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PyDelhi
Jan 2024

# Build an ETL pipeline with Apache Airflow

# Agenda

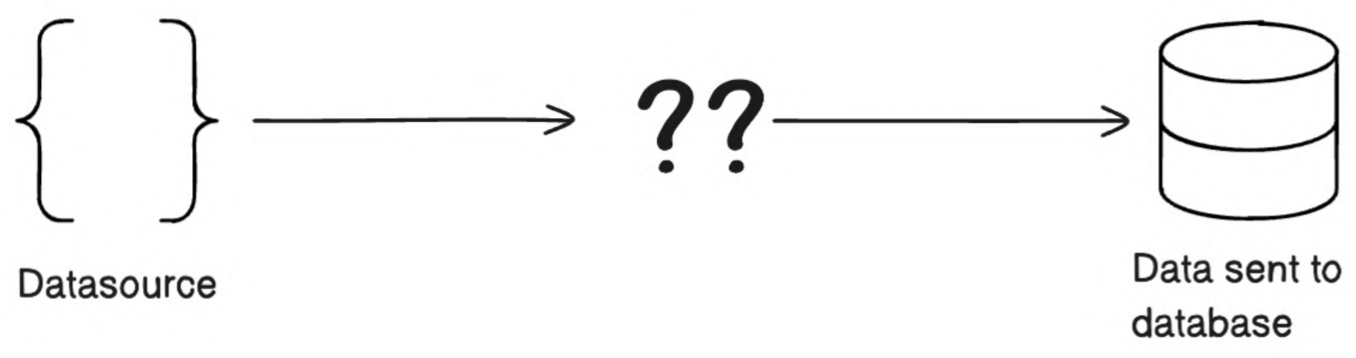
**Data Engineering**

1. What is Data Engineering
2. Key Concepts

**Airflow**

1. A quick tour of Airflow
2. DAGs
3. More Airflow concepts
4. Building an ETL pipeline

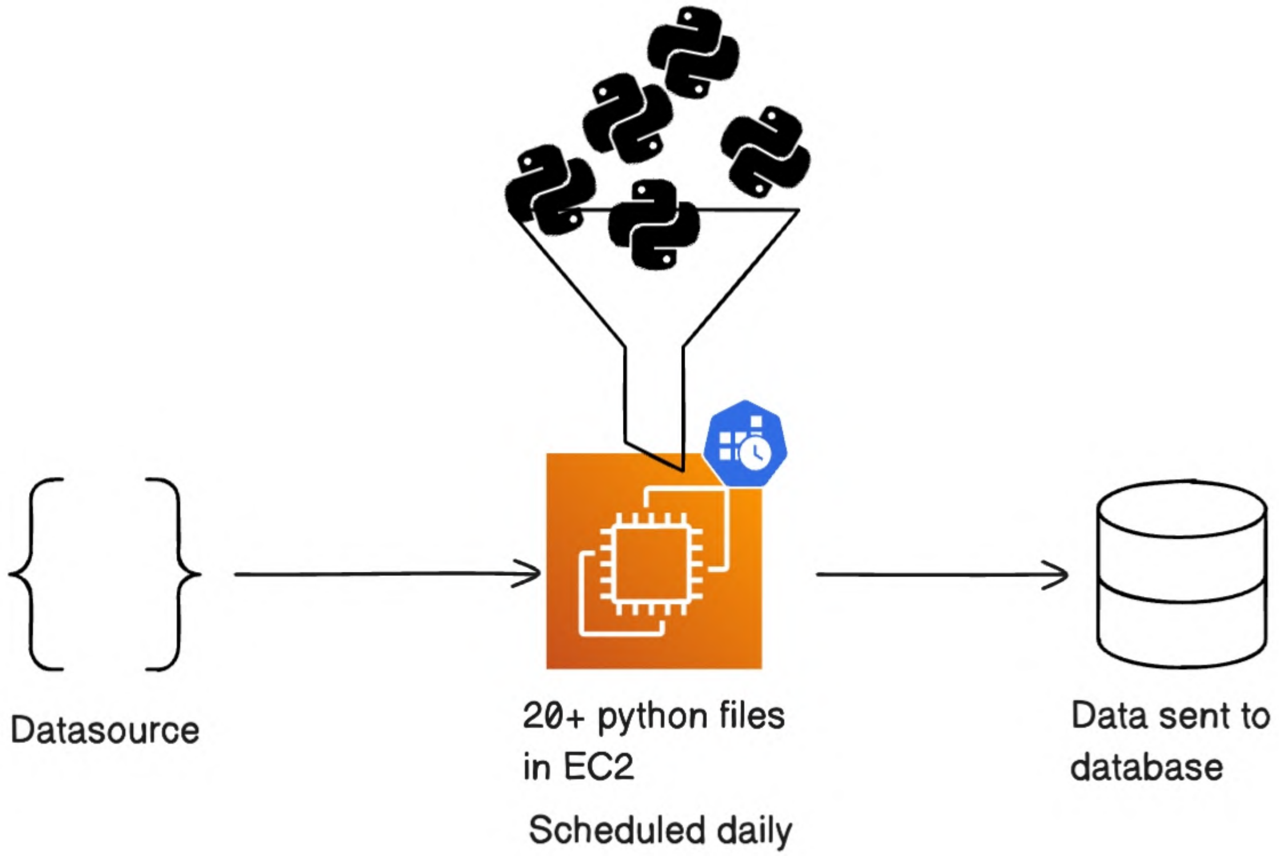
# A data collection service at Intern co.




Challenge:

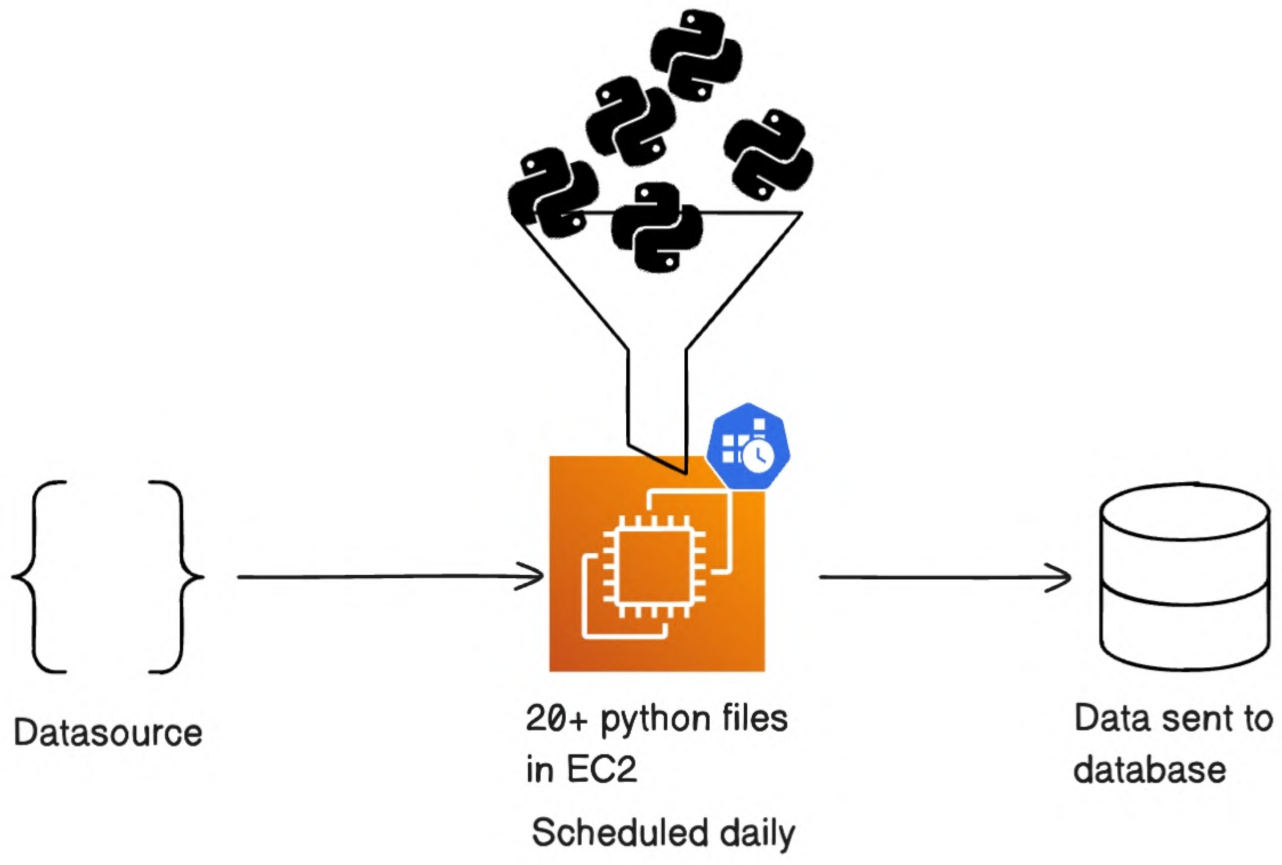
- Need to setup a system to collect, clean, normalize and store data from multiple datasources

# A data collection service at Intern co.




Try Pitch

# A data collection service at Intern co.



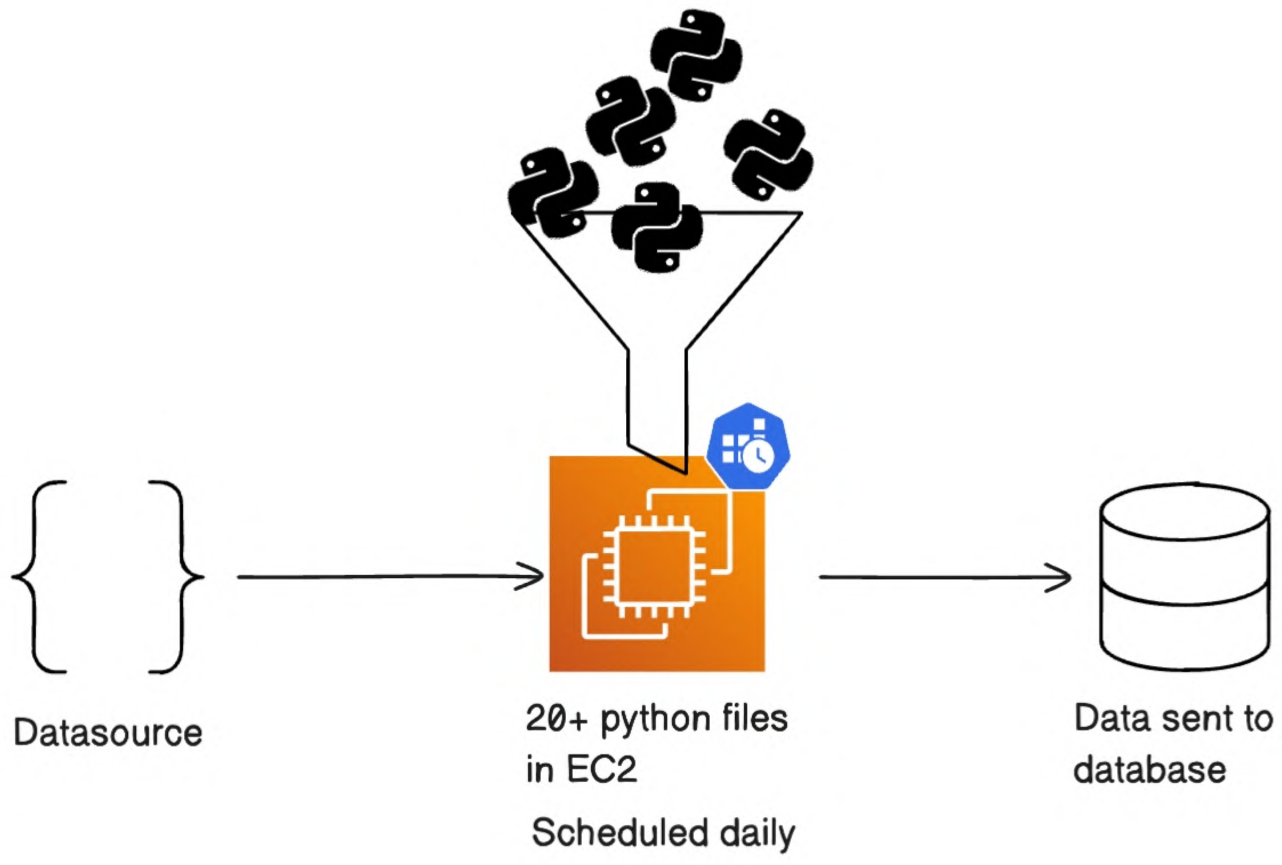

Pros:

- Simple setup

Cons:

- Need to add logging
- Don't know when or where failure happens
- Gets complex fast

# A data collection service at Intern co.

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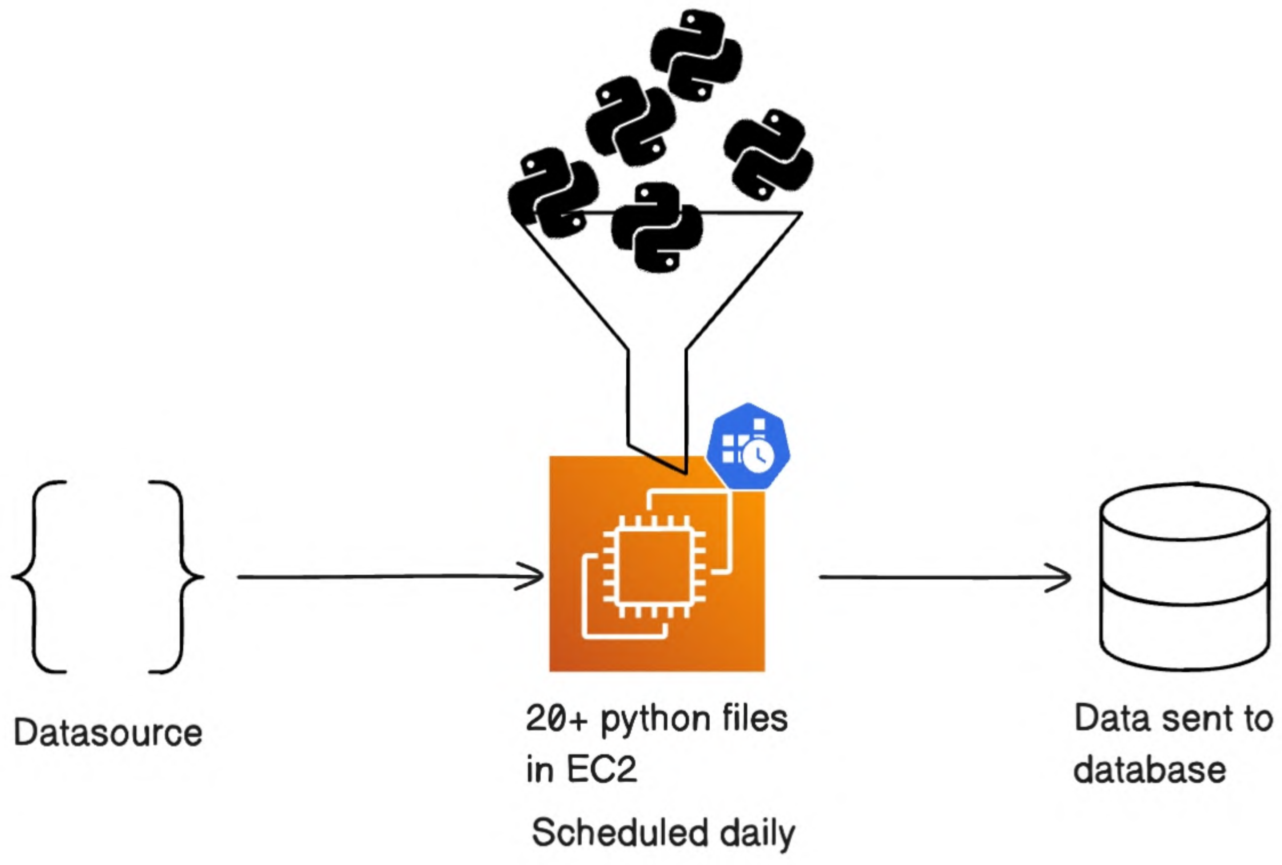
Where we failed:

- Terrible data quality in DB and we didn't know why
- ML and frontend team couldn't realistically use collected data
- DB wasn't getting data for 3 days and nobody noticed

# A data collection service at Intern co.




Pros:
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- Gets complex fast

Where we failed:
- Terrible data quality in DB and we didn't know why
- ML and frontend team couldn't realistically use collected data
- DB wasn't getting data for 3 days and nobody noticed

We needed a better way to collect and store data

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# Data Engineering

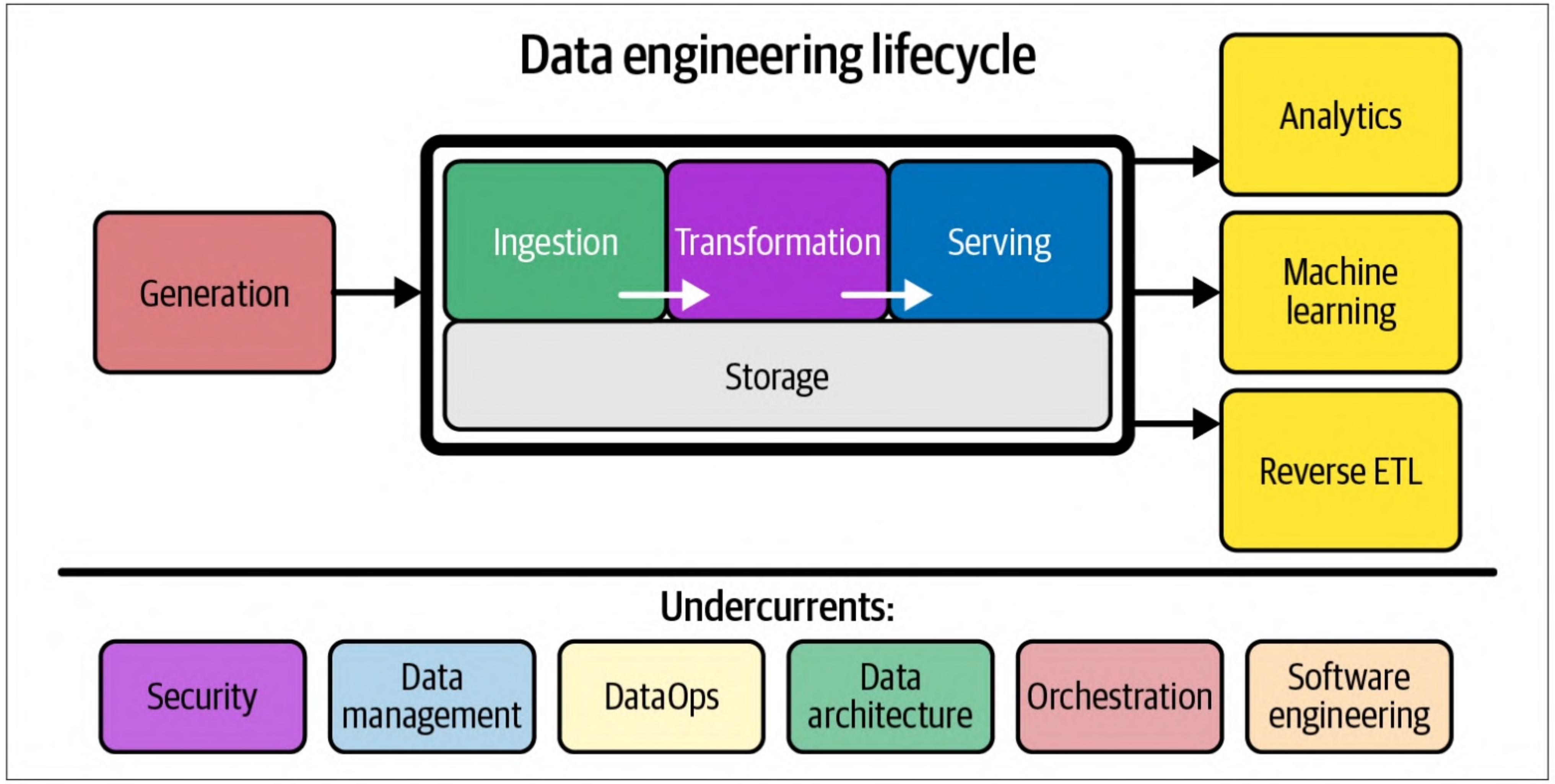
↘

## Data Engineering

*Data engineering* is the **development, implementation**, and **maintenance** of systems and processes that **take in raw data** and **produce high-quality, consistent information** that **supports downstream use cases**, such as analysis and machine learning.

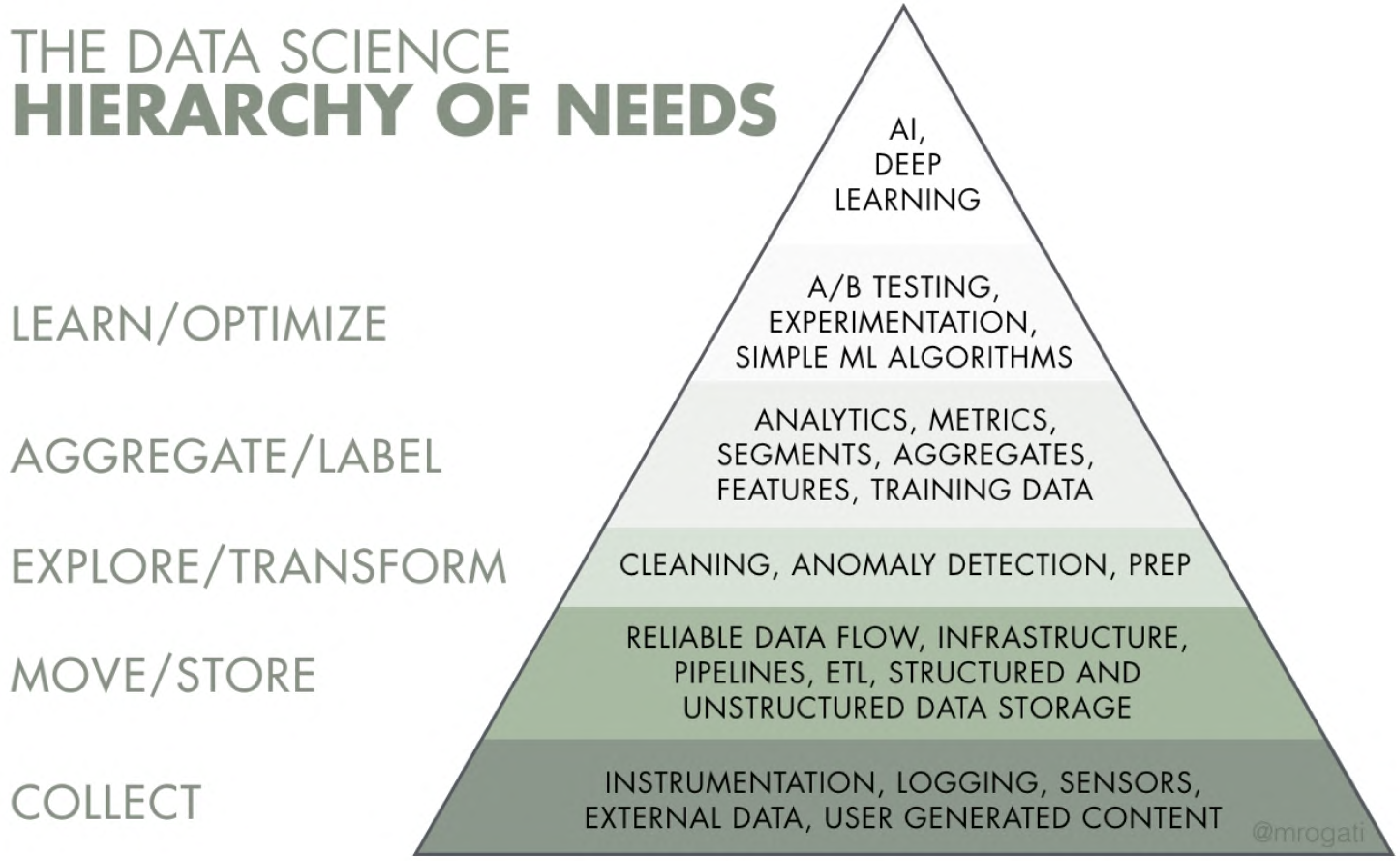
Data engineering is the intersection of security, data management, DataOps, data architecture, orchestration, and software engineering.

A *data engineer* manages the data engineering lifecycle, **beginning with getting data from source** systems and **ending with serving data** for use cases, such as analysis or machine learning.




https://www.oreilly.com/library/view/fundamentals-of-data/9781098108298/ch02.html

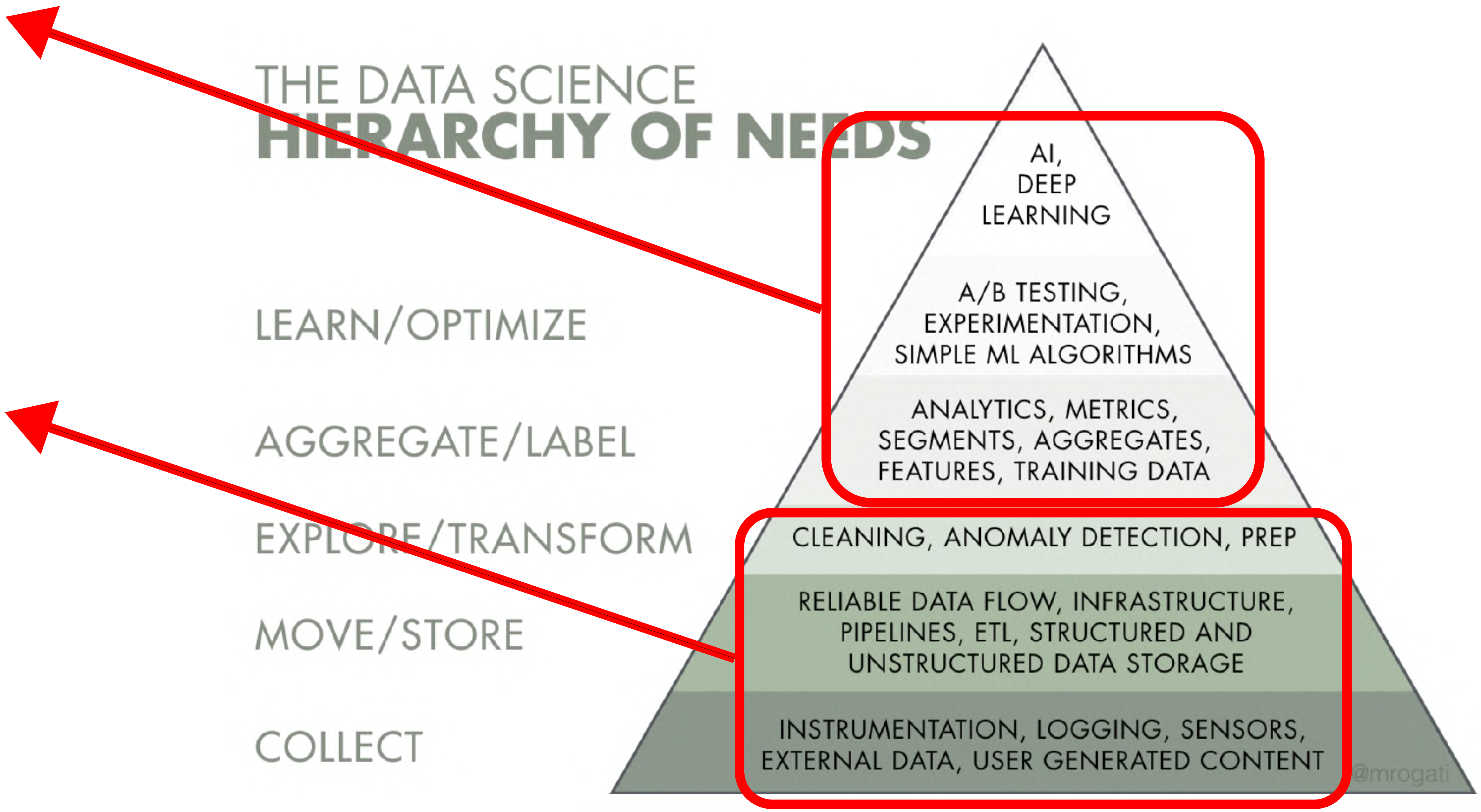
Although many data scientists are eager to build and tune ML models, the reality is an estimated 70% to 80% of their time is spent toiling in the bottom three parts of the hierarchy**—gathering data, cleaning data, processing data—**and only a tiny slice of their time on analysis and ML.




https://oreil.ly/pGg9U

In an ideal world, data scientists spend more than 90% of their time focused on the top layers of the pyramid

When data engineers focus on these bottom parts of the hierarchy, they build a solid foundation for data scientists to succeed.



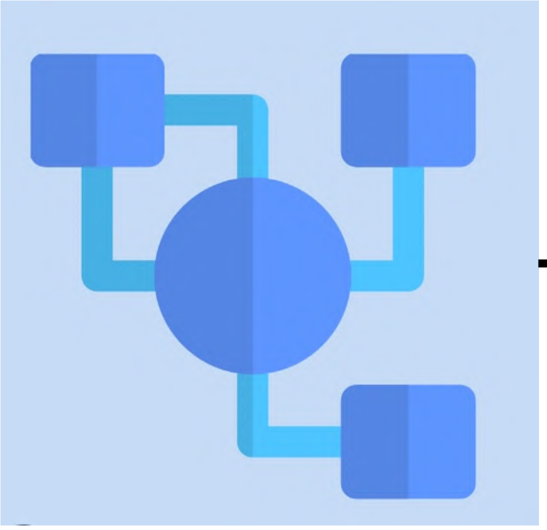

https://oreil.ly/pGg9U

Data Engineering:

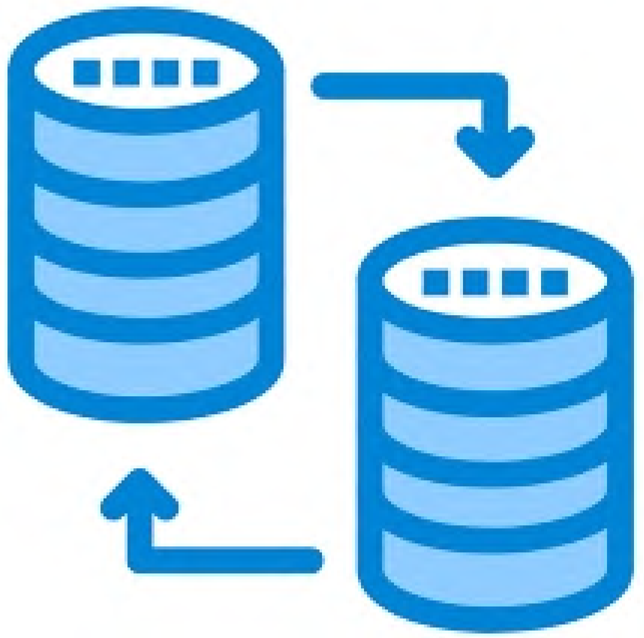
# Key Concepts

## Ingestion

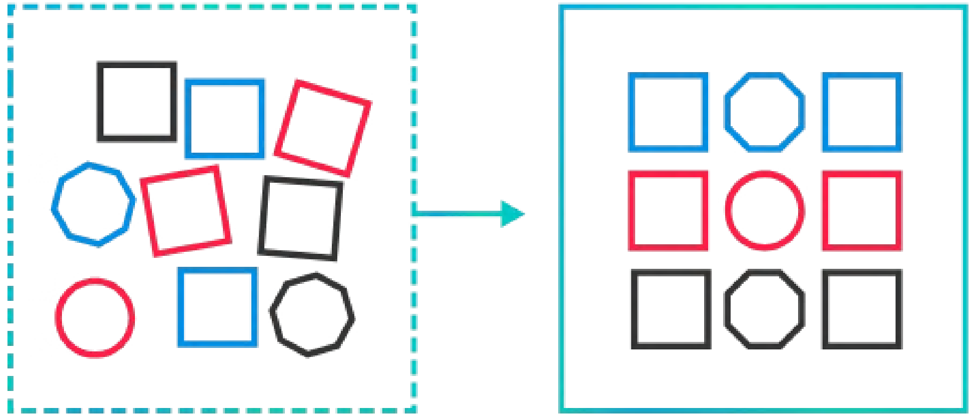
## Processing



## Storage



## Transformation



Data Engineering:

# Key Concepts

## Ingestion

Collect and bring in raw data from various sources.

It occurs either in real-time or batches.

## Processing

Perform initial operations on the raw data to make it more manageable.

Tools: Apache Spark, Apache Flink, or Hadoop MapReduce

## Transformation

Convert, cleanse, and structure the processed data for analysis.

## Storage

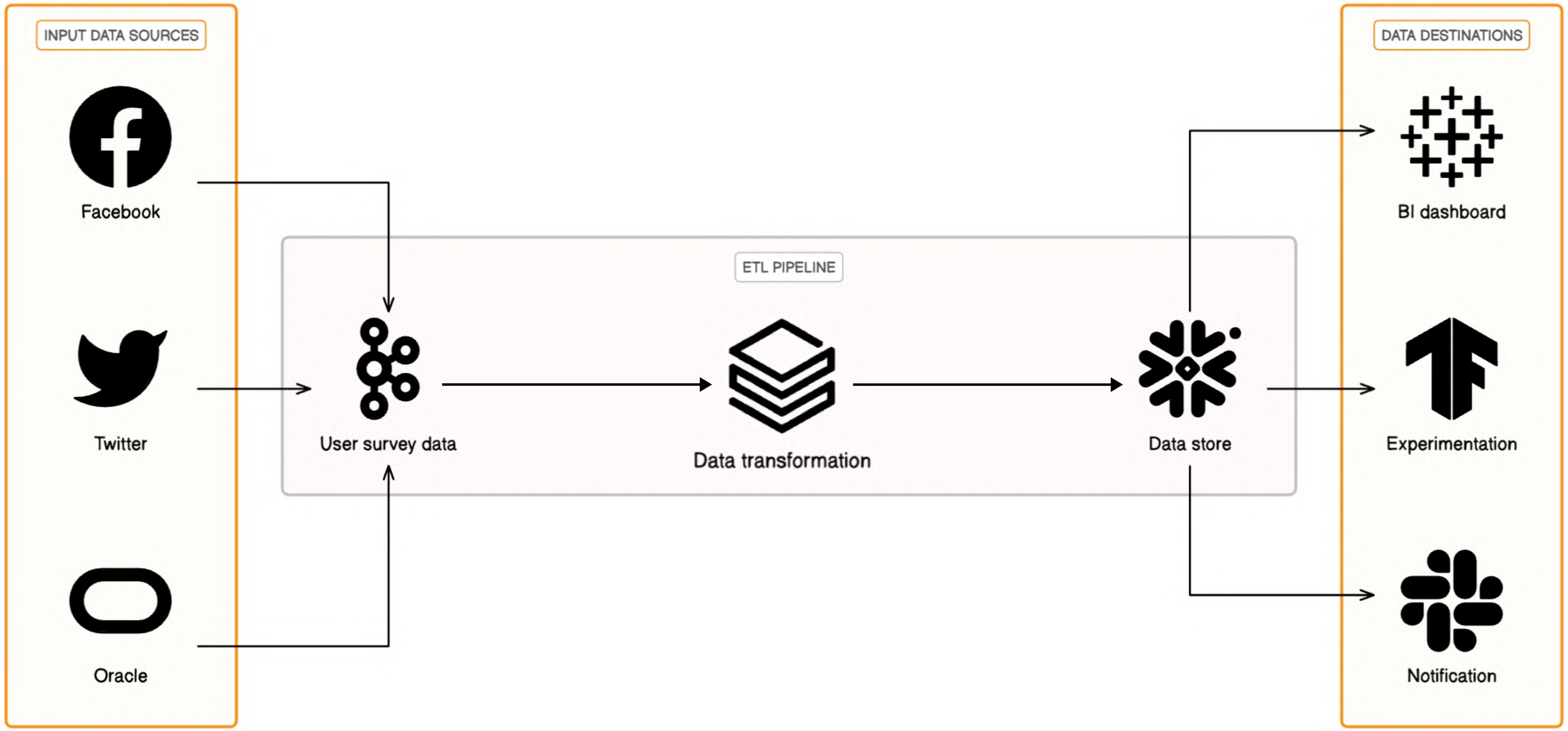
The recording of information in a storage medium.

Ex. databases, warehouses, cloud storage, and distributed systems

# ETL/ELT Pipelines

These involve moving data from source systems to a target system for analysis, reporting, and decision-making.

**Extract - Transform - Load**




In ETL, the transformation occurs in a separate staging area before loading data into the target system.
In ELT, the transformation happens directly within the target data warehouse.

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# Apache Airflow ↘

Airflow:

# What is it?

Apache Airflow is an open-source platform to control, monitor, and schedule data engineering pipelines.

Pipelines are configured as code, allowing for dynamic pipeline generation.

Created at Airbnb as an open-source project in 2014, Airflow was brought into the Apache Software Incubator Program in 2016 and announced as a Top-Level Apache Project in 2019.

Airflow:

# Why Airflow?

## Pure Python

No more command-line or XML black-magic! Use standard Python features to create your workflows, including date time formats for scheduling and loops to dynamically generate tasks. This allows you to maintain full flexibility when building your workflows.

## Easy to Use

Anyone with Python knowledge can deploy a workflow. Apache Airflow™ does not limit the scope of your pipelines; you can use it to build ML models, transfer data, manage your infrastructure, and more.

## Useful UI

Monitor, schedule and manage your workflows via a robust and modern web application. No need to learn old, cron-like interfaces. You always have full insight into the status and logs of completed and ongoing tasks.

## Open Source

Wherever you want to share your improvement you can do this by opening a PR. It's simple as that, no barriers, no prolonged procedures. Airflow has many active users who willingly share their experiences. Have any questions? Check out our buzzing slack.

Airflow:

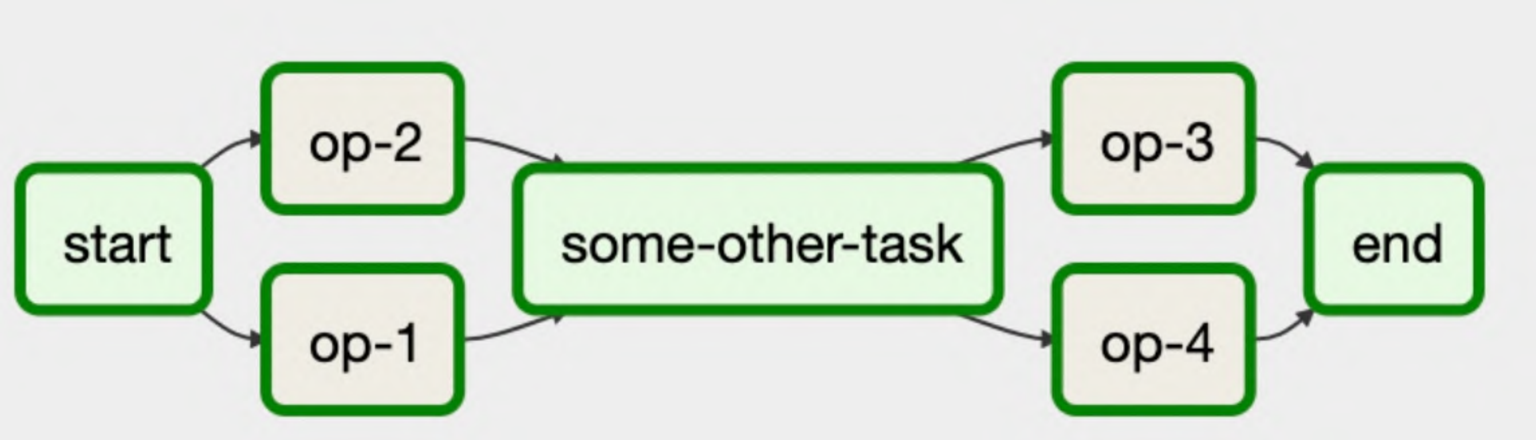
# Directed Acyclic Graphs (DAGs)

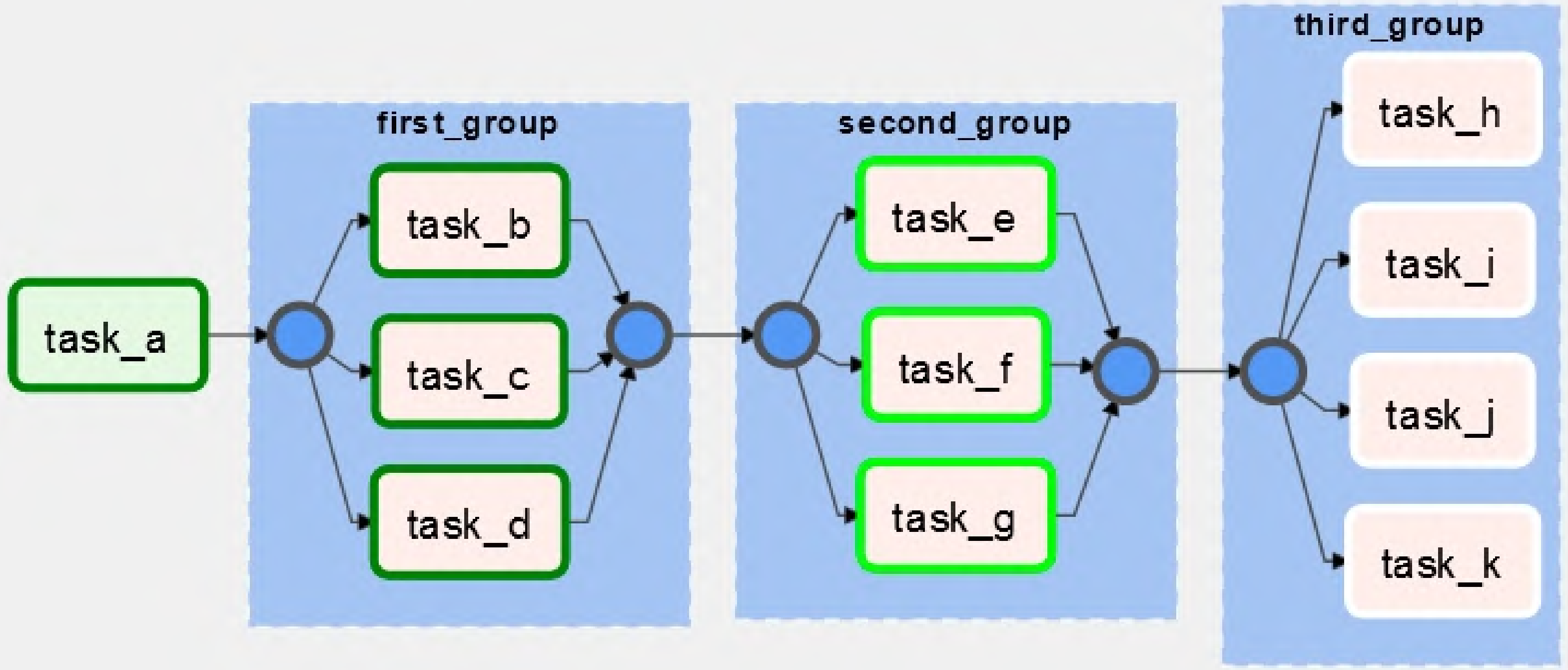
DAGs are a fundamental concept in Airflow.

They allow users to express the sequence of tasks and the dependencies between them in a structured way.

Each node in the DAG represents a task—a unit of work that needs to be executed.

Dependencies define the order in which tasks should be executed.



Airflow:

# Some more key concepts

## Operators

Operators define the atomic, indivisible units of work within a task. Each task in a DAG is associated with an operator that specifies what work should be done.

Ex: BashOperator, PythonOperator

## Sensors

Sensors are a type of operator that waits for a certain condition to be met before allowing the workflow to proceed.

Good for when waiting on an external event or condition (like checking for changes in a DB)

## Hooks

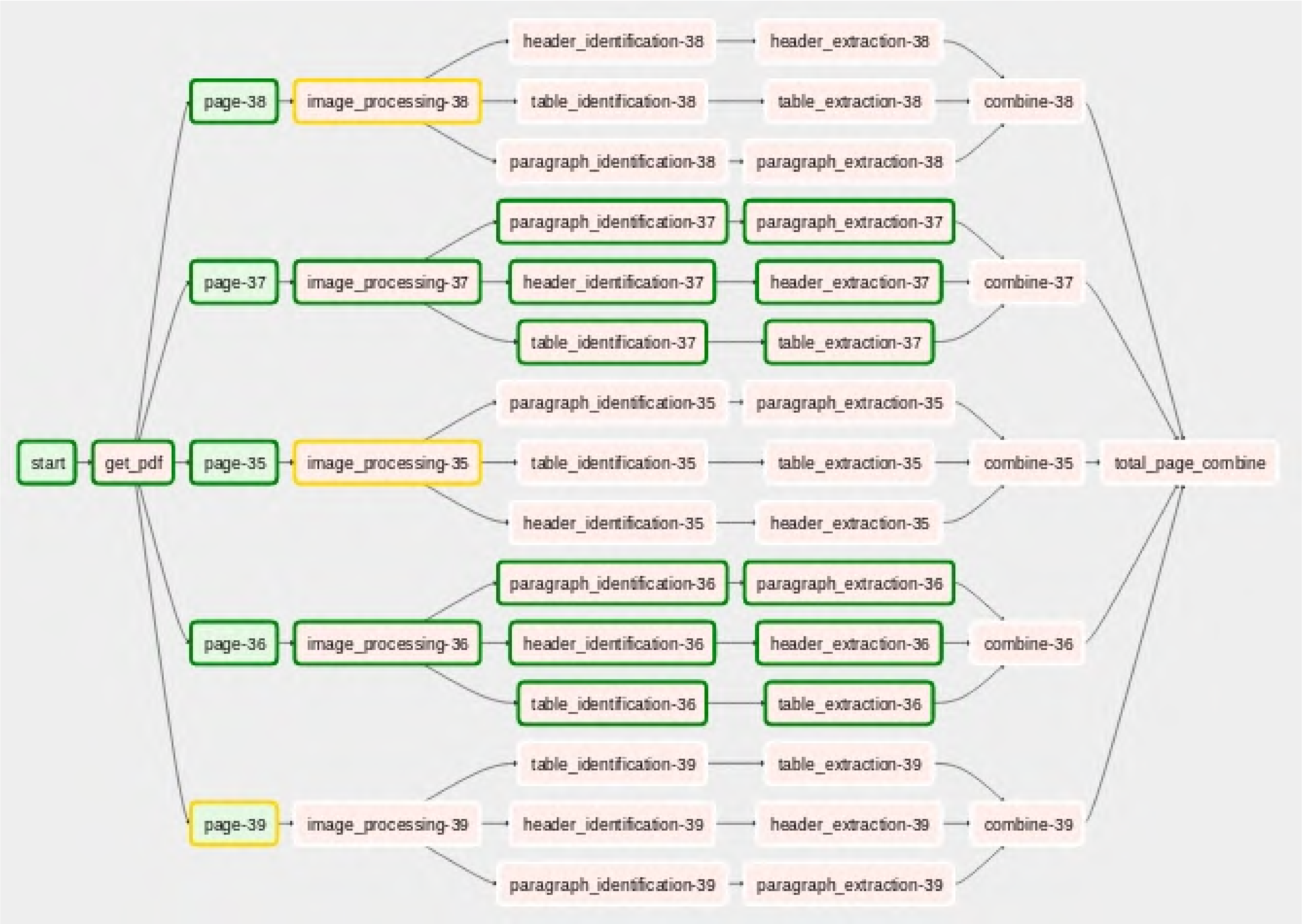
Hooks are a way to interact with external systems or services from within tasks. They provide a Pythonic interface to connect and communicate with databases, APIs, and other external resources.

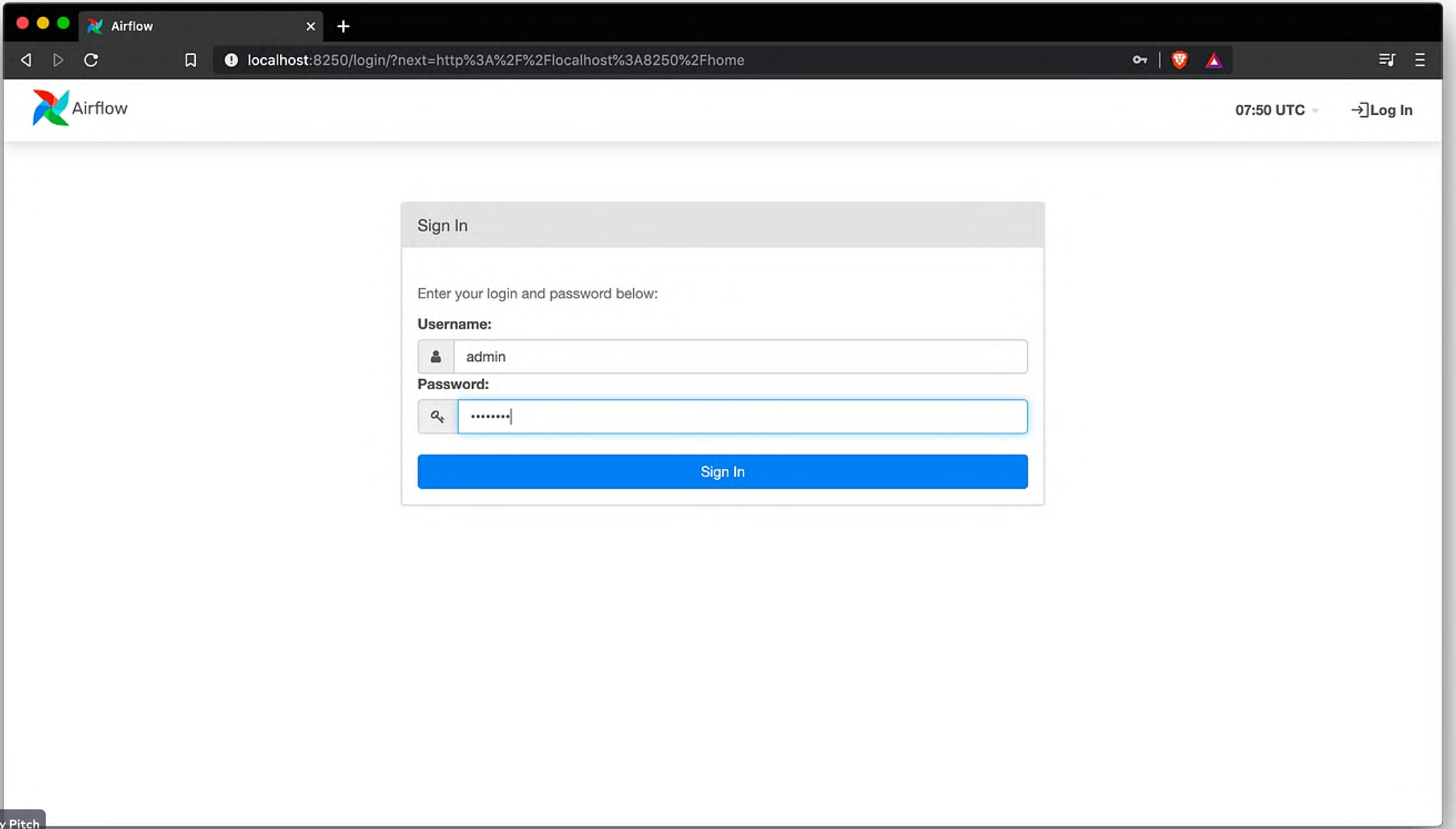
## XCom (Cross-Communication)

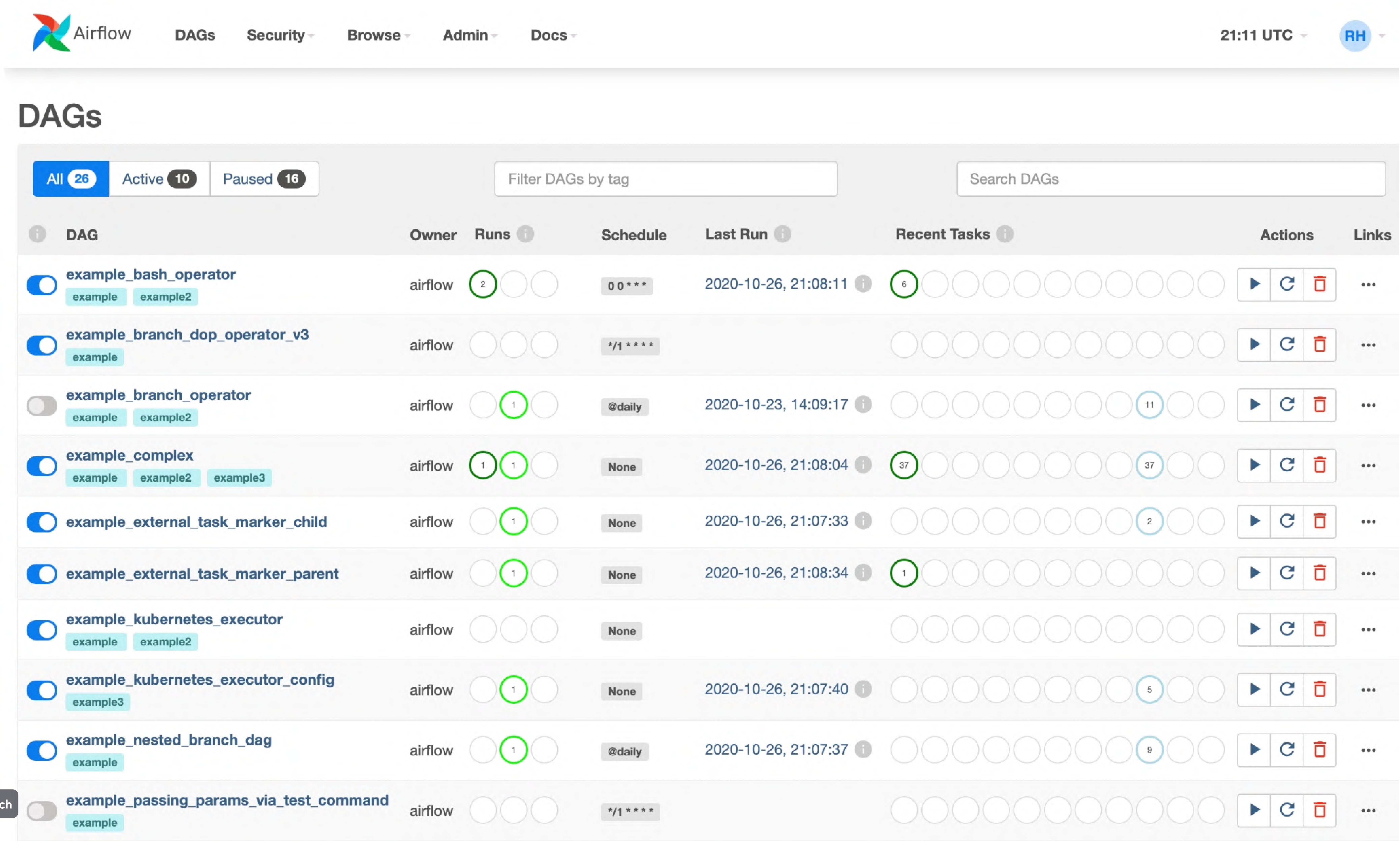
Com is a mechanism for tasks to exchange small amounts of data between them during runtime. It allows tasks to communicate and share information within the context of a single DAG run.

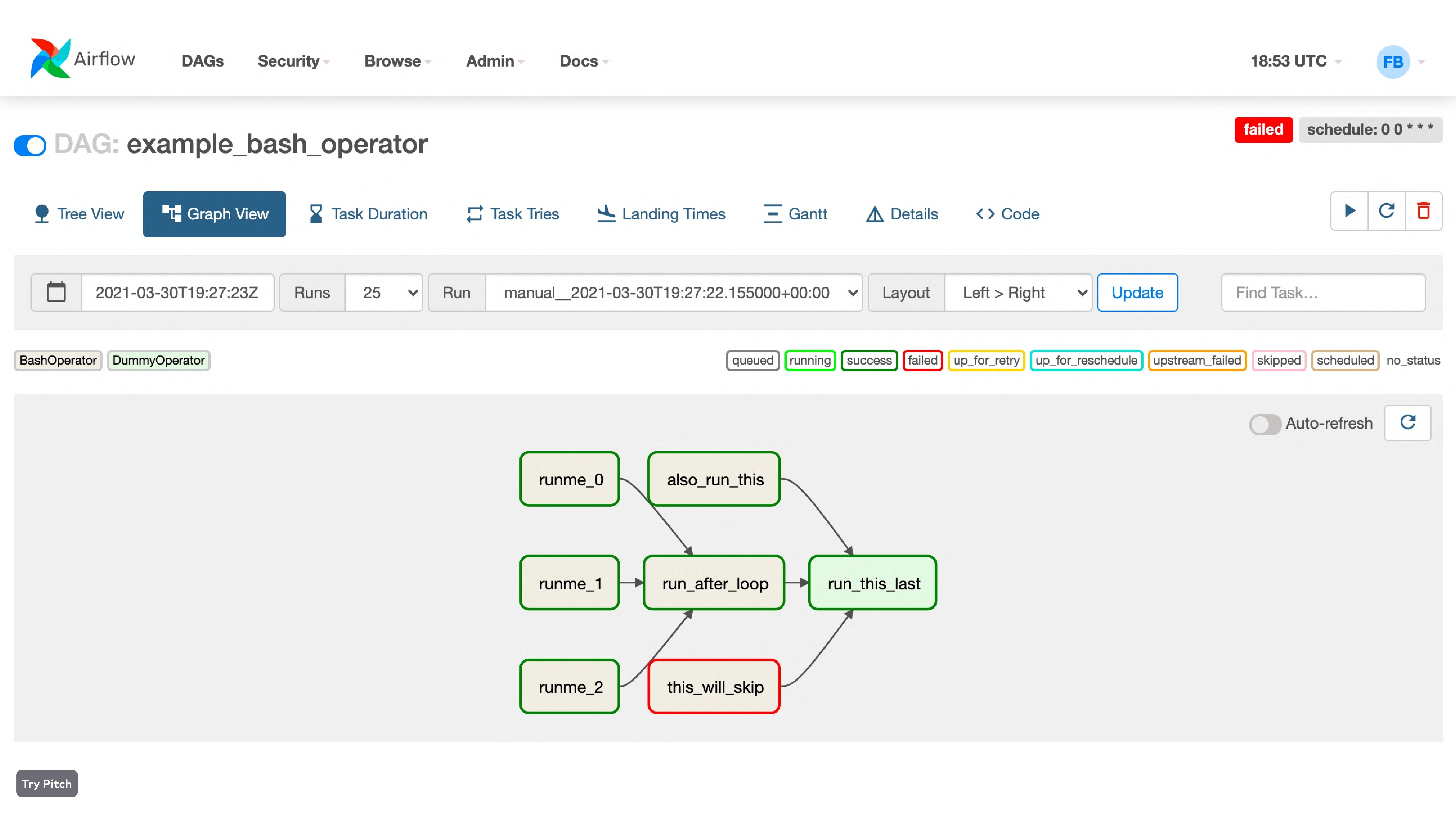
Airflow:

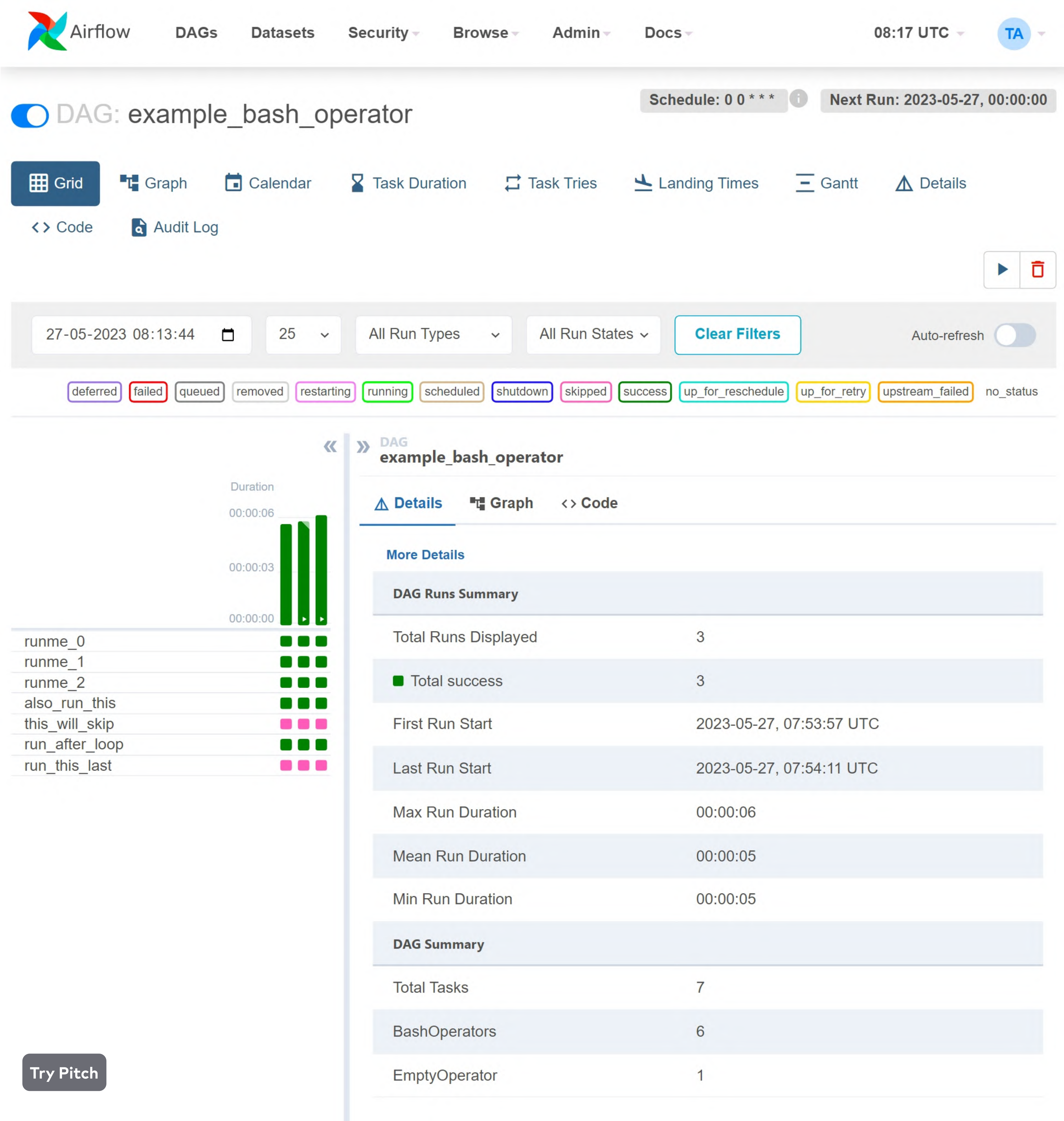
# DAGs can get crazy




Airflow
localhost:8250/login/?next=http%3A%2F%2Flocalhost%3A8250%2Fhome
Airflow
07:50 UTC
Log In
Sign In
Enter your login and password below:
Username:
admin
Password:
Sign In

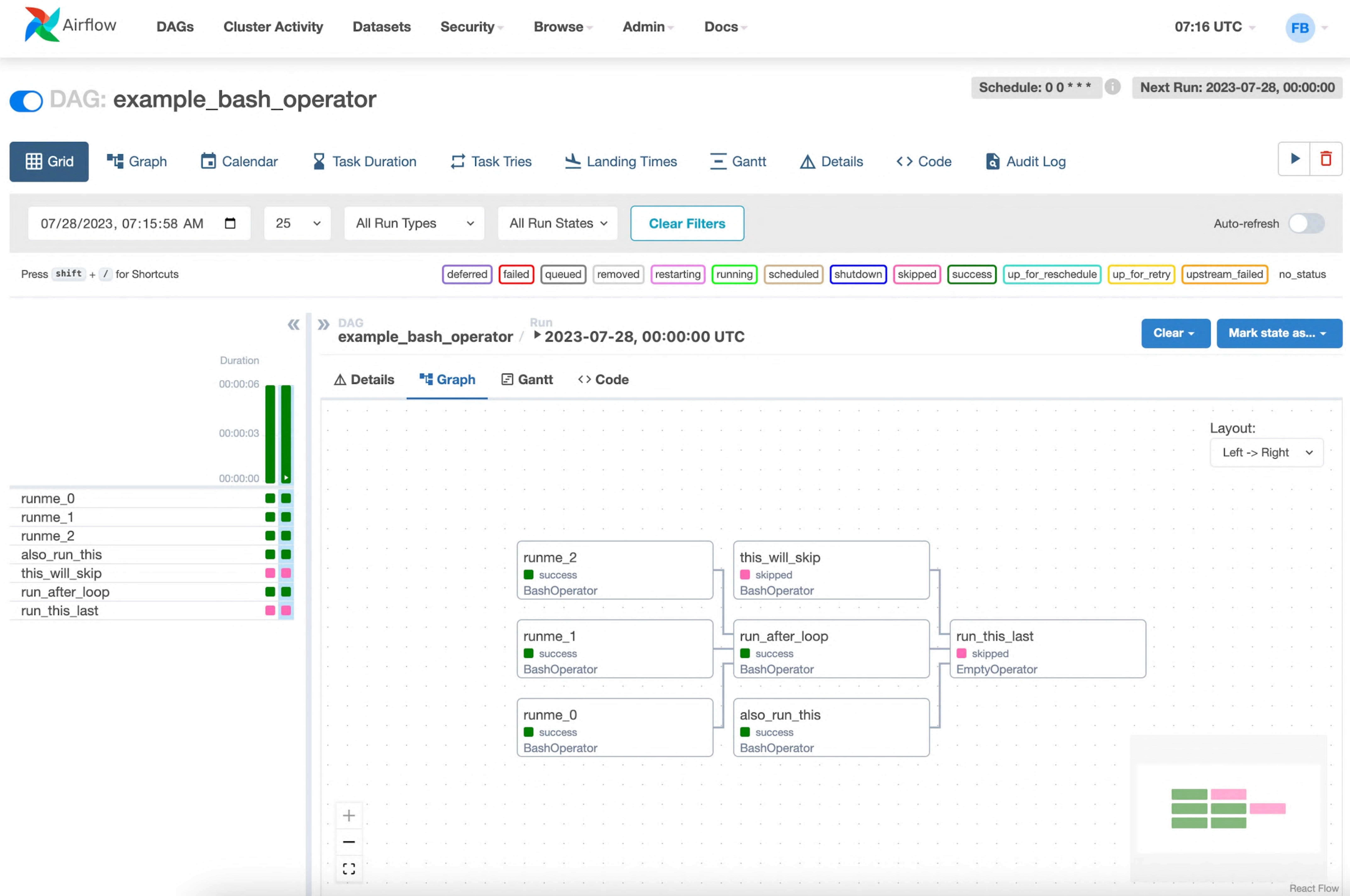

Airflow
DAGs
Security
Browse
Admin
Docs
21:11 UTC
RH
DAGs
All 26
Active 10
Paused 16
Filter DAGs by tag
Search DAGs
DAG
Owner
Runs
Schedule
Last Run
Recent Tasks
Actions
Links
example_bash_operator
example
example2
airflow
2
0 0 * * *
2020-10-26, 21:08:11
6
example_branch_dop_operator_v3
example
airflow
*/1 * * * *
example_branch_operator
example
example2
airflow
1
@daily
2020-10-23, 14:09:17
11
example_complex
example
example2
example3
airflow
1
1
None
2020-10-26, 21:08:04
37
37
example_external_task_marker_child
airflow
1
None
2020-10-26, 21:07:33
2
example_external_task_marker_parent
airflow
1
None
2020-10-26, 21:08:34
1
example_kubernetes_executor
example
example2
airflow
None
example_kubernetes_executor_config
example3
airflow
1
None
2020-10-26, 21:07:40
5
example_nested_branch_dag
example
airflow
1
@daily
2020-10-26, 21:07:37
9
example_passing_params_via_test_command
example
airflow
*/1 * * * *

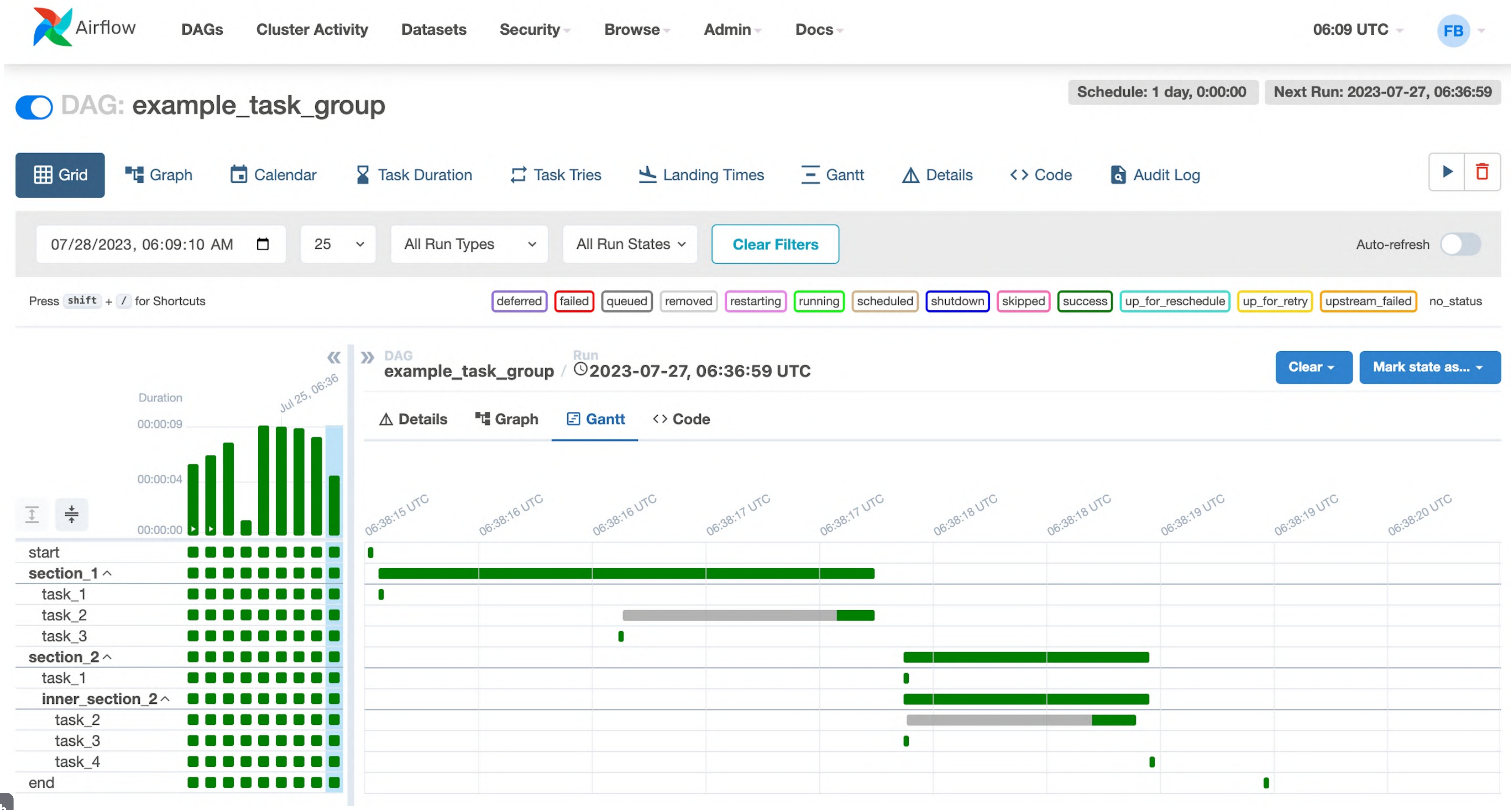

Airflow
DAGs
Security
Browse
Admin
Docs
18:53 UTC
FB
failed
schedule: 0 0 * * *
DAG: example_bash_operator
Tree View
Graph View
Task Duration
Task Tries
Landing Times
Gantt
Details
Code
2021-03-30T19:27:23Z
Runs
25
Run
manual__2021-03-30T19:27:22.155000+00:00
Layout
Left > Right
Update
Find Task...
BashOperator
DummyOperator
queued
running
success
failed
up_for_retry
up_for_reschedule
upstream_failed
skipped
scheduled
no_status
Auto-refresh
runme_0
also_run_this
runme_1
run_after_loop
run_this_last
runme_2
this_will_skip
Try Pitch



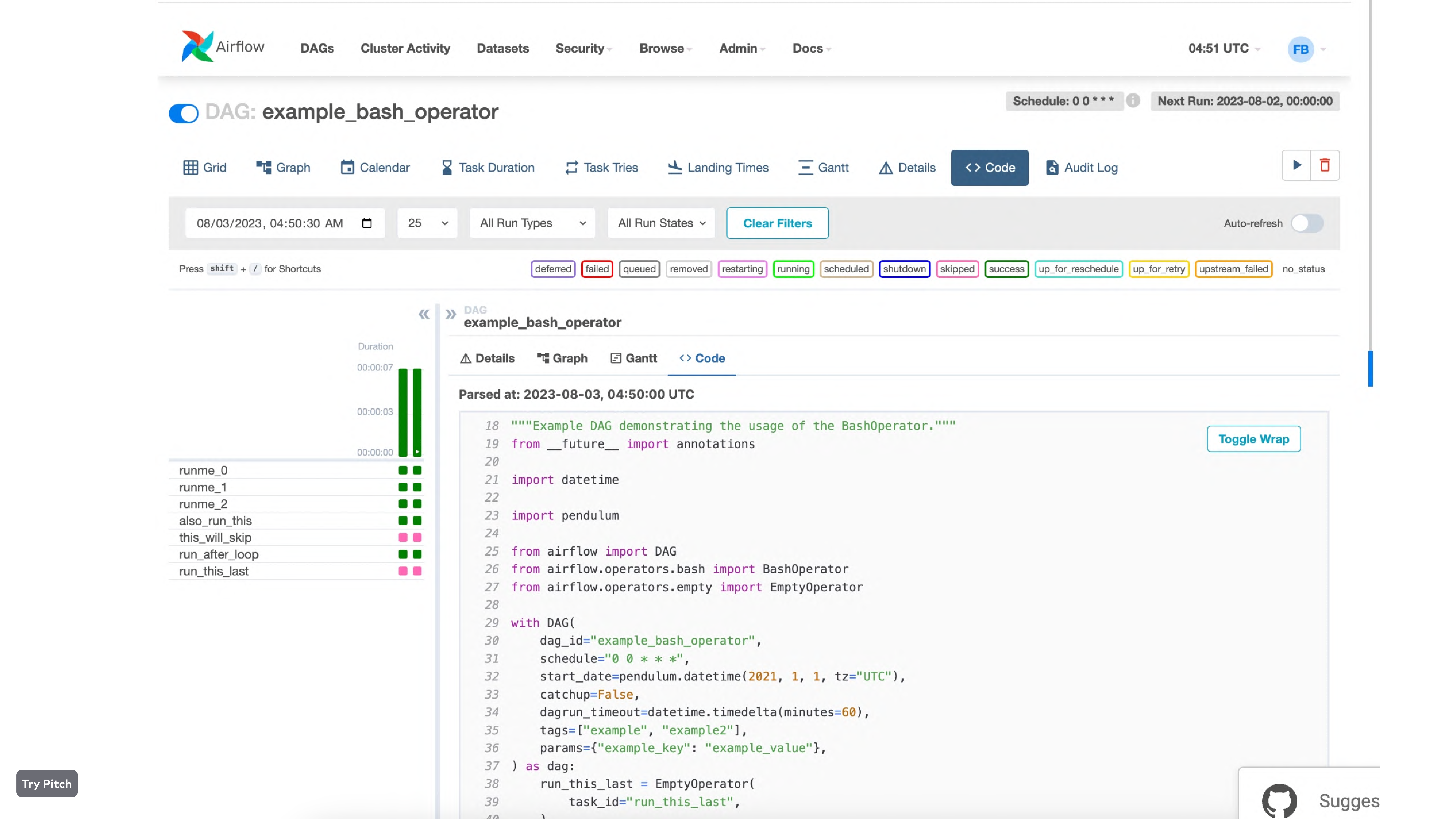



A bar chart and grid representation of the DAG that spans across time. The top row is a chart of DAG Runs by duration, and below, task instances. If a pipeline is late, you can quickly see where the different steps are and identify the blocking ones.


Airflow
DAGs
Cluster Activity
Datasets
Security
Browse
Admin
Docs
07:16 UTC
FB
DAG: example_bash_operator
Schedule: 0 0 * * *
Next Run: 2023-07-28, 00:00:00
Grid
Graph
Calendar
Task Duration
Task Tries
Landing Times
Gantt
Details
Code
Audit Log
07/28/2023, 07:15:58 AM
25
All Run Types
All Run States
Clear Filters
Auto-refresh
Press shift + / for Shortcuts
deferred
failed
queued
removed
restarting
running
scheduled
shutdown
skipped
success
up_for_reschedule
up_for_retry
upstream_failed
no_status
DAG
example_bash_operator
Run
2023-07-28, 00:00:00 UTC
Clear
Mark state as...
Duration
00:00:06
00:00:03
00:00:00
runme_0
runme_1
runme_2
also_run_this
this_will_skip
run_after_loop
run_this_last
Details
Graph
Gantt
Code
Layout:
Left -> Right
runme_2
success
BashOperator
this_will_skip
skipped
BashOperator
runme_1
success
BashOperator
run_after_loop
success
BashOperator
run_this_last
skipped
EmptyOperator
runme_0
success
BashOperator
also_run_this
success
BashOperator
React Flow



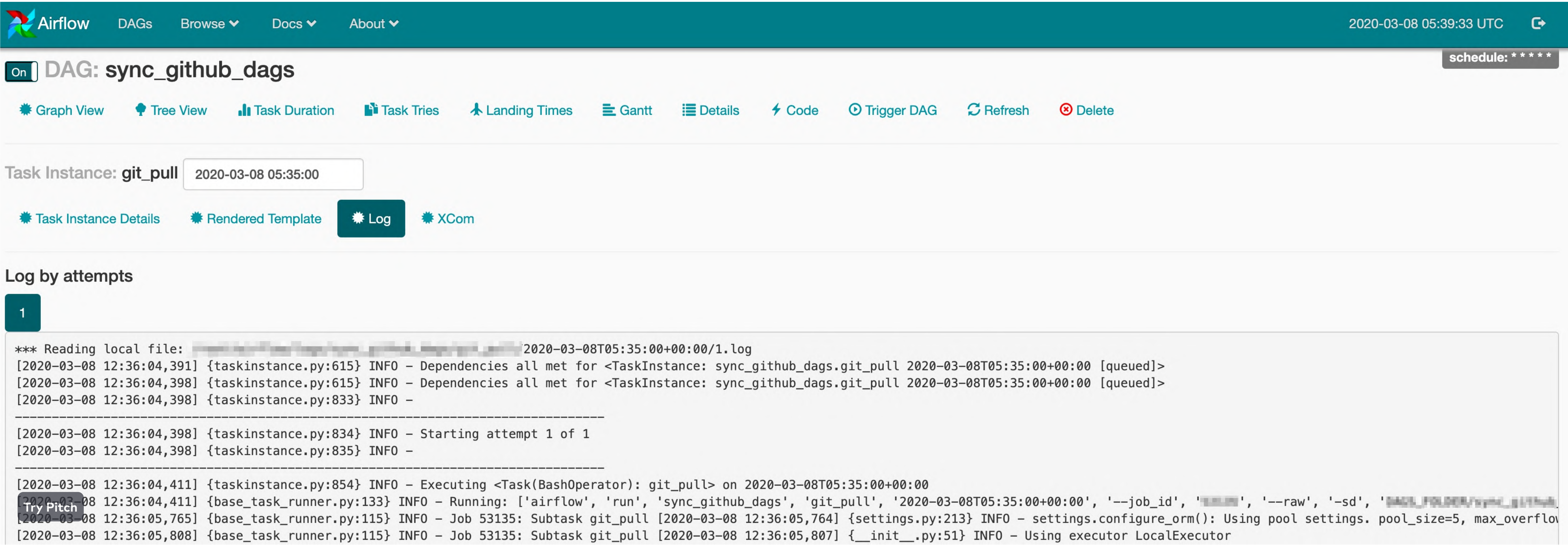
Airflow
DAGs
Cluster Activity
Datasets
Security
Browse
Admin
Docs
06:09 UTC
FB
DAG: example_task_group
Schedule: 1 day, 0:00:00
Next Run: 2023-07-27, 06:36:59
Grid
Graph
Calendar
Task Duration
Task Tries
Landing Times
Gantt
Details
Code
Audit Log
07/28/2023, 06:09:10 AM
25
All Run Types
All Run States
Clear Filters
Auto-refresh
Press shift + / for Shortcuts
deferred
failed
queued
removed
restarting
running
scheduled
shutdown
skipped
success
up_for_reschedule
up_for_retry
upstream_failed
no_status
Duration
Jul 25, 06:36
00:00:09
00:00:04
00:00:00
DAG
example_task_group
Run
2023-07-27, 06:36:59 UTC
Clear
Mark state as...
Details
Graph
Gantt
Code
06:38:15 UTC
06:38:16 UTC
06:38:16 UTC
06:38:17 UTC
06:38:17 UTC
06:38:18 UTC
06:38:18 UTC
06:38:19 UTC
06:38:19 UTC
06:38:20 UTC
start
section_1
task_1
task_2
task_3
section_2
task_1
inner_section_2
task_2
task_3
task_4
end



Airflow
DAGs
Cluster Activity
Datasets
Security
Browse
Admin
Docs
04:51 UTC
FB
DAG: example_bash_operator
Schedule: 0 0 * * *
Next Run: 2023-08-02, 00:00:00
Grid
Graph
Calendar
Task Duration
Task Tries
Landing Times
Gantt
Details
Code
Audit Log
08/03/2023, 04:50:30 AM
25
All Run Types
All Run States
Clear Filters
Auto-refresh
Press shift + / for Shortcuts
deferred
failed
queued
removed
restarting
running
scheduled
shutdown
skipped
success
up_for_reschedule
up_for_retry
upstream_failed
no_status
DAG
example_bash_operator
Duration
00:00:07
00:00:03
00:00:00
runme_0
runme_1
runme_2
also_run_this
this_will_skip
run_after_loop
run_this_last
Details
Graph
Gantt
Code
Parsed at: 2023-08-03, 04:50:00 UTC
Toggle Wrap
"""Example DAG demonstrating the usage of the BashOperator."""
from __future__ import annotations
import datetime
import pendulum
from airflow import DAG
from airflow.operators.bash import BashOperator
from airflow.operators.empty import EmptyOperator
with DAG(
dag_id="example_bash_operator",
schedule="0 0 * * *",
start_date=pendulum.datetime(2021, 1, 1, tz="UTC"),
catchup=False,
dagrun_timeout=datetime.timedelta(minutes=60),
tags=["example", "example2"],
params={"example_key": "example_value"},
) as dag:
run_this_last = EmptyOperator(
task_id="run_this_last",
Try Pitch
Sugges

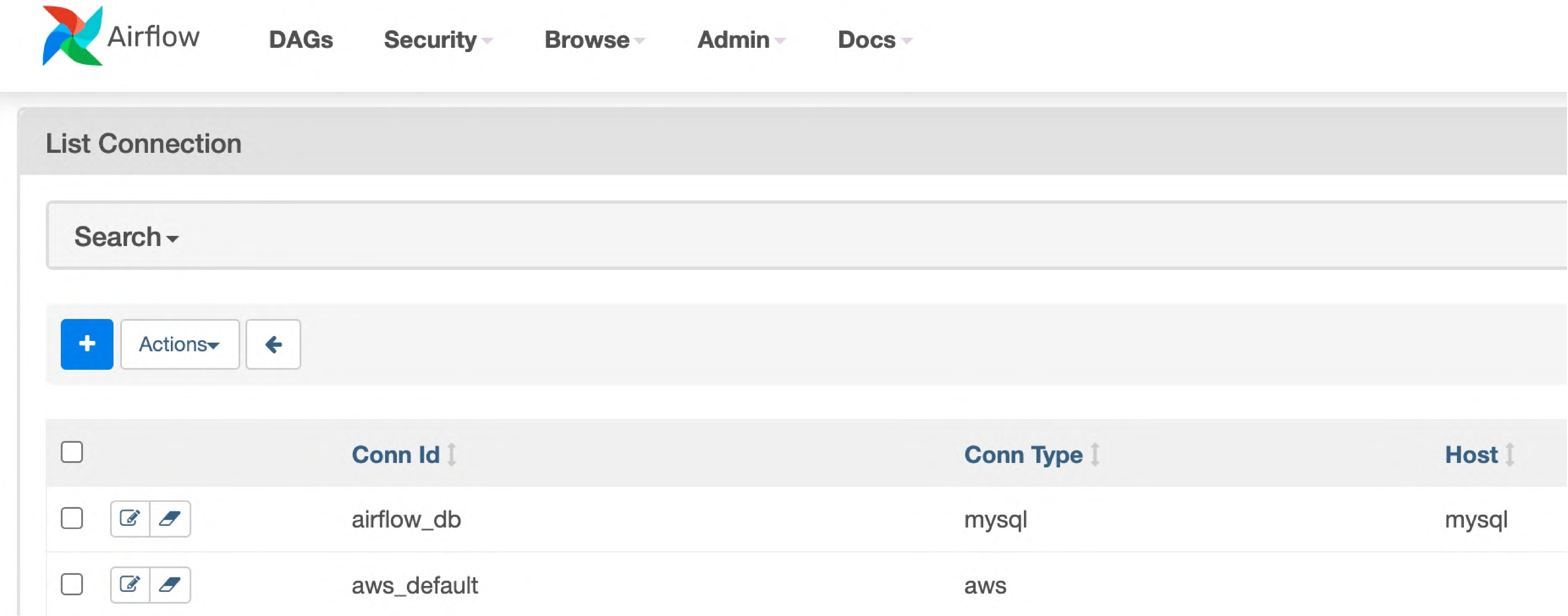
Logs View

Airflow generates task-specific logs for each execution, documenting key information such as start times, durations, and encountered errors.



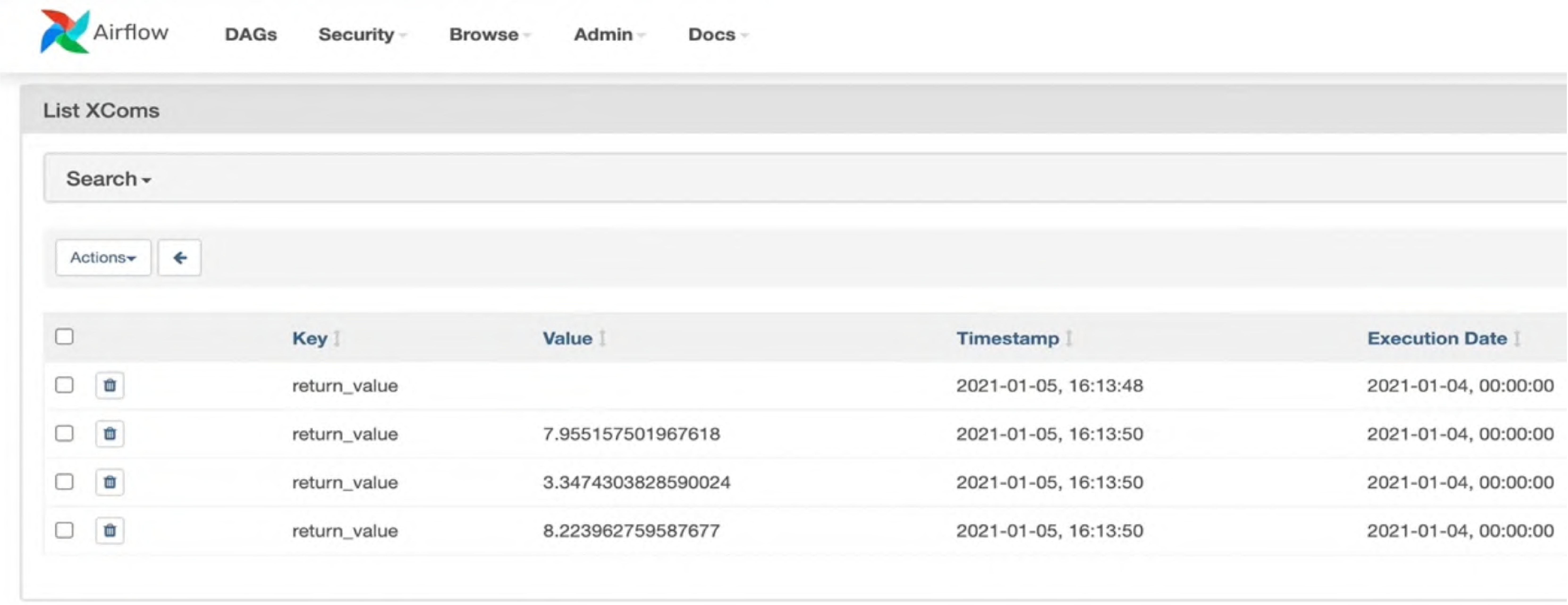
## Connections Screen

used for configuring and managing external connections to various data sources, APIs, databases, and services, allowing tasks within Airflow DAGs to interact with these external systems.

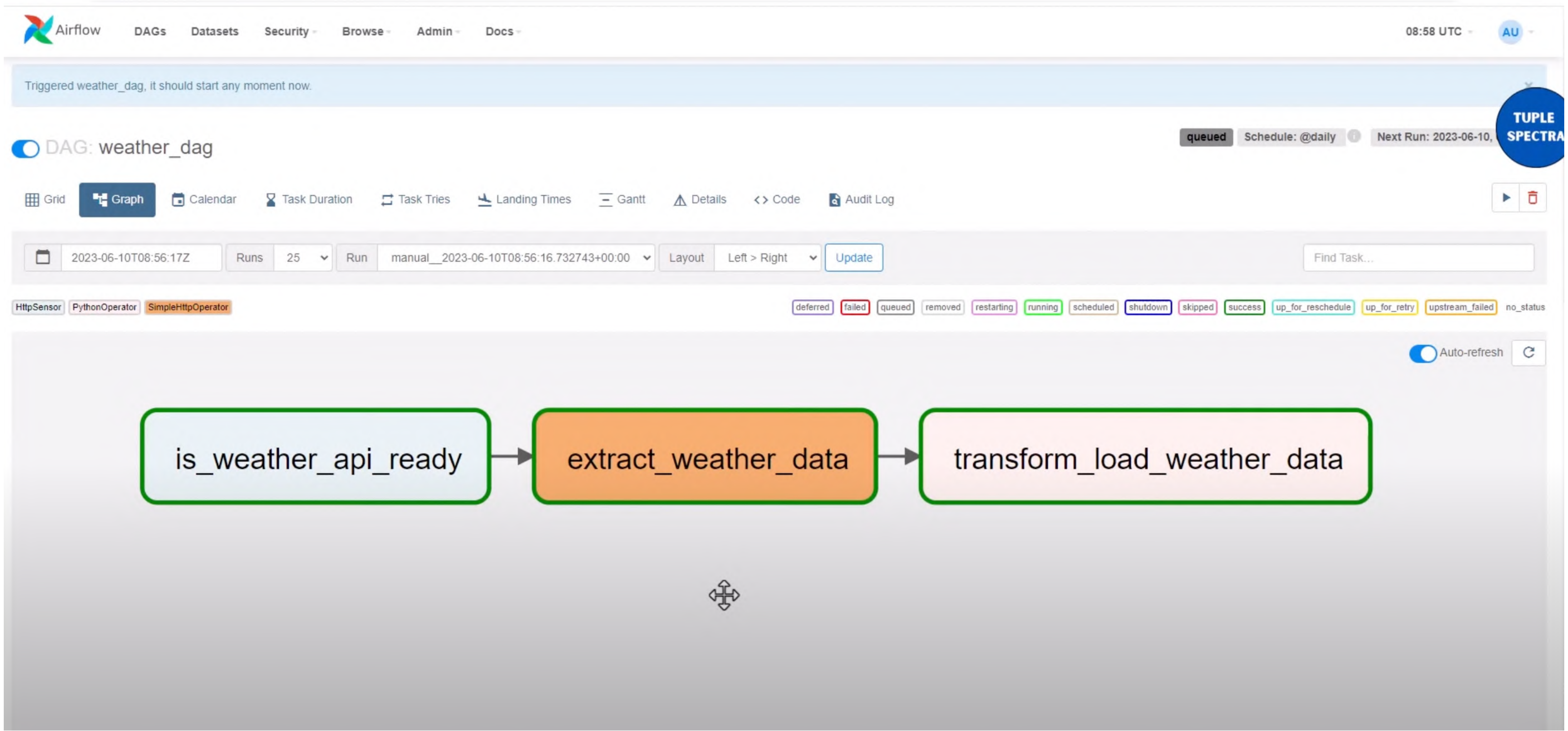


XComs Screen

**Data Exchange:** The XCom screen in Airflow allows tasks within a DAG to share small amounts of data, enabling communication between different parts of a workflow.



# Building a basic DAG




Try Pitch

# Initializing the DAG

This Airflow code defines default parameters for a DAG, including the owner, start date, email notifications, and retry behavior. The code then creates a DAG named 'weather_dag' with the specified default parameters, scheduling it to run daily and disabling catch-up for missed runs.

```python
default_args = {
    'owner': 'airflow',
    'depends_on_past': False,
    'start_date': datetime(2023, 1, 8),
    'email': ['myemail@domain.com'],
    'email_on_failure': False,
    'email_on_retry': False,
    'retries': 2,
    'retry_delay': timedelta(minutes=2)
}


with DAG('weather_dag',
        default_args=default_args,
        schedule_interval = '@daily',
        catchup=False) as dag:
```

```python
default_args = {
    'owner': 'airflow',
    'depends_on_past': False,
    'start_date': datetime(2023, 1, 8),
    'email': ['myemail@domain.com'],
    'email_on_failure': False,
    'email_on_retry': False,
    'retries': 2,
    'retry_delay': timedelta(minutes=2)
}


with DAG('weather_dag',
        default_args=default_args,
        schedule_interval = '@daily',
        catchup=False) as dag:
```

Alerts on failure

Retry policies builtin!

DAGs can be scheduled - No cron jobs needed!

```
is_weather_api_ready = HttpSensor(
task_id ='is_weather_api_ready',
http_conn_id='weathermap_api',
endpoint='/data/2.5/weather?q=Portland&APPID=5031cde3d1a8b9469fd47e998d7aef79'
)


extract_weather_data = SimpleHttpOperator(
task_id = 'extract_weather_data',
http_conn_id = 'weathermap_api',
endpoint='/data/2.5/weather?q=Portland&APPID=5031cde3d1a8b9469fd47e998d7aef79',
method = 'GET',
response_filter= lambda r: json.loads(r.text),
log_response=True
)

transform_load_weather_data = PythonOperator(
task_id= 'transform_load_weather_data',
python_callable=transform_load_data
)



is_weather_api_ready >> extract_weather_data >> transform_load_weather_data
```

Try Pitch

# Defining Tasks

Define three tasks within a DAG: checking the readiness of a weather API, extracting weather data via an HTTP request, and executing a Python function for transforming and loading the data.

# Ordering Tasks

(defining dependencies)

```
is_weather_api_ready = HttpSensor(
task_id ='is_weather_api_ready',
http_conn_id='weathermap_api',
endpoint='/data/2.5/weather?q=Portland&APPID=5031cde3d1a8b9469fd47e998d7aef79'
)


extract_weather_data = SimpleHttpOperator(
task_id = 'extract_weather_data',
http_conn_id = 'weathermap_api',
endpoint='/data/2.5/weather?q=Portland&APPID=5031cde3d1a8b9469fd47e998d7aef79',
method = 'GET',
response_filter= lambda r: json.loads(r.text),
log_response=True
)

transform_load_weather_data = PythonOperator(
task_id= 'transform_load_weather_data',
python_callable=transform_load_data
)



is_weather_api_ready >> extract_weather_data >> transform_load_weather_data
```



Whats this?

- **task_id**: Specifies the unique ID of a task.
- **http_conn_id:** Associates the task with the Airflow connection named 'weathermap_api'.
- **endpoint**: Defines the API endpoint for the HTTP request, targeting weather data for Portland with a specific API key.
- **response_filter**: Utilizes a lambda function as a response filter to parse the HTTP response text as JSON, converting it into a Python dictionary.
- **Python callable:** A custom Python function called transform_load_data

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# Thanks