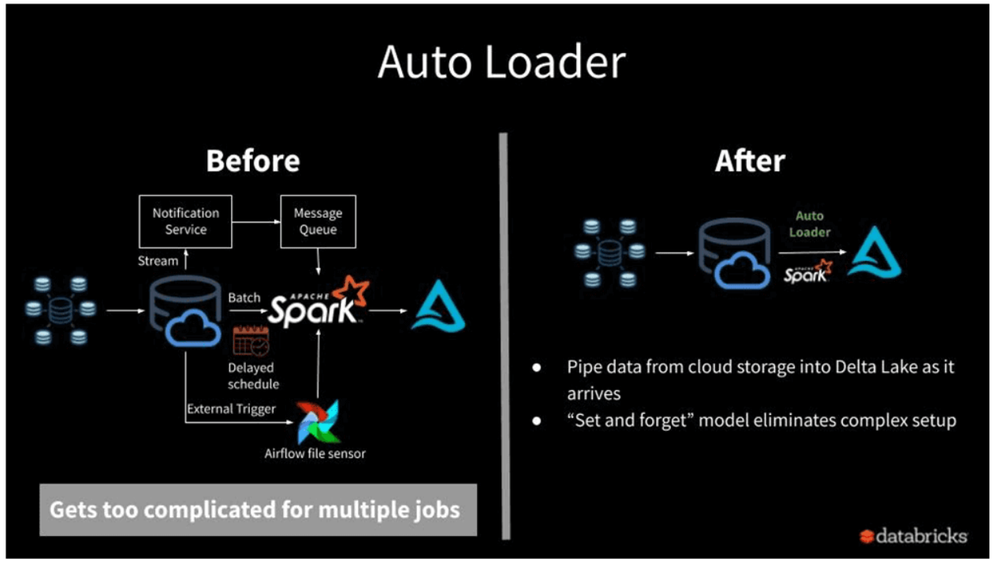
```
df
  .groupBy(col('region'))
  .agg(sum(col('sales')))
```

Auto Loader

Auto Loader processes new data files as they land in a data lake.

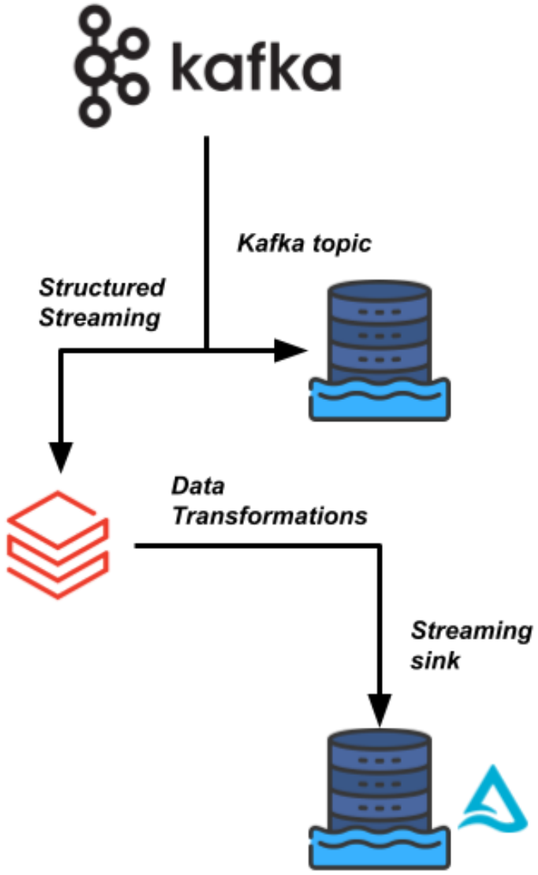
- Incremental processing
- Efficient processing
- Automatic

```
spark.readStream
  .format("cloudFiles")
  .option("cloudFiles.format", "json")
  .load(file_path)
```



[1] https://www.databricks.com/blog/2020/02/24/introducing-databricks-ingest-easy-data-ingestion-into-delta-lake.html

Structured Streaming




```
spark.readStream
    .format("kafka")
    .option("subscribe", "<topic>")
    .load()
    .join(table_df,
      on="<id>", how="left")
    .writeStream
    .format("kafka")
    .option("topic", "<topic>")
    .start()
```

Let's practice!

DATABRICKS CONCEPTS

Orchestration in Databricks

DATABRICKS CONCEPTS

Kevin Barlow
Data Analytics Practitioner

What is data orchestration?

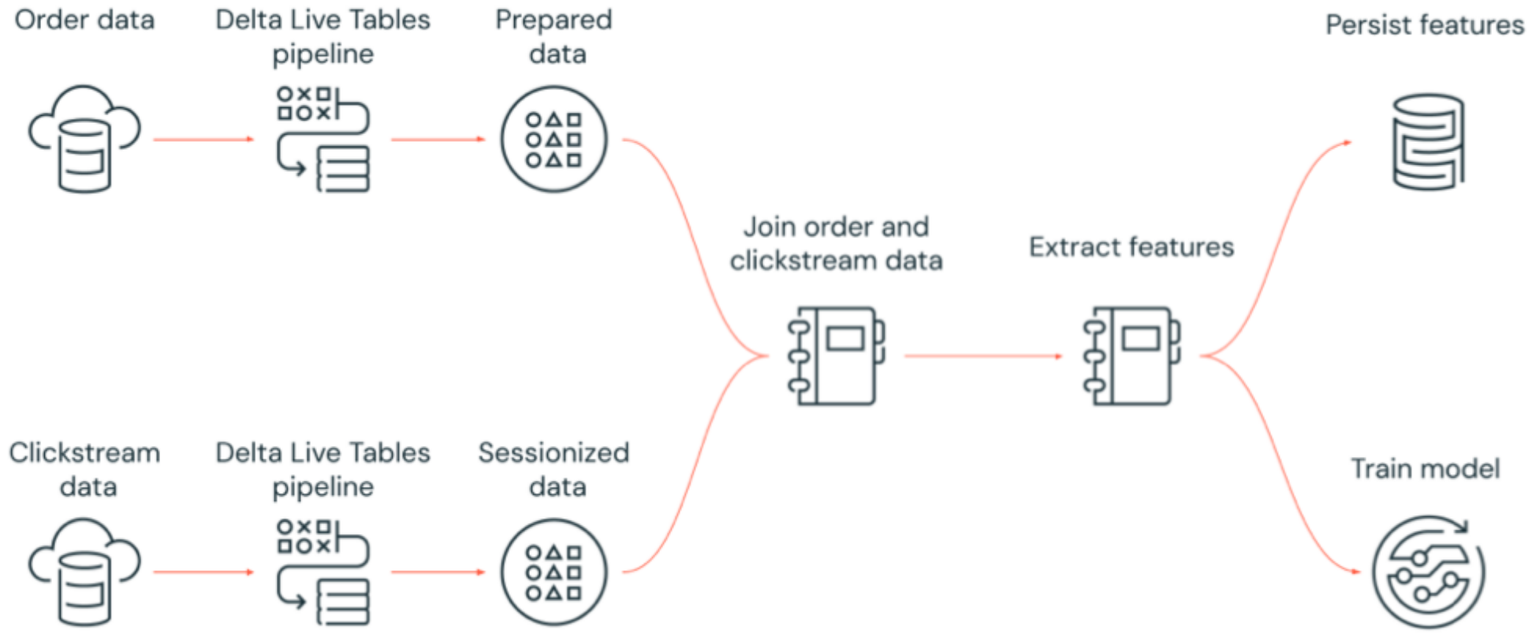
- Data orchestration is a form of automation!

- Enables data engineers to automate the end-to-end data life cycle

Databricks Workflows

Databricks Workflows is a collection of built-in capabilities to orchestrate all your data processes, at no additional cost!

Example Databricks Workflow



[1] https://docs.databricks.com/workflows

What can we orchestrate?

Data engineers/data scientists

Databricks Notebook

Delta Live Tables

JAR

APACHE Spark™

dbt™

Data analysts

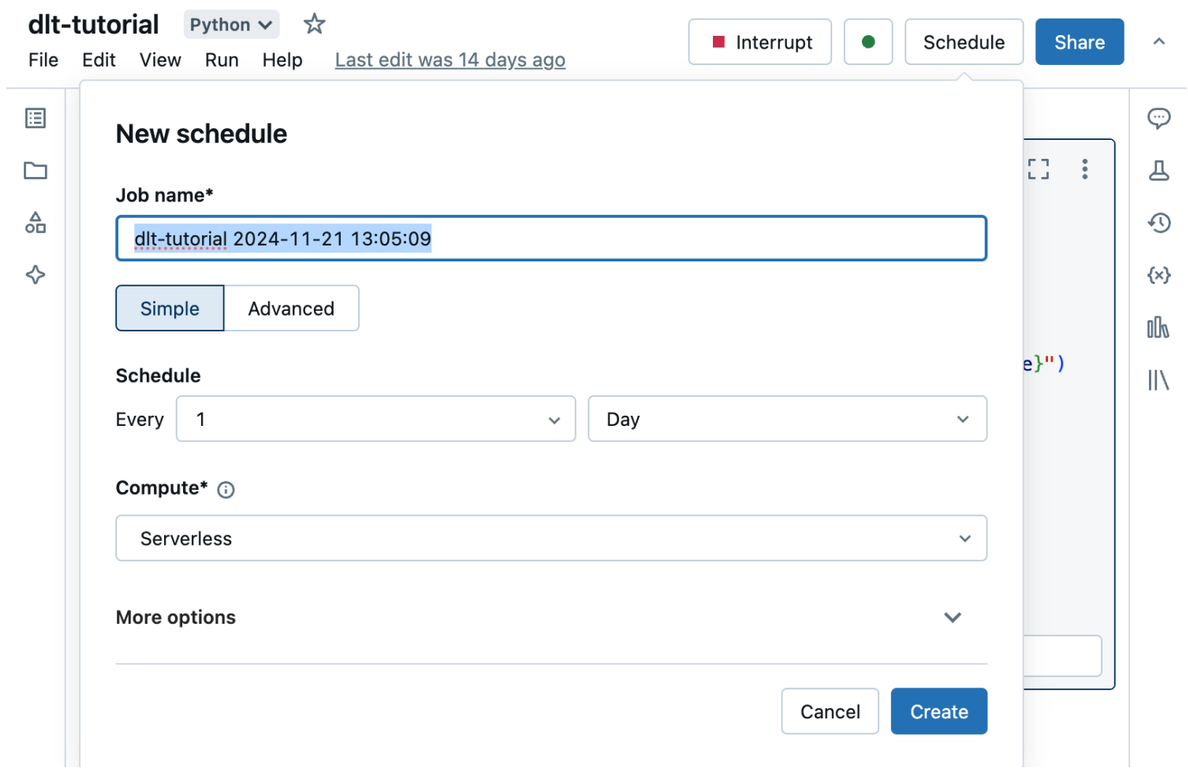
SQL

Databricks Jobs

Workflows UI

Users can create jobs directly from the Databricks UI:

- Directly from a notebook
- In the Workflows section



[1] https://docs.databricks.com/workflows/jobs

Databricks Jobs

Programmatic

Users can also programmatically create jobs using the Jobs CLI or Jobs API with the Databricks platform.

```
{
  "name": "A multitask job",
  "tags": {},
  "tasks": [],
  "job_clusters": [],
  "format": "MULTI_TASK",
}
```

Delta Live Tables

Delta Live Tables understands and coordinates data flow between your queries

Delta Live Tables Pipeline		Data
`CREATE LIVE TABLE raw_data as SELECT * FROM cloud_files("/data","json")`	→	raw_data
`CREATE LIVE TABLE clean_data as SELECT ... FROM LIVE. raw_data`	→	clean_data

`@dlt.table`
`def scord_records():`
`return read("clean_data").map(lambda d: model_score(d))`
	→	scored_records

Delta Live Tables

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Delta Live Tables Pipeline

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CREATE LIVE TABLE clean_data as SELECT ... FROM LIVE. raw_data
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Data

raw_data

clean_data

scored_records

Delta Live Tables

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Data

raw_data

clean_data

scored_records

Let's practice!

DATABRICKS CONCEPTS

End-to-end data pipeline example in Databricks

DATABRICKS CONCEPTS

Kevin Barlow
Data Practitioner

Let's practice!

DATABRICKS CONCEPTS