



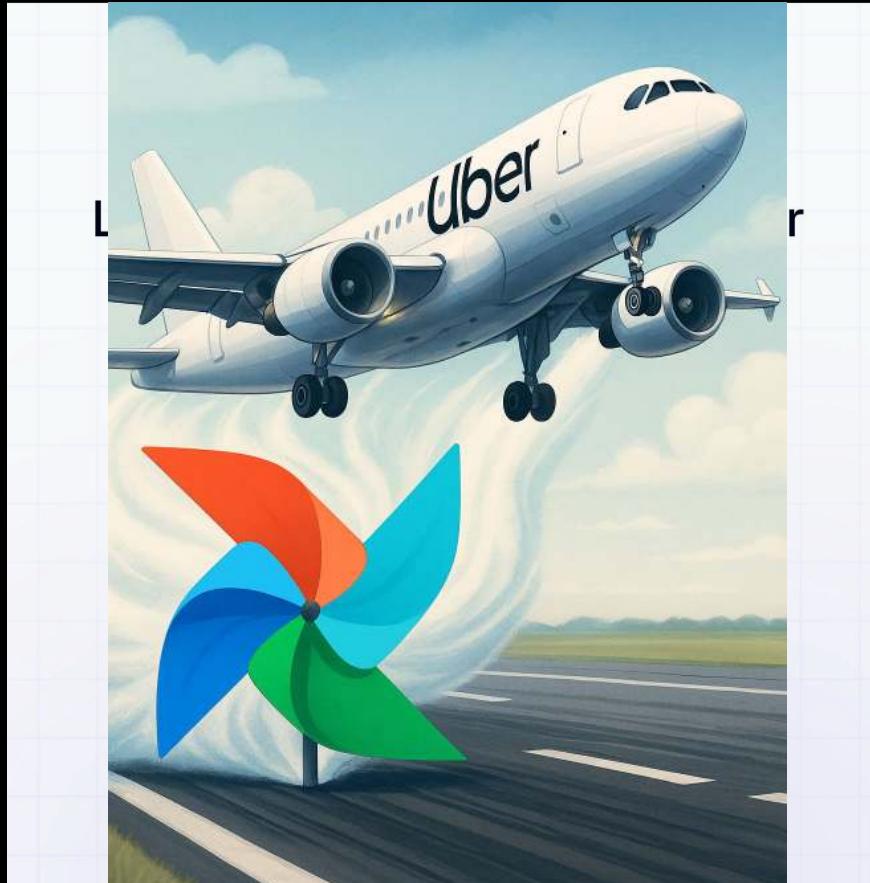
Operation Airlift

Uber's ongoing journey to
migrate to Airflow 3

Sumit Maheshwari

Tech Lead @Uber, PMC Apache Airflow

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Agenda

- **The Story of Piper:** A Look Back
- **The Need for Change:** Challenges with Piper
- **The Path Forward:** Why Apache Airflow?
- **Under the Hood:** Implementation Details
- **Making the Move:** Adoption & Migration
- **Conclusion & Next Steps**

The Story of Piper

A Look Back

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Recap

- Uber's internal fork of Airflow
- Called Piper, born out of Airflow 1.x in 2017
- 200K+ Pipelines
- 800K+ TIs per day
- 1000+ Celery machines
- 50K+ python files
- 1K+ teams

<https://youtu.be/EhrtShXSrsw>

Evolution of Airflow at Uber

Presented at Airflow Summit 2024

Up until a few years ago, teams at Uber used multiple data workflow systems, with some based on open source projects such as Apache Oozie, Apache Airflow, and Jenkins while others were custom built solutions written in Python and Clojure.

Every user who needed to move data around had to learn about and choose from these systems, depending on the specific task they needed to accomplish. Each system required additional maintenance and operational burdens to keep it running, troubleshoot issues, fix bugs, and educate users.

After this evaluation, and with the goal in mind of converging on a single workflow system capable of supporting Uber's scale, we settled on an Airflow-based system. The Airflow-based DSL provided the best trade-off of flexibility, expressiveness, and ease of use while being accessible for our broad range of users, which includes data scientists, developers, machine learning experts, and operations employees.

This talk will focus on scaling Airflow to Uber's scale and providing a no-code seamless user experience

[!\[\]\(6bb0e4f14c4133b37d2887cb37e67ddd_img.jpg\) Download slides](#)



Shobhit Shah
Staff Software Engineer
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Apache Airflow

Divergence

- DAG serialization format defined in JSON (17-18)
- Scheduler was divided and converted into 4 different services (17-18)
 - Organizer (Python) - Similar to DAG processor to serialize pipelines into JSON
 - Orchestrator (Java) - To assign pipelines to different scheduler nodes using Zookeeper
 - Scheduler (Java) - The brain of the system to do the real scheduling of tasks
 - Prioritizer (Java) - Service to enqueue tasks into Redis
- UI driven backfills (19)
- Connections backed by internal secrets platform (19)

Divergence - cont

- In house Disaster Recovery architecture (21)
- Drag & Drop interface to create pipelines (uWorc) (20-21)
- Utilizing read-replicas for load distribution from primary Mysql node (22)
- Jumpstart - Data aware scheduling (22)
- Various framework based pipeline creation frameworks (OneETL etc) (22)
- Full fledged workflow governance (23)
- Hybrid strategy - on-prem and cloud infra running in parallel (24)
- GenAI analysis for task failure summary & mitigation steps (25)

The Need For Change

Challenges With Piper

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Piper - Pain Points

Modernization

No Task Level Identities
Slow Version Upgrades

Efficiency

Duplicate Pipelines
No Dynamic Pipelines
Missing Event Driven Scheduling

Reliability

Celery + Redis
Noisy Neighbours
Safe Deployments

Dev Velocity

Lack of local dev setup
No proper REST APIs
Outdated SDK authoring exp

The Path Forward

Why Apache Airflow

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Why Airflow

Popularity

- Most Popular
- Battle Tested
- Active Community

EcoSystem

- Plenty of Connectors
- Support of all major cloud vendors

Familiarity

- Similar DSL to Piper
- Known-unknowns

Airflow 3

- Isolated workers
- Modern UI & APIs
- DAG versioning
- Tasks in any lang*

Piper < > Airflow

1	Feature	Piper	Airflow 3	Feature	Piper	Airflow 3
2	Serialised DAGs	Y	Y	Isolated Workers	N	Y
3	Scheduler HA	Y	Y	REST APIs	Y*	Y
4	UI Backfills	Y	Y	Custom Timetables	N	Y
5	Dynamic DAGs	N	Y	One pipeline for Trigger & Schedule	N	Y
6	Decorators	N	Y	Disaster Recovery	Y	N
7	Async Tasks	Y	Y	Drag & Drop UI	Y	N
8	K8s Executors/Operators	N	Y	YAML Frameworks	Y	Y*
9	Secret Manager	Y	Y	Governance	Y	N
10	Custom XCom Backends	N	Y	DB Read Replicas	Y	N
11	Data Aware Scheduling	Y*	Y	Non-Pythonic Tasks	N	Y*
12	Event Driven Scheduling	N	Y	GenAI Summary & Mitigation	Y	N
13	DAG Versioning	N	Y	Open Source Community	N	Y

Convergence

- Piper's backfill replaced by Airflow's native backfill functionality
- YAML based frameworks like OneETL rewritten using Dag-Factory
- Data aware scheduling (Jumpstart) moves to Airflow's event driven scheduling
- uWorc (drag & drop UI) gets upgraded to work with Airflow as well

Challenges

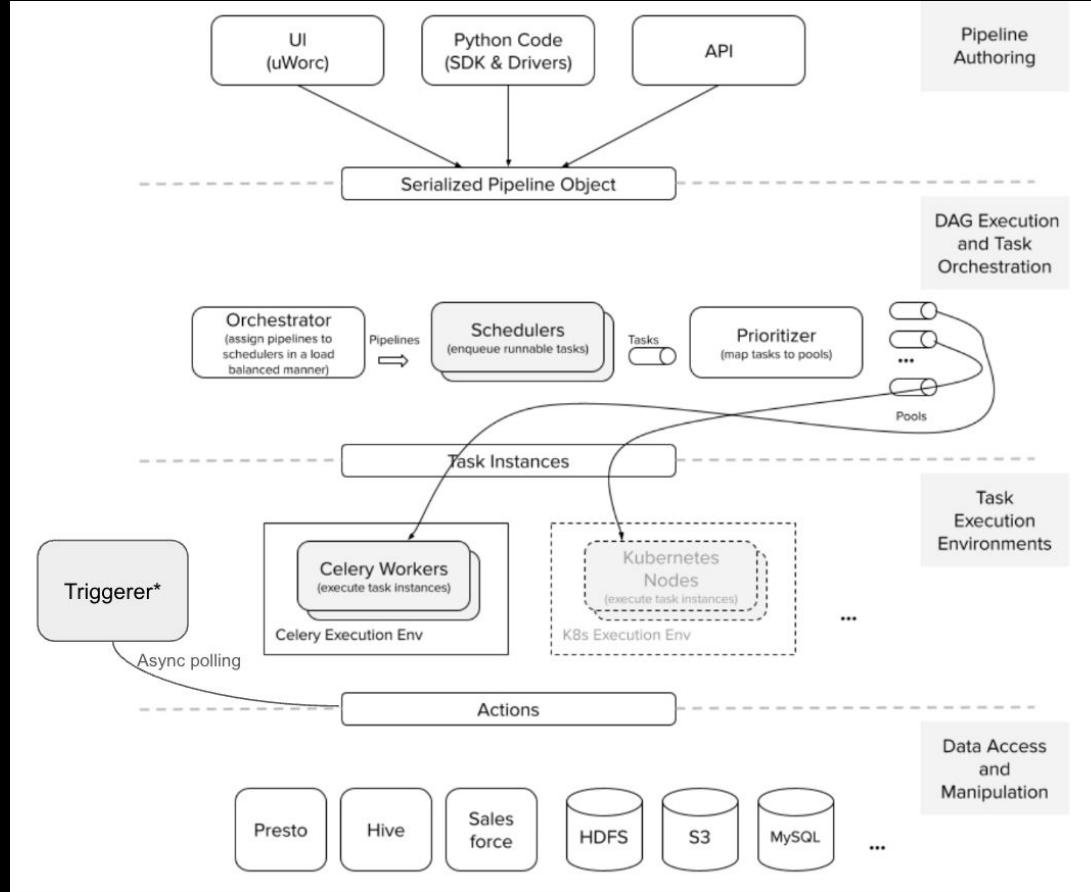
- DAG-Processor is still running in control-plane, exposing metadata DB (AIP-92)
- All Airflow services connects to the same database in read-write mode (AIP-94)
- Airflow's inbuilt Scheduler HA may not be sufficient for Uber's scale (AIP-XX)
- Disaster Recovery framework needs to be rewritten for Airflow
- Missing safe-deployment constructs like auto rollbacks, incremental rollouts, etc

Under The Hood

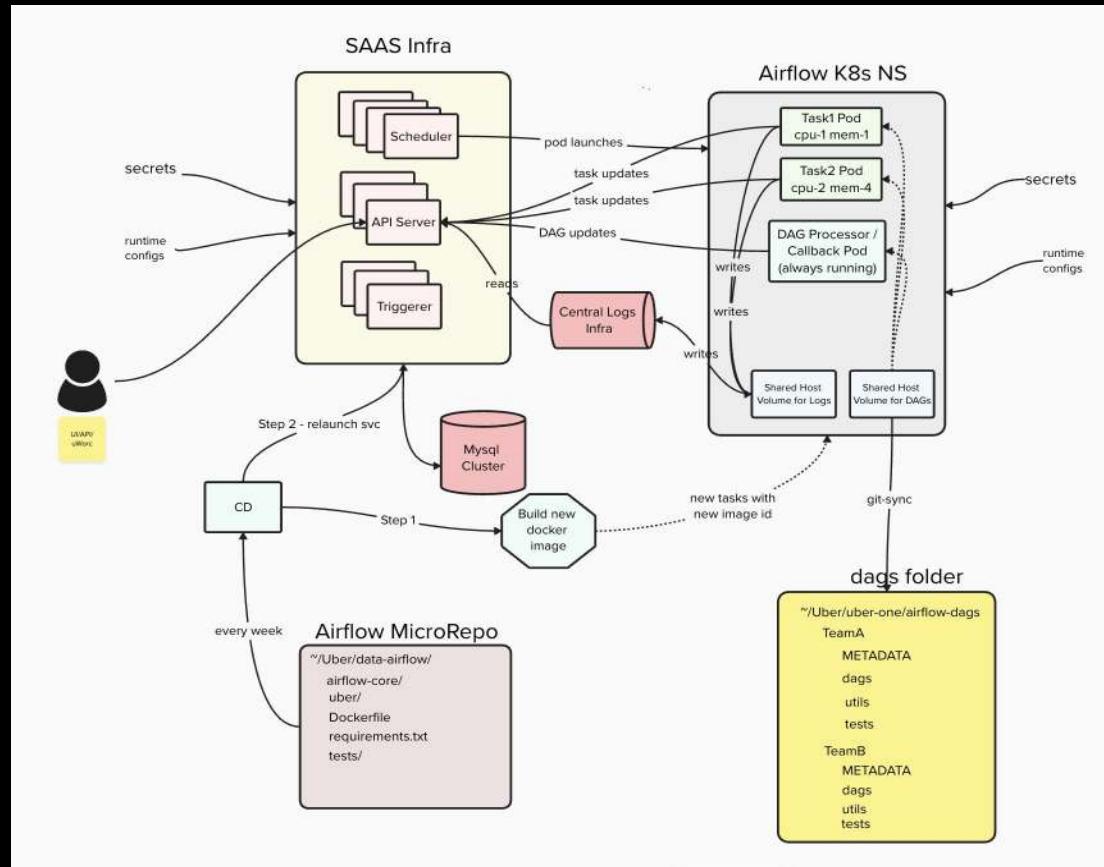
Implementation Details

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Piper HDL

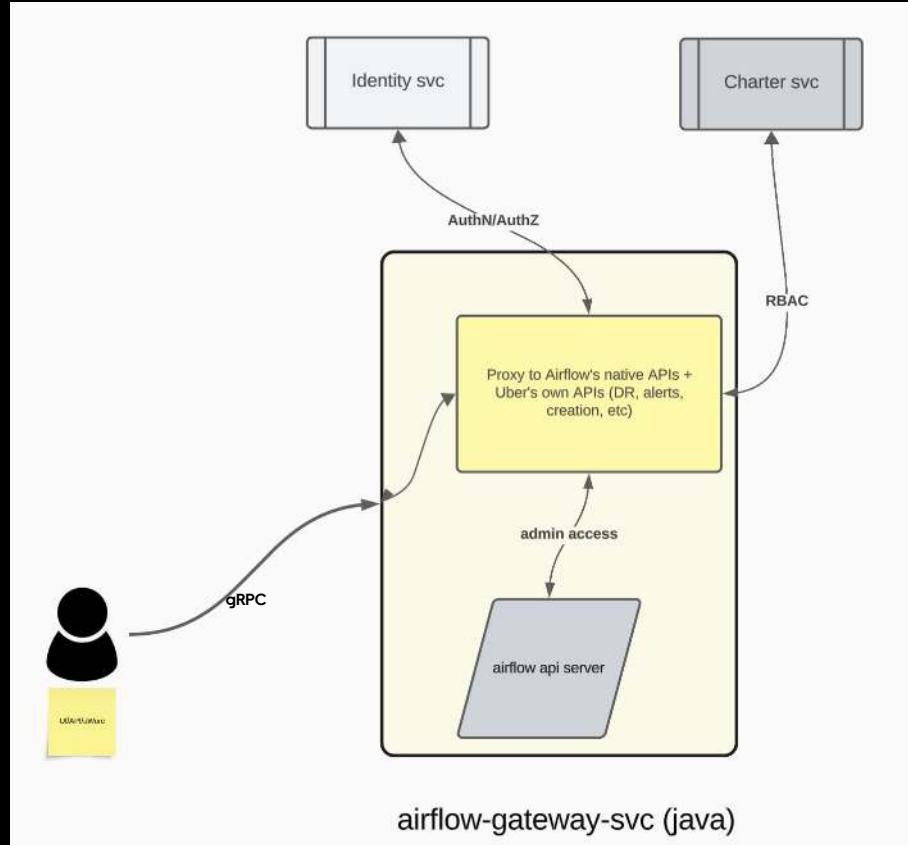


Airflow HLD

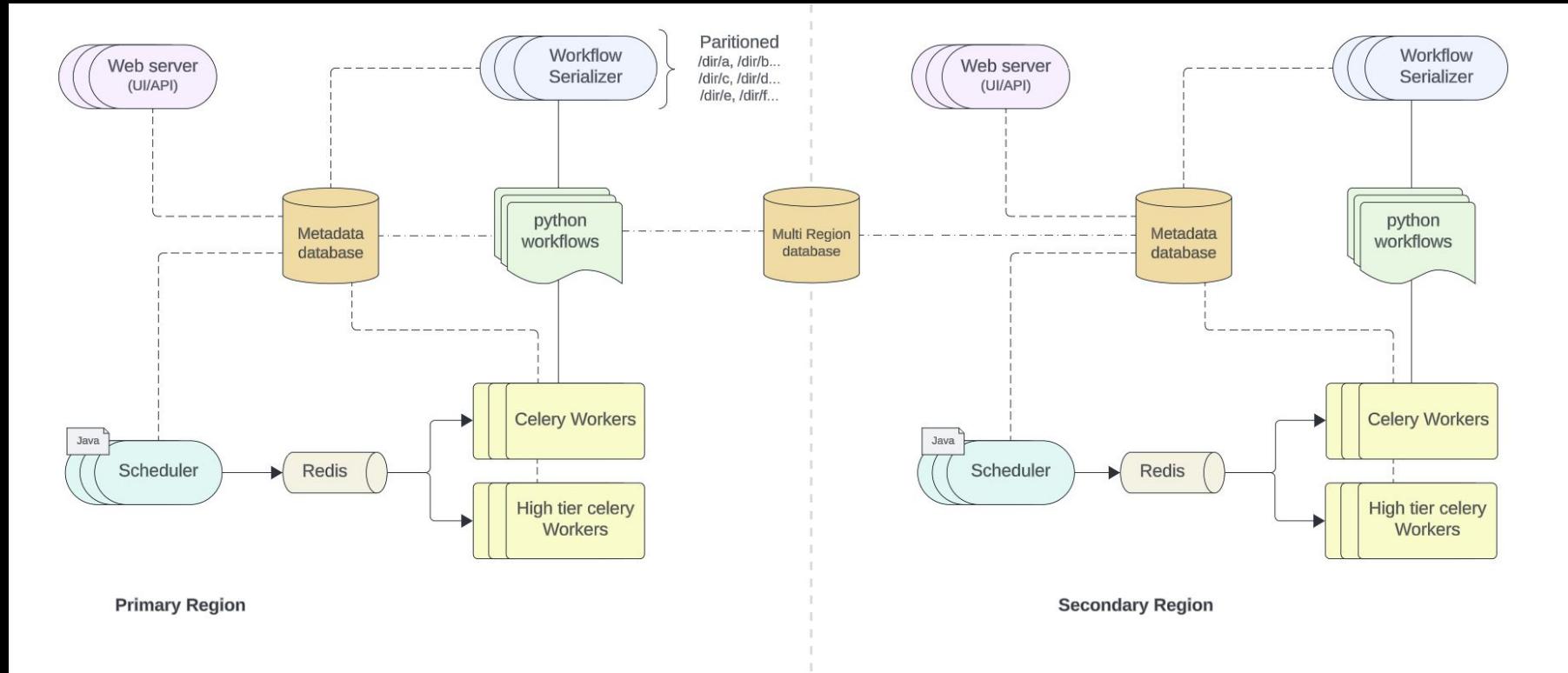


AuthN & AuthZ

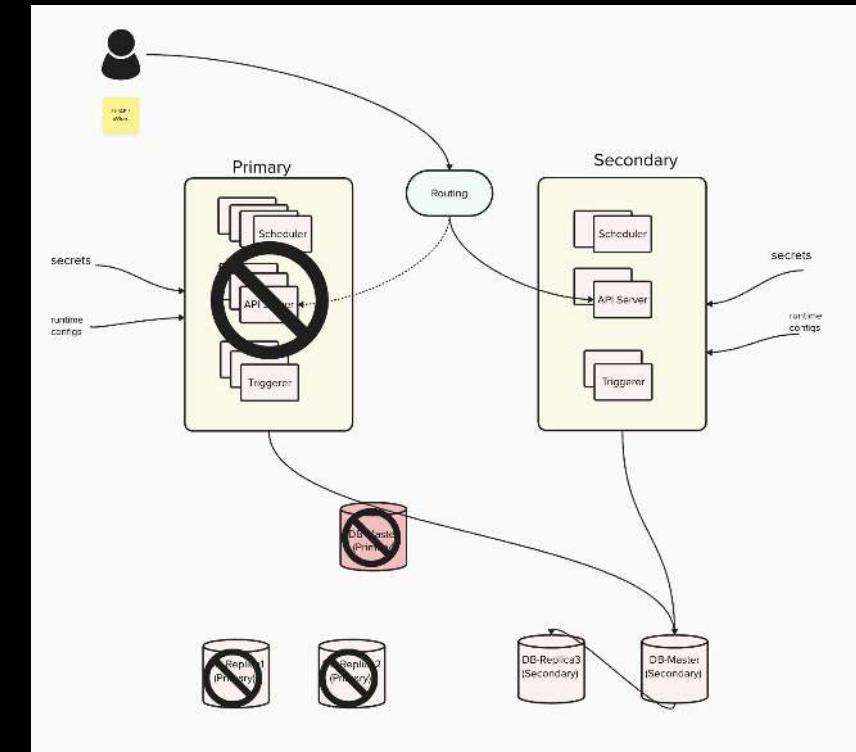
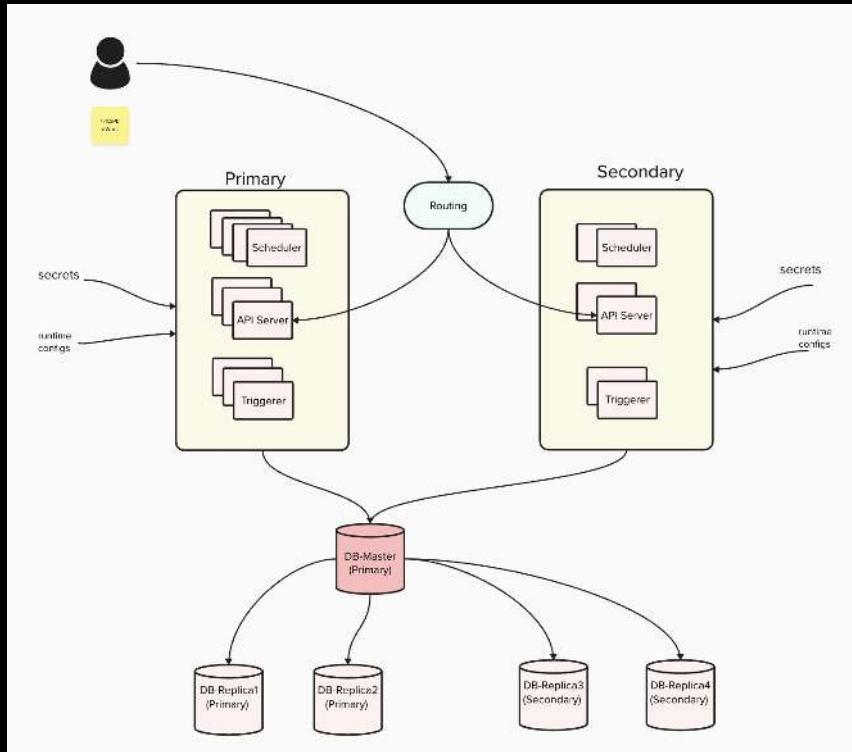
Airflow-web-gateway service written in Java to do all Uber specific authentication & authorization out of Airflow core.



Piper - DR



Airflow - DR



Making The Move

Adoption & Migration

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Types of Pipelines

SDK

Pythonic in nature
Syntax similar to Airflow 1.x

Managed

Drag & Drop pipelines
Stored in DB as JSON

Backfill

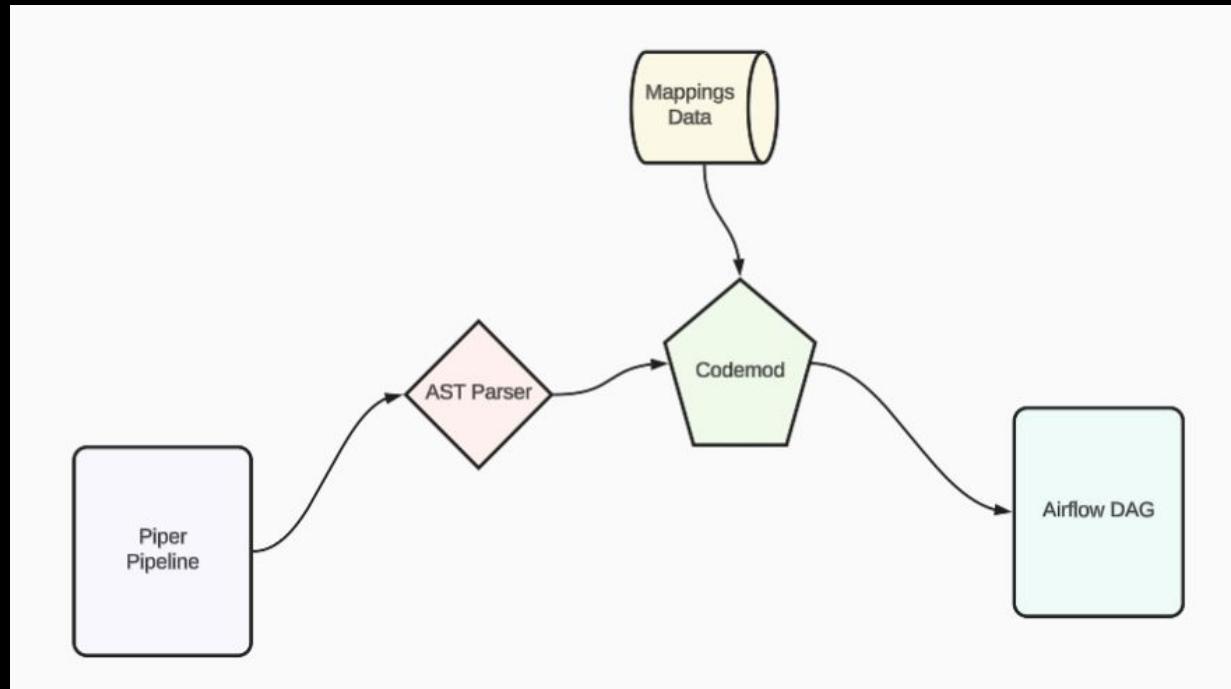
Associated with Parent Pipelines
UI based creation
Stored in DB as JSON

Framework

YAML based pipelines
Dozens of diff frameworks

Conversion of SDK Pipelines

```
# Convert a single pipelines  
piperdev convert  
pipelines/pipeline_watcher/pipeline_  
tier_check_watcher.py  
  
# Convert a whole folder  
piperdev convert  
pipelines/pipeline_watcher/
```



- 27 removals

32 lines Copy

27 lines Copy

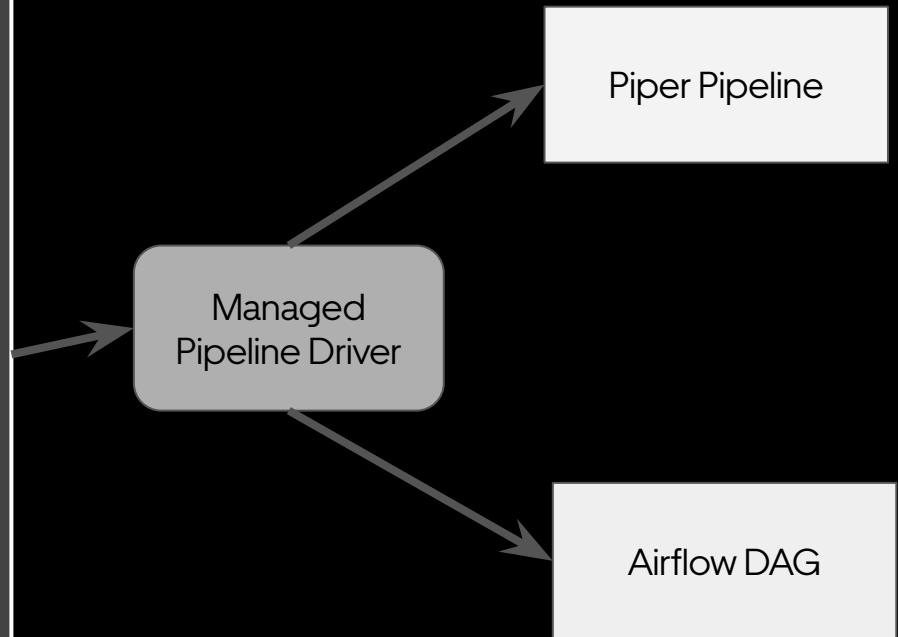
```
1 # -*- coding: utf-8 -*-
2 """ Pipeline to watch pipeline failed status and publish stats """
3 from piper.models import Pipeline
4 from clay import config
5 from datetime import datetime, timedelta
6 from piper.tasks.dummy_task import DummyTask
7 from pipelines.core.dwm_admin.pipeline_watcher.tasks.watch_pipeline_failed_task import WatchPipelineFailTask
8 from piper.models.pipeline import RUN_IN_ALL_DATACENTERS
9 logger = config.get_logger('piper')
10 POOL_NAME = 'piper_admin'
11 PID = 'metric_pipeline_fail_watcher'
12 args = {
13     'owner': 'data_workflow_management',
14     'owner_ldap_groups': ['piper', 'data_workflow_management'],
15     'depends_on_past': False,
16     'auto_backfill': False,
17     'pool': POOL_NAME,
18     'email': ['redacted@abc.com'],
19     'retries': 3,
20 }
21 pipeline = Pipeline(
22     pipeline_id=PID,
23     schedule_interval=timedelta(hours=4),
24     secure=True,
25     start_date=datetime(2020, 5, 6, 0, 0, 0),
26     default_args=args,
27     datacenter_choice_mode=RUN_IN_ALL_DATACENTERS
28 )
29 # last task
30 complete_task = DummyTask(task_id='complete', pipeline=pipeline, default_args=args)
31 watch_pipeline_failed_task = WatchPipelineFailTask(task_id='watch_pipeline_fail',
32     pipeline=pipeline, default_args=args)
33 watch_pipeline_failed_task.set_downstream(complete_task)
```

+ 20 additions

```
1 """ Pipeline to watch pipeline failed status and publish stats """
2 from airflow.models import DAG
3 from airflow.configuration import conf as config
4 from datetime import datetime, timedelta
5 from airflow.providers.standard.operators.empty import EmptyOperator
6 from pipelines.core.dwm_admin.pipeline_watcher.tasks.watch_pipeline_failed_task import (
7     WatchPipelineFailTask,
8 )
9 POOL_NAME = "piper_admin"
10 PID = "metric_pipeline_fail_watcher"
11 args = {
12     "owner": "data_workflow_management",
13     "depends_on_past": False,
14     "pool": POOL_NAME,
15     "email": ["redacted@abc.com"],
16     "retries": 3,
17 }
18 pipeline = DAG(
19     dag_id=PID,
20     schedule=timedelta(hours=4),
21     start_date=datetime(2020, 5, 6, 0, 0, 0),
22     default_args=args,
23 )
24 complete_task = EmptyOperator(task_id="complete", dag=pipeline)
25 watch_pipeline_failed_task = WatchPipelineFailTask(
26     task_id="watch_pipeline_fail", dag=pipeline)
27 watch_pipeline_failed_task << complete_task
```

Conversion of Managed Pipelines

```
{  
    "owner": "abc",  
    "tasks":  
    [  
        {  
            "pool": "adhoc",  
            "retries": 1,  
            "task_id": "emit_metric_to_m3",  
            "task_class": "pipelines.core.dwm.emit_metric_to_m3_task.EmitMetricToM3Task",  
            "task_params": {},  
            "dependencies": []  
        }  
    ],  
    "end_date": "2025-04-13T16:00:48Z",  
    "execution_engine": "airflow",  
    "start_date": "2024-04-13T16:00:00Z",  
    "pipeline_id": "000046de-f9af-11ee-af7e-1070fd426416",  
    "json_version": "1.0",  
    "pipeline_name": "managed_pipeline_test_sample",  
    "owner_ldap_groups": ["piper"],  
    "schedule_interval": 600,  
    "selected_datacenters": [],  
    "datacenter_choice_mode": "run_in_all_datacenters"  
}
```



Conversion of Framework Pipelines

Config directory format for pipelines

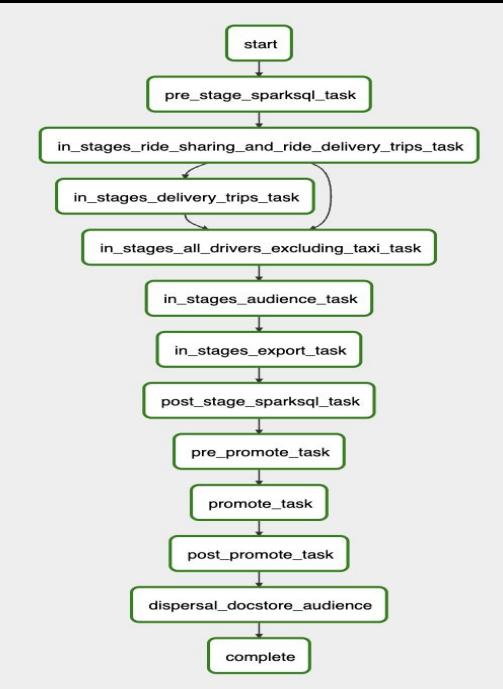
```

one_etl/
  config/
    ddl/
      //CREATE TABLE statement
      <table_1_name>.ddl
      <table_2_name>.ddl
    jobs/
      //Pipeline configuration
      <table_1_name>.yaml
      <table_2_name>.yaml
    sql/
      //Transformation logic
      <table_1_name>.sql
      <table_2_name>.sql
  
```

Example pipeline yaml

```

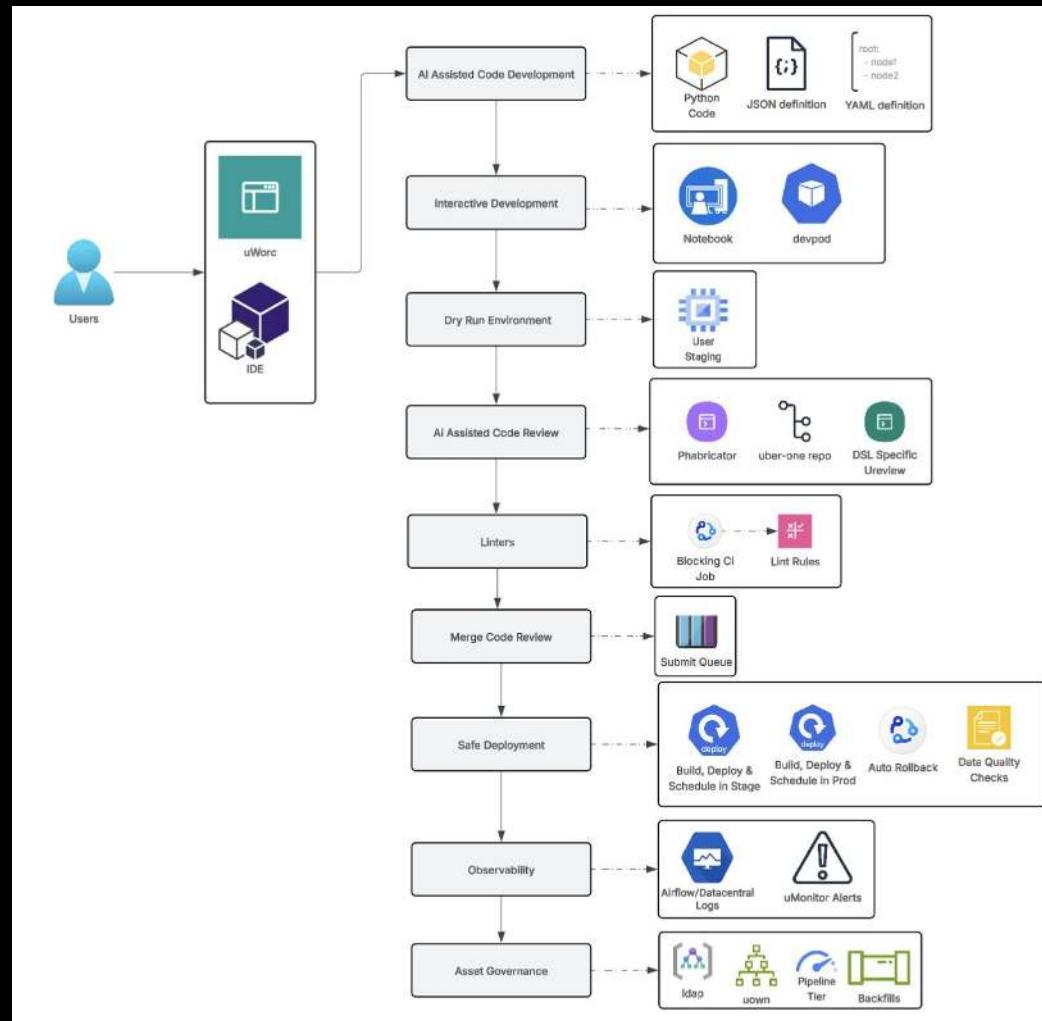
owner: alice
hive_table: schema.table
spark_opts:
  queue: spark-adhoc
  ddl_file: <TEAM>/ddl/example_ddl.ddl
  sql_file: <TEAM>/sql/example_sql.sql
  execution_engine: spark
  start_date: '2025-09-15'
  hive_staging_schema: stg_schema
  hive_test_schema: test_schema
  hive_partition_key: datestr
execution_engine: airflow
  
```



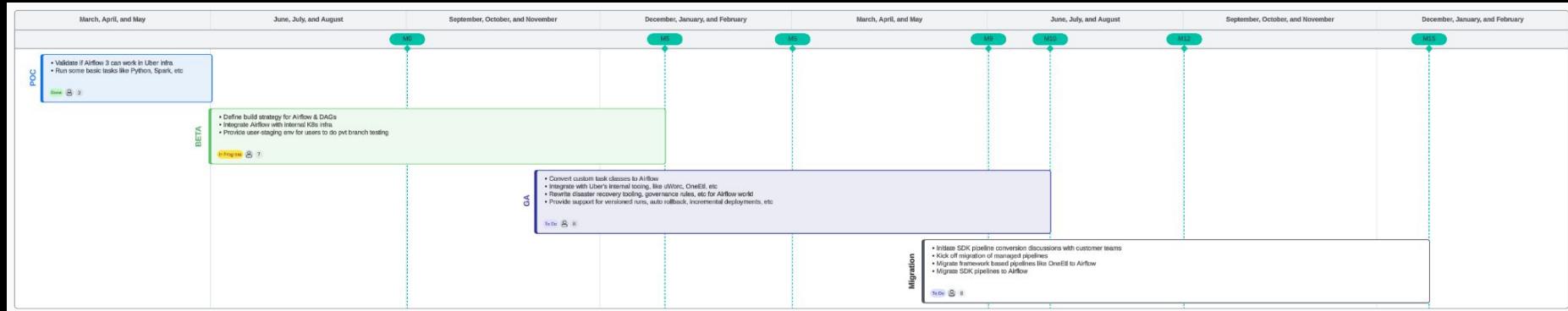
Conclusion & Next Steps

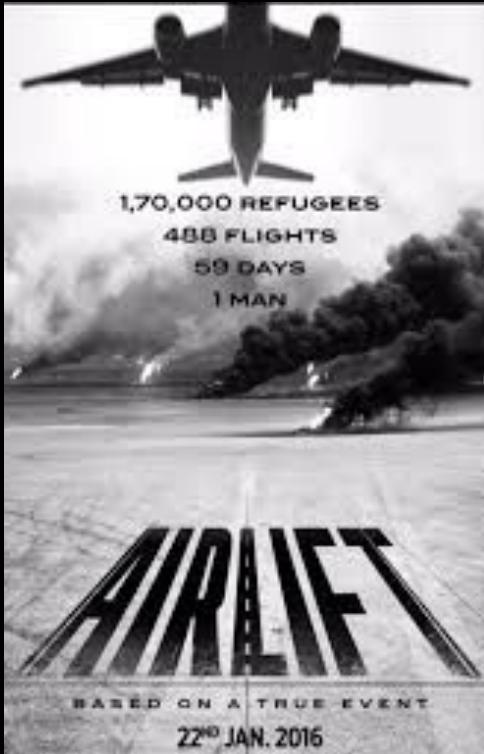
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End Goal



Timelines





PC: bollywooddirect.com



PC: chat.openai.com

Questions?

