Airflow training

Thursday 8th July 2020

Fokko Driesprong

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About Fokko Driesprong

- Master Distributed System at University of Groningen
- Principal Code Connoisseur at GoDataDriven for 4 years
- Member of the Apache Software Foundation
- Committer on Apache `{Avro,Parquet,Druid,Airflow}`
- Started with Airflow over 4 years ago

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About you (1 sentence per question)

- Background?
- Knowledge of Airflow?
- Plans to apply Airflow?
- Expectations of the training?

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First remote edition

- Did the training many times (in RL)
- Balance between questions and progress
- Feel free to interrupt me
- Let's embrace the awkwardness

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Program

- Introduction into Airflow
- Setup training environment
- Writing a first DAG
- Scheduling
- Templating
- Branching
- Putting it together

Airflow - Introduction

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What is Apache Airflow?

- Open source platform for creating, scheduling and monitoring workflows

- Started at AirBnB in 2015
  - Developed by Maxime Beauchemin
    - (https://medium.com/@maximebeauchemin)
  - Now used by 200+ companies (ING, LinkedIn, Paypal, HBO, …)
  - Contributions from 600+ developers

- Written in Python

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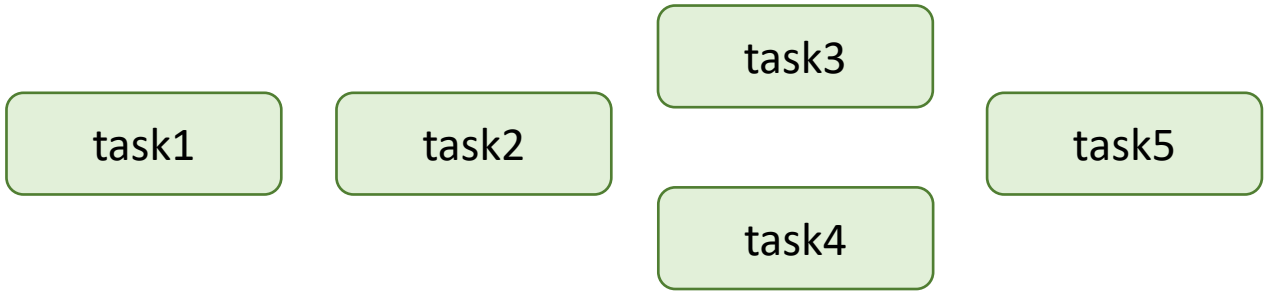
Why use Airflow?

- Scenario
  - We have a workflow consisting of 5 tasks
    - Some tasks need to run before others
    - Some tasks can run in parallel (tasks 3 + 4)
  - We want to run this workflow every day
  - We would like to have independent logs and be able to re-run tasks if they fail



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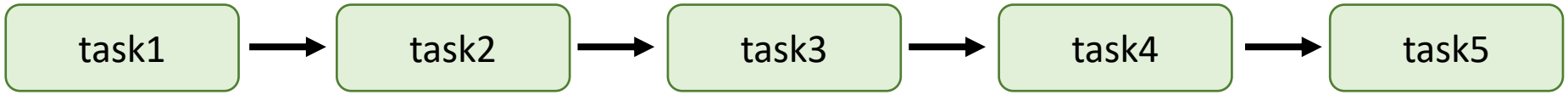
Scenario – Single script

- We could write a simple (bash) script the executes tasks linearly, scheduled with CRON



- Drawbacks
  - No parallelism between tasks 3 + 4
  - No independent logs + re-running of individual tasks

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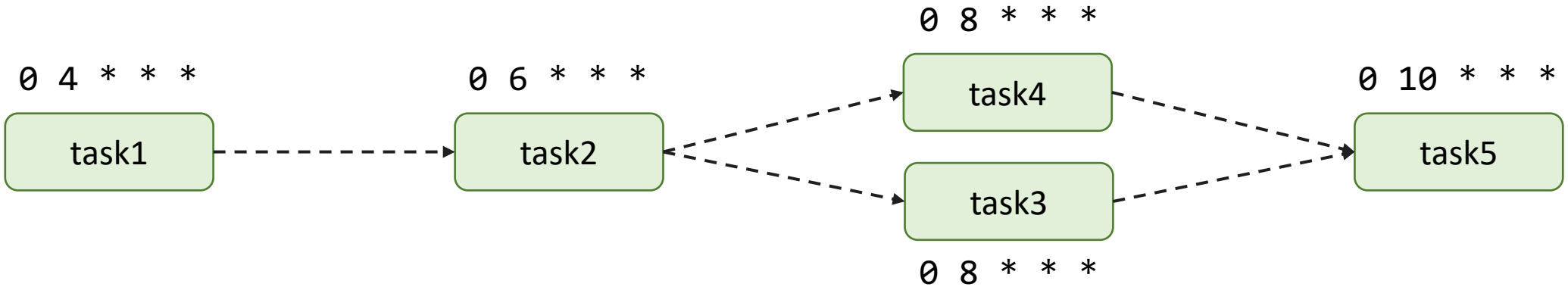
Scenario – Multiple scripts + cron

- Alternatively – split the tasks into separate scripts and schedule these using cron



- But what if a task fails?
  What if a task takes longer than expected?

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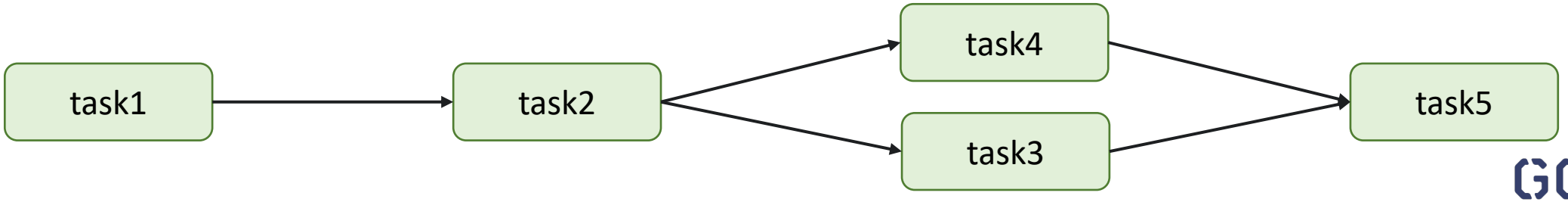
Scenario - Airflow

- Workflows built as graphs (DAG) of tasks
  - Dependencies between tasks as edges
  - Workflow runs on a given schedule (or can be triggered)
  - Results/logs monitored per-task by Airflow

```
DAG interval: 0 4 * * *
```



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When to use Airflow

- Running complex (data) pipelines
  - Batch-oriented data processing
  - Running at regular intervals
- Workflows as code
- Everything is Python (Airflow and Dags)
- Reusable components

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When NOT to use Airflow

- Airflow is not a (data) processing framework (such as Spark), focusses on orchestration

- Not for streaming data solutions

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Airflow alternatives?

- There are many, many workflow managers:
  - Azkaban (LinkedIn)
  - Oozie (Apache)
  - Luigi (Spotify)
  - Pinball† (Pinterest)
  - Snakemake
  - Argo

- So why use Airflow?
  - Define workflows in Python
  - Easy to integrate + extend
  - Strong scheduling semantics

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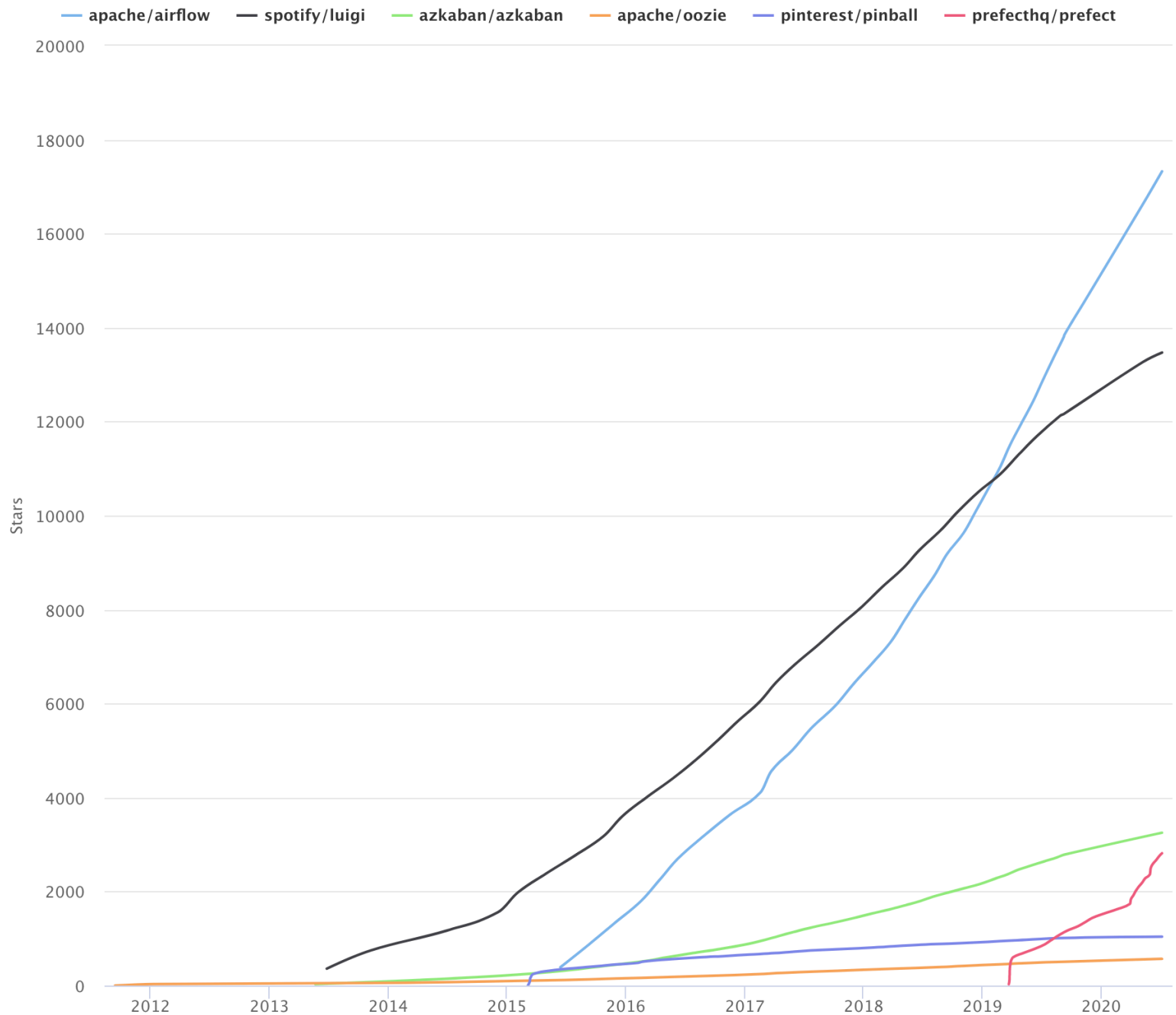

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Use case – Recommendations

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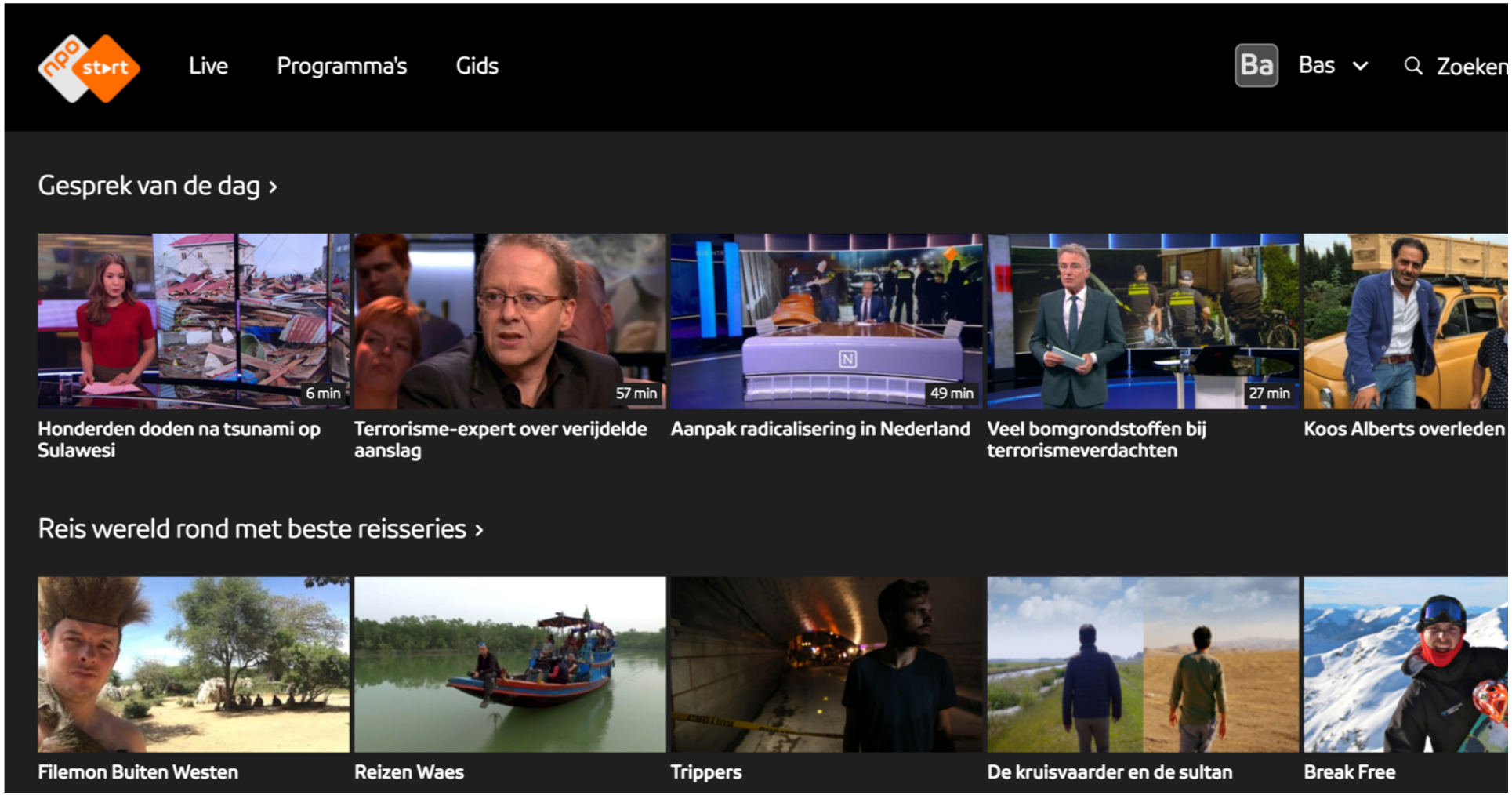
Recommendations



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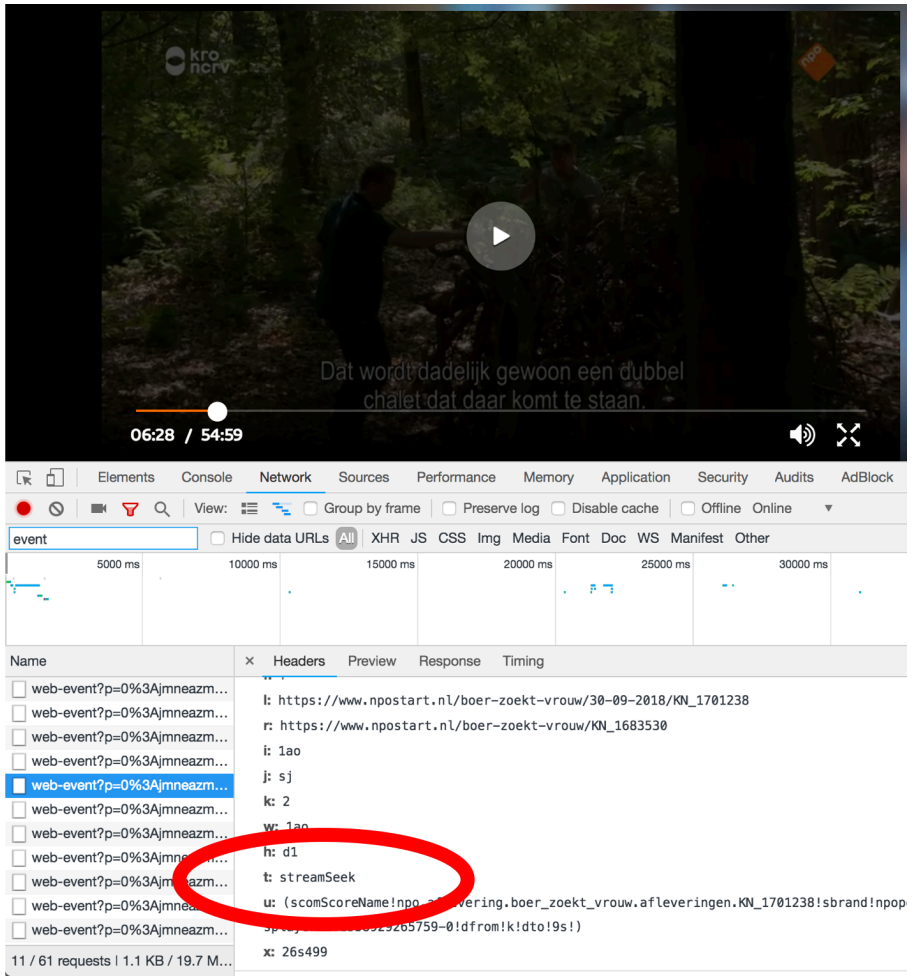
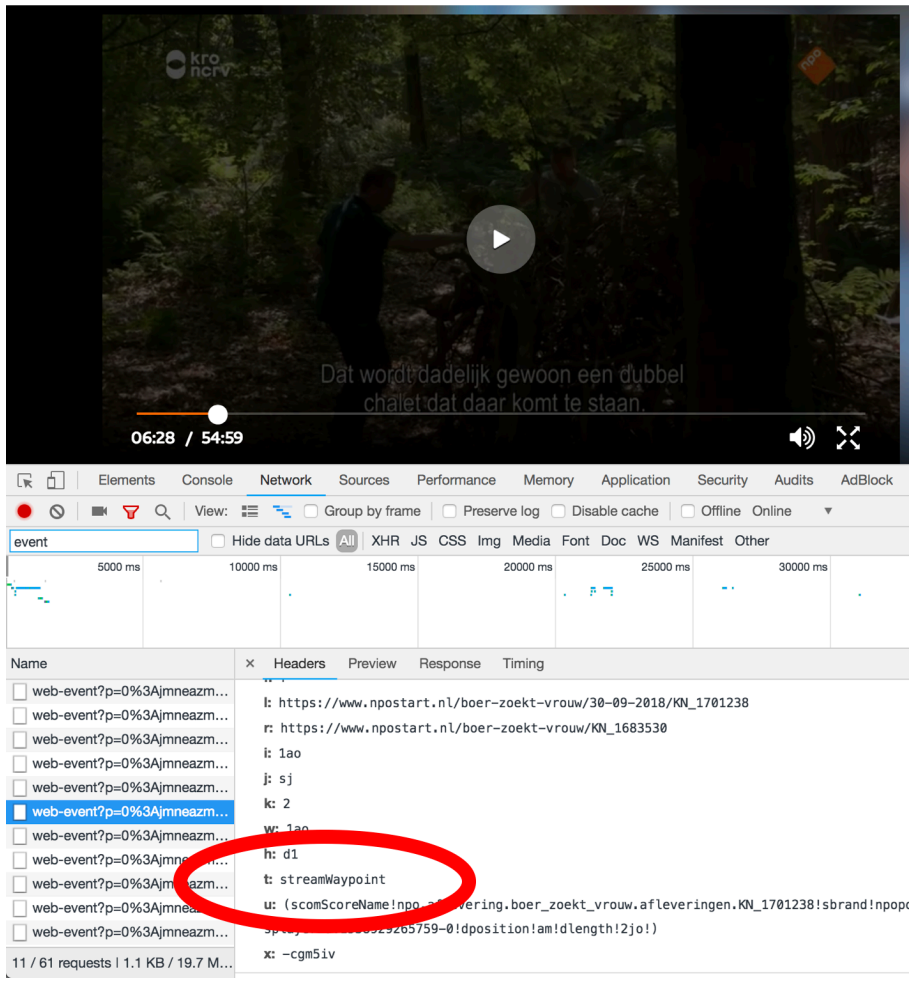
User streaming events





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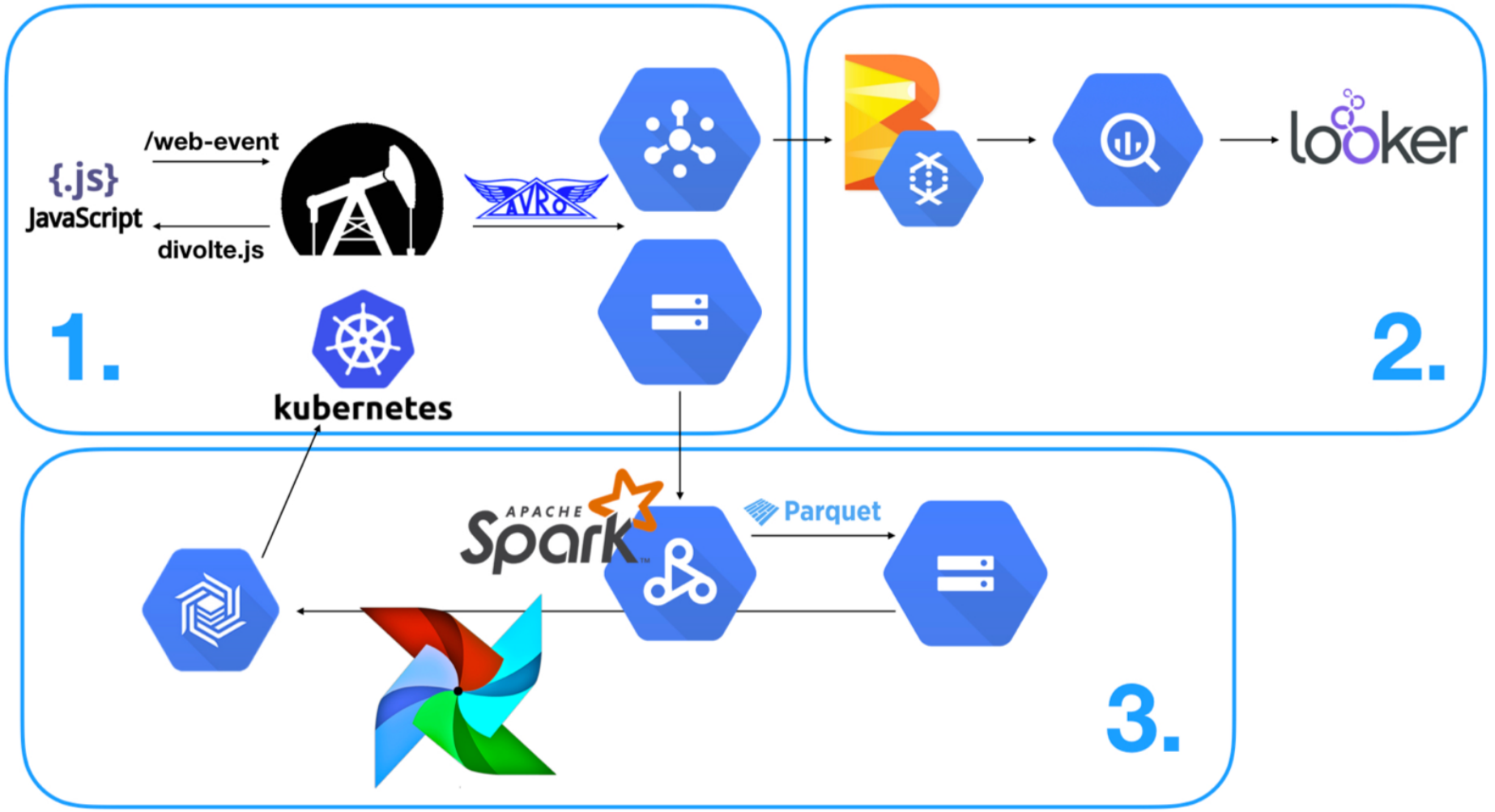
Architecture



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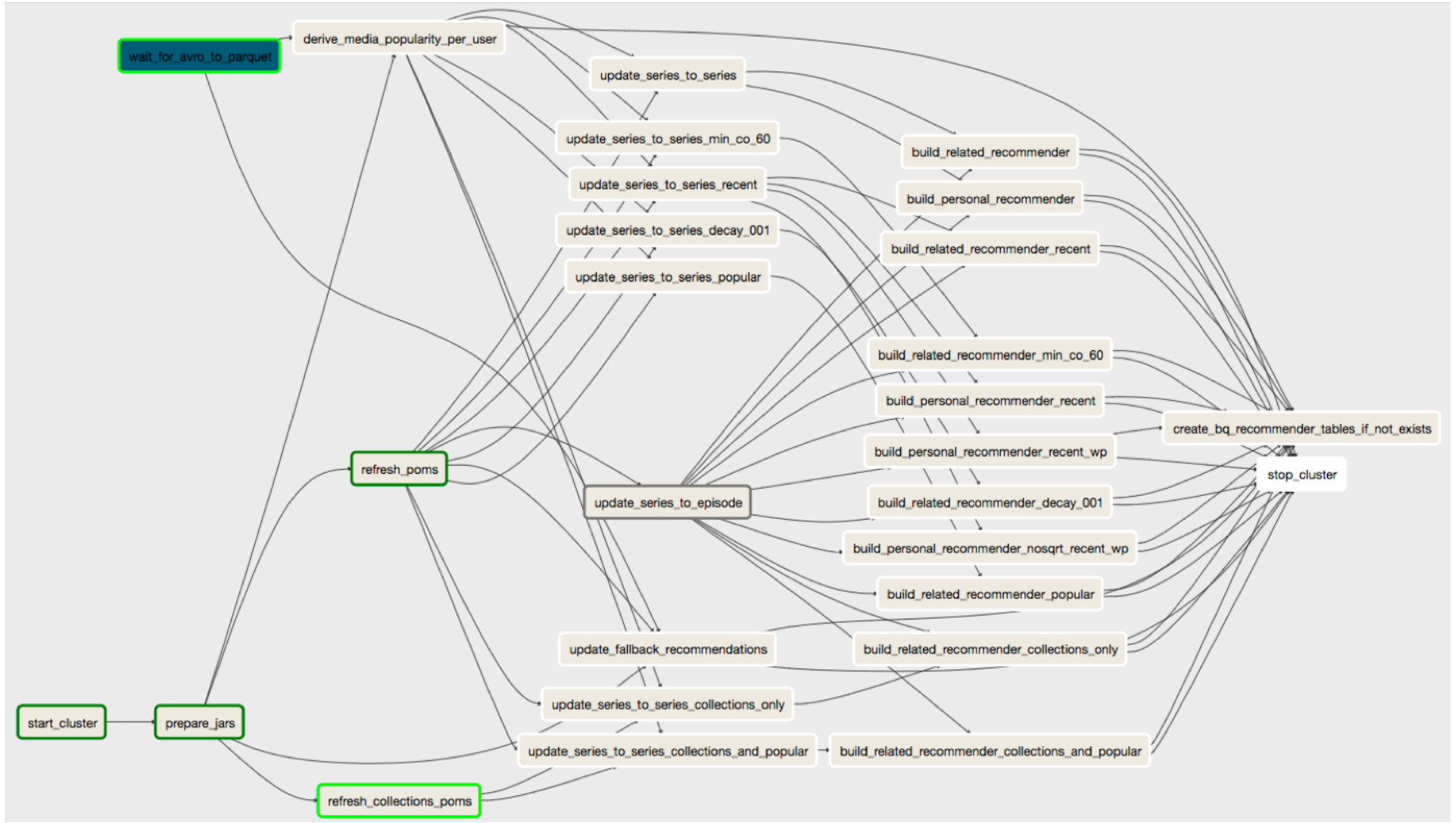
Recommender DAG



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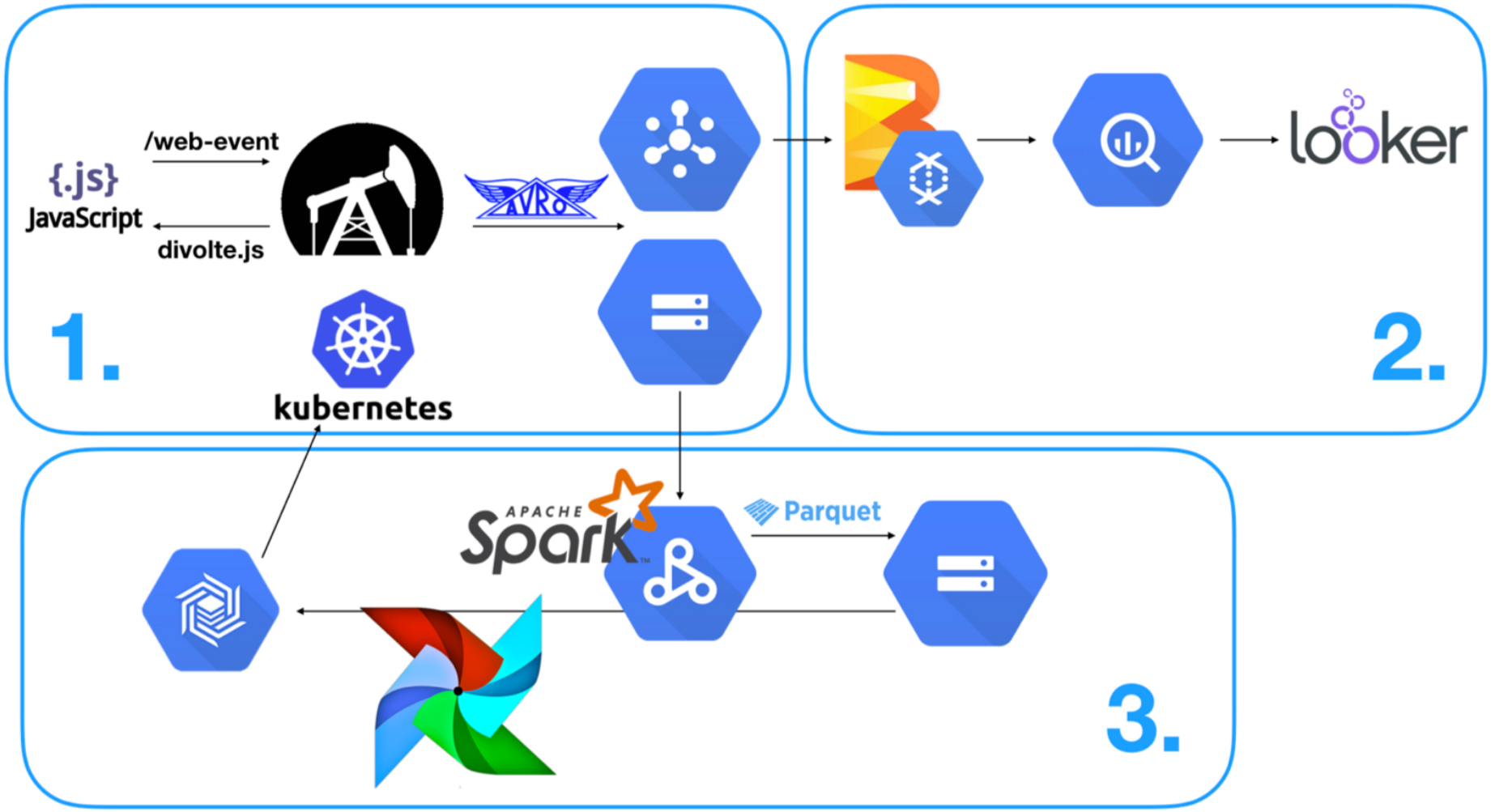
Architecture



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Setting up the environment

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Google Cloud Composer

- Managed Apache Airflow on Google Cloud Platform
- https://cloud.google.com/composer/docs?hl=nl
- Takes some time to spin up

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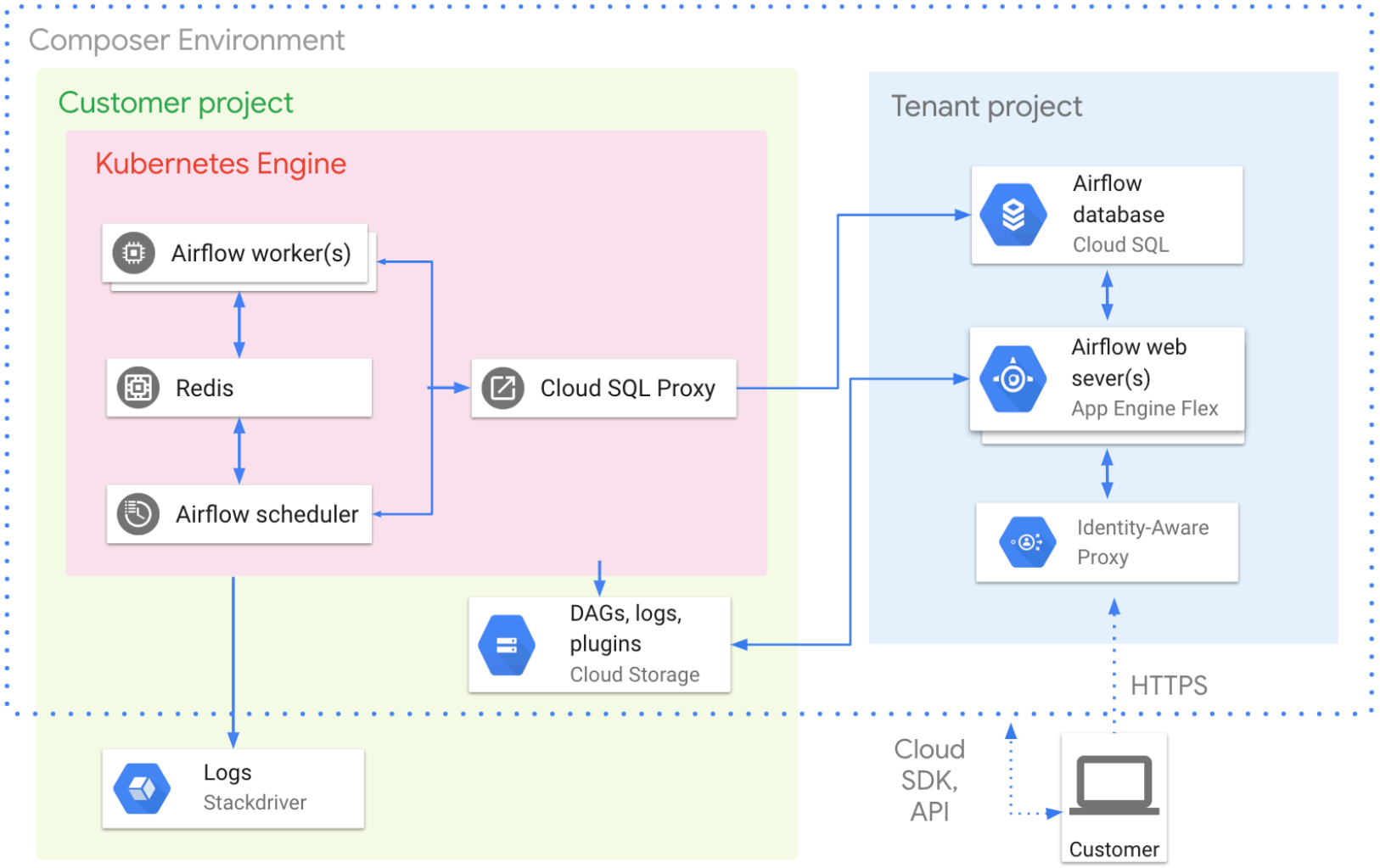
Google Cloud Composer



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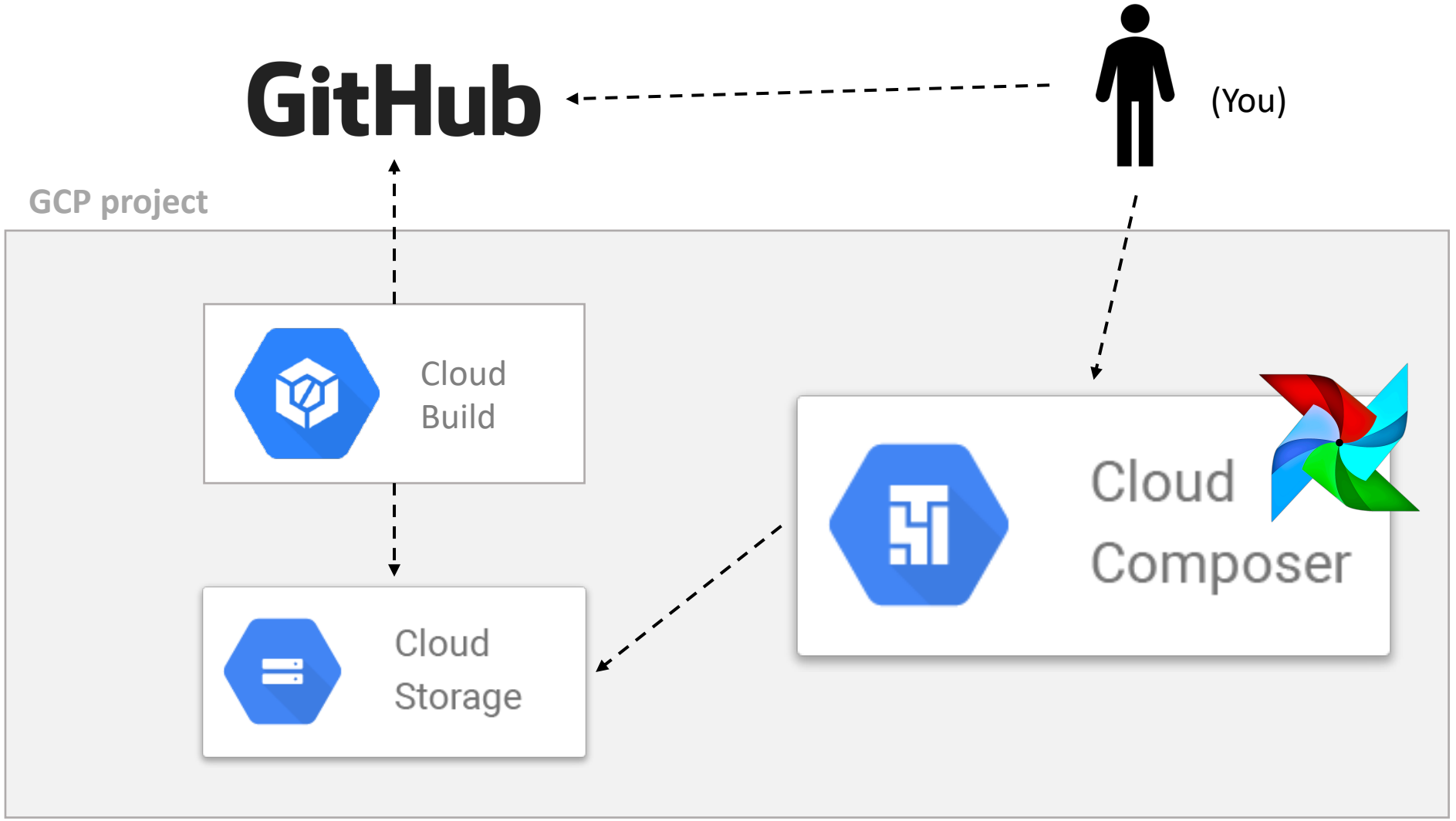
Training environment



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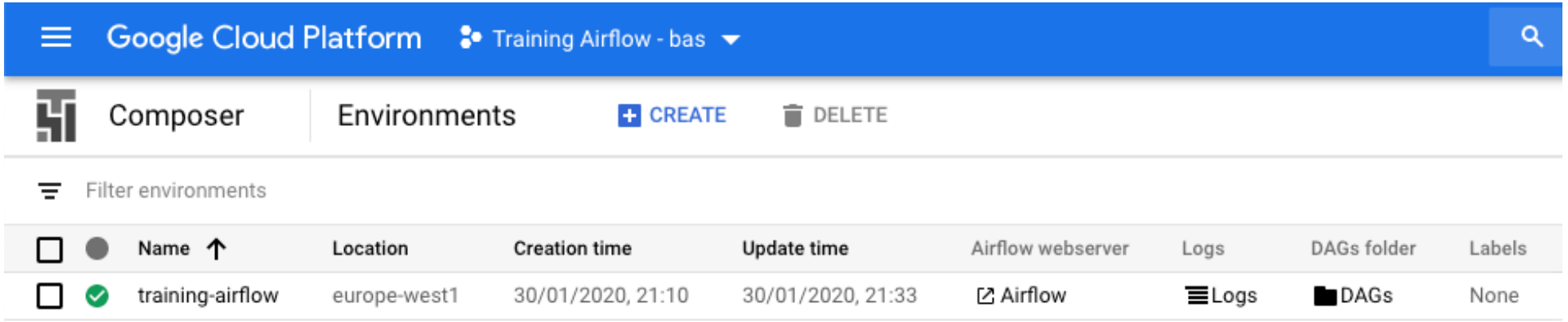
Opening Google Composer

- Go to https://console.cloud.google.com
- Open the project named “Training Airflow - [name]”
- Go to the Composer service (Google-managed Airflow)
- Docs: https://cloud.google.com/composer/docs



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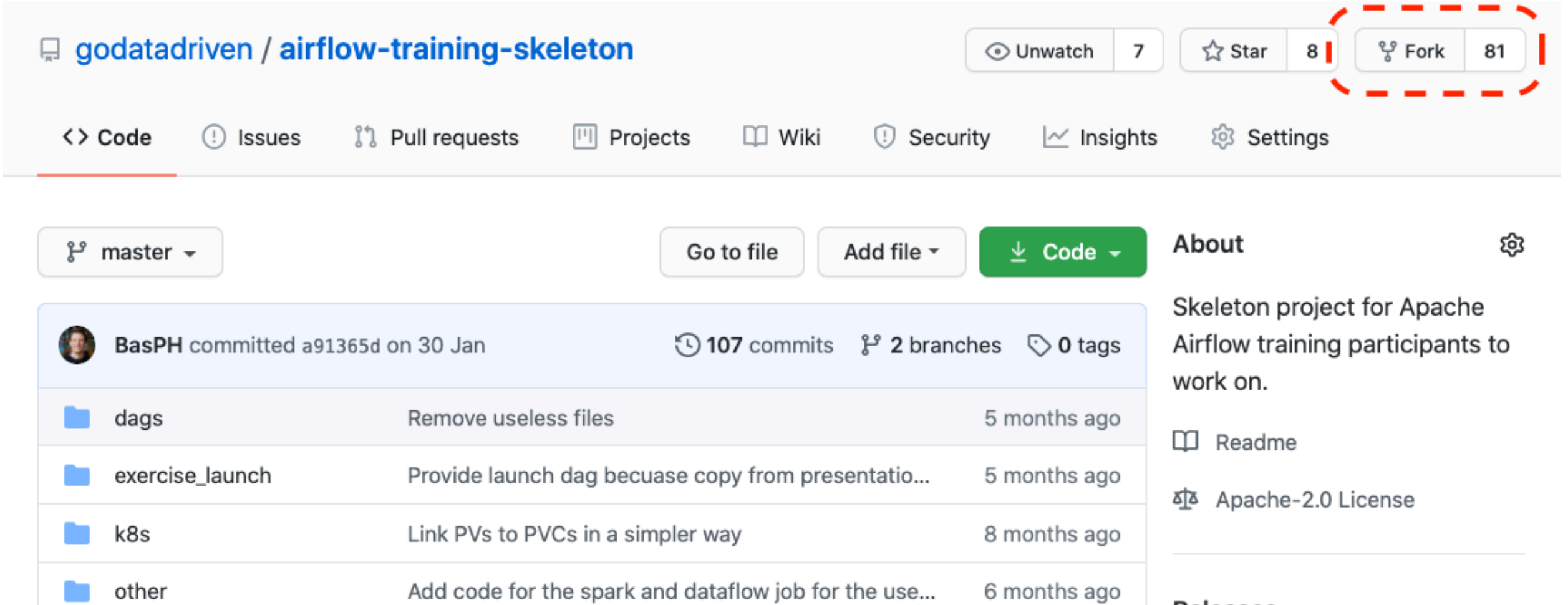
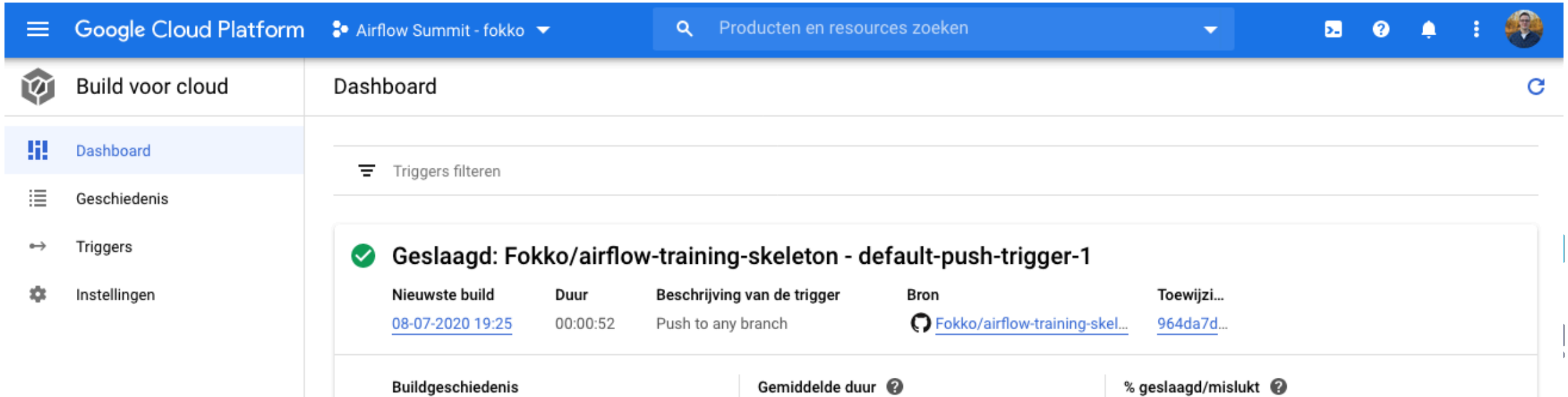
Setting up code deployment

- Fork https://github.com/godatadriven/airflow-training-skeleton

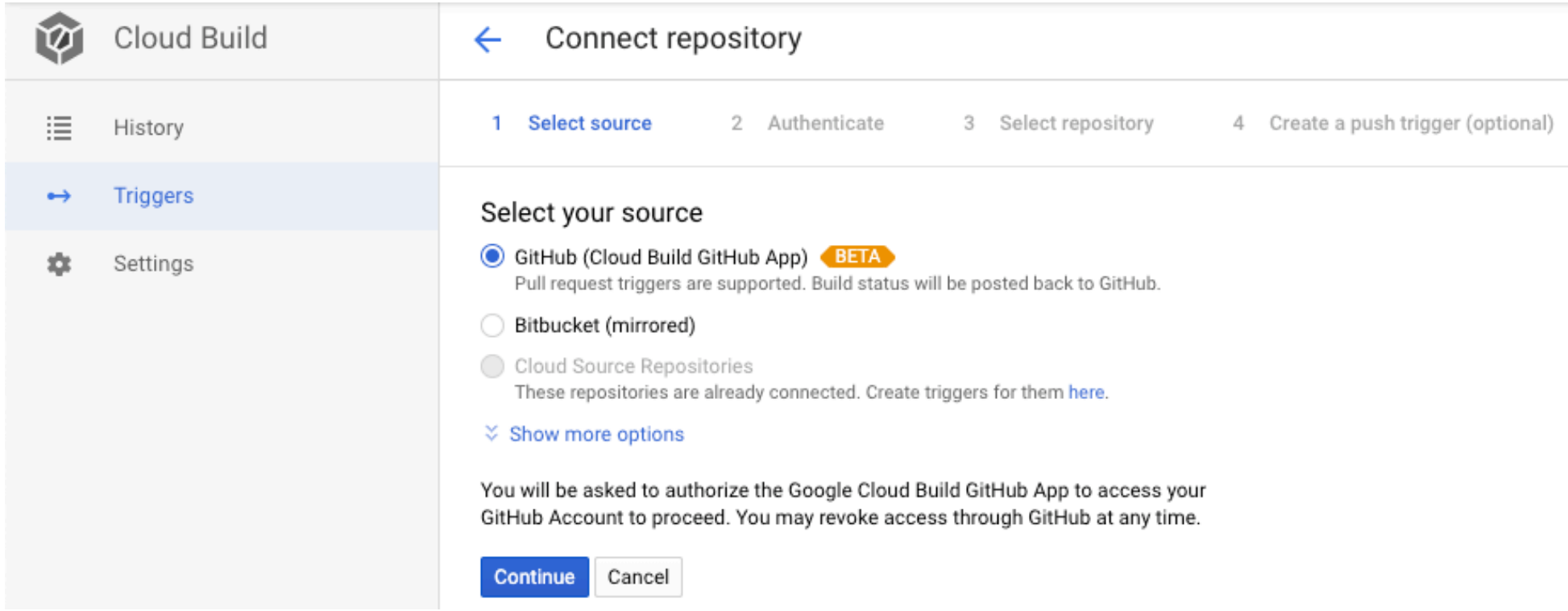


Setting up code deployment

- Open the Cloud Build service in GCP
  - https://console.cloud.google.com/cloud-build/
- Connect Cloud Build to your GitHub account (Triggers).
- Create a build trigger linked to your repo.



Connect to your GitHub account



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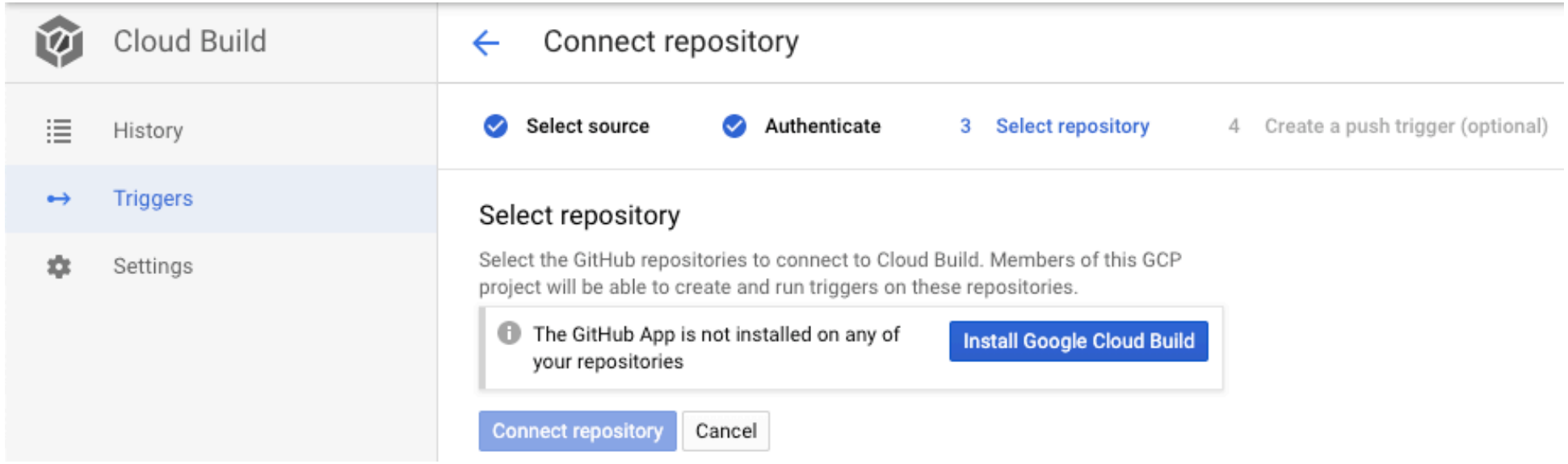
Select repository to connect



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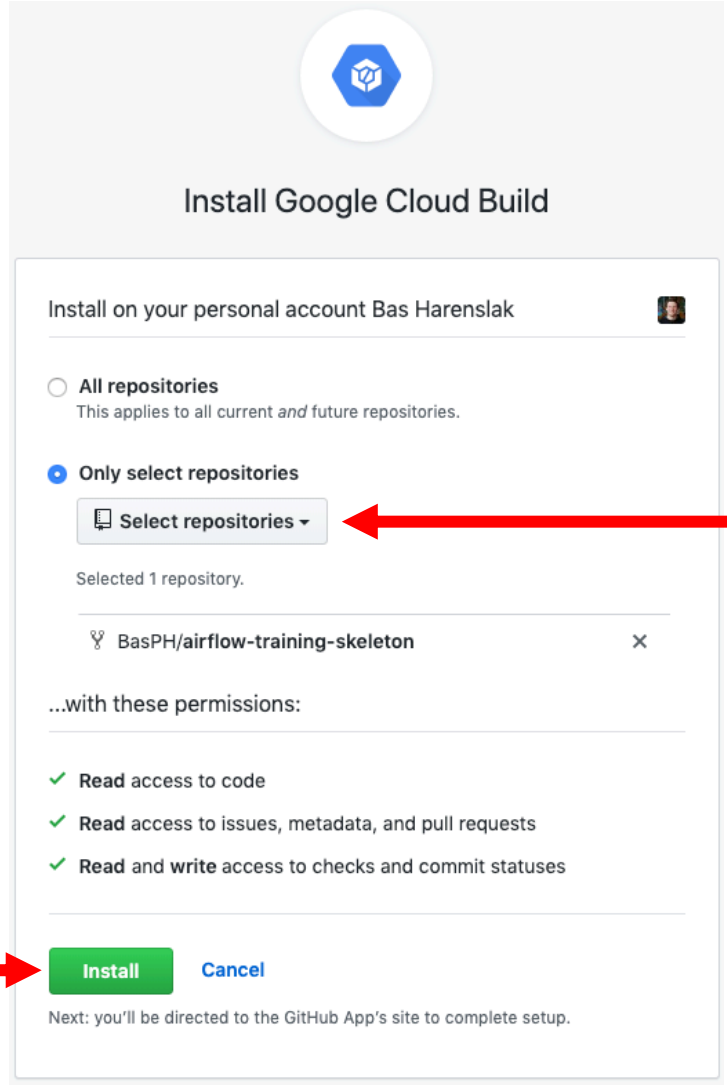
Select repository to connect



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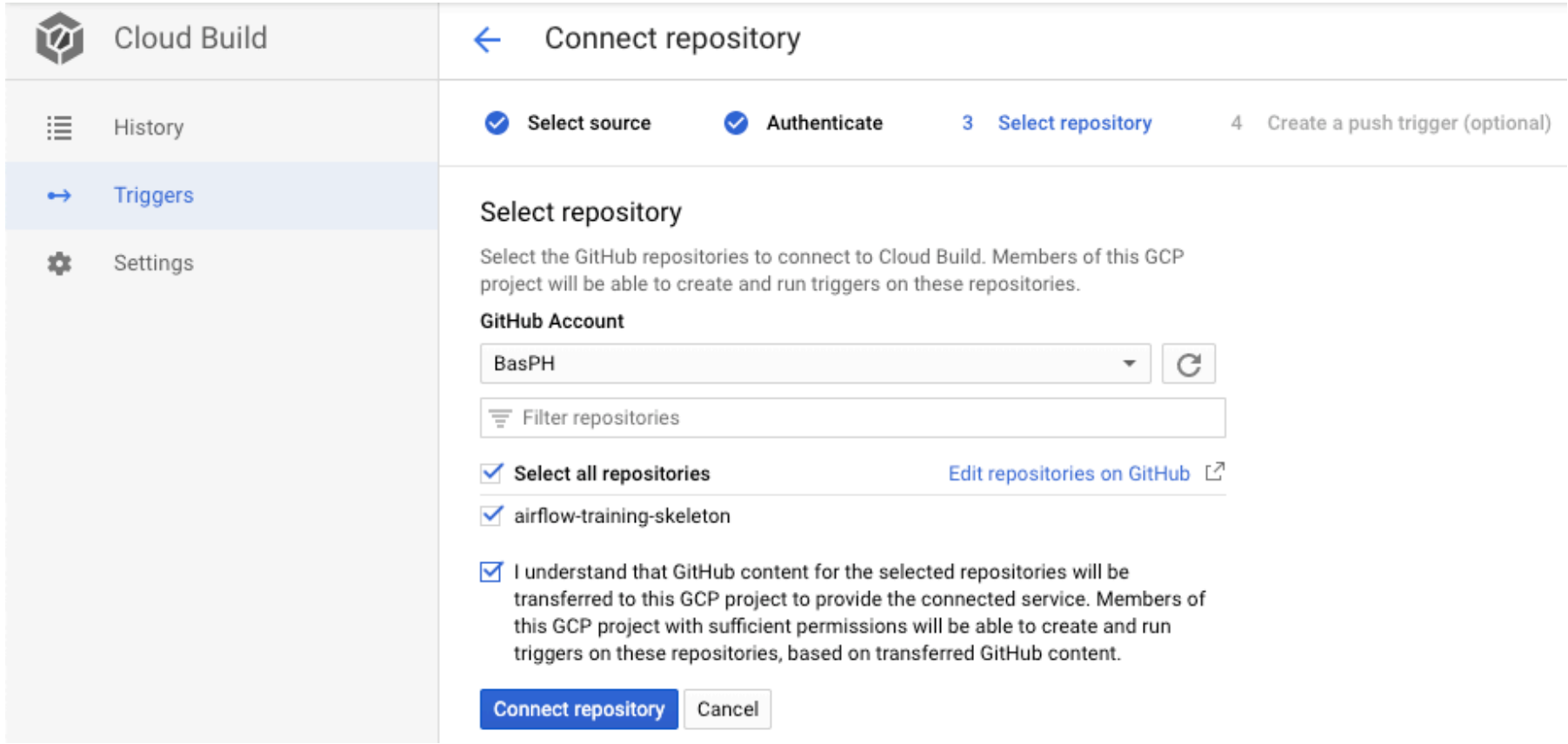
Select repository to connect



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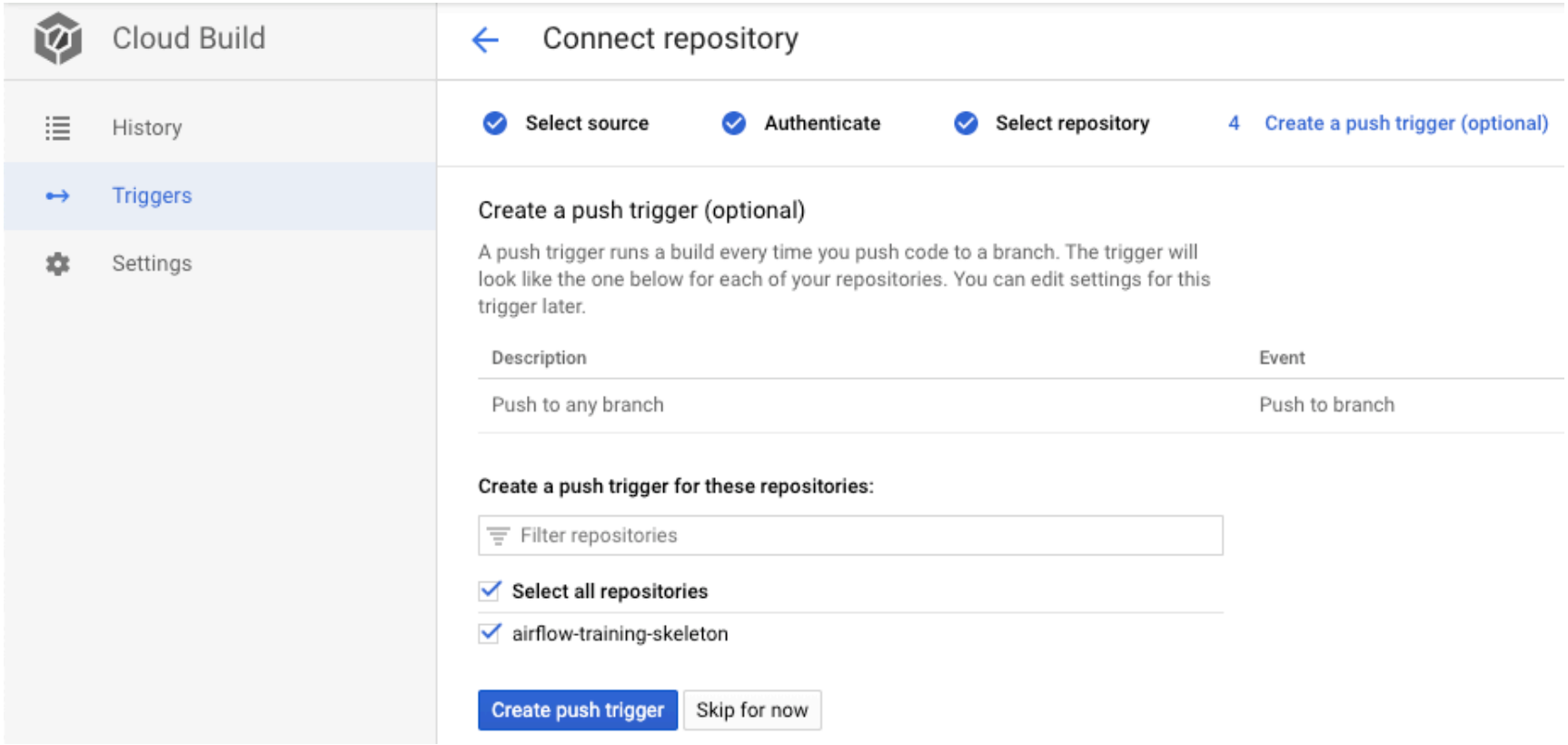
Create a push trigger



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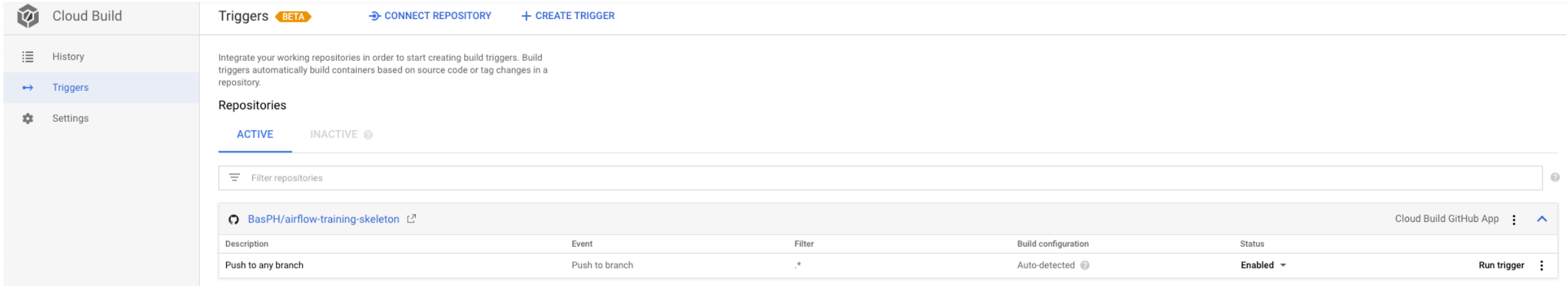
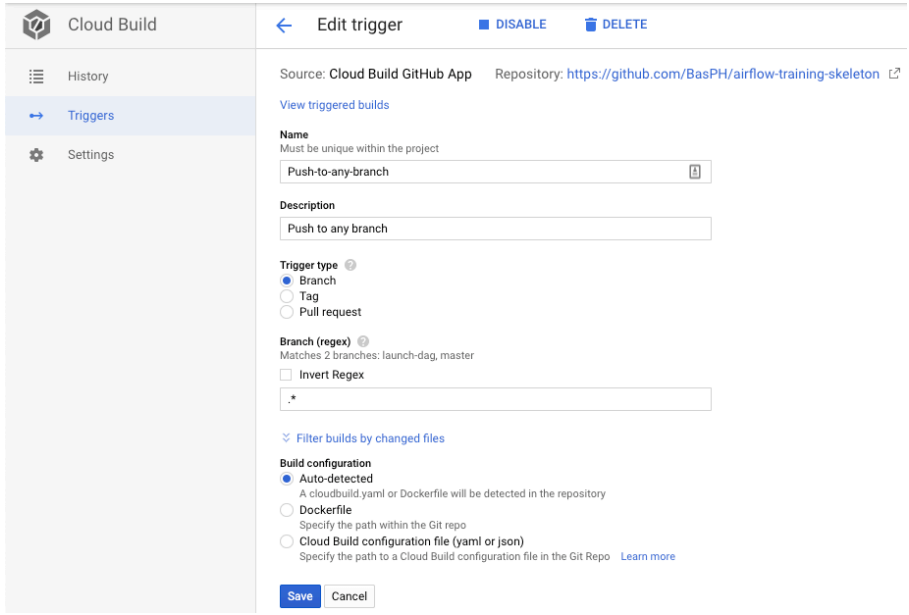
Done!





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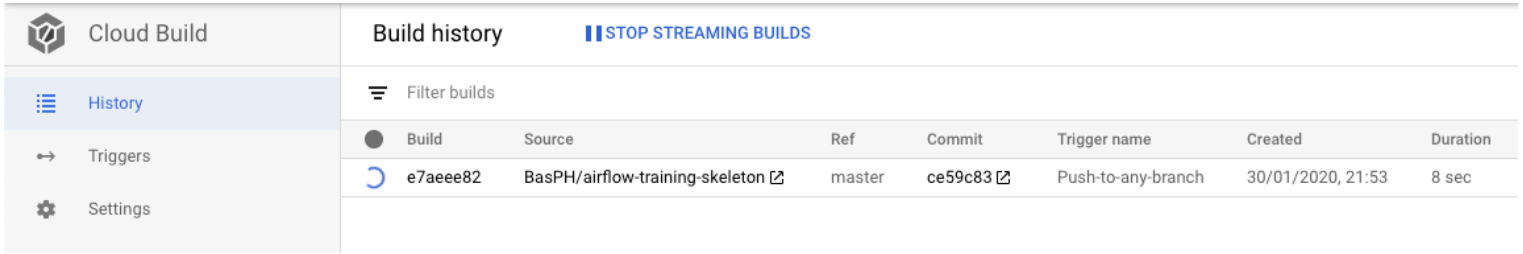
Done!

- We now trigger a pipeline on every push
- cloudbuild.yaml is automatically detected
- You can test by triggering manually
- Or, make a commit and push:



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Note

- I'll leave the environment running a hour after the training
- Don't waste resources
- Free 300$ credits for 12 months:
  - https://cloud.google.com/free/docs/gcp-free-tier

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Exercise

- Configure the trigger
- Open the Airflow webserver from Composer
- Do you see the freshly deployed example_bash_operator dag?
- Try exploring the Airflow web UI
- What do you find?

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Airflow – Getting started

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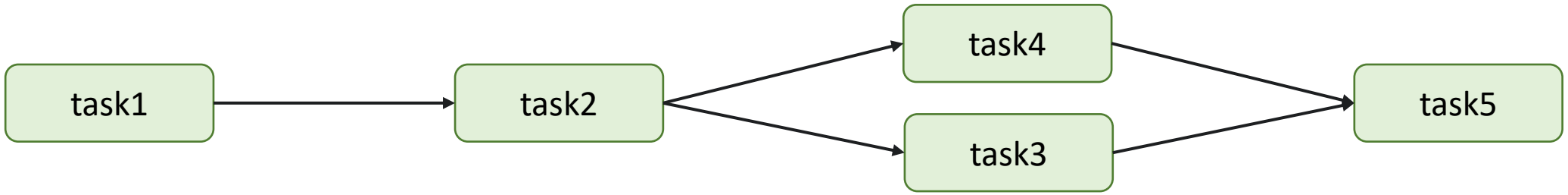
Airflow concepts - DAGs

- Airflow workflows are created using DAGs
  - DAG = Directed Acyclic Graph
  - Tasks as nodes, dependencies as edges

- DAGs are defined in Python code



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Airflow concepts - Operators

- Tasks are executed using Operators
  - Allow you to execute tasks on different systems
  - Abstract logic of interacting with these systems

- Many built-in operators
  - BashOperator – execute a Bash command
  - PythonOperator – execute a Python function
  - EmailOperator – send an e-mail

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An example DAG

Imports

```
import airflow
from airflow.models import DAG
from airflow.operators.bash_operator import BashOperator
```

Configuration

```
args = {
    "owner": "airflow",
    "start_date": airflow.utils.dates.days_ago(2),
}
```

DAG initialization

```
dag = DAG(
    dag_id="hello_dag",
    default_args=args,
    description="Demo DAG showing a hello world example.",
)
```

Tasks

```
t1 = BashOperator(task_id="sleep_a_bit", bash_command="sleep 5", dag=dag)

t2 = BashOperator(task_id="print_date", bash_command="date", dag=dag)
```

Dependencies

```
t1 >> t2
```

DAGs – Two different styles

- Explicit reference

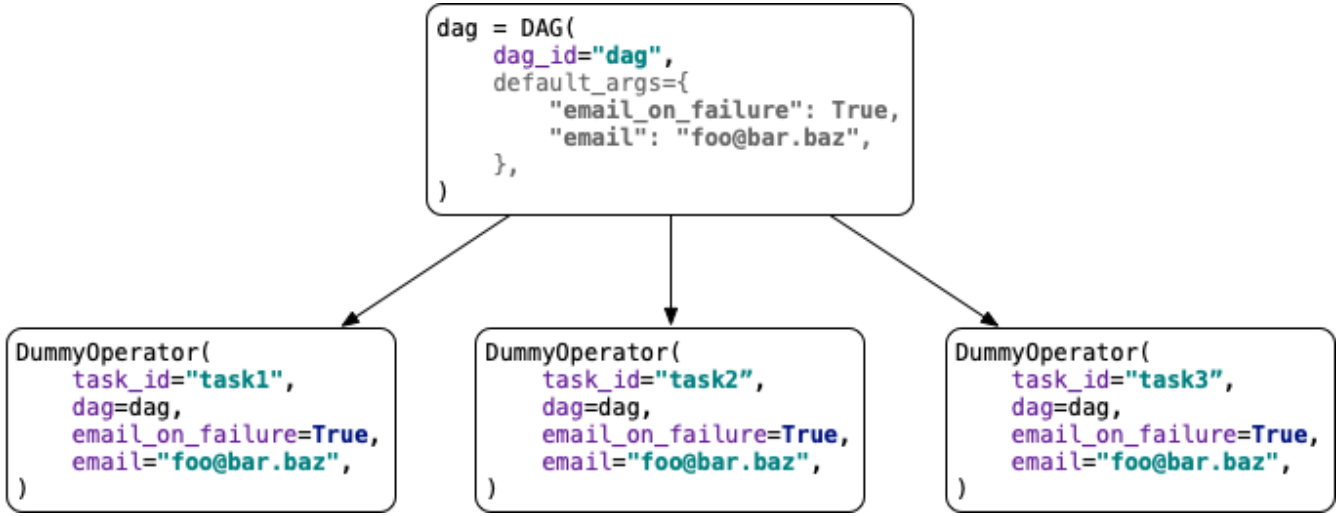
```
dag = DAG(...)
t1 = DummyOperator(task_id="task1", dag=dag)
t2 = DummyOperator(task_id="task2", dag=dag)
```

- Implicit reference

```
with DAG(...) as dag:
    t1 = DummyOperator(task_id="task1")
    t2 = DummyOperator(task_id="task2")
```

DAGs – default_args

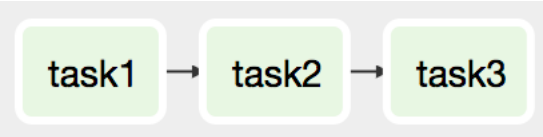
```
from airflow.models import DAG
from airflow.operators.dummy_operator import DummyOperator

dag = DAG(
    dag_id="dag",
    default_args={
        "email_on_failure": True,
        "email": "foo@bar.baz",
    },
)

DummyOperator(task_id="task1", dag=dag)
DummyOperator(task_id="task2", dag=dag)
DummyOperator(task_id="task3", dag=dag, email="john@doe.com")
```

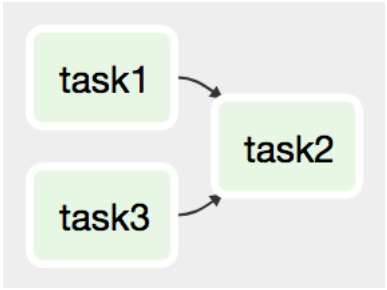


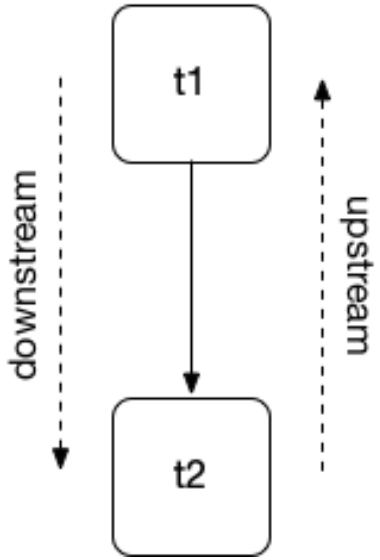
Overrides the default_args

DAGs – defining dependencies

- Chaining multiple tasks:
  - `task1 >> task2 >> task3`
- Other direction is also possible:
  - `task3 << task2 << task1`
- Combinations are also possible:
  - `task1 >> task2 << task3`
- Is the same as:
  - `task1 >> task2`
    `task3 >> task2`

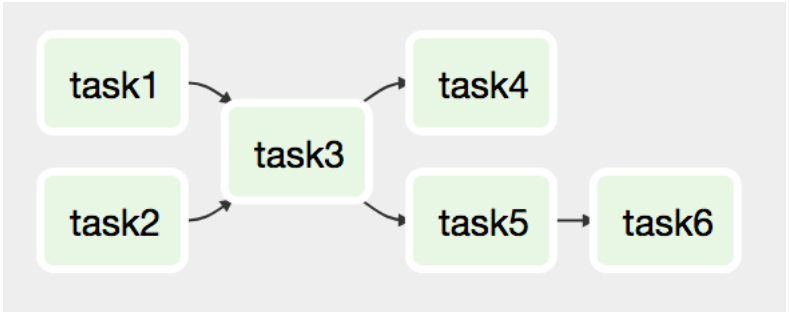






DAGs – defining dependencies

- Is also the same as:
  - `[t1, t3] >> t2`

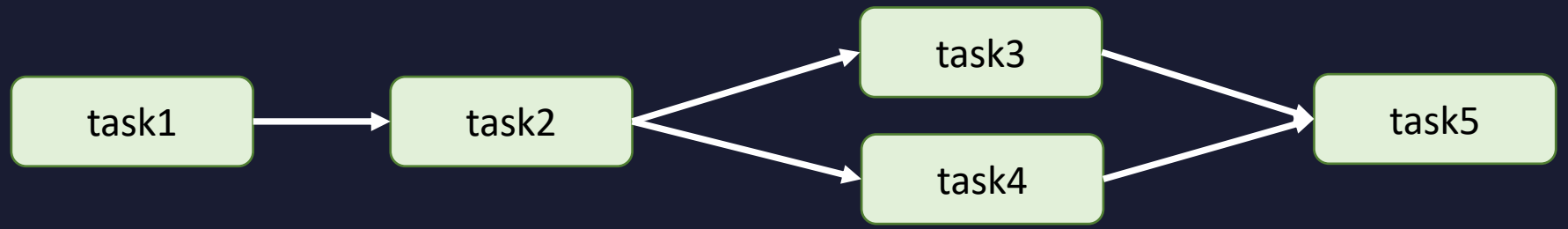


- More complex examples require multiple lines:

```
t1 = DummyOperator(task_id="task1", dag=dag)
t2 = DummyOperator(task_id="task2", dag=dag)
t3 = DummyOperator(task_id="task3", dag=dag)
t4 = DummyOperator(task_id="task4", dag=dag)
t5 = DummyOperator(task_id="task5", dag=dag)
t6 = DummyOperator(task_id="task6", dag=dag)

[t1, t2] >> t3 >> t4
t3 >> t5 >> t6
```

First Exercise

- Create a first DAG, that looks as follows:



- Use the DummyOperator + schedule_interval = None
- Try triggering a (manual) run from the Airflow UI

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Airflow – Scheduling

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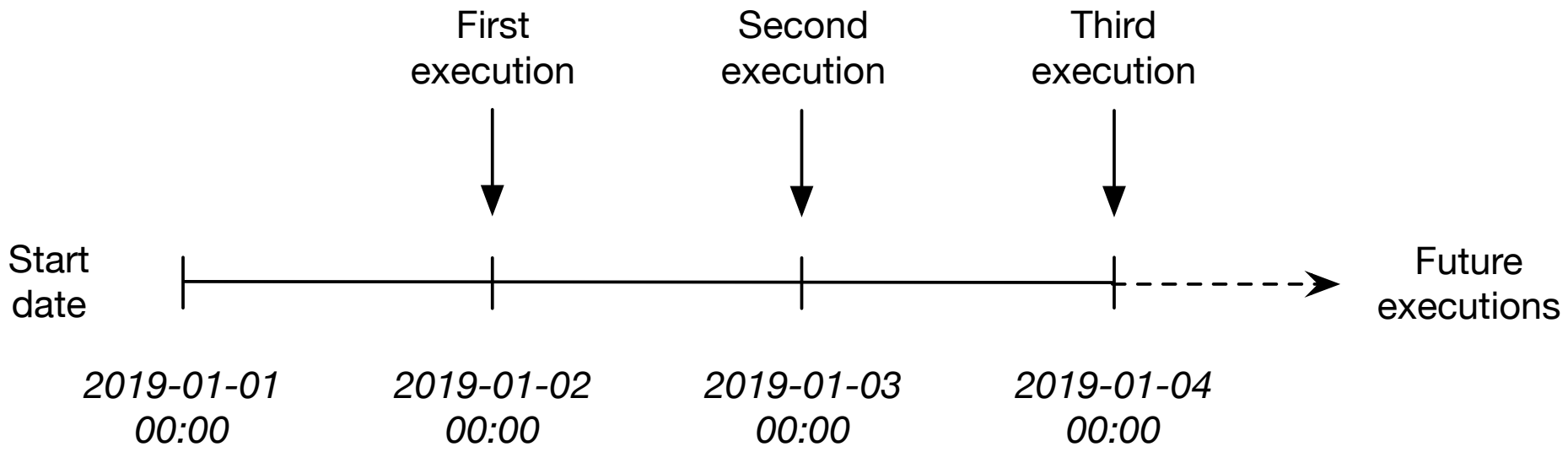
Schedule intervals

```
dag = DAG(
    dag_id="demo",
    description="Showing execution intervals.",
    start_date=datetime.datetime(2019, 1, 1),
    schedule_interval="@daily",
)
```



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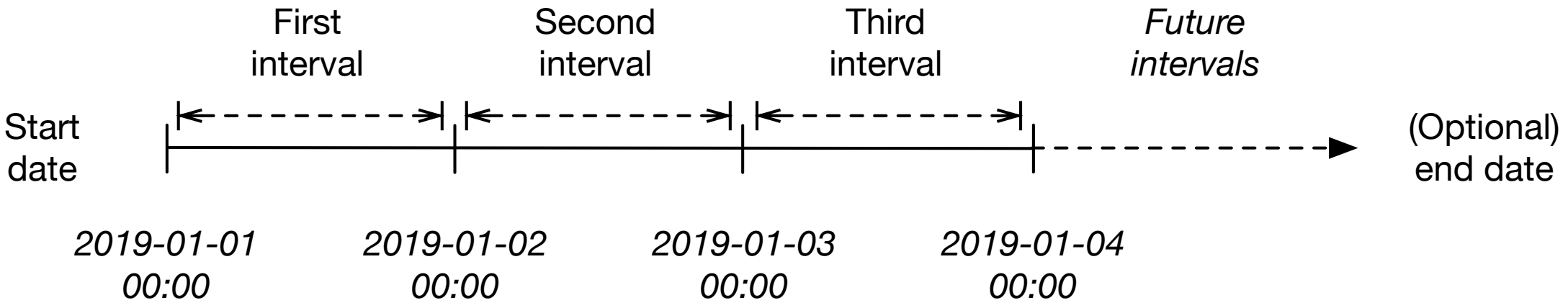
Schedule intervals



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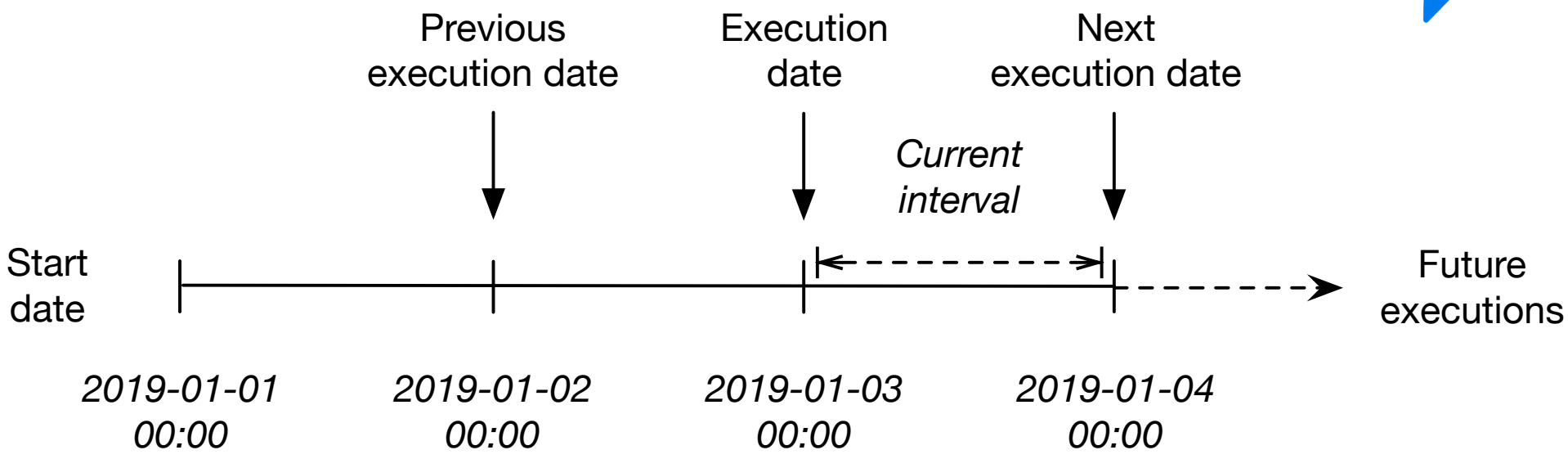
Schedule intervals - dates



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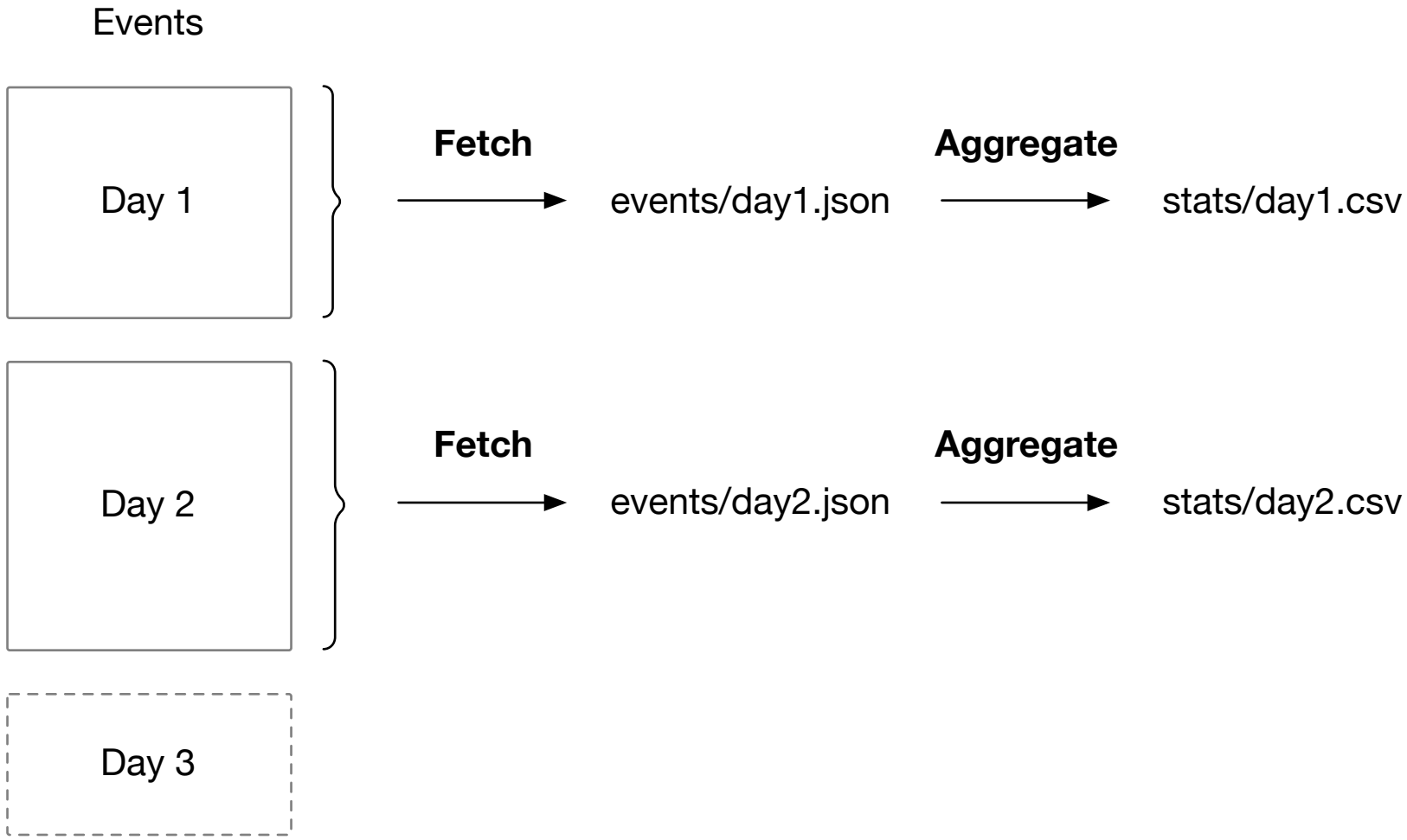
Using intervals for incremental loads



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Things to avoid

- Changing start date or schedule interval
  - Scheduler will get confused
  - Better to create new version of DAG

- Dynamic dates
  - Dates move along as time progresses
  - May come to never pass, or not line up with existing runs

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Backfilling

- Backfilling is the concept of (re-)running Airflow tasks back in time.

- For example:
  - You created a daily job and want to run it 1 year back.
  - A task failed due to a missing file. You placed the file manually and now you want to re-run the task.
  - You changed code in a DAG and want to re-run specific tasks with the changed code.

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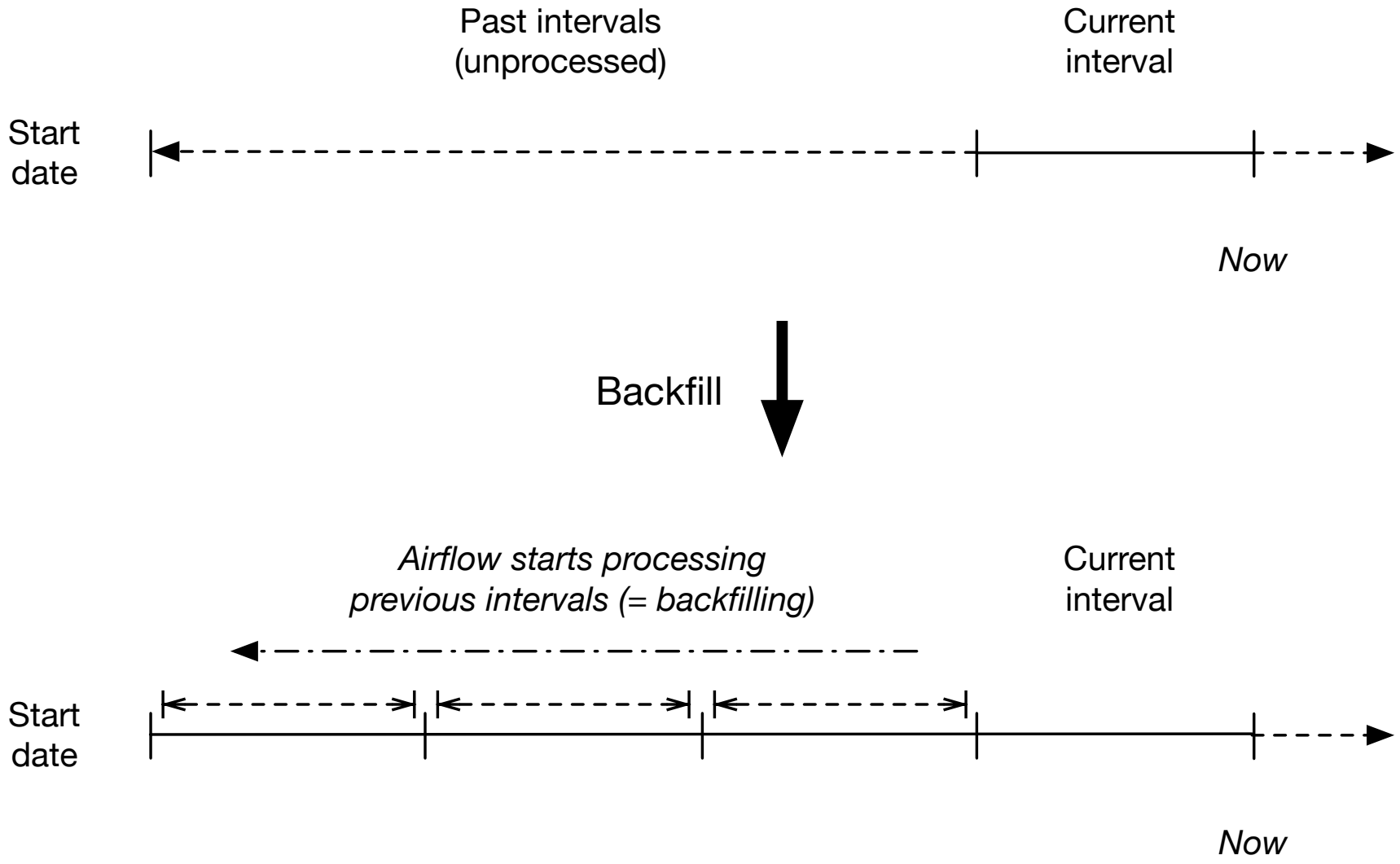
Backfilling



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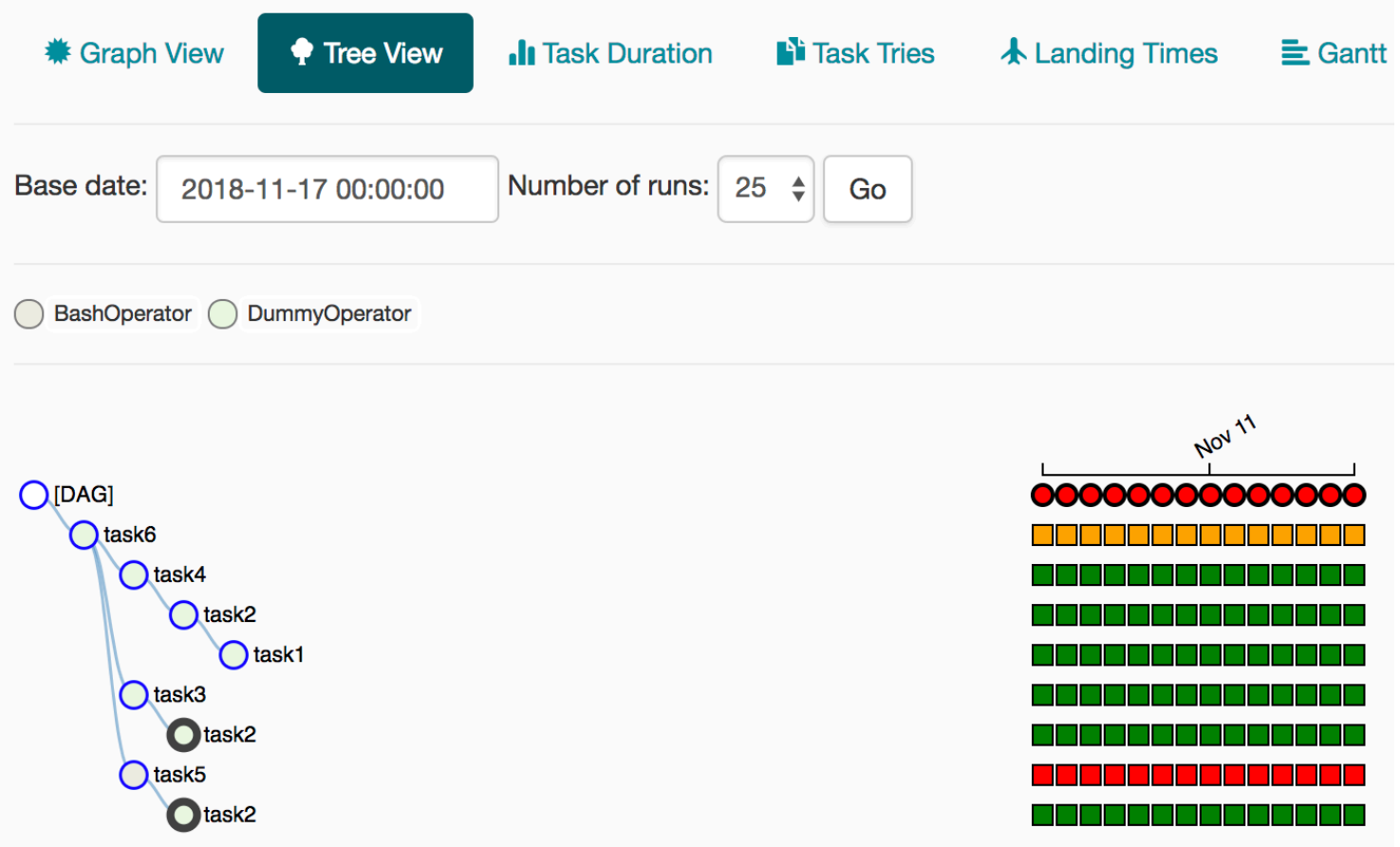
Backfilling - Example



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Backfilling - Example

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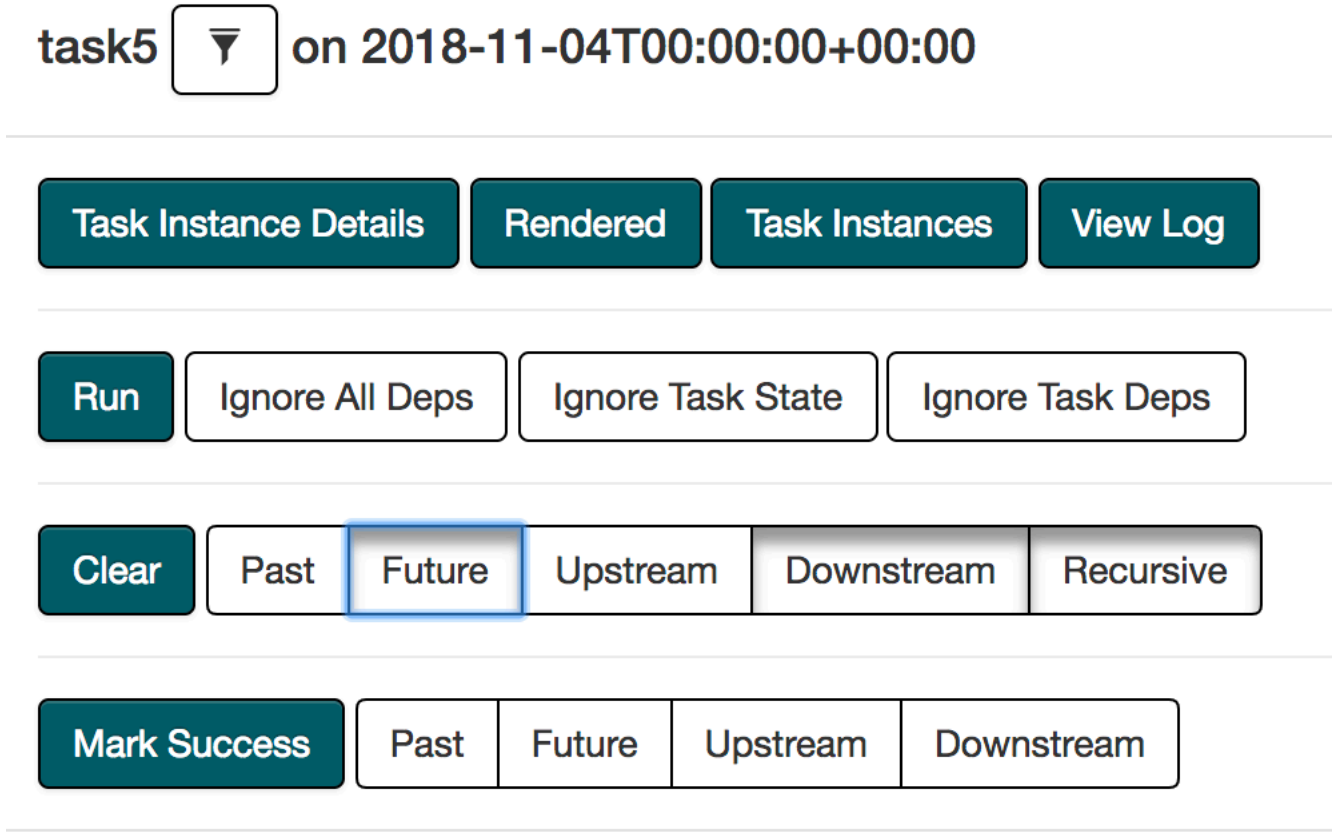
Backfilling - Example



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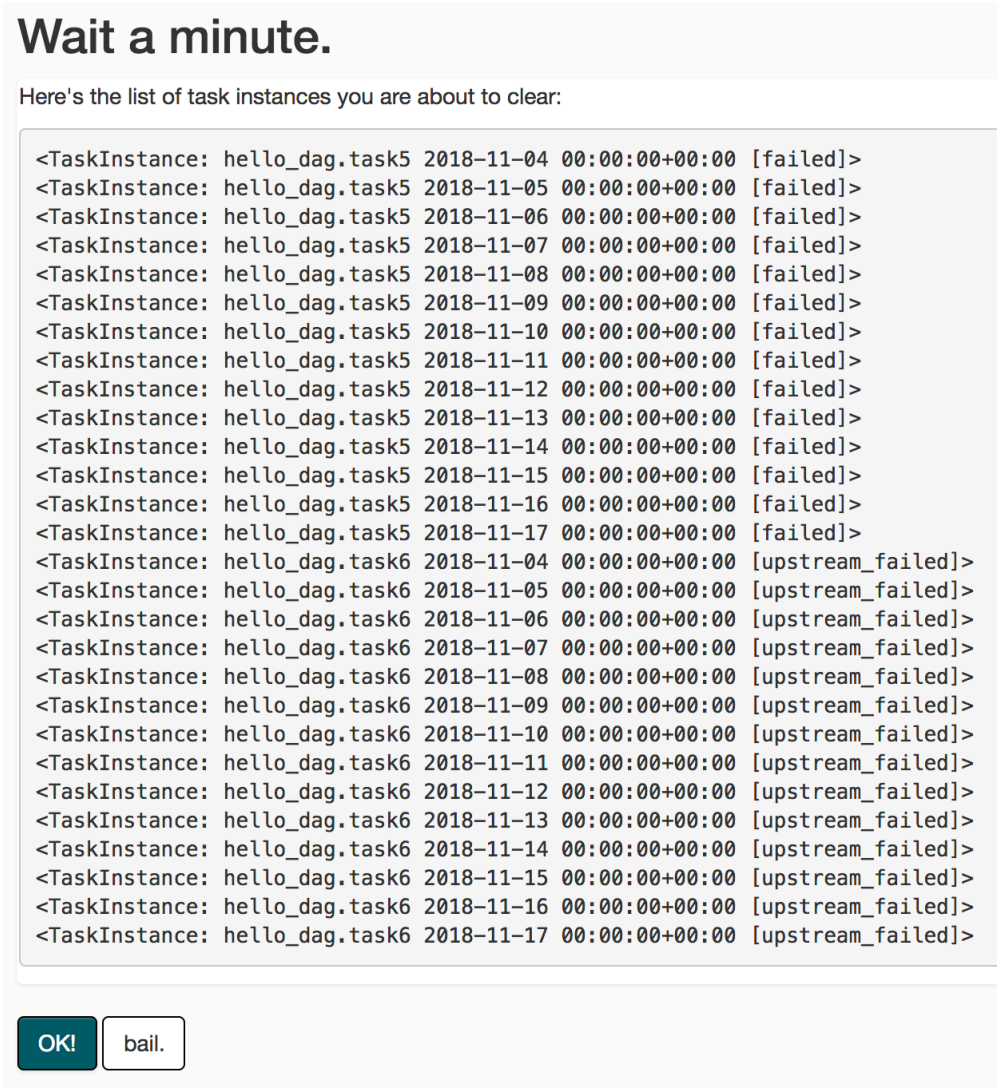
Backfilling - Example



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Backfilling - Example

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Designing tasks for backfilling

- Tasks should be atomic and idempotent

- Atomic
  - Tasks either succeed fully or not at all (no partial result)

- Idempotent
  - Re-running a task gives the same result
  - (Assuming other circumstances have not changed)

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Second Exercise

- Set a daily schedule for the previously created DAG
- Check if your DAG ran successfully using the tree view
  - See if you can inspect individual task results
  - Do you understand the execution dates for each run?
- Can you re-run (backfill) tasks in the past?
- Bonus questions – schedule (a copy of) the DAG to run:
  1. At 13:45 every Mon/Wed/Fri
  2. Every 2,5 hours

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Airflow – Templating

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The Airflow ‘context’

- Airflow provides information about the current execution in the Airflow ‘context’

- This includes:
  - The execution_date of the DAG run
  - Previous and next execution dates

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Jinja templating (string parameters)

- Many operators allow you to include context variables in their (string) parameters using templating:

```
print_exec_date = BashOperator(
    task_id="demo_templating",
    bash_command="echo {{ execution_date }}",
    dag=dag,
)
```

- Other examples:
  - SQL (database operators)
  - Input/output file paths

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Context kwargs (Python)

- The Python operator allows you to access the context using the context keyword-arguments:

```python
def _print_exec_date(**context):
    print(context["execution_date"])
```

```python
# Same result, different notation:
def _print_exec_date(execution_date: Datetime, **context):
    print(execution_date)
```

```python
print_exec_date = PythonOperator(
    task_id="demo_templating",
    python_callable=_print_exec_date,
    provide_context=True,
    dag=dag,
)
```

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What's in the context?

```
{'END_DATE': '2018-01-01',
 'conf': <module 'airflow.configuration' from '/opt/conda/lib/python3.6/site-packages/airflow/configuration.py'>,
 'dag': <DAG: templated_task_dag>,
 'dag_run': None,
 'ds': '2018-01-01',
 'ds_nodash': '20180101',
 'end_date': '2018-01-01',
 'execution_date': <Pendulum [2018-01-01T00:00:00+00:00]>,
 'inlets': [],
 'latest_date': '2018-01-01',
 'macros': <module 'airflow.macros' from '/opt/conda/lib/python3.6/site-packages/airflow/macros/__init__.py'>,
 'next_ds': '2018-01-02',
 'next_execution_date': datetime.datetime(2018, 1, 2, 0, 0, tzinfo=<TimezoneInfo [UTC, GMT, +00:00:00, STD]>),
 'outlets': [],
 'params': {},
 'prev_ds': '2017-12-31',
 'prev_execution_date': datetime.datetime(2017, 12, 31, 0, 0, tzinfo=<TimezoneInfo [UTC, GMT, +00:00:00, STD]>),
 'run_id': None,
 'tables': None,
 'task': <Task(PythonOperator): demo_templating>,
 'task_instance': <TaskInstance: templated_task_dag.demo_templating 2018-01-01T00:00:00+00:00 [None]>,
 'task_instance_key_str': 'templated_task_dag__demo_templating__20180101',
 'templates_dict': None,
 'test_mode': True,
 'ti': <TaskInstance: templated_task_dag.demo_templating 2018-01-01T00:00:00+00:00 [None]>,
 'tomorrow_ds': '2018-01-02',
 'tomorrow_ds_nodash': '20180102',
 'ts': '2018-01-01T00:00:00+00:00',
 'ts_nodash': '20180101T000000+0000',
 'var': {'json': None, 'value': None},
 'yesterday_ds': '2017-12-31',
 'yesterday_ds_nodash': '20171231'}
```

https://airflow.apache.org/docs/stable/macros.html#default-variables

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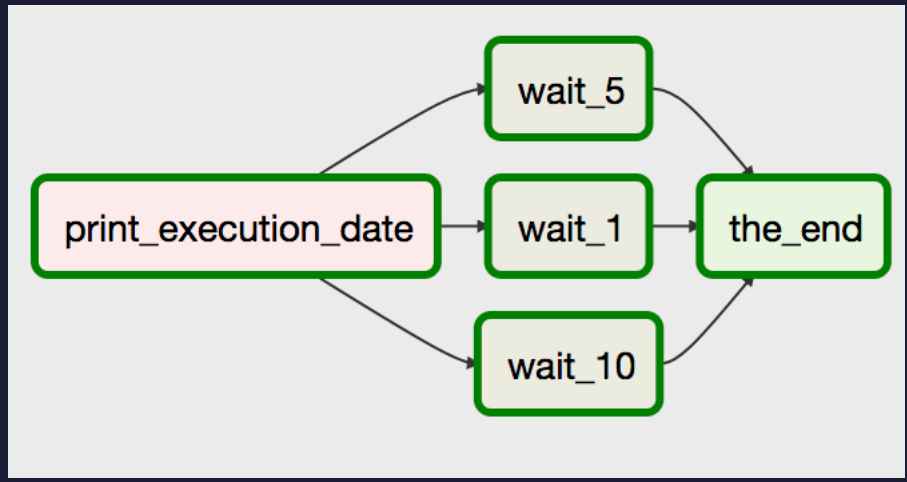
Third Exercise

- Write a DAG with the following stages:
  1. PythonOperator printing execution date
  2. BashOperator doing sleep 1, sleep 5 and sleep 10
  3. DummyOperator to finish it off

- Desired result:



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Airflow – Branching

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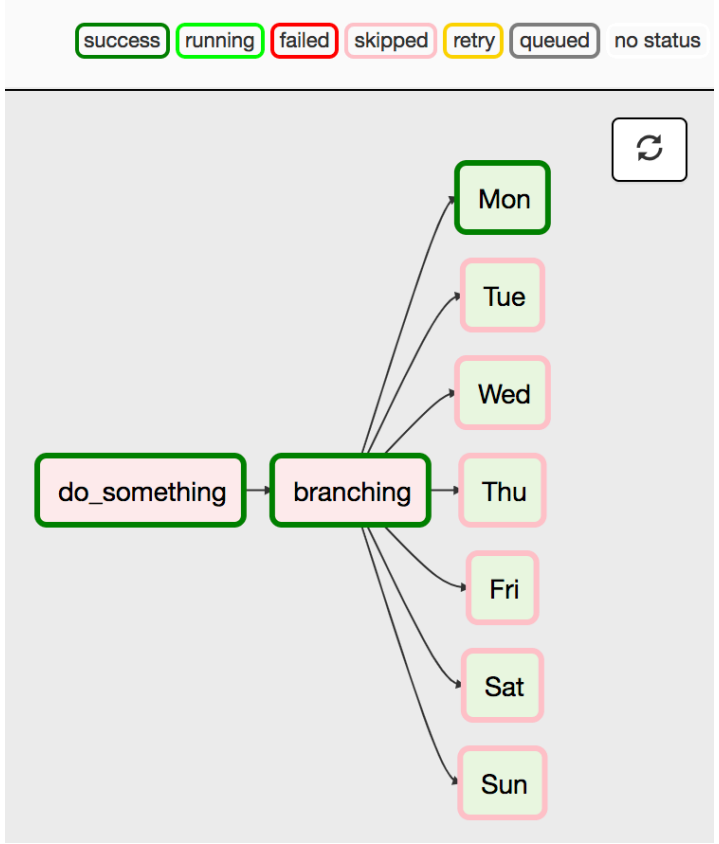
Branching

- Sometimes you'd like to execute some tasks based on a specific condition

- Examples:
  - Running tasks on certain days of the week
  - Running a different set of tasks after a specific date (e.g. to account for a schema change)



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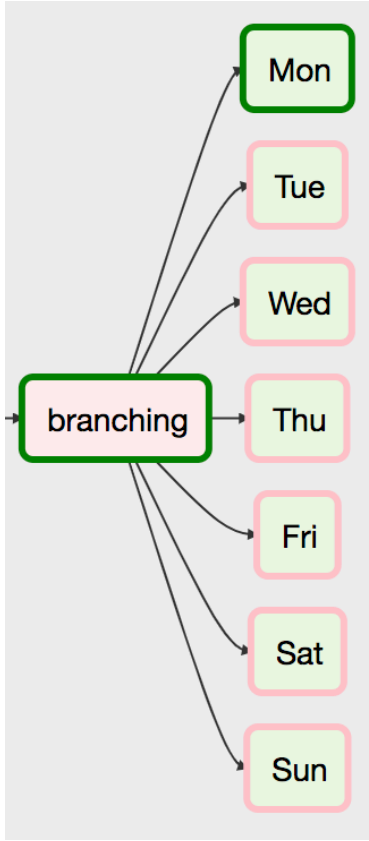
The PythonBranchOperator

- Branches on a certain condition
  - Accepts a callable, which when called should return the name of downstream task(s) to run
  - Other tasks are automatically skipped

- Note that tasks should be a (direct) downstream dependency of the branch task



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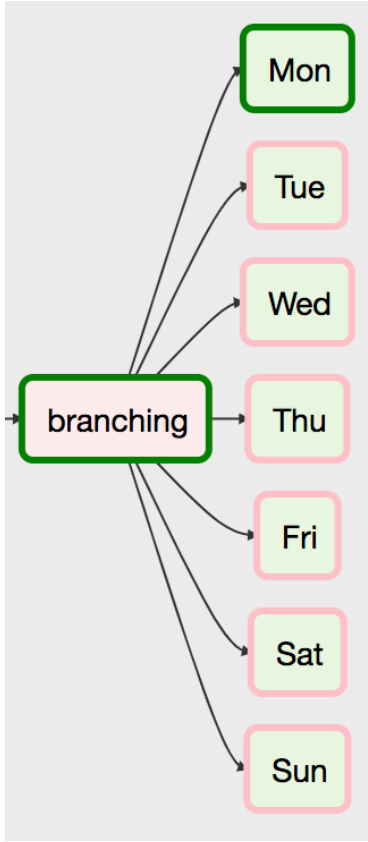
The PythonBranchOperator

```
def _get_weekday(execution_date, **context):
    return execution_date.strftime("%a")

branching = BranchPythonOperator(
    task_id="branching",
    python_callable=_get_weekday,
    provide_context=True,
    dag=dag
)

days = ["Mon", "Tue", "Wed", "Thu", "Fri", "Sat", "Sun"]
for day in days:
    branching >> DummyOperator(task_id=day, dag=dag)
```



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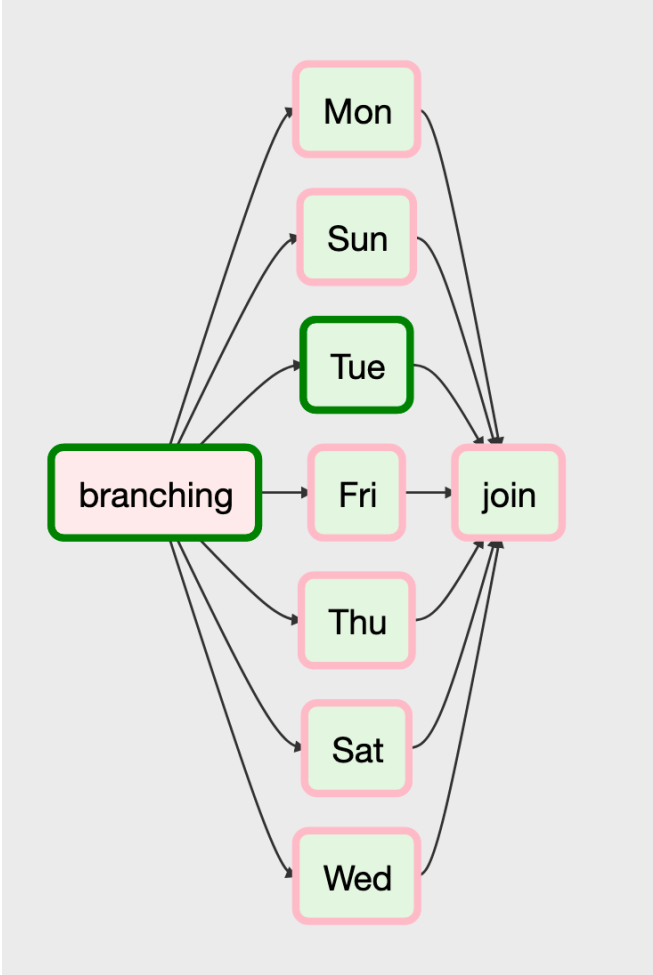
Continuing after a branch

- Typically, execution after a branch is continued after a (dummy) join task
- This allows downstream tasks to be ‘unaware’ of the branch
- However, naively adding a join does not work. Any idea why?



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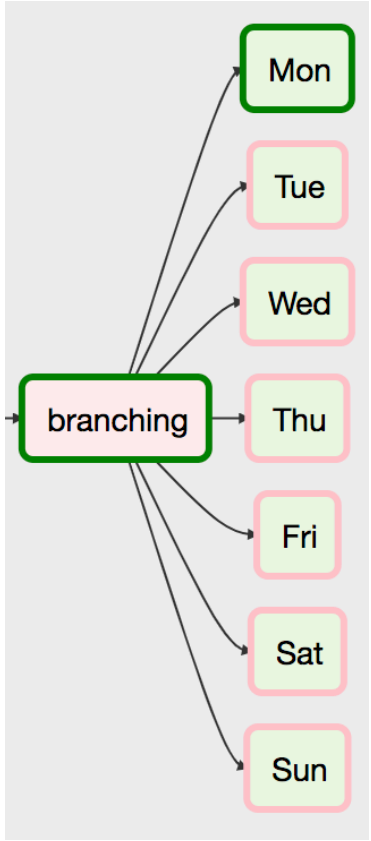
Trigger rules

- Trigger rules determine when a task is executed
  - Defined using the `trigger_rule` Operator argument
  - Default rule is `all_success` (all upstream tasks must have completed successfully)



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Trigger rules

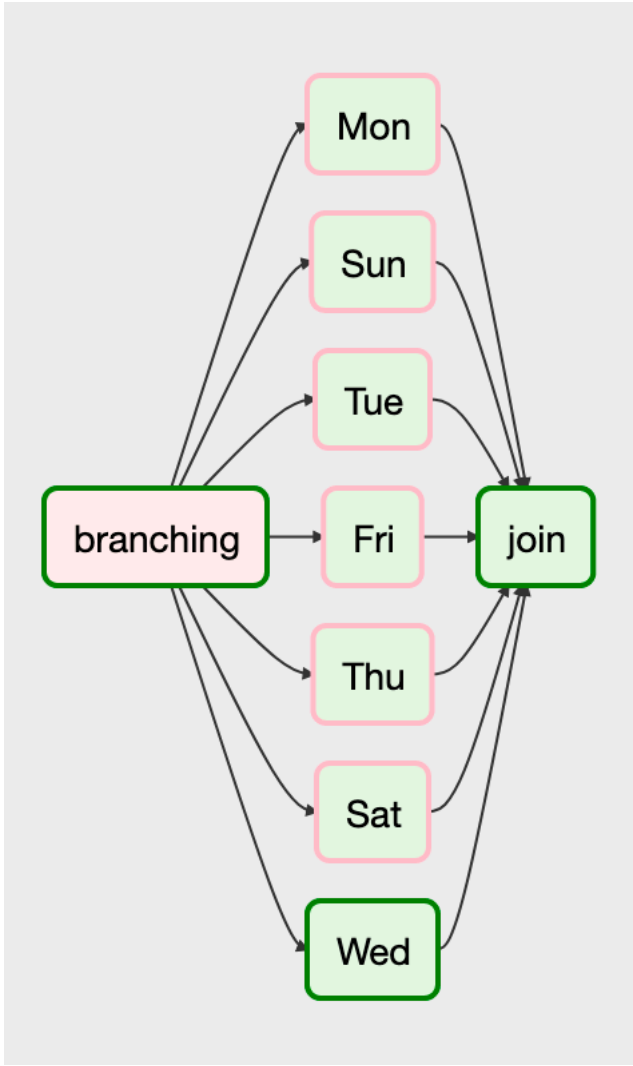
`TriggerRule.ALL_SUCCESS`	(Default) all parents have succeeded.
`TriggerRule.ALL_FAILED`	All parents are in a failed or upstream_failed state.
`TriggerRule.ALL_DONE`	All parents are done with their execution.
`TriggerRule.ONE_FAILED`	Fires as soon as at least one parent has failed, it does not wait for all parents to be done.
`TriggerRule.ONE_SUCCESS`	Fires as soon as at least one parent succeeds, it does not wait for all parents to be done.
`TriggerRule.DUMMY`	Dependencies are just for show, trigger at will.

Fixing the join

- Changing the trigger rule is enough:

```
join = DummyOperator(
    task_id="join",
    trigger_rule="none_failed"
)
```

- Ensures join will run if none of the upstream tasks fail



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Skipping some tasks

- Sometimes you might like to skip tasks based on a condition
- For example
  - Only running tasks for the most recent run
  - Skipping load if there is no data
- For this you can use the ShortCircuitOperator

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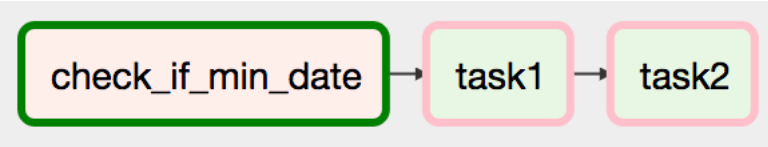
The ShortCircuitOperator

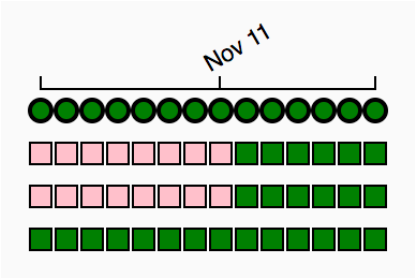
```
def check_date(execution_date, **context):
    return execution_date > (datetime.datetime.now() - relativedelta(weeks=1))


check_date = ShortCircuitOperator(
    task_id="check_if_min_date",
    python_callable=check_date,
    provide_context=True,
    dag=dag,
)

task1 = DummyOperator(task_id="task1", dag=dag)
task2 = DummyOperator(task_id="task2", dag=dag)

check_date >> task1 >> task2
```





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Another option – Skip exceptions

```
def _check_date(execution_date, **context):
    min_date = datetime.datetime.now() - relativedelta(weeks=1)
    if execution_date < min_date:
        raise AirflowSkipException(f"No data available on this execution_date ({execution_date}).")

check_date = PythonOperator(
    task_id="check_if_min_date",
    python_callable=_check_date,
    provide_context=True,
    dag=dag,
)

task1 = DummyOperator(task_id="task1", dag=dag)
task2 = DummyOperator(task_id="task2", dag=dag)

check_date >> task1 >> task2
```

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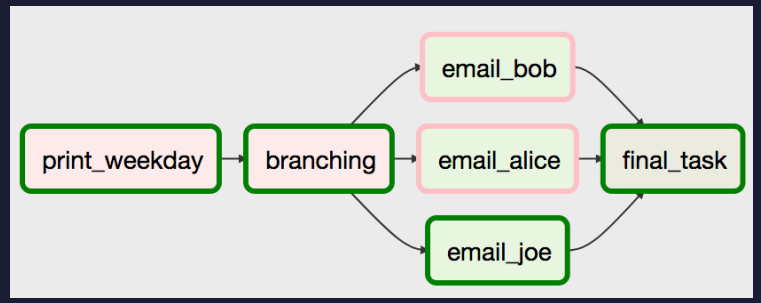
Fourth Exercise

- Write a DAG that does the following:
  1. Start by printing the weekday using the PythonOperator
  2. Run a DummyOperator for given person, based on weekday
  3. Finish DAG with BashOperator

- Desired result:




```
weekday_person_to_email = {
    0: "Bob",  # Monday
    1: "Joe",  # Tuesday
    2: "Alice",  # Wednesday
    3: "Joe",  # Thursday
    4: "Alice",  # Friday
    5: "Alice",  # Saturday
    6: "Alice",  # Sunday
}
```

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Airflow – ‘Advanced’ components

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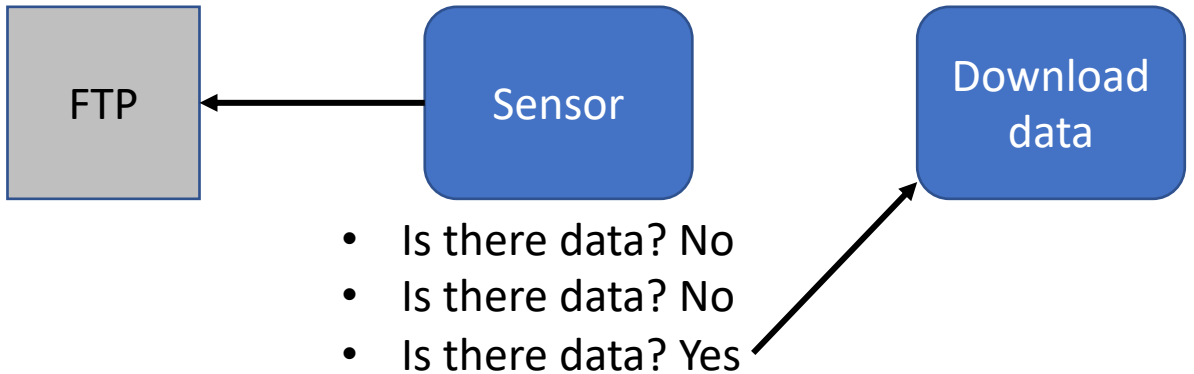
Sensors

- Subclass of Operators
- Main method -> Poke
  - Checks if certain condition is met
  - Starts once that condition is True (or timed out).
- Useful if you want to process directly after an event, such as delivery of the data



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Sensors

```
import airflow.utils.dates
from airflow.contrib.sensors.ftp_sensor import FTPSensor
from airflow.models import DAG

dag = DAG(
    dag_id="example_sensor",
    default_args={"owner": "Bob", "start_date": airflow.utils.dates.days_ago(5)},
    schedule_interval=None,
)

wait_for_data = FTPSensor(
  task_id="wait_for_data",
  path="/path/to/data",
  ftp_conn_id="ftp_connection",
  dag=dag,
)

download_data = PythonOperator(
  task_id="download_data",
  python_callable=lambda: print("do magic"),
  dag=dag,
)

wait_for_data >> download_data
```

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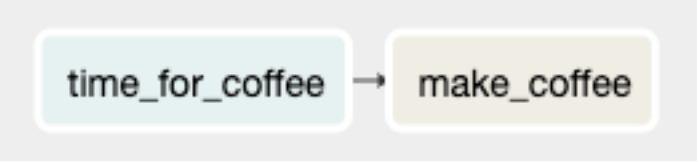
Sensors – custom check with PythonSensor

```python
from datetime import datetime

import airflow.utils.dates
from airflow.contrib.sensors.python_sensor import PythonSensor
from airflow.models import DAG
from airflow.operators.bash_operator import BashOperator

dag = DAG(
    dag_id="example_python_sensor",
    default_args={"owner": "GoDataDriven", "start_date": airflow.utils.dates.days_ago(3)},
    schedule_interval="0 0 * * *",
    description="Is it time for coffee?",
)


def _time_for_coffee():
    """I drink coffee between 6 and 12"""
    if 6 <= datetime.now().hour < 12:
        return True
    else:
        return False


time_for_coffee = PythonSensor(
    task_id="time_for_coffee", python_callable=_time_for_coffee, mode="reschedule", dag=dag
)

make_coffee = BashOperator(task_id="make_coffee", bash_command="echo 'Time for coffee!'", dag=dag)

time_for_coffee >> make_coffee
```

True = continue
False = retry



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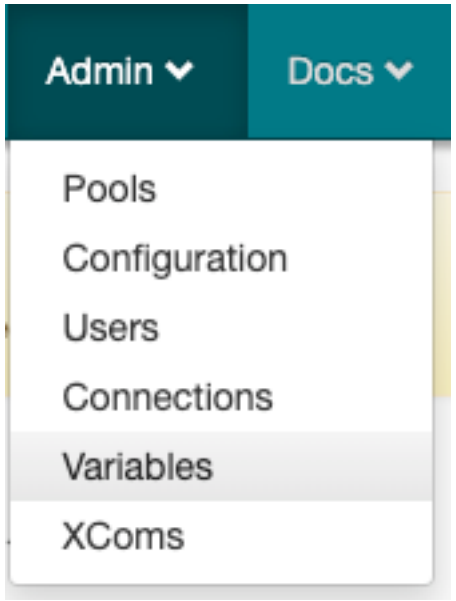
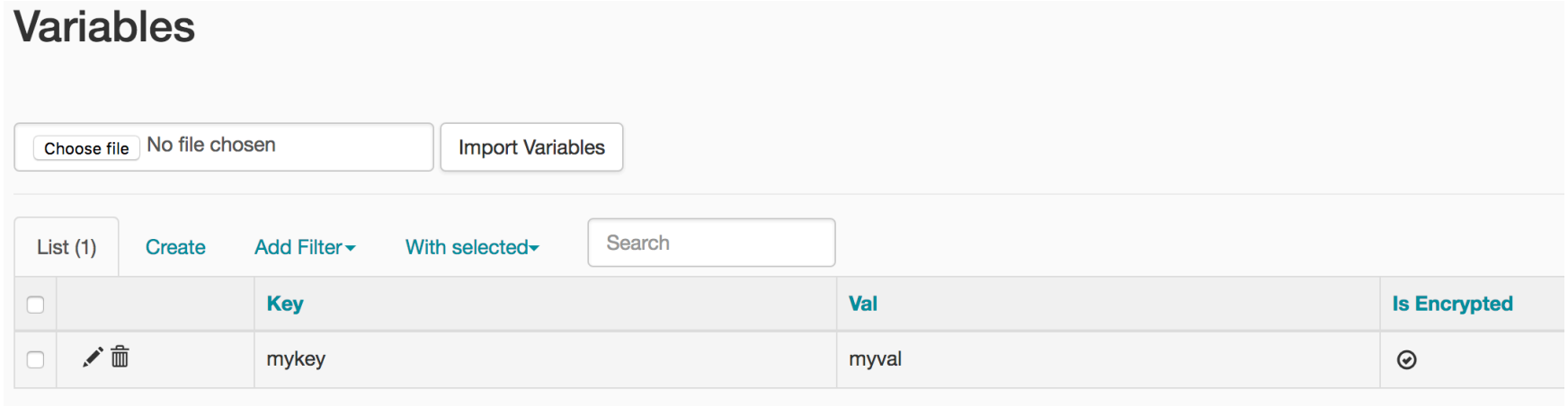
Variables

- Just like connections, variables (non-secret) can also be stored in Airflow





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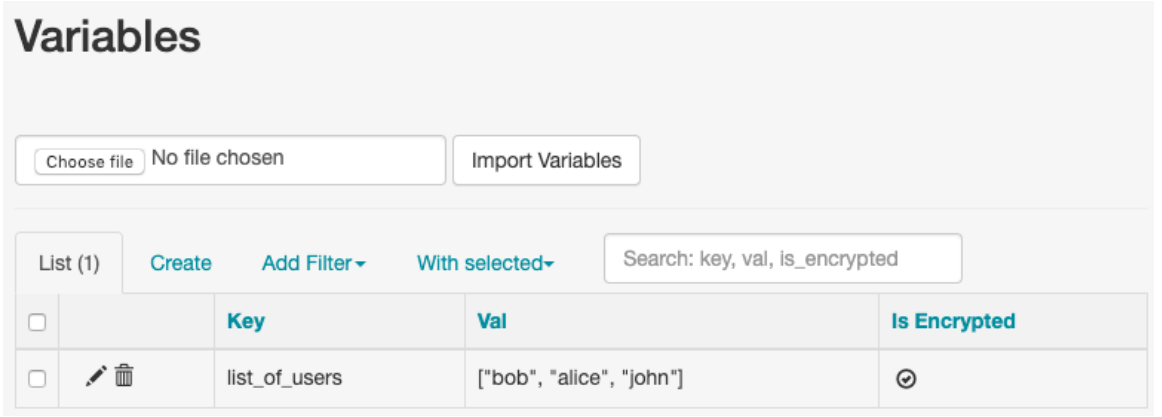
Variables




```
import airflow.utils.dates
from airflow.models import DAG, Variable
from airflow.operators.python_operator import PythonOperator

dag = DAG(
    dag_id="example_variable_usage",
    default_args={"owner": "GoDataDriven", "start_date": airflow.utils.dates.days_ago(5)},
    schedule_interval=None,
)


def _do_magic():
    users = Variable.get("list_of_users", deserialize_json=True)
    for user in users:
        ...


do_magic = PythonOperator(task_id="do_magic", python_callable=_do_magic, dag=dag)
```

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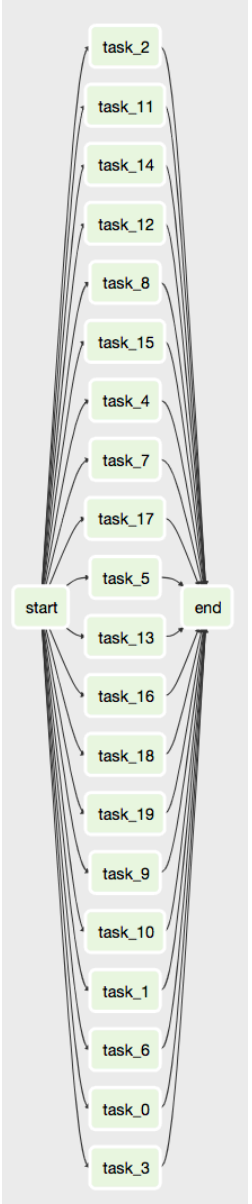
Pools

- Pools are used to limit parallelism in Airflow tasks
- There is a global config for maximum parallel tasks
- Pools can be used to limit parallelism within that global maximum



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XComs

- Data can be communicated between tasks with the help of XComs (cross-communication)
- Works for anything that can be pickled
- Pickled objects are stored in the Airflow metastore

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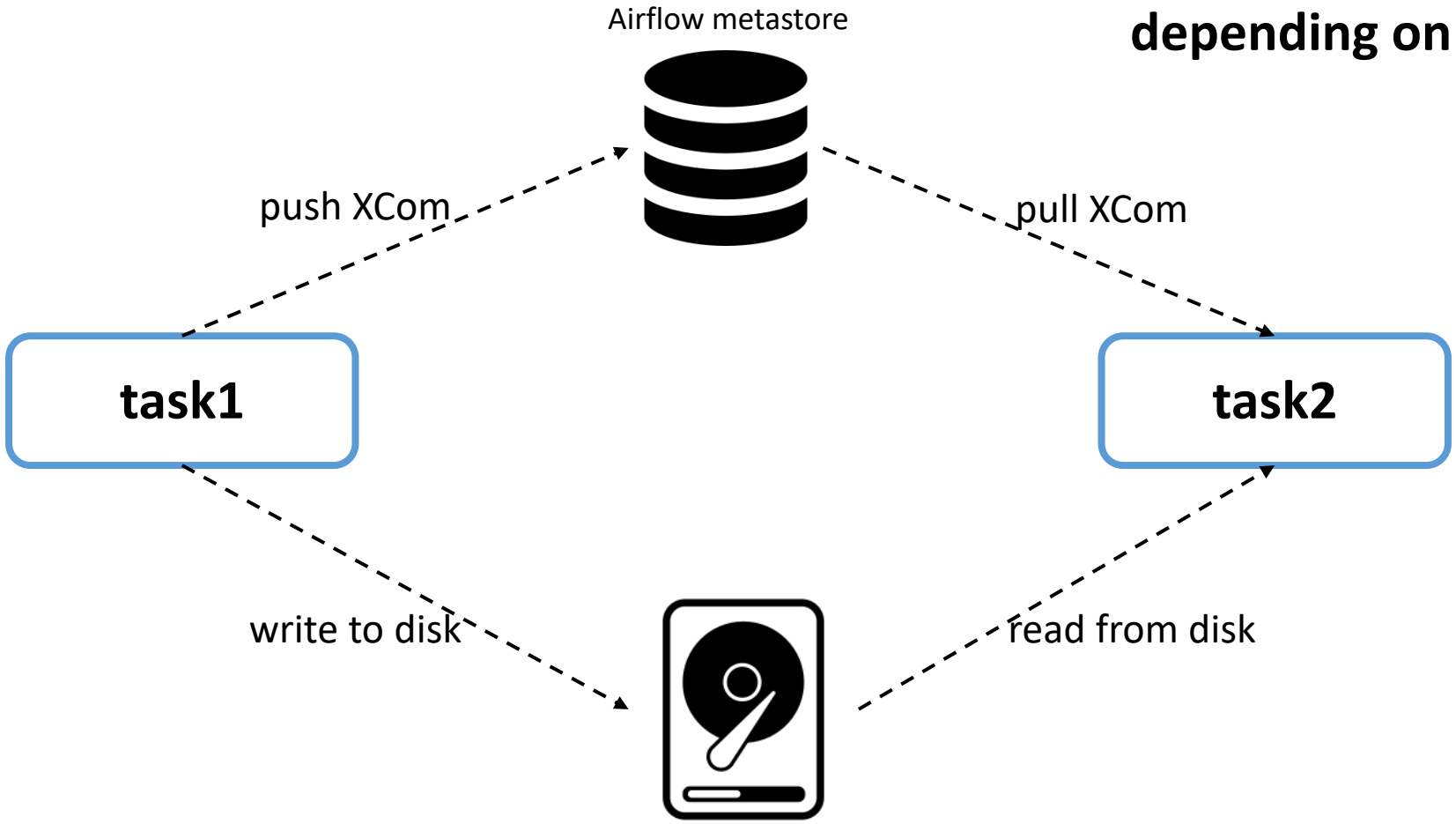
XComs

Decide XCom/other depending on size of data



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XComs

```
import airflow.utils.dates
from airflow.models import DAG
from airflow.operators.python_operator import PythonOperator

dag = DAG(
    dag_id="example_xcom",
    default_args={"owner": "GoDataDriven", "start_date": airflow.utils.dates.days_ago(5)},
    schedule_interval=None,
)

pushtask = BashOperator(task_id="pushtask", bash_command="echo 'Hoi Fokko'", xcom_push=True)
```

```
def _pushtask(task_instance, **_):
    return "Hoi Fokko"

pushtask = PythonOperator(task_id="pushtask", python_callable=_pushtask, xcom_push=True)

def _pulltask(task_instance, **_):
    print(task_instance.xcom_pull(task_ids="pushtask"))
    # prints "Hoi Fokko"
```

```
pulltask = PythonOperator(task_id="pulltask", python_callable=_pulltask, xcom_push=True)

pushtask >> pulltask
```

XComs

```
def _pushtask():
    print("do stuff")
    return "foobar"  # automatic XCom push (be aware of this!)


pushtask = PythonOperator(
    task_id="pushtask",
    python_callable=_pushtask
)
```

Airflow - Custom components

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Re-cap – Operators and hooks

- Hooks
  - Used to interact with (external) systems
- Operators
  - Actually execute tasks on (remote) systems
  - Typically use one or more hooks

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Building your own Operator

```python
class MyOwnOperator(BaseOperator):

    @apply_defaults
    def __init__(self, *args, **kwargs):
        super().__init__(*args, **kwargs)

    def execute(self, context):
        pass
```

All variables in default_args will be applied to this operator

implement this

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Building your own Operator

```
class MyOwnOperator(BaseOperator):

    ui_color = '#555'
    ui_fgcolor = '#fff'

    @apply_defaults
    def __init__(self, *args, **kwargs):
        super().__init__(*args, **kwargs)

    def execute(self, context):
        pass
```

Change the look of the operator in the UI

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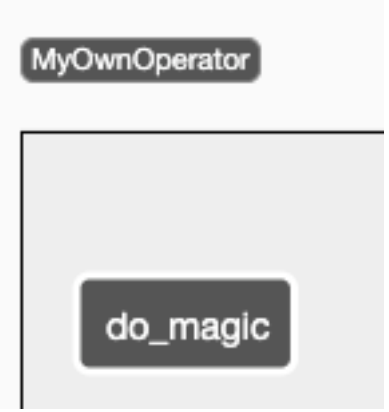
Building your own Operator




```
class MyOwnOperator(BaseOperator):

    template_fields = ('_myvar1',)

    ui_color = '#555’
    ui_fgcolor = '#fff'

    @apply_defaults
    def __init__(self, myvar1, myvar2, *args, **kwargs):
        super().__init__(*args, **kwargs)
        self._myvar1 = myvar1
        self._myvar2 = myvar2

    def execute(self, context):
        pass
```

Determines which fields are templated (note the underscore!)

```
task1 = MyOwnOperator(
    myvar1="it is now {{ execution_date }}",
    myvar2="i won't be templated :("
)
```

Building your own Hook

```
class MyOwnHook(BaseHook):
    def __init__(self, conn_id):
        super().__init__(source=None)
        self._conn_id = conn_id
        self._conn = None

    def get_conn(self):
        if self._conn is None:
            self._conn = object()  # create connection instance here
        return self._conn

    def do_stuff(self, arg1, arg2, **kwargs):
        session = self.get_conn()
        session.do_stuff(# perform some action...)
```

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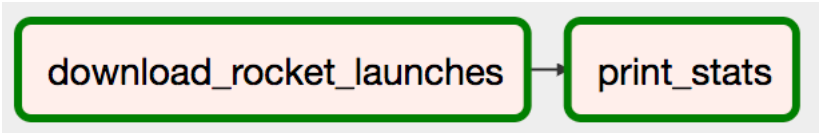
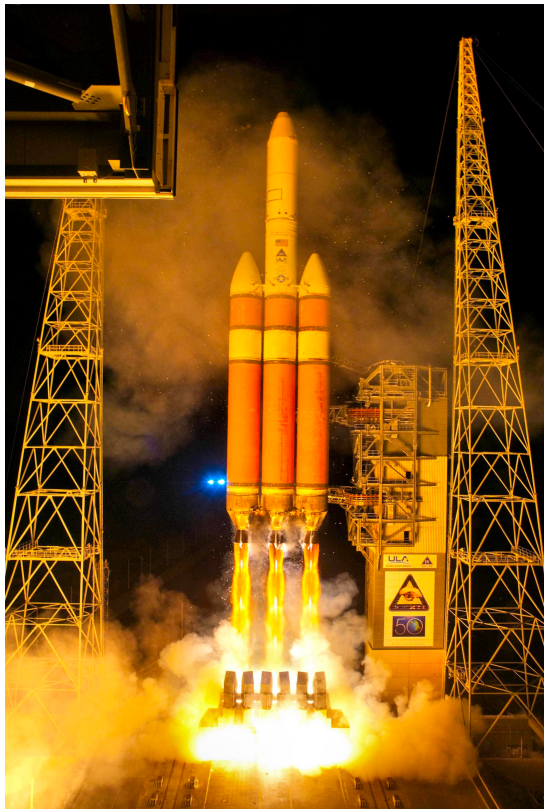
Use case - Fetching rocket launches

- https://launchlibrary.net
- Fetch data about rocket launches from an API
  - Hook -> Interact with API
  - Operator -> Fetch + write results





```python
import json
import pathlib
import posixpath

import airflow
import requests
from airflow.models import DAG
from airflow.operators.python_operator import PythonOperator

args = {"owner": "godatadriven", "start_date": airflow.utils.dates.days_ago(10)}

dag = DAG(
    dag_id="download_rocket_launches",
    default_args=args,
    description="DAG downloading rocket launches from Launch Library.",
    schedule_interval="0 0 * * *",
)


def _download_rocket_launches(ds, tomorrow_ds, **_):
    query = f"https://launchlibrary.net/1.4/launch?startdate={ds}&enddate={tomorrow_ds}"
    result_path = f"/tmp/rocket_launches/ds={ds}"
    pathlib.Path(result_path).mkdir(parents=True, exist_ok=True)
    response = requests.get(query)
    print(f"response was {response}")

    with open(posixpath.join(result_path, "launches.json"), "w") as f:
        print(f"Writing to file {f.name}")
        f.write(response.text)


def _print_stats(ds, **_):
    with open(f"/tmp/rocket_launches/ds={ds}/launches.json") as f:
        data = json.load(f)
        rockets_launched = [launch["name"] for launch in data["launches"]]

        if rockets_launched:
            rockets_str = f" ({' & '.join(rockets_launched)})"
            print(f"{len(rockets_launched)} rocket launch(es) on {ds}{rockets_str}.")
        else:
            print(f"No rockets found in {f.name}")


download_rocket_launches = PythonOperator(
    task_id="download_rocket_launches",
    python_callable=_download_rocket_launches,
    provide_context=True,
    dag=dag,
)

print_stats = PythonOperator(
    task_id="print_stats", python_callable=_print_stats, provide_context=True, dag=dag
)

download_rocket_launches >> print_stats
```

Exercise: Refactor the previous DAG

1. Implement a LaunchOperator which
   fetches launches and stores them in xcom
2. Rebuild the DAG from the previous slide using
   your own operator (exercise_launch/launch-dag.py)
3. Bonus: Store the data in GCS instead

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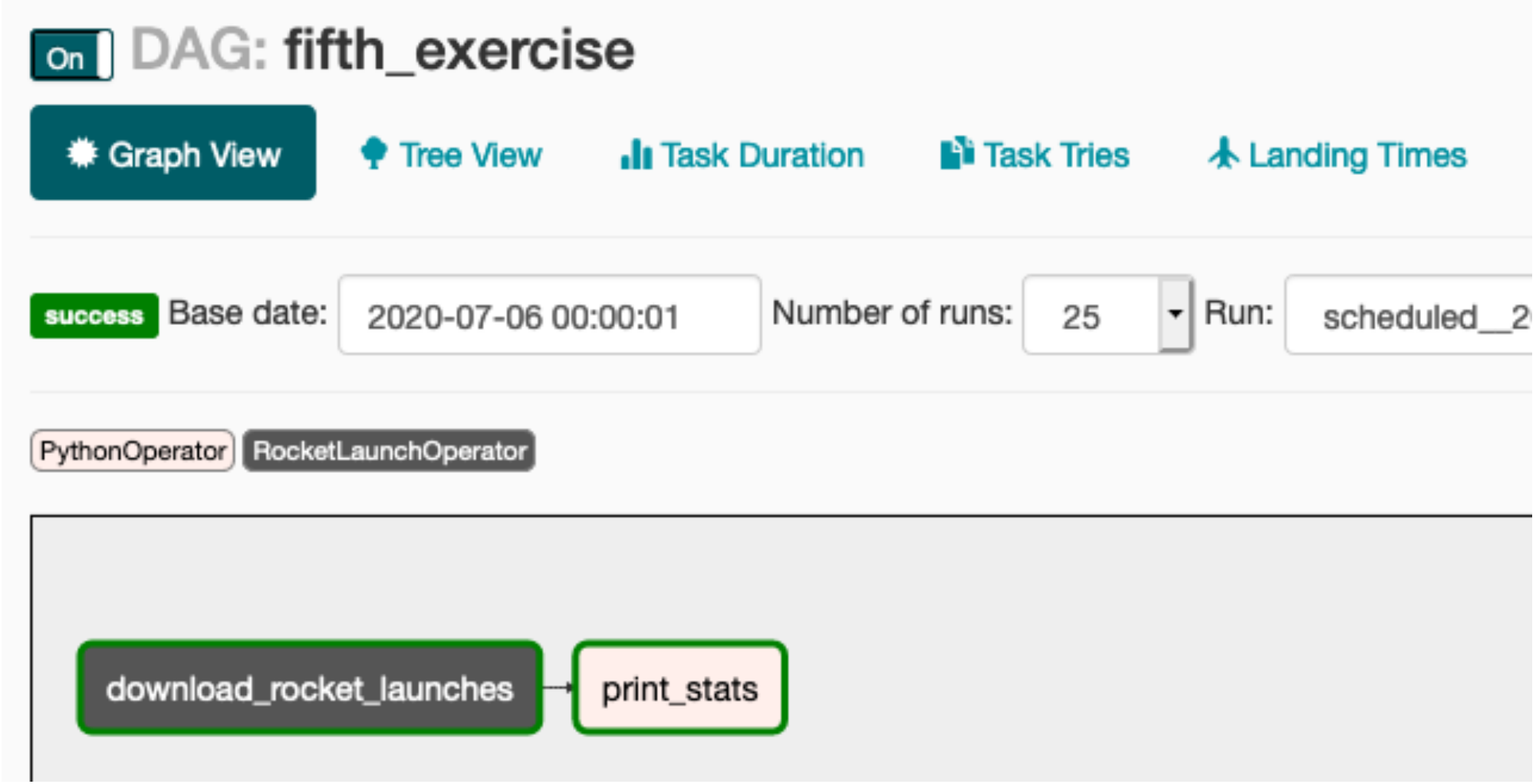
End goal

```
if response.status_code not in (200, 404):
    # Launch Library returns 404 if no rocket launched in given interval.
    response.raise_for_status()
```



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End goal

```
args = {"owner": "Airflow", "start_date": airflow.utils.dates.days_ago(10)}

dag = DAG(
    dag_id="fifth_exercise",
    default_args=args,
    schedule_interval="@daily",
    dagrun_timeout=timedelta(minutes=60),
)

download_rocket_launches = RocketLaunchOperator(
    task_id="download_rocket_launches", dag=dag
)


def _print_stats(ds, task_instance, **context):
    data = task_instance.xcom_pull(task_ids="download_rocket_launches")
    print("Date from xcom: {}".format(data))
    rockets_launched = [launch["name"] for launch in data["launches"]]
    rockets_str = ""

    if rockets_launched:
        rockets_str = f" ({' & '.join(rockets_launched)})"
        print(f"{len(rockets_launched)} rocket launch(es) on {ds}{rockets_str}.")
    else:
        print(f"No rockets found in {f.name}")


print_stats = PythonOperator(
    task_id="print_stats", python_callable=_print_stats, provide_context=True, dag=dag
)

download_rocket_launches >> print_stats
```

Airflow - Testing

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Testing in Airflow

- Unit test your custom Airflow components

- Testing full DAGs is inherently difficult; often external systems are not accessible from your development machine
  - Mock external system calls/responses
  - Create a local Docker development environment
  - Check if development endpoints are available

- https://blog.godatadriven.com/testing-and-debugging-apache-airflow

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7 Circles of Data Testing Hell with Airflow

https://medium.com/wbaa/datas-inferno-7-circles-of-data-testing-hell-with-airflow-cef4adff58d8

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Testing in Airflow

- Verifies correctness of your DAGs
  - Don’t contain cycles
  - No duplicate tasks
  - Etc.

- Run on your local machine (requires pytest installed):
  - `pytest tests/`

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Testing operators with Pytest

```python
import pytest
from airflow import DAG

pytest_plugins = ["helpers_namespace"]

@pytest.fixture
def test_dag():
    """Airflow DAG for testing."""
    return DAG(
        "test_dag",
        default_args={"owner": "airflow", "start_date": datetime.datetime(2018, 1, 1)},
        schedule_interval=datetime.timedelta(days=1),
    )

@pytest.helpers.register
def run_task(task, dag):
    """Run an Airflow task."""
    dag.clear()
    task.run(
        start_date=dag.default_args["start_date"],
        end_date=dag.default_args["start_date"],
    )
```

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Testing operators with Pytest

```python
class TestOperator:

    def test_operator(self, test_dag, mocker, tmpdir):
        # Mock get_connection because we have no metastore and no connection
        mocker.patch.object(BaseHook, "get_connection", return_value=Connection())

        # TODO: Mock any external calls in hooks.

        # Force run task with Operator
        task = MyOperator(...)
        pytest.helpers.run_task(task=task, dag=test_dag)

        # TODO: Check result.
```

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Testing tasks from the CLI

```
airflow test dag-name task-name 2018-01-01
```

```
$ gcloud composer environments run --project airflowbolcom-102b0f55fa0b9585 training-airflow --location europe-west1 test --
exercise1 print_exec_date 2018-11-20

kubeconfig entry generated for europe-west1-training-airfl-24c2c786-gke.
[2018-11-21 23:09:54,285] {models.py:1569} INFO - Executing <Task(BashOperator): print_exec_date> on 2018-11-20T00:00:00+00:00@-@{}
[2018-11-21 23:09:54,389] {bash_operator.py:74} INFO - Tmp dir root location:
 /tmp
[2018-11-21 23:09:54,393] {bash_operator.py:87} INFO - Temporary script location: /tmp/airflowtmp9eek03qx/print_exec_date7ck3860q
[2018-11-21 23:09:54,394] {bash_operator.py:97} INFO - Running command: echo 2018-11-20T00:00:00+00:00
[2018-11-21 23:09:54,400] {bash_operator.py:106} INFO - Output:
[2018-11-21 23:09:54,404] {bash_operator.py:110} INFO - 2018-11-20T00:00:00+00:00
[2018-11-21 23:09:54,405] {bash_operator.py:114} INFO - Command exited with return code 0
```

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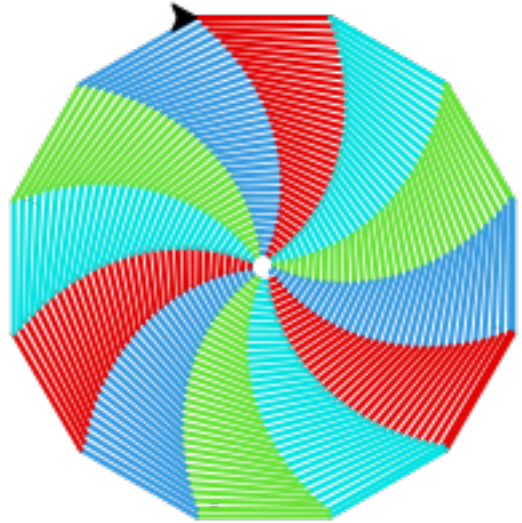
Testing DAGs with Whirl



- *“Fast iterative local development and testing of Apache Airflow workflows“*
- Uses Docker to run Airflow + simulate other components of your workflow (MySQL, SFTP, S3, APIs, etc.)
- https://github.com/godatadriven/whirl

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Other useful tools

- Black (others: YAPF & autopep8)
  - Code formatter according to PEP8 standards

- PyLint (others: Flake8, pep8 & pyflakes)
  - Checks syntactical issues and potential problems but does not improve code
  - E.g. unused function arguments/Python 2 usage

Exercise

- Write the following tests for our previous DAG (using pytest)
  - The basic DAG integrity test
  - Unit test(s) for the LaunchHook
  - Unit test(s) for the LaunchOperator
  - Bonus: try running Black/Pylint

- Tip: for the LaunchHook tests, you might consider mocking responses from the API

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Airflow - Architectures

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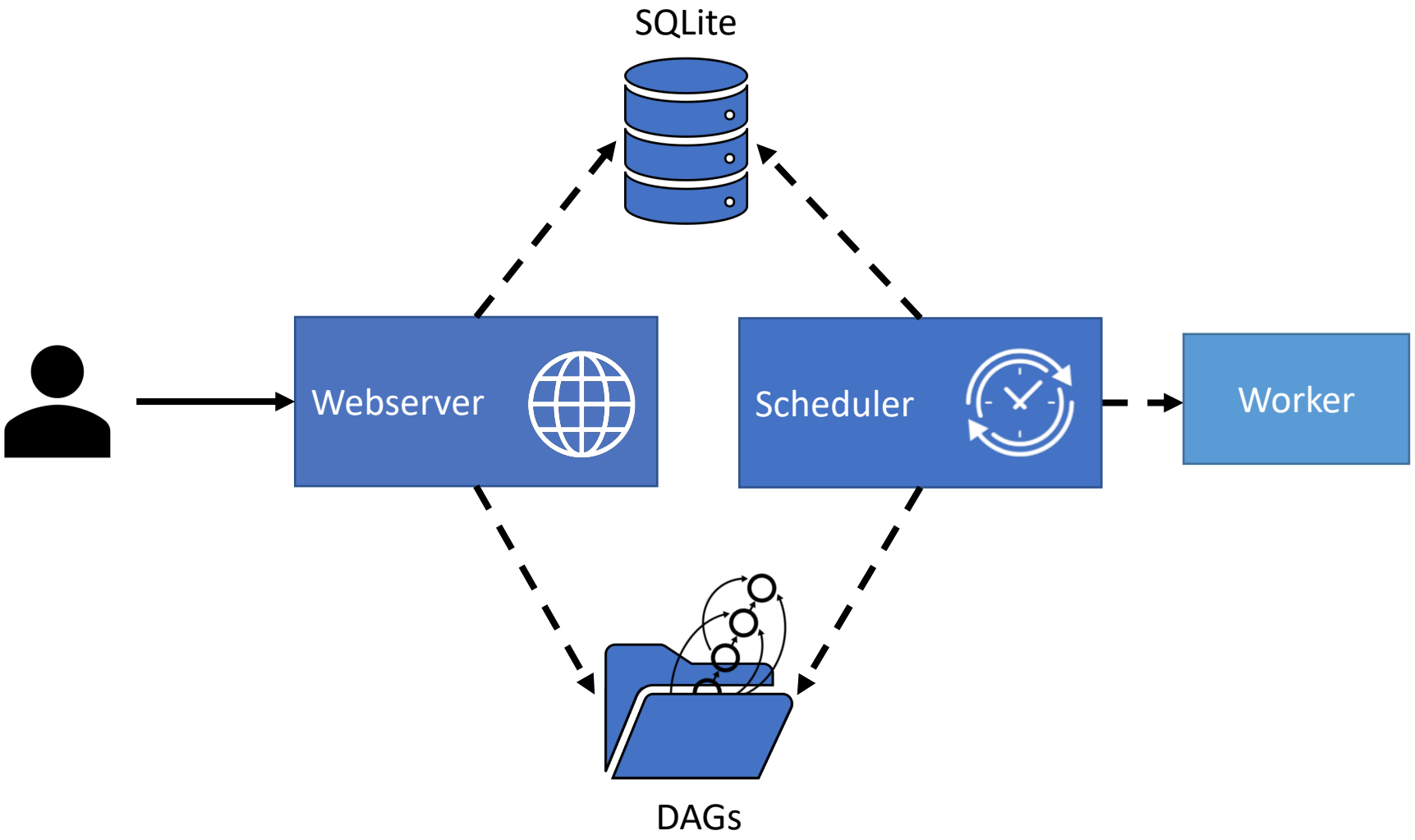
Sequential Executor



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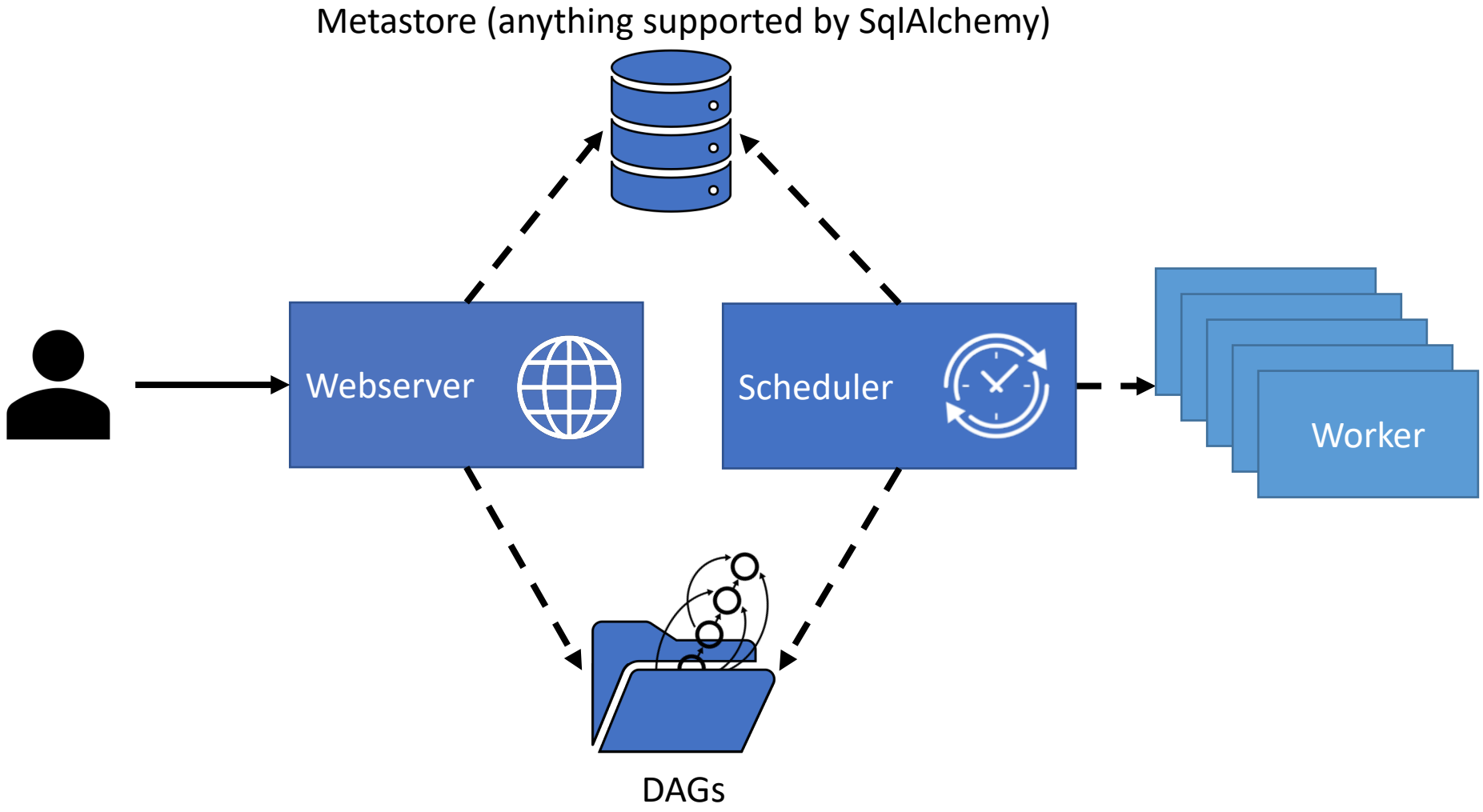
Local Executor



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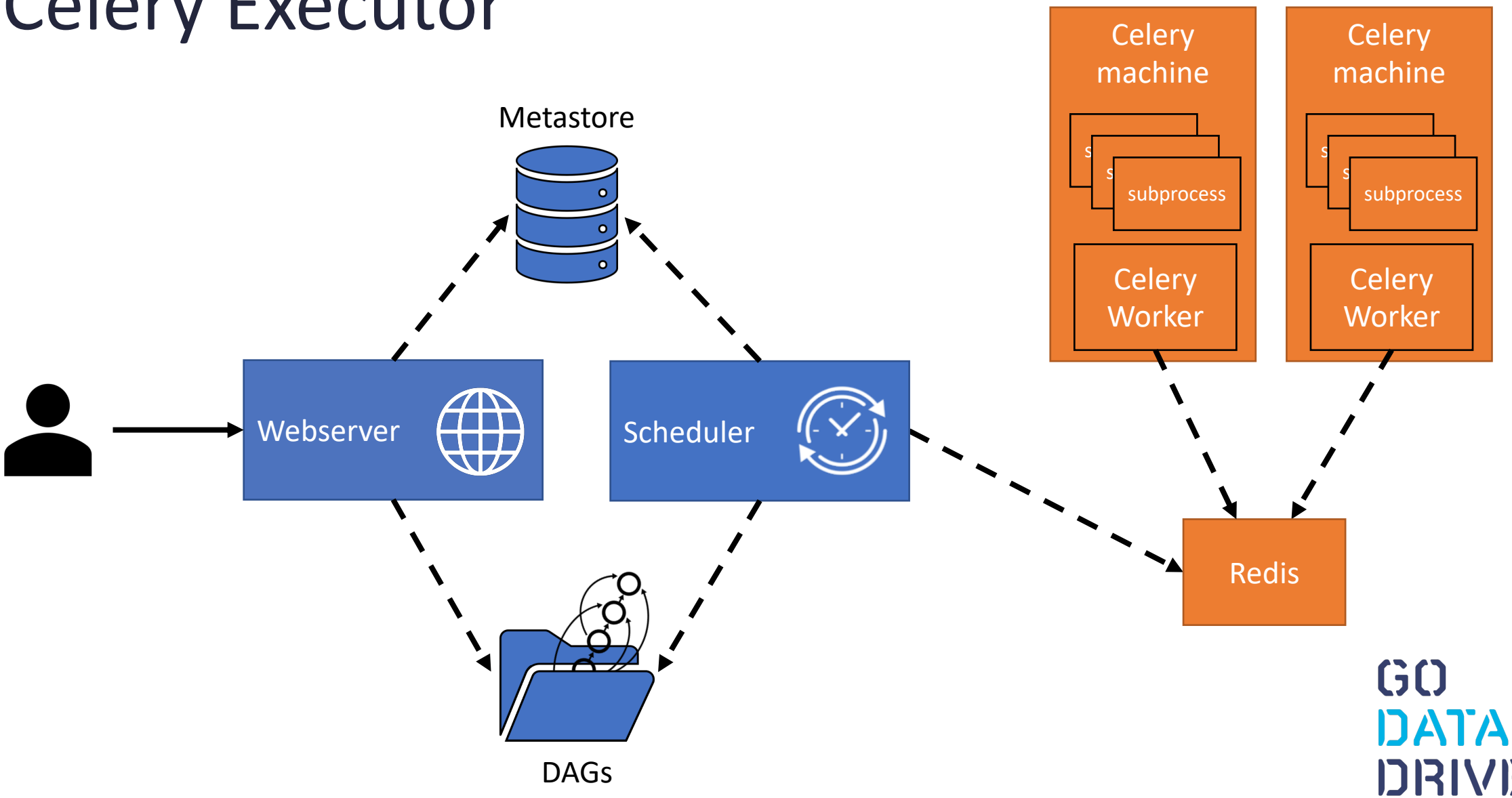
Celery Executor



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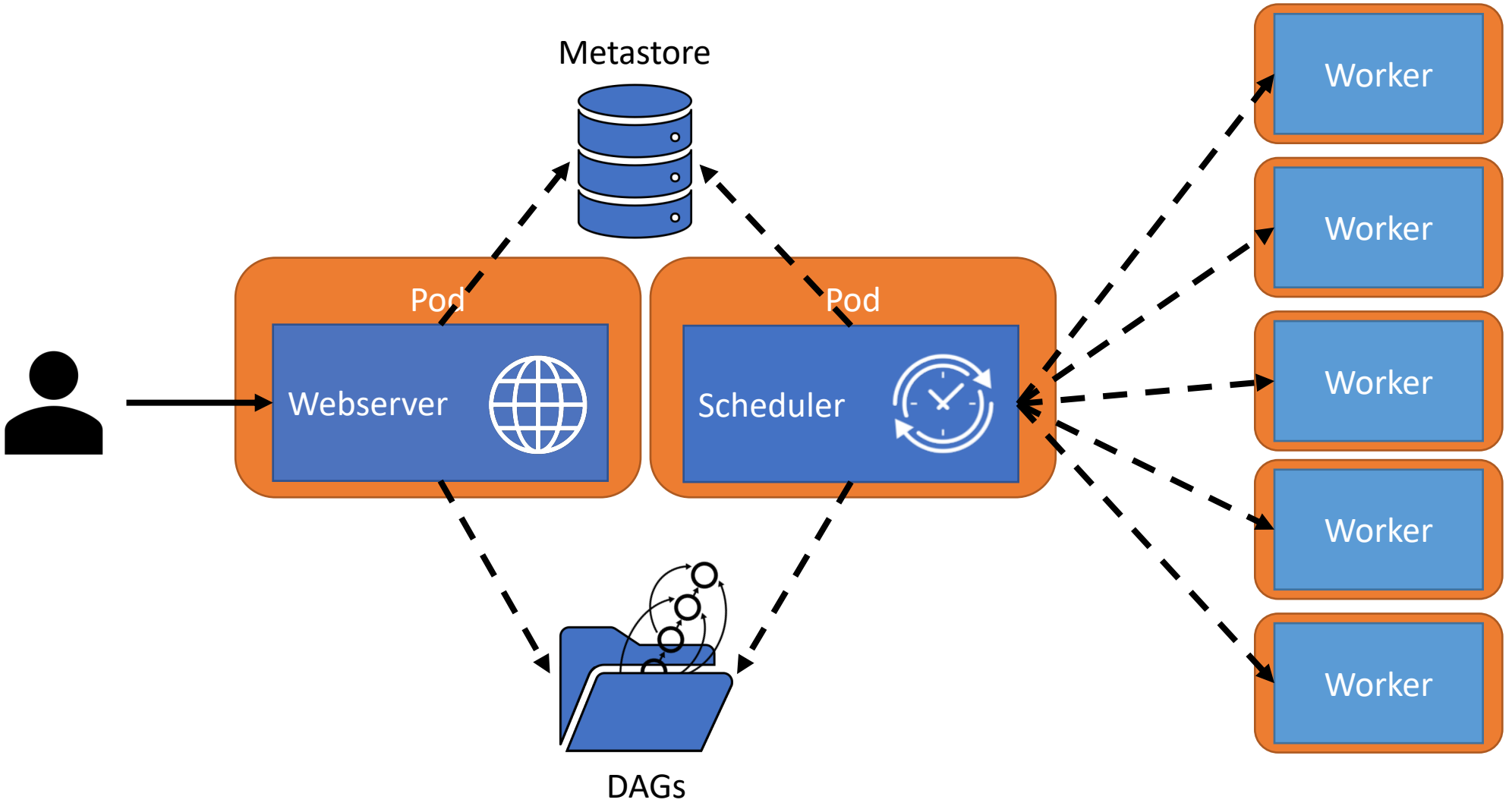
Kubernetes Executor



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Extras

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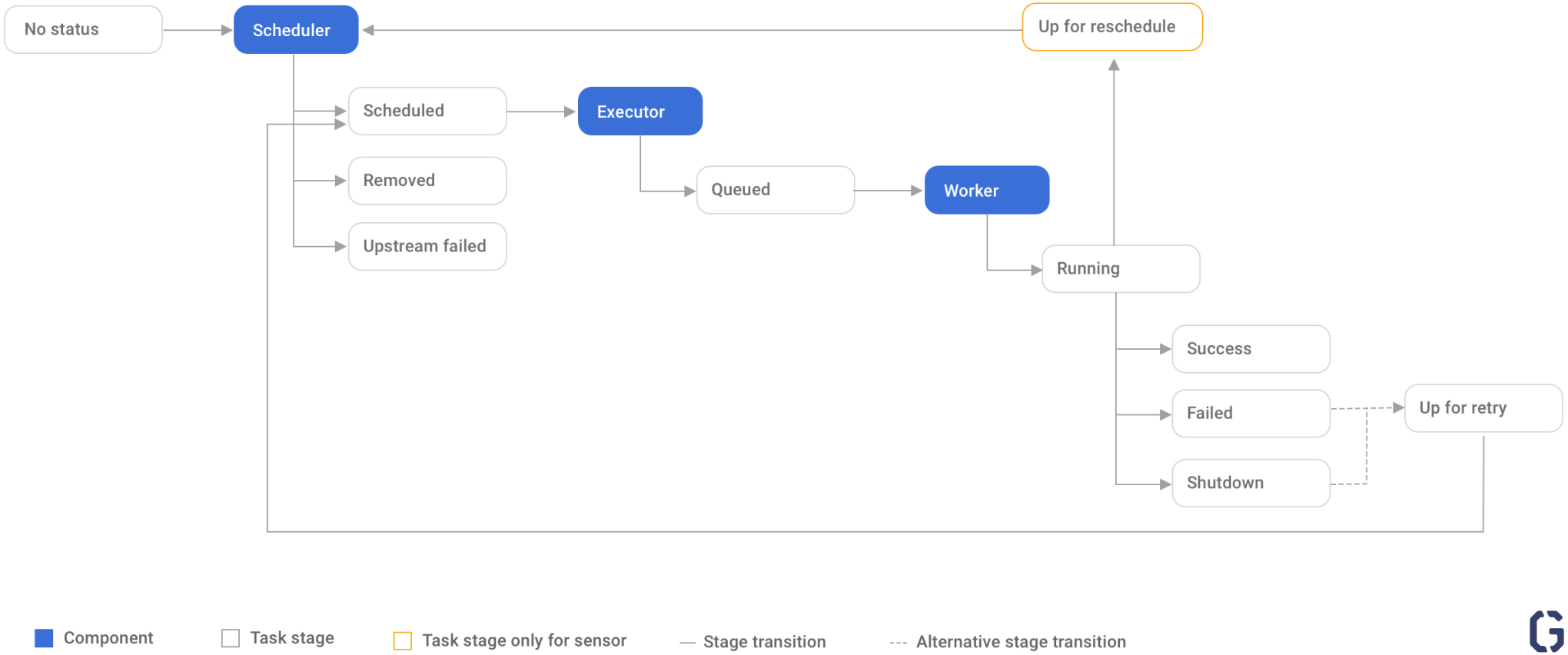
Task lifecycle



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Questions?

- Email me at fokko@apache.org

- Solutions at:

https://github.com/Fokko/airflow-training-skeleton

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