Modern day workflow management

BUILDING DATA ENGINEERING PIPELINES IN PYTHON

Oliver Willekens
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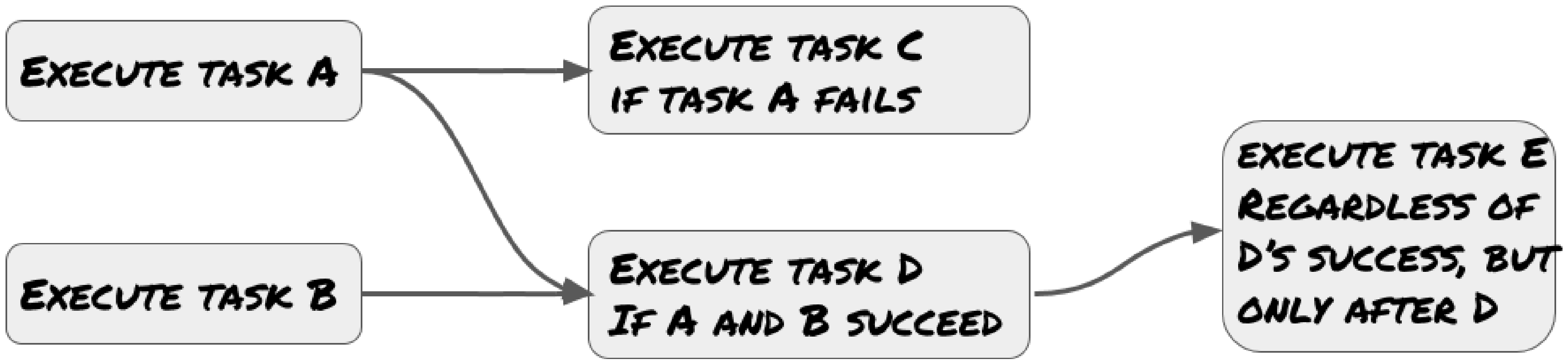
What is a workflow?

A workflow:

- Sequence of tasks



- *Scheduled* at a time or *triggered* by an event
- Orchestrate data processing pipelines

Scheduling with cron

Cron reads “crontab” files:

- tabulate tasks to be executed at certain times
- one task per line

```
*/15 9-17 * * 1-3,5 log_my_activity
```

Scheduling with cron

```
*/15 9-17 * * 1-3,5 log_my_activity

----
```

Scheduling with cron

The Airflow task:

- An instance of an Operator class
  - Inherits from `BaseOperator` -> Must implement `execute()` method.
- Performs a specific action (delegation):
  - `BashOperator` -> run bash command/script
  - `PythonOperator` -> run Python script
  - `SparkSubmitOperator` -> submit a Spark job with a cluster

Scheduling with cron

```
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          -
```

Scheduling with cron

```
*/15 9-17 * * 1-3,5 log_my_activity

            _
```

Scheduling with cron

```
*/15 9-17 * * 1-3,5 log_my_activity
                    -----
```

Scheduling with cron

```
*/15 9-17 * * 1-3,5 log_my_activity
```

Scheduling with cron

```
*/15 9-17 * * 1-3,5 log_my_activity


# Minutes    Hours    Days    Months    Days of the week    Command
*/15         9-17     *       *         1-3,5               log_my_activity
```

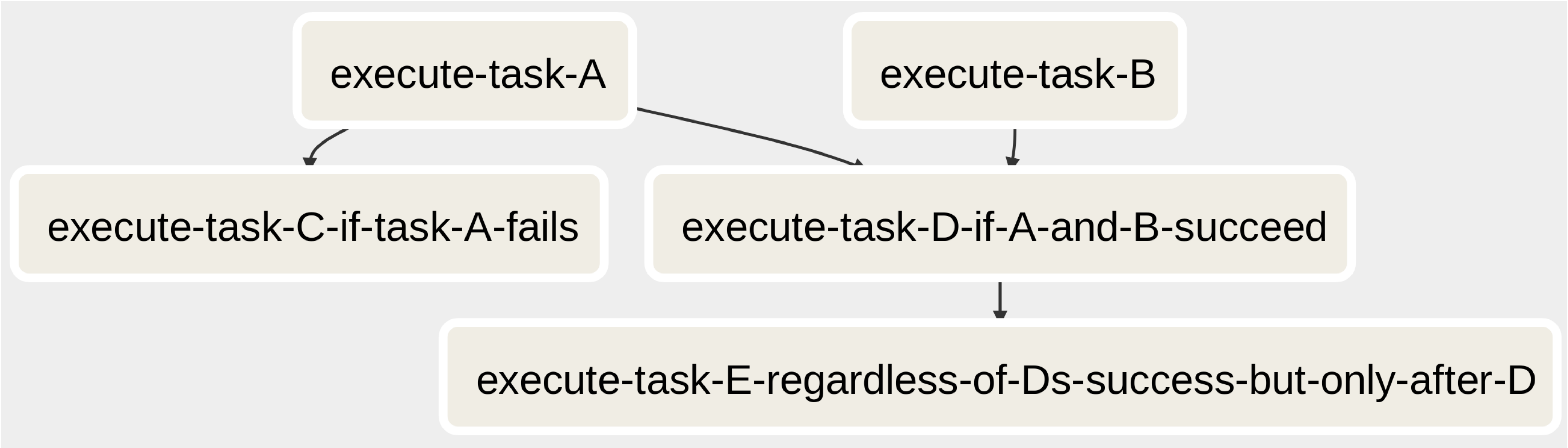
Cron is a dinosaur.

Modern workflow managers:

- Luigi (Spotify, 2011, Python-based)
- Azkaban (LinkedIn, 2009, Java-based)
- Airflow (Airbnb, 2015, Python-based)

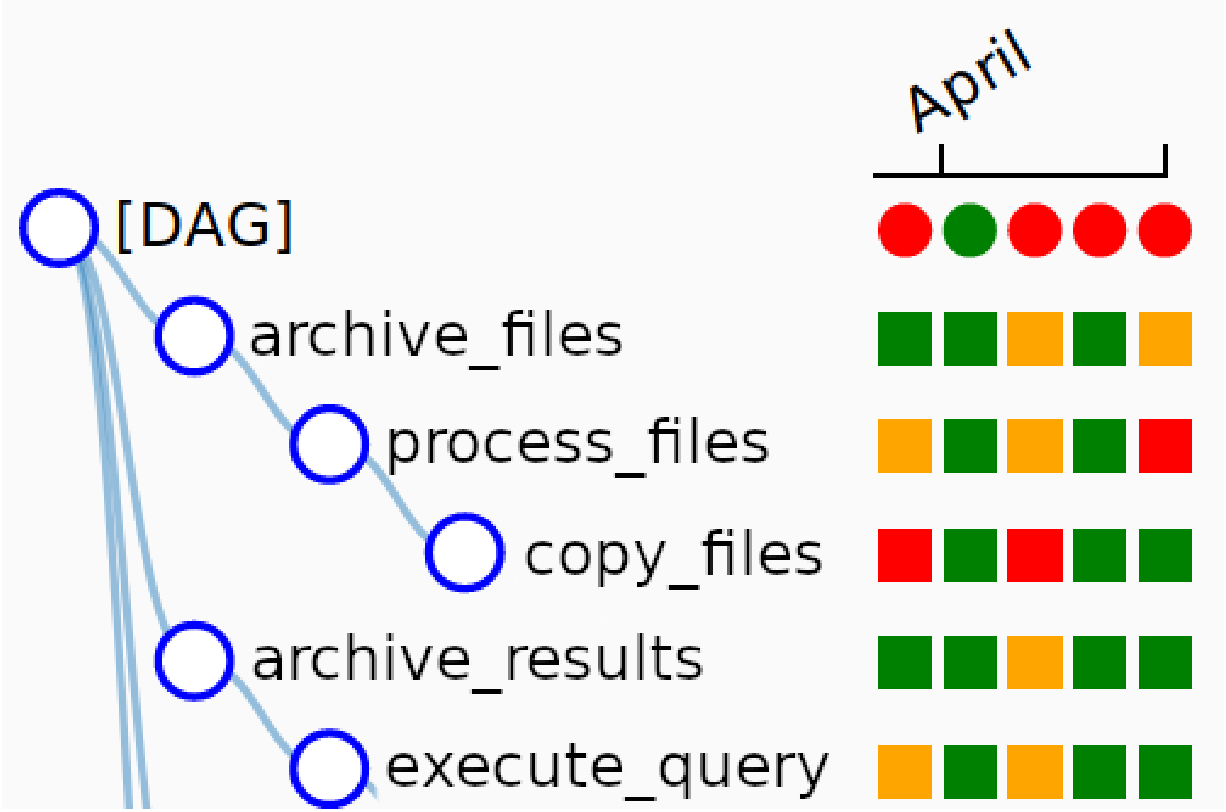
Apache Airflow fulfills modern engineering needs

1. Create and visualize complex workflows,



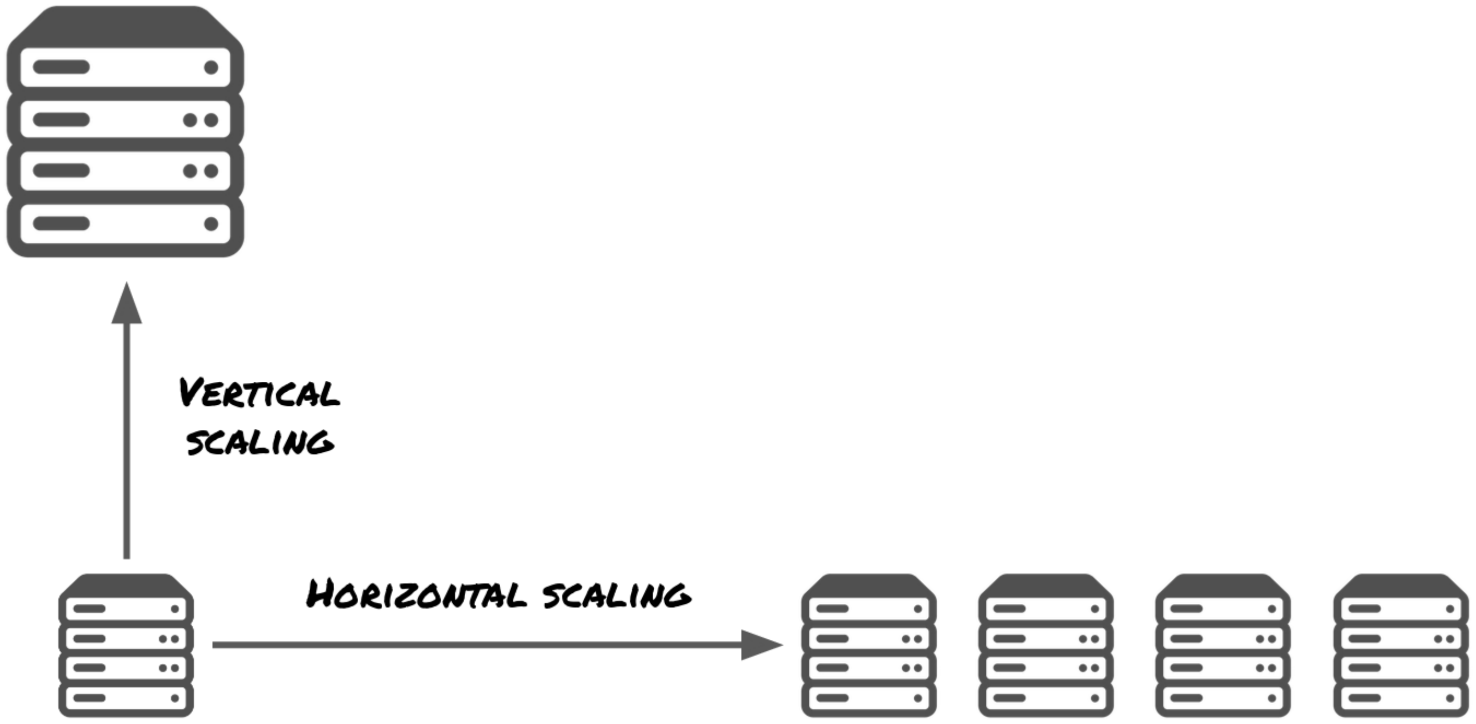
Apache Airflow fulfills modern engineering needs

1. Create and visualize complex workflows,
2. Monitor and log workflows,

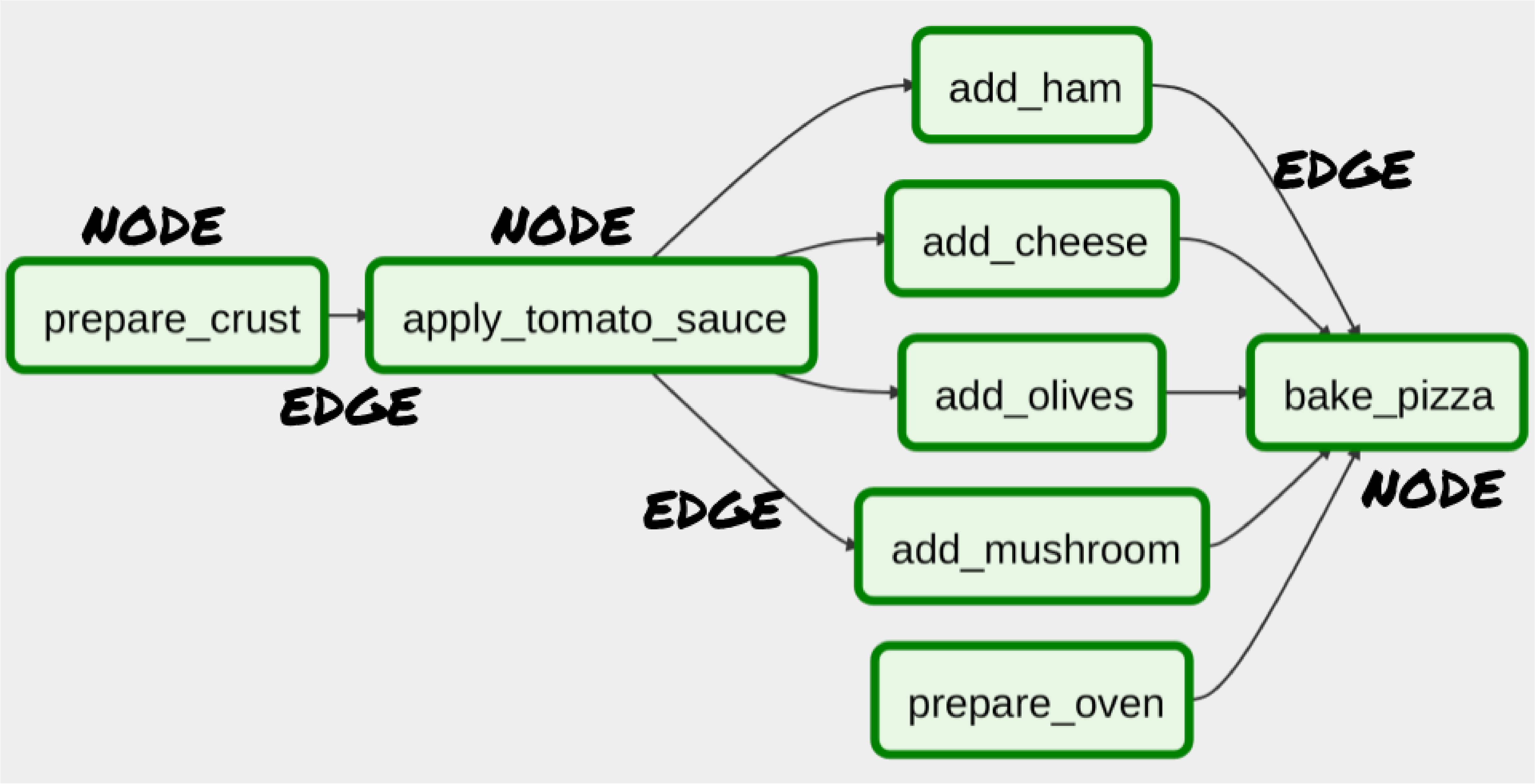


Apache Airflow fulfills modern engineering needs

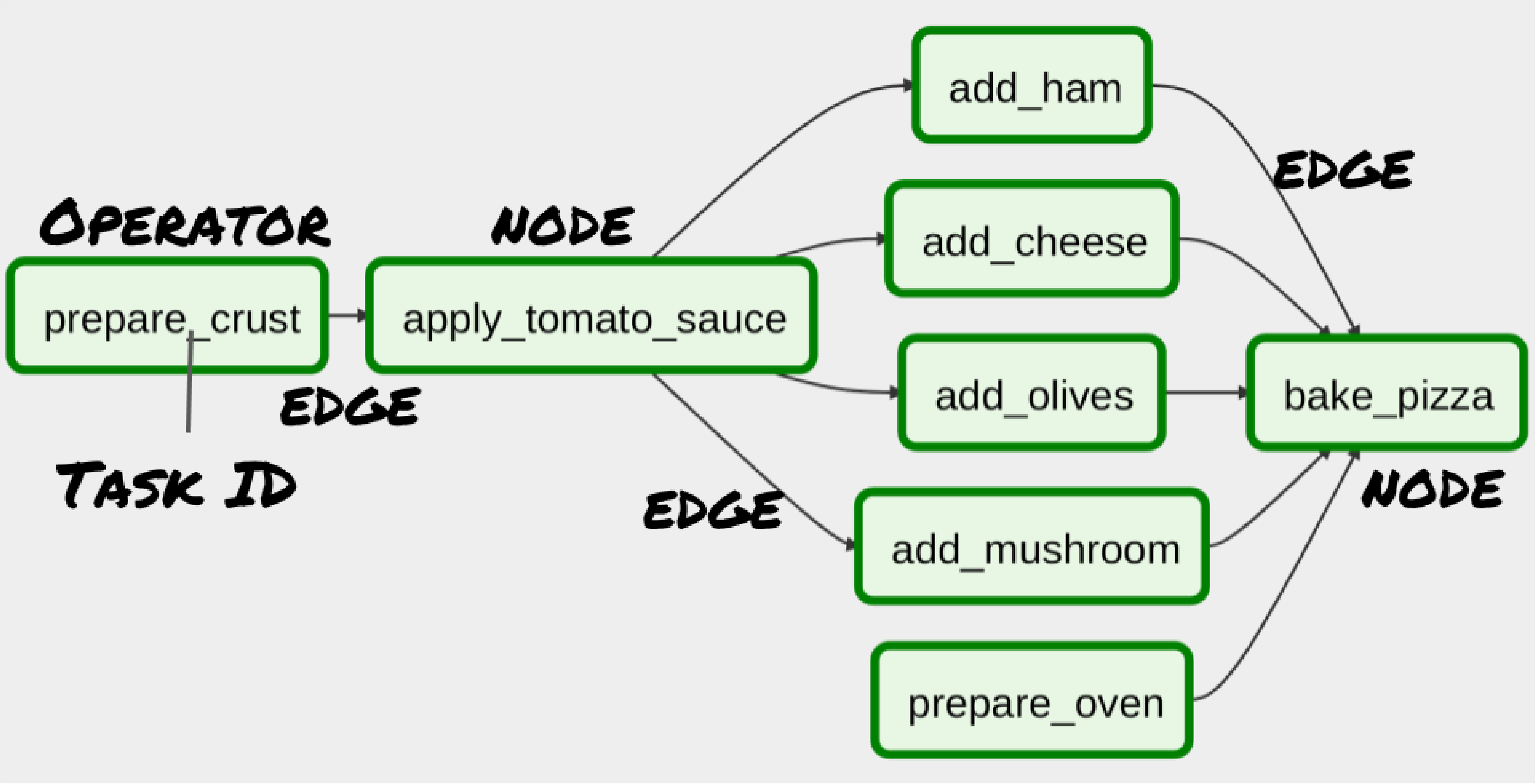
1. Create and visualize complex workflows,
2. Monitor and log workflows,
3. Scales horizontally.



The Directed Acyclic Graph (DAG)



The Directed Acyclic Graph (DAG)



The Directed Acyclic Graph in code

```
from airflow import DAG


my_dag = DAG(
  dag_id="publish_logs",
  schedule_interval="* * * * *",
  start_date=datetime(2010, 1, 1)
)
```

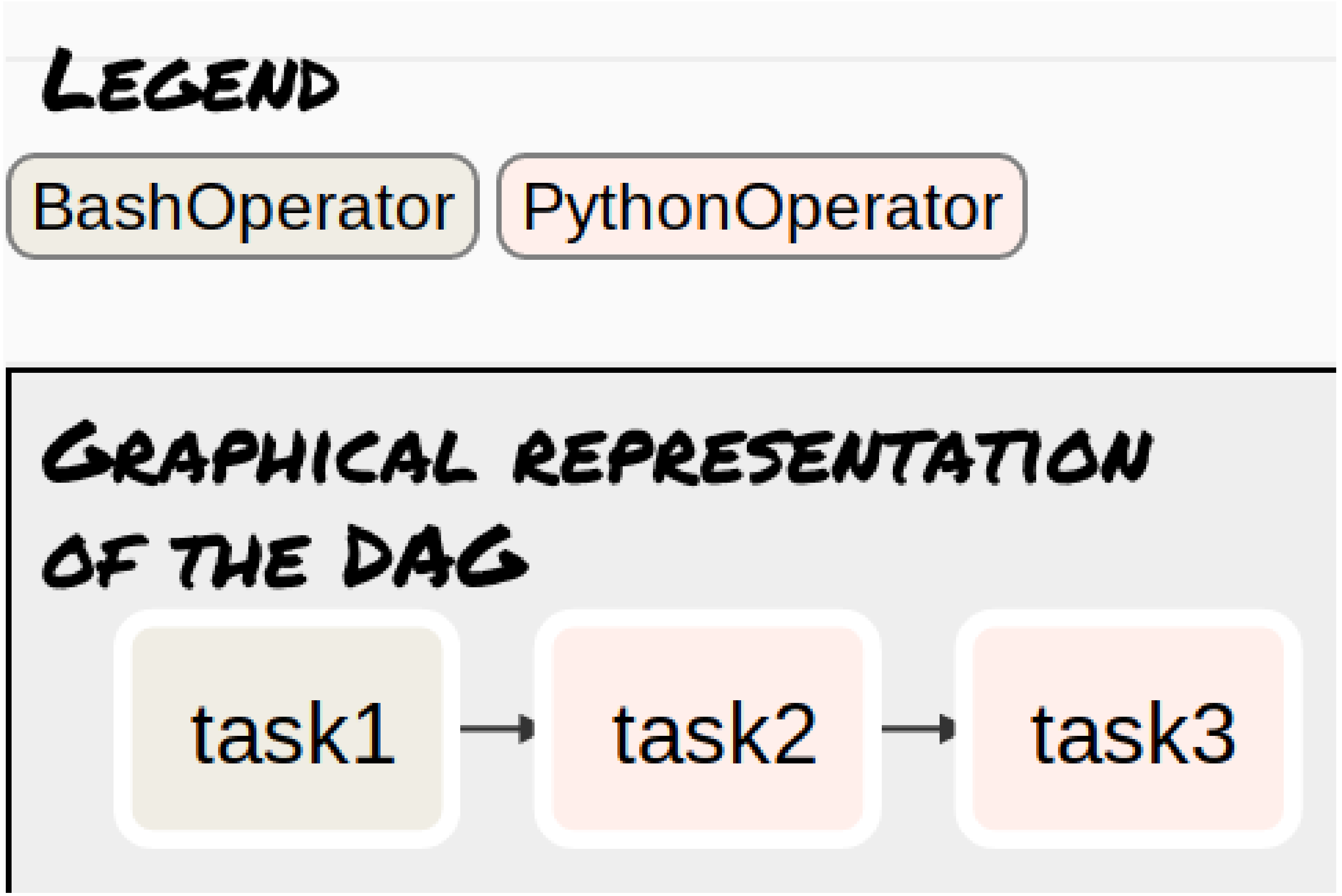
Classes of operators

The Airflow task:

- An instance of an Operator class
  - Inherits from `BaseOperator` -> Must implement `execute()` method.
- Performs a specific action (delegation):
  - `BashOperator` -> run bash command/script
  - `PythonOperator` -> run Python script
  - `SparkSubmitOperator` -> submit a Spark job with a cluster

Expressing dependencies between operators

```
dag = DAG(…)
task1 = BashOperator(…)
task2 = PythonOperator(…)
task3 = PythonOperator(…)
task1.set_downstream(task2)
task3.set_upstream(task2)
# equivalent, but shorter:
# task1 >> task2
# task3 << task2
# Even clearer:
# task1 >> task2 >> task3
```



Let's practice!

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Building a data pipeline with Airflow

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Airflow's BashOperator

- Executes bash commands
- Airflow adds logging, retry options and metrics over running this yourself.

```
from airflow.operators.bash_operator import BashOperator

bash_task = BashOperator(
        task_id='greet_world',
        dag=dag,
        bash_command='echo "Hello, world!"'
)
```

Airflow's PythonOperator

- Executes Python callables

```
from airflow.operators.python_operator import PythonOperator
from my_library import my_magic_function

python_task = PythonOperator(
    dag=dag,
    task_id='perform_magic',
    python_callable=my_magic_function,
    op_kwargs={"snowflake": "*", "amount": 42}
)
```

Running PySpark from Airflow

- BashOperator:

```
spark_master = (
  "spark://"
  "spark_standalone_cluster_ip"
  ":7077")

command = (
  "spark-submit "
  "--master {master} "
  "--py-files package1.zip "
  "/path/to/app.py"
).format(master=spark_master)
BashOperator(bash_command=command, …)
```

- SSHOperator

```
from airflow.contrib.operators\
  .ssh_operator import SSHOperator

task = SSHOperator(
    task_id='ssh_spark_submit',
    dag=dag,
    command=command,
    ssh_conn_id='spark_master_ssh'
)
```

Running PySpark from Airflow

- SparkSubmitOperator

```
from airflow.contrib.operators\
  .spark_submit_operator \
  import SparkSubmitOperator

spark_task = SparkSubmitOperator(
    task_id='spark_submit_id',
    dag=dag,
    application="/path/to/app.py",
    py_files="package1.zip",
    conn_id='spark_default'
)
```

- SSHOperator

```
from airflow.contrib.operators\
  .ssh_operator import SSHOperator

task = SSHOperator(
    task_id='ssh_spark_submit',
    dag=dag,
    command=command,
    ssh_conn_id='spark_master_ssh'
)
```

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Deploying Airflow

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Installing and configuring Airflow

```
export AIRFLOW_HOME=~/airflow
pip install apache-airflow
airflow initdb
```

```
airflow/
├── logs
├── airflow.cfg
├── airflow.db
└── unittests.cfg
```

```
[core]
# lots of other configuration settings
# …

# The executor class that airflow should u
# Choices include SequentialExecutor,
# LocalExecutor, CeleryExecutor, DaskExecu
# KubernetesExecutor
executor = SequentialExecutor
```

Setting up for production

- *dags*: place to store the dags (configurable)
- *tests*: unit test the possible deployment, possibly ensure consistency across DAGs
- *plugins*: store custom operators and hooks
- *connections*, *pools*, *variables*: provide a location for various configuration files you can import into Airflow.

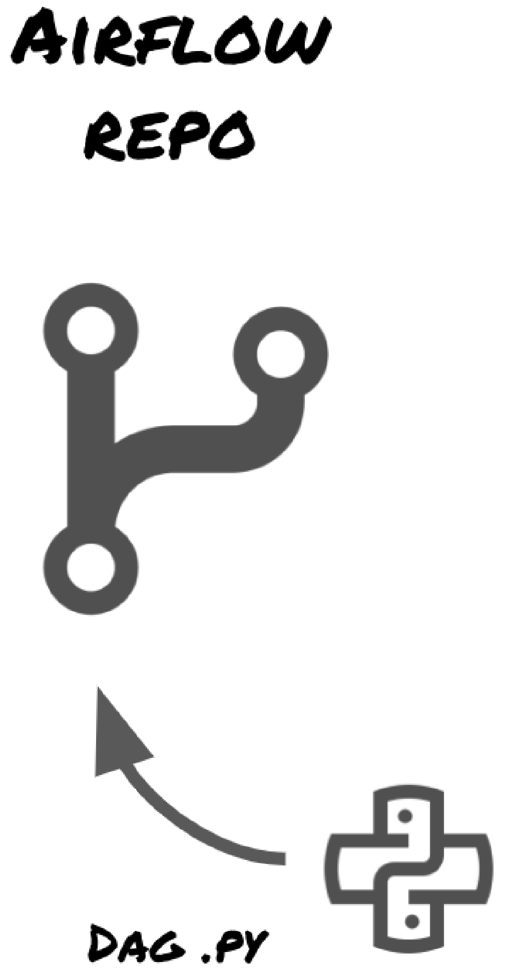
```
airflow/
├── connections
├── dags
├── logs
├── plugins
├── pools
├── script
├── tests
├── variables
├── airflow.cfg
├── README.md
├── requirements.txt
├── unittests.cfg
└── unittests.db
```

Example Airflow deployment test

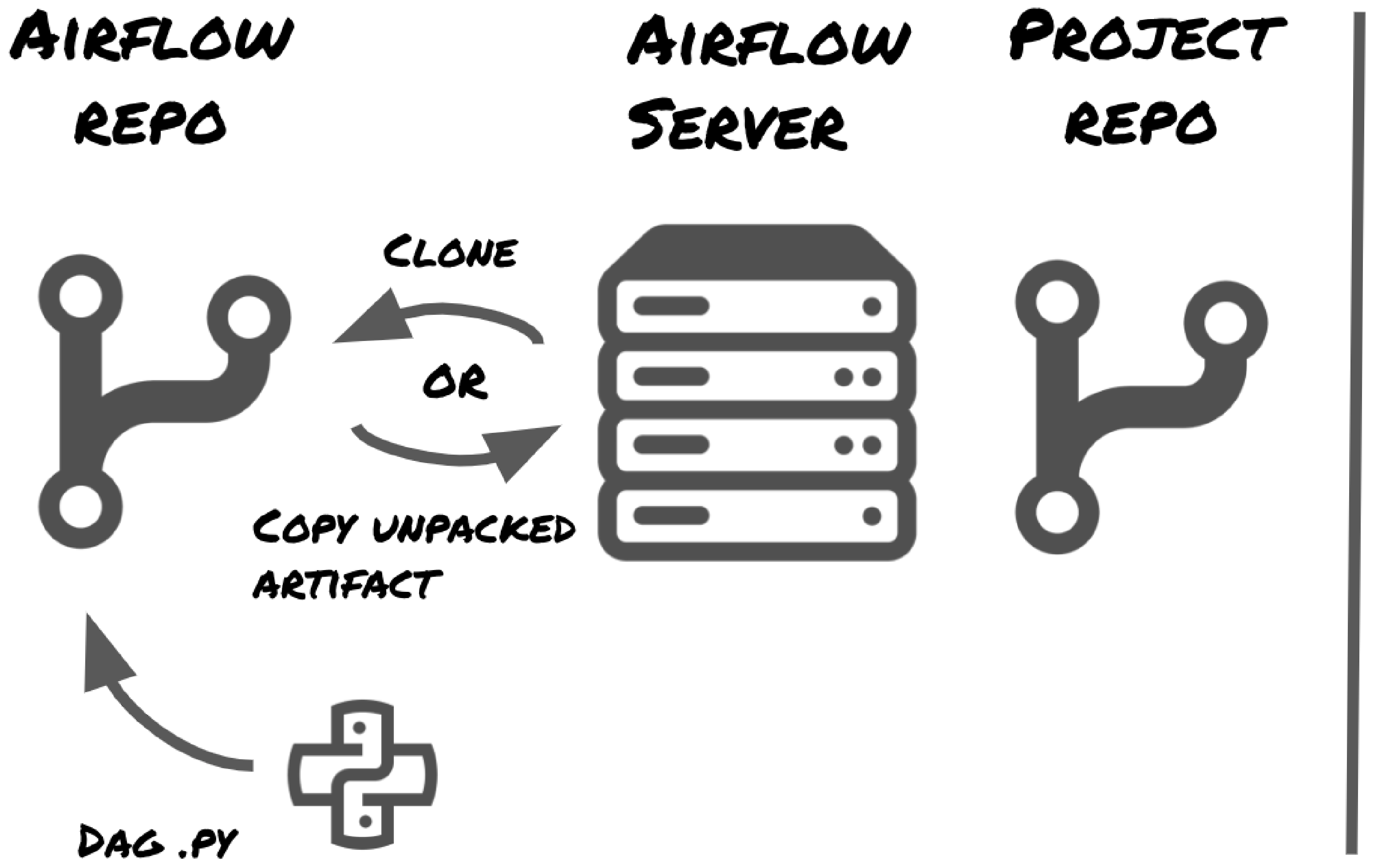
```python
from airflow.models import DagBag

def test_dagbag_import():
    """Verify that Airflow will be able to import all DAGs in the repository."""
    dagbag = DagBag()
    number_of_failures = len(dagbag.import_errors)
    assert number_of_failures == 0, \
        "There should be no DAG failures. Got: %s" % dagbag.import_errors
```

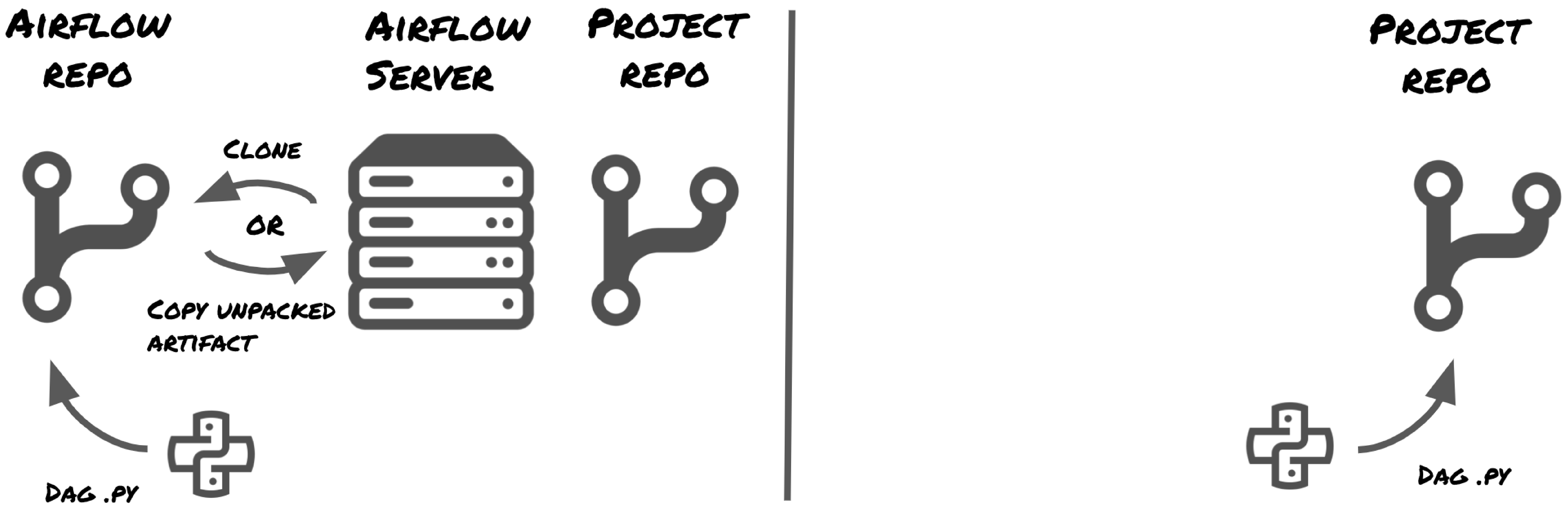
Transferring DAGs and plugins



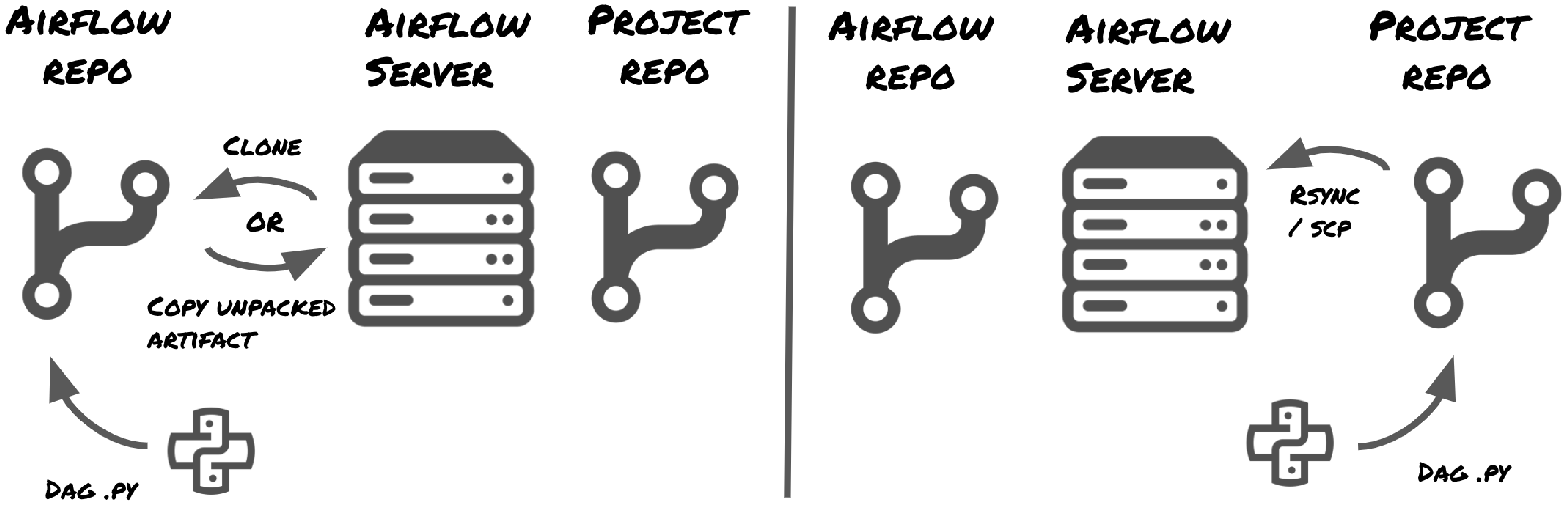
Transferring DAGs and plugins



Transferring DAGs and plugins



Transferring DAGs and plugins



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Final thoughts

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What you learned

- Define purpose of components of data platforms
- Write an ingestion pipeline using Singer
- Create and deploy pipelines for big data in Spark
- Configure automated testing using CircleCI
- Manage and deploy a full data pipeline with Airflow

Additional resources

External resources

- Singer: https://www.singer.io/
- Apache Spark: https://spark.apache.org/
- Pytest: https://pytest.org/en/latest/
- Flake8: http://flake8.pycqa.org/en/latest/
- Circle CI: - https://circleci.com/
- Apache Airflow: https://airflow.apache.org/

DataCamp courses

- Software engineering: https://www.datacamp.com/courses/software-engineering-for-data-scientists-in-python
- Spark: https://www.datacamp.com/courses/cleaning-data-with-apache-spark-in-python (and other courses)
- Unit testing: link yet to be revealed

Congratulations! ????

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