

ARTHUR WIEDMER / FEBRUARY 2017

# Apache Airflow @ Airbnb

AND BEYOND  
(IF THERE IS TIME)





## About Me

- **Data Engineer on the Data Platform Team at Airbnb.**
- **Working on Airflow since 2014, Apache Airflow committer**
- **I work on both Airflow and building internal frameworks on top of it.**
- **Most of my free time is spent with my wife and our 1 year-old son :)**

**What is Airflow?**

**What can Airflow do for you?**

**What should you know  
before you start?**



**Airflow?**





## Why does Airflow exist?

- Companies grow to have a **complex network of processes that have intricate dependencies**.
- Analytics & batch processing are **mission critical**. They serve decision makers and power machine learning models that can feed into production.
- There is a lot of **time invested in writing and monitoring jobs and troubleshooting issues**.

# What is Airflow?

**An open source platform to author, orchestrate and monitor batch processes**

- It's the **glue** that binds your data ecosystem together
- It **orchestrates** tasks in a complex networks of job dependencies
- It's **Python** all the way down
- It's **popular** and has a thriving open source community
- It's **expressive** and **dynamic**, workflows are defined in code

# Concepts

- **Workflows** are called **DAGs** for Directed Acyclic Graph.

# On DAG: airflow\_maintenance

schedule: 1 day, 0:00:00

Graph View

Tree View

Task Duration

Task Tries

Landing Times

Gantt

Details

Code

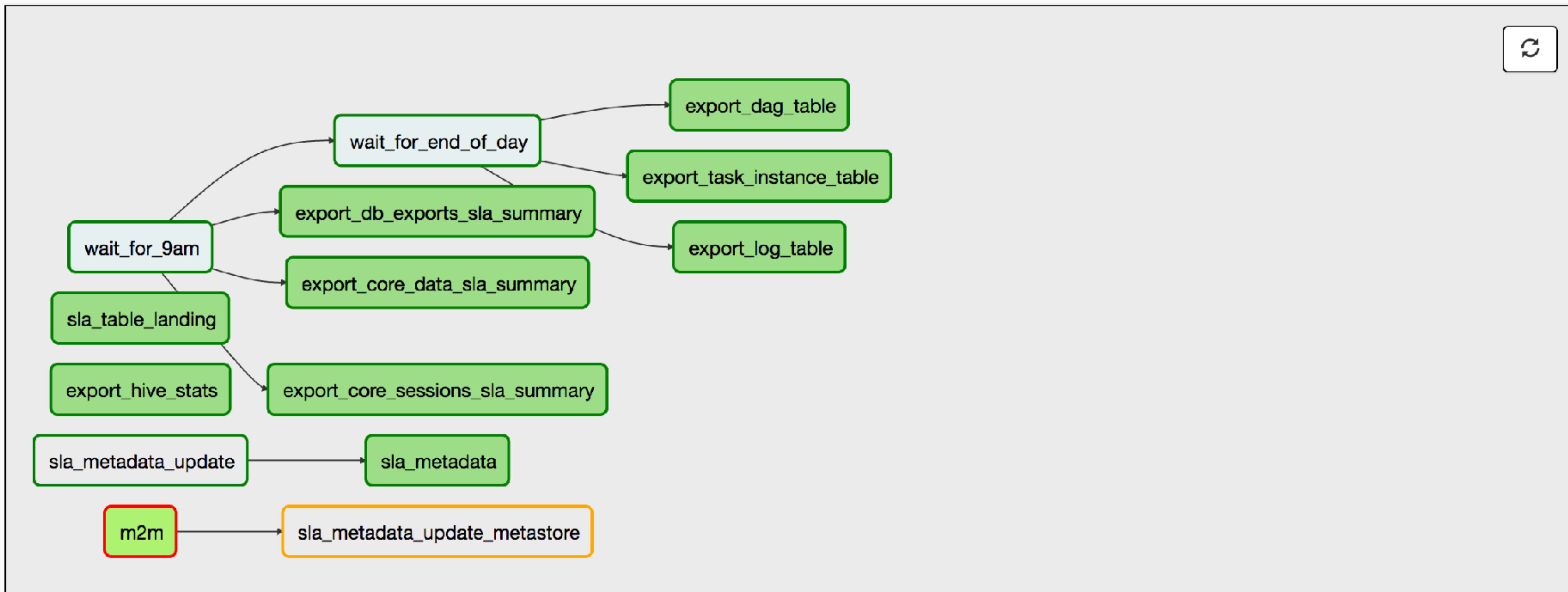
Refresh

failed Run: scheduled\_\_2017-02-15T00:00:00 Layout: Left->Right Go

Search for...

GenericTransfer MySqlOperator MySqlToHiveTransfer TimeSensor

success running failed skipped retry queued no status



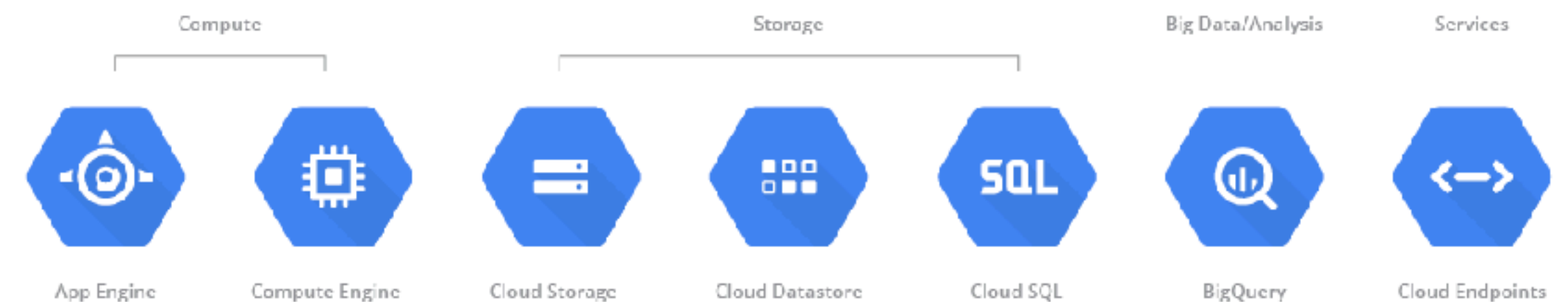


```
dag = DAG(  
    'tutorial',  
    default_args=default_args,  
    description='A simple tutorial DAG',  
    schedule_interval=timedelta(days=1))
```

# Concepts



- **Tasks:** Workflows are composed of tasks called **Operators**.
- Operators can do pretty much anything that can be run on the Airflow machine.
- We tend to classify operators in 3 categories : **Sensors, Operators, Transfers.**





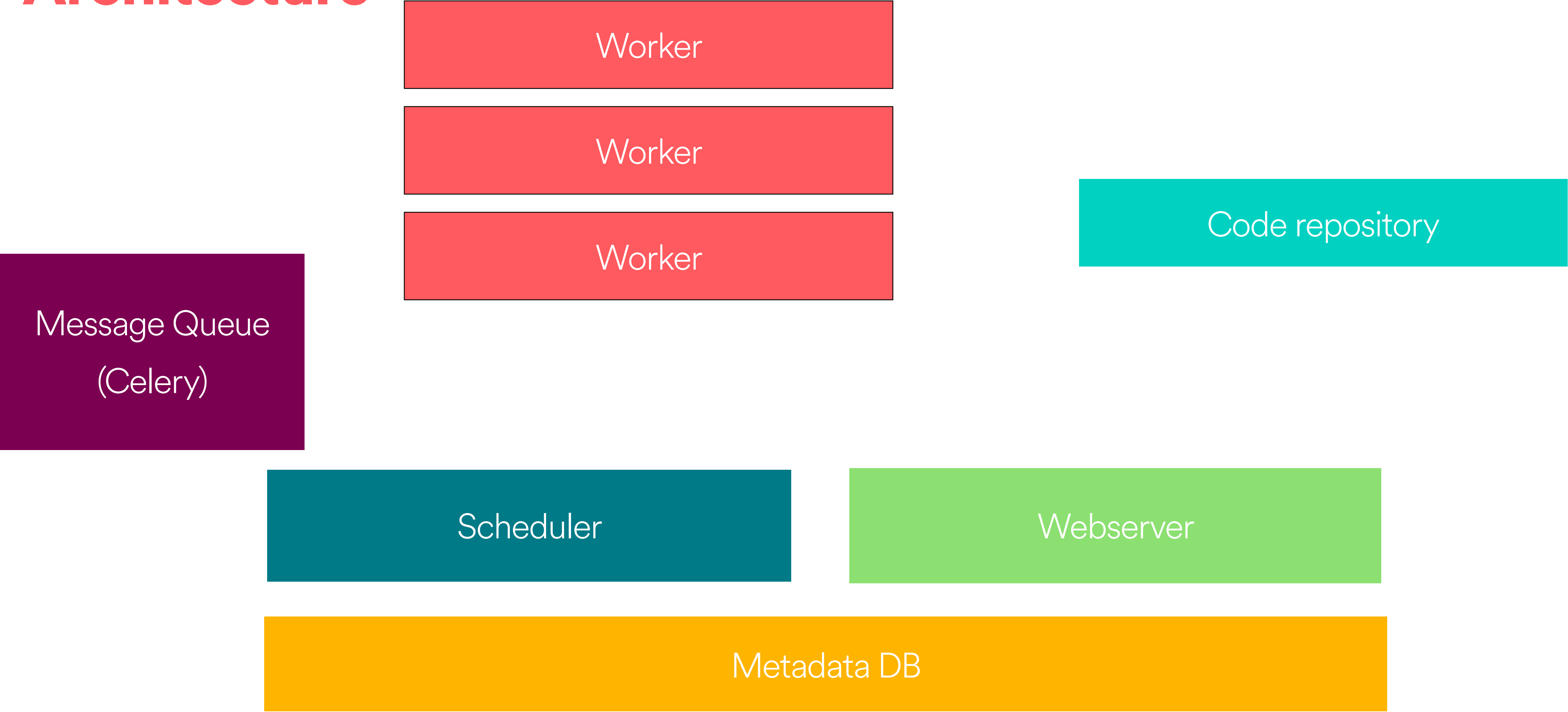
```
t1 = BashOperator(  
    task_id='print_date',  
    bash_command='date',  
    dag=dag)
```

# Setting dependencies

```
t2.set_upstream(t1)
```



# Architecture





A photograph of a modern, open-plan kitchen and living area. Four people are present: a man on the left leaning on a table, a woman in the center leaning on a long wooden kitchen island, another woman to her right also leaning on the island, and a man on the far right sitting on a stool. The kitchen features a long wooden island with a built-in cooktop, a sink, and various items like a dish rack and a towel. Large windows in the background offer a view of greenery. The entire image is overlaid with a semi-transparent red filter.

**What can Airflow do for you?**



# Monitoring

# Monitoring DAG Status

## DAGs

Show  entries

Search:

		DAG	Schedule	Owner	Recent Tasks	Last Run	DAG Runs	Links
	On	airflow_maintenance	1 day, 0:00:00	maxime_beauchemin		2017-02-23 00:00	<div><div>143</div><div>1</div><div>332</div></div>	
	On	core_data	1 day, 0:00:00	maxime_beauchemin		2017-02-23 00:00	<div><div>391</div><div>2</div><div>83</div></div>	

Last Run	DAG Runs
2017-02-23 00:00	<div><div>143</div><div>1</div><div>332</div></div>
2017-02-23 00:00	<div><div>391</div><div>2</div><div>83</div></div>



# Monitoring DAG Status

On

DAG: airflow\_maintenance

Schedule: 1 day, 0:00:00

- Graph View

Tree View

Task Duration

Task Tries

Landing Times

Gantt

Details

Code

Refresh

## DAG details

None118

failed29

running1

success410

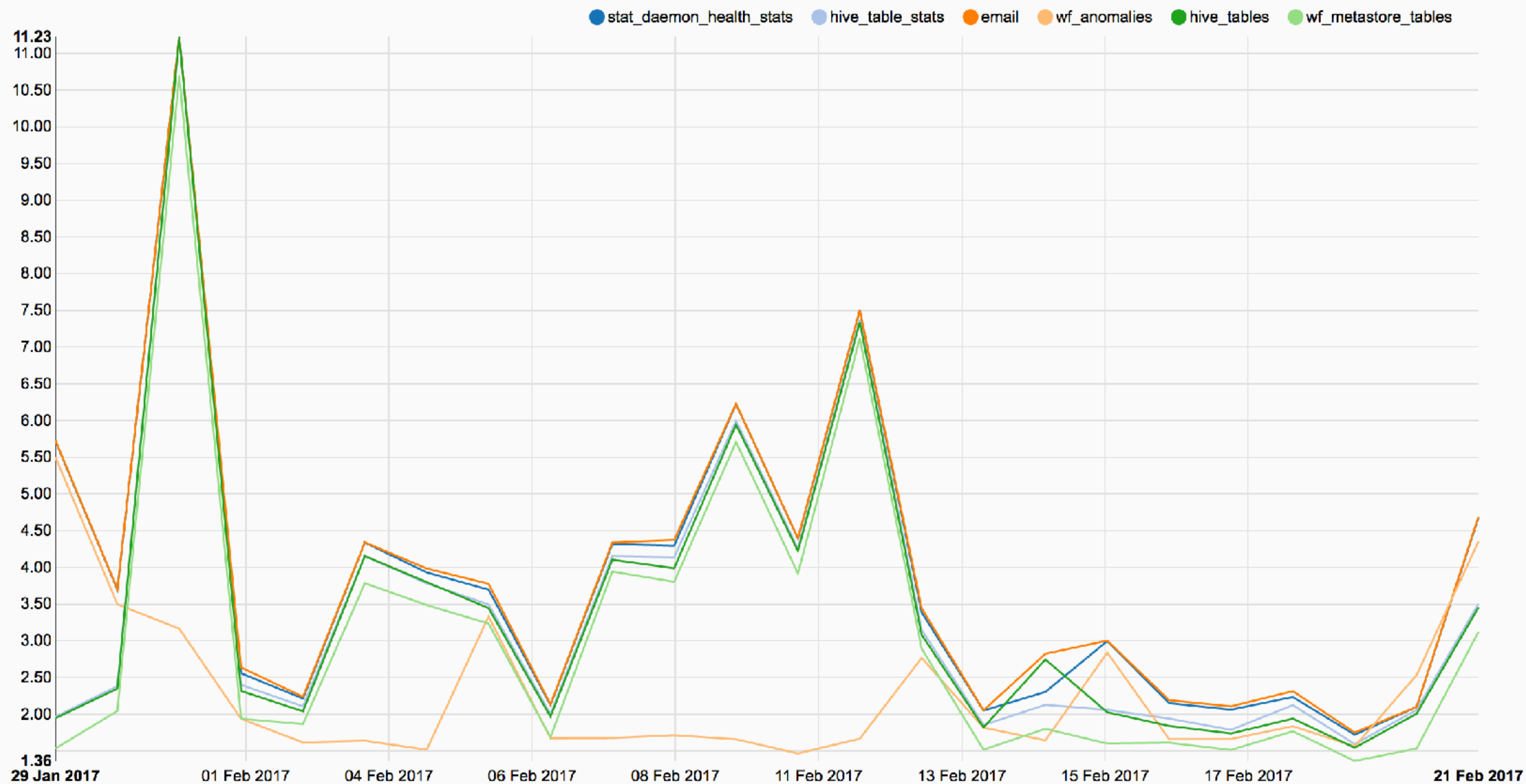
upstream\_failed30

schedule_interval	1 day, 0:00:00
max_active_runs	0 / 16
concurrency	16

# Monitoring Gantt Chart style





[Graph View](#) [Tree View](#) [Task Duration](#) [Task Tries](#) [Landing Times](#) [Gantt](#) [Details](#) [Code](#) [Refresh](#)Base date:  Number of runs:  

**Scale**

# Airflow @ Airbnb : scale

- We currently run 800+ DAGs and about ~**80k tasks** as day.
- We have DAGs running at **daily, hourly and 10 minute** granularities. We also have ad hoc DAGs.
- About **100 people @ Airbnb have authored or contributed to a DAG** directly and 500 have contributed or modified a configuration to one of our frameworks.
- We use the Celery executor with Redis as a backend.



**Flexibility**

# Airflow @ Airbnb

**Experimentation**

Growth Analytics

Search Ranking

Operational Work

**Data Warehousing**

Engagement Analytics

Anomaly Detection

Infrastructure Monitoring

Data Exports  
from/to production

Sessionization

Email Targeting

# Common Pattern

## Input

Edit Experiment Schema **Active**

Name:

Intention:

Product Spec:

Owner:

Team:

Status:

Start Date:

Exposure:

Subject:

Remote Clients:

CX Support

Needs Support?:

Control and Treatments

Control:

Description:

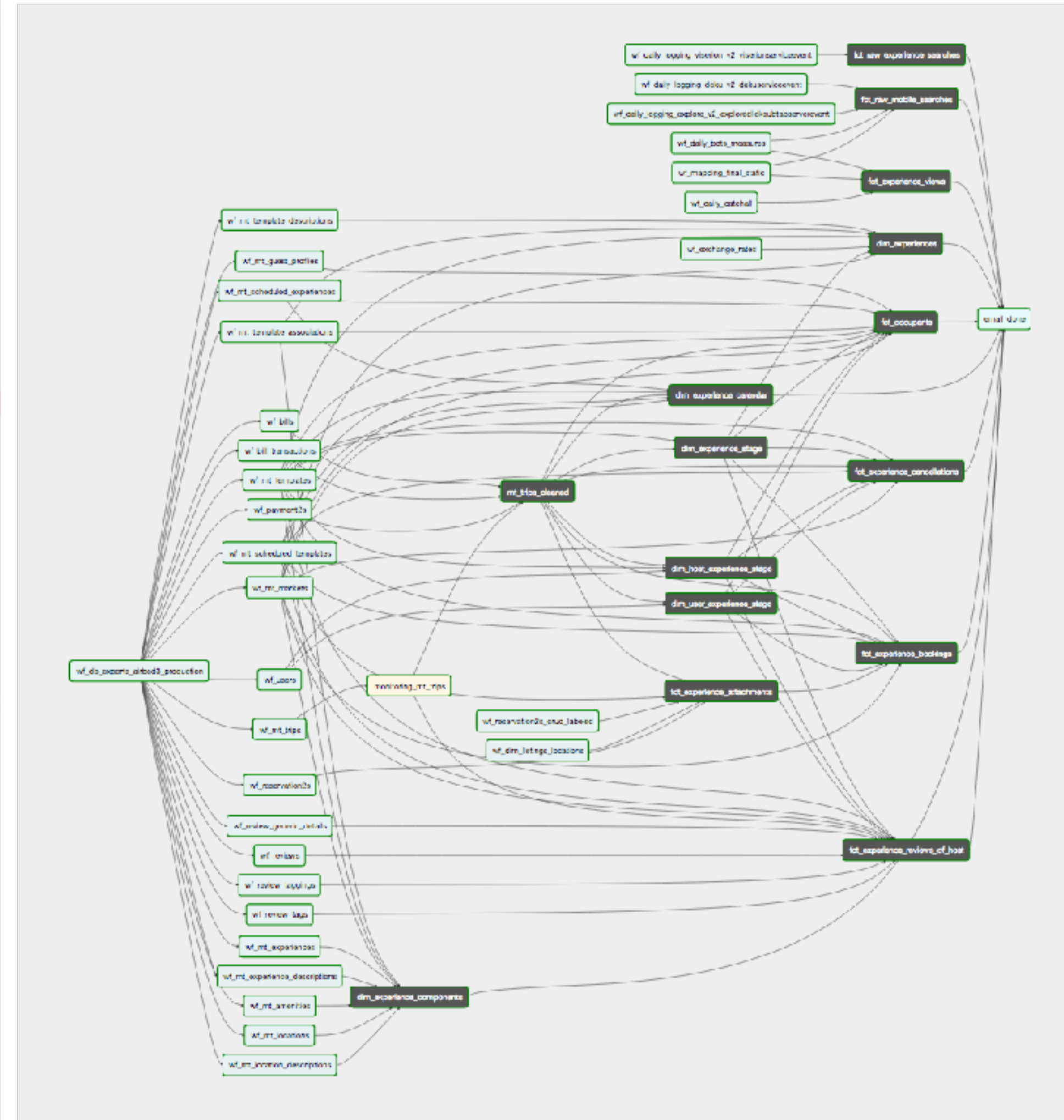
Buckets:

Screenshot:

Treatment:

Description:

## Data Processing



## Output

0.18 128/713	420% ± 290		★★★ < 0.01
0.56 5/9	▼ 2.8% ± 66		☆☆☆ 0.95
0.05 34/713	320% ± 290		★★★ 0.03
0.22 2/9	56% ± 260		☆☆☆ 0.68
0.04 27/713	180% ± 340		☆☆☆ 0.31
0.22 2/9	▼ 48% ± 110		☆☆☆ 0.38



# CumSum

## Efficient cumulative metrics computation

- Live to date metrics per subject (user, listings, advertiser, ...) are a common pattern
- Computing the SUM since beginning of time is inefficient, it's preferable to add up today's metrics to yesterday's total

```
SELECT userid, COUNT(*) as ltd_bookings  
FROM fct_bookings  
WHERE ds <= '{{ ds }}'  
GROUP BY userid
```

```
metric: bookings  
owner: data-engineering@airbnb.com  
subject: user  
sql: |  
    SELECT userid, COUNT(1) as metric  
    FROM fct_bookings  
    WHERE ds = '{{ ds }}'  
    GROUP BY userid  
dependencies:  
    core_data.fct_bookings:  
        partition: ds
```

```
SELECT userid, SUM(ltd_bookings)  
FROM (  
    -- Yesterday's total from summary table  
    SELECT userid, ltd_bookings  
    FROM cumsum  
    WHERE ds = '{{ yesterday_ds }}'  
    UNION ALL  
    --- Today's transaction to add to existing total  
    SELECT userid, 1 AS ltd_bookings  
    FROM fct_bookings  
    WHERE ds = '{{ ds }}'  
) as subqry  
GROUP BY userid
```

# CumSum

## Efficient cumulative metrics computation

- Live to date metrics per subject (user, listings, advertiser, ...) are a common pattern
- Computing the SUM since beginning of time is inefficient, it's preferable to add up today's metrics to yesterday's total

## Outputs

- An efficient pipeline
- Easy / efficient backfilling capabilities
- A centralized table, partitioned by metric and date, documented by code
- Allows for efficient time range deltas by scanning 2 partitions

```
SELECT user_id, SUM(ltd_bookings)
FROM fct_bookings
WHERE ds < '{{ yesterday_ds }}'
GROUP BY user_id
```

```
metric: bookings
owner: data-engineering@airbnb.com
subject: user
sql: |
    SELECT user_id, COUNT(1) as metric
    FROM fct_bookings
    WHERE ds = '{{ ds }}'
    GROUP BY user_id
dependencies:
  core_data.fct_bookings:
    partition: ds
```

```
SELECT user_id, SUM(ltd_bookings)
FROM (
  -- yesterday's total from summary table
  SELECT user_id, ltd_bookings
  FROM cumsum
  WHERE ds = '{{ yesterday_ds }}'
  UNION ALL
  -- today's transaction to add to existing total
  SELECT user_id, 1 AS ltd_bookings
  FROM fct_bookings
  WHERE ds = '{{ ds }}'
)
GROUP BY user_id
```



A photograph of a modern, open-plan kitchen and living area. Four people are present: a man on the left leaning on a table, a woman in the center leaning on a long wooden counter, another woman behind her, and a man on the right sitting on a stool. The room features large windows, wooden floors, and modern decor. The entire image is overlaid with a semi-transparent red filter.

**What should you know to get started?**



# Monitoring and Alerting

- Enable the email feature and EmailOperator/SlackOperator for monitoring.
- Ease of monitoring will help you keep track of your jobs as their number grows.
- Checkout the SLA feature to know when your jobs are not completing on time.
- The scheduler is still the weakest link as it is a single point of failure. Enabling service monitoring with runit, monit can be useful if you need to guarantee uptime.



# Metadata Database

- As the number of jobs you run on Airflow increases, so does the load on the Airflow database.
- SQLite is used for tutorials but cannot handle concurrent connections. We highly recommend switching to MySQL/MariaDB or Postgres.
- Some people have tried other databases, but we cannot currently test against them, so it might break in the future.

# Best Practices about DAG building

- Try to make you tasks idempotent. Airflow will then be able to handle retrying for you in case of failure.
- You can setup pools for resource management.
- SubDAGs are still not completely without issues.

# Configuration as Code!

**As an alternative to static YAML, JSON or worse: drag and drop tools**

- Code is more expressive, powerful & compact
- Reusable components (functions, classes, object factories) come naturally in code
- An API has a clear specification with defaults, input validation and useful methods
- Nothing gets lost into translation: Python is the language of Airflow.
- The API can be derived/extended as part of the workflow code. Build your own Operators, Hooks etc...
- In its minimal form, it's as simple as static configuration



A photograph of a modern, open-plan kitchen and living area. Four people are present: a man on the left with a backpack, a woman in the center with curly hair, another woman leaning over a long wooden kitchen island, and a man on the right sitting on a stool. The room features large windows, pendant lights, and a clean, minimalist design. The entire image is overlaid with a semi-transparent red filter.

# The future of Airflow



## Quick history of Airflow @ Airbnb

- Back in 2014 we were using **Chronos** a Framework for long running jobs on top of **Mesos**.
- Defining data dependencies was near impossible. Debugging why data was not landing on time was really difficult.
- Max Beauchemin joined Airbnb and was interested in open sourcing an entirely rewritten version of Data Swarm, the job authoring platform at Facebook.
- Introduced **Jan 2015** for our main warehouse pipeline.
- Open sourced in **early 2015**, donated to the **Apache Foundation** for Incubation in **march 2016**.

# Apache Airflow

- The community is **currently working on version 1.8.0**. To be released soon.
- The **focus** has been on **stability** and **monitoring/troubleshooting** enhancements.
- We hope to graduate to Top Level Project this year.
- We are looking for contributors. Check out the project and come hack with us.





# Resources



# Airflow Resources

- The Airflow community is active on **Gitter** at <https://gitter.im/apache/incubator-airflow> and has a lot of user to user help.
- If you have more advanced questions, the dev mailing list at [http://mail-archives.apache.org/mod\\_mbox/incubator-airflow-dev/](http://mail-archives.apache.org/mod_mbox/incubator-airflow-dev/) has the core developers on it.
- The documentation is available at [\*\*https://airflow.incubator.apache.org/\*\*](https://airflow.incubator.apache.org/)
- The project also has a wiki : <https://cwiki.apache.org/confluence/display/AIRFLOW/Airflow+Home>

# Airflow Talks

- The Bay Area Airflow meet up :

<https://www.meetup.com/Bay-Area-Apache-Airflow-Incubating-Meetup/>

- Matt Davis at PyBay 2016:

<https://speakerdeck.com/pybay2016/matt-davis-a-practical-introduction-to-airflow>

- Laura Lorenz at PyData DC 2016 How I learned to time travel, or, data pipelining and scheduling with Airflow :

<https://www.youtube.com/watch?v=60FUHEkcPyY>



A photograph of a modern, open-plan kitchen and living area. Four people are present: a man on the left leaning on a table, a woman in the center leaning on a long wooden counter, another woman behind her looking at something on the counter, and a man on the right sitting on a stool. The room features large windows, wooden floors, and modern decor. The word "Questions?" is overlaid in white text in the center.

# Questions?



