Orchestration with Airflow Data wrangling Deployment

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v1.1

UMD DATA605 - Big Data Systems

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Orchestration with Airflow

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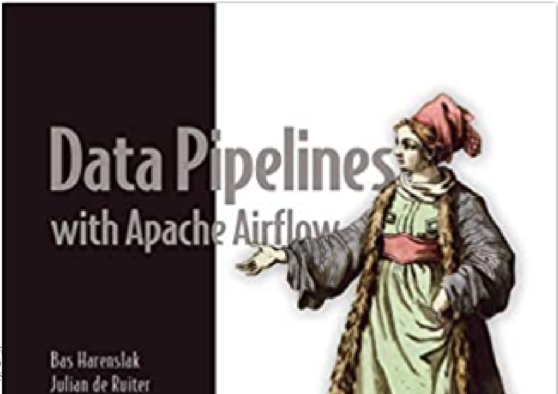
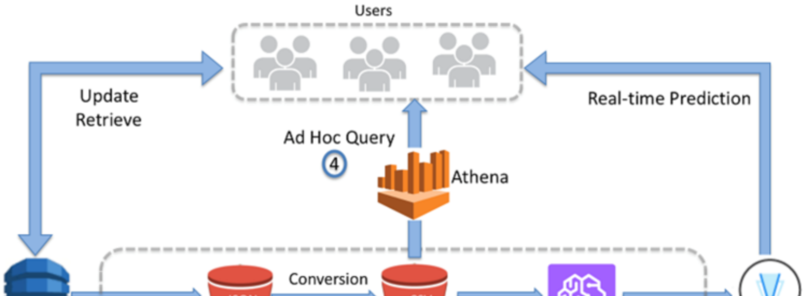
Orchestration - Resources

- Concepts in the slides
- Airflow tutorial
- Web resources
- Documentation
- Tutorial
- Mastery
- Data Pipelines with Apache Airflow

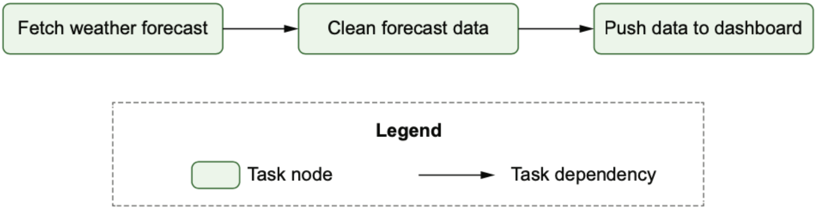


Workflow Managers

- **Data pipelines** move/transform data across data stores
- **Orchestration problem** = data pipelines require to coordinate jobs across systems
    - Run tasks on a certain schedule
    - Run tasks in a specific order (dependencies)
    - Monitor tasks
        - Notify devops if a job fails
        - Retry on failure
        - Track how long it takes to run
    - Meet real-time constraints
    - Scale performance



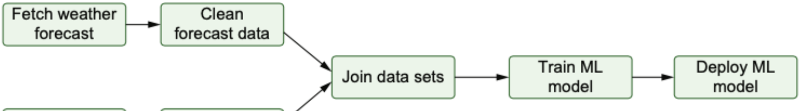
Workflow Managers



- **E.g., live weather dashboard**
  - Fetch the weather data from API
  - Clean / transform the data
  - Push data to the dashboard/ website
- Problems
  - Tasks schedule
  - Tasks dependencies
  - Monitor functionality and performance
  - Quickly one wants to add machine learning
  - Quickly the complexity increases

Workflow Managers

- **Workflow managers address the orchestration problem**
  - E.g., Airflow, Luigi, Metaflow, make, cron . . .
- **Represent data pipelines as DAGs**
  - Nodes are tasks
  - Direct edges are dependencies
  - A task is executed only when all the ancestors have been executed
  - Independent tasks can be executed in parallel
  - Re-run failed tasks incrementally
- **How to describe data pipelines**
  - Static files (e.g., XML, YAML)
  - Workflows-as-code (e.g., Python in Airflow)
- **Provide scheduling**
  - How to describe what and when to run
- **Provide backfilling and catch-up**
  - Horizontally scalable (e.g., multiple runners)
- **Provide monitoring web interface**



Airflow

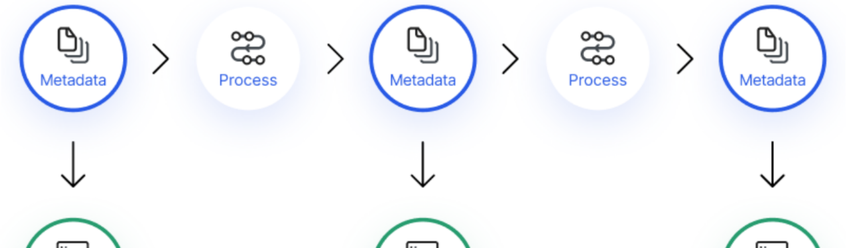
- Developed at AirBnB in 2015
  - Open-sourced as part of Apache project
- **Batch oriented framework** for building data pipelines (not streaming)
- **Data pipelines**
  - Represented as DAGs
  - Described as Python code
- **Scheduler with rich semantics**
- Web-interface for monitoring
- Large ecosystem
  - Support many DBs
  - Many actions (e.g., emails, pager notifications)
- **Hosted and managed solution**
  - Run Airflow on your laptop (e.g., in tutorial)
  - Managed solution (e.g., AWS)

Airflow: Execution Semantics

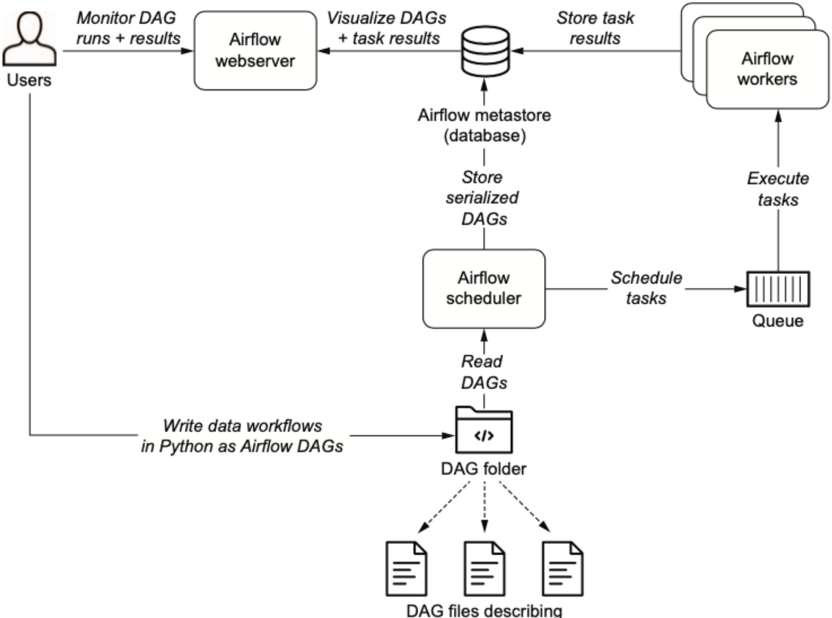
- **Scheduling semantic**
  - Describe when the next scheduling interval is
    - E.g., "every day at midnight", "every 5 minutes on the hour"
  - Similar to **cron**
- **Retry**
  - If a task fails, it can be re-run (after a wait time) to recover from intermittent failures
- **Incremental processing**
  - Time is divided into intervals given the schedule
  - Execute DAG only for data in that interval, instead of processing the entire data set
- **Catch-up**
  - Run all the missing intervals up to now (e.g., after a downtime)
- **Backfilling**
  - Execute DAG for historical schedule intervals that occurred in the past
  - E.g., if the data pipeline has changed one needs to re-process data from scratch

Airflow: What Doesn't Do Well

- **Not great for streaming pipelines**
  - Better for recurring batch-oriented tasks
  - Time is assumed to be discrete and not continuous
    - E.g., schedule every hour, instead of process data as it comes
- **Prefer static pipelines**
  - DAGs should not change (too much) between runs
- **No data lineage**
  - No tracking of how data is transformed through the pipeline
  - Need to be implemented manually
- **No data versioning**
  - No tracking of updates to the data
  - Need to be implemented manually



Airflow: Components



Airflow: Concepts

- Each DAG run represents a data interval, i.e., an interval between two times
  - E.g., a DAG scheduled **@daily**
  - Each data interval starts at midnight for each day, ends at midnight of next day
- DAG scheduled after data interval has ended
- Logical date
  - Simulate the scheduler running DAG / task for a specific date
  - Even if it is physically run now

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Airflow: Tutorial

- Follow Airflow Tutorial in README
- From the tutorial for Airflow

Airflow: Tutorial

- The script describes the DAG structure as Python code
  - There is no computation inside the DAG code
  - It only defines the DAG structure and the metadata (e.g., about scheduling)
- The **Scheduler** executes the code to build DAG
- **BashOperator** creates a task wrapping a Bash command

airflow/example_dags/tutorial.py [view source]

```
from datetime import datetime, timedelta
from textwrap import dedent

# The DAG object; we'll need this to instantiate a DAG
from airflow import DAG

# Operators; we need this to operate!
from airflow.operators.bash import BashOperator
```

Airflow: Tutorial

- Dict with various default params to pass to the DAG constructor
  - E.g., different set-ups for dev vs prod
- Instantiate the DAG

airflow/example_dags/tutorial.py — view source

```python
# These args will get passed on to each operator
# You can override them on a per-task basis during operator initialization
default_args = {
    'owner': 'airflow',
    'depends_on_past': False,
    'email': ['airflow@example.com'],
    'email_on_failure': False,
    'email_on_retry': False,
    'retries': 1,
    'retry_delay': timedelta(minutes=5),
    # 'queue': 'bash_queue',
    # 'pool': 'backfill',
    # 'priority_weight': 10,
    # 'end_date': datetime(2016, 1, 1),
    # 'wait_for_downstream': False,
    # 'dag': dag,
    # 'sla': timedelta(hours=2),
    # 'execution_timeout': timedelta(seconds=300),
    # 'on_failure_callback': some_function,
    # 'on_success_callback': some_other_function,
```

Airflow: Tutorial

- DAG defines tasks by instantiating **Operator** objects
  - The default params are passed to all the tasks
  - Can be overridden explicitly
- One can use a Jinja template
- Add tasks to the DAG with dependencies

airflow/example_dags/tutorial.py [view source]

```
t1 = BashOperator(
    task_id='print_date',
    bash_command='date',
)

t2 = BashOperator(
    task_id='sleep',
    depends_on_past=False,
    bash_command='sleep 5',
    retries=3,
)
```

airflow/example_dags/tutorial.py [view source]

```
templated_command = dedent(
    """
```