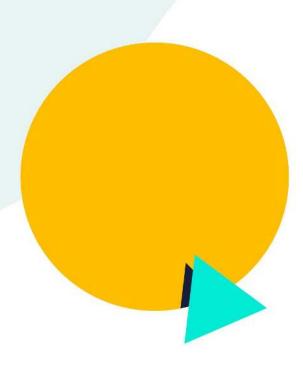


Reasoning Reliability in Wrike's Data Pipeline



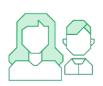
Wrike - A Collaborative Work Management Platform



Founded in 2006



10 Offices Globally



20,000+ Customers Globally



1000+ Employees



5 years in the Fast 500

20,000+

Organizations choose Wrike to orchestrate their digital work

With an additional 35,000 starting trials each month

- 2M users
- 130+ countries
- 10 languages
- 100M+ completed tasks

















Panasonic







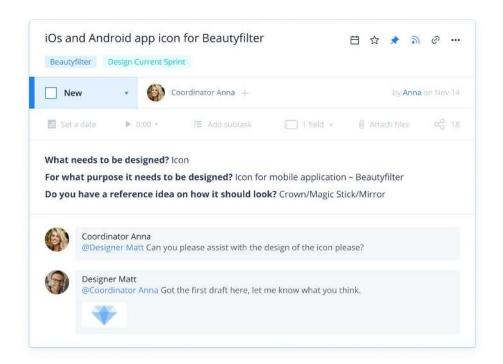


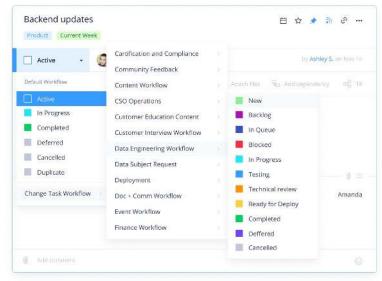


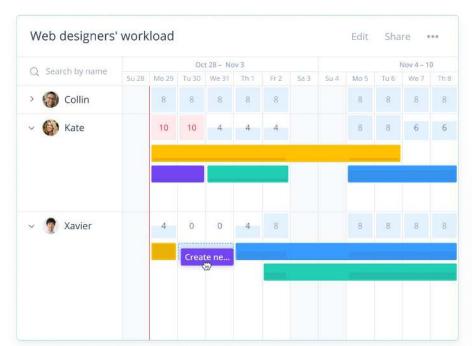


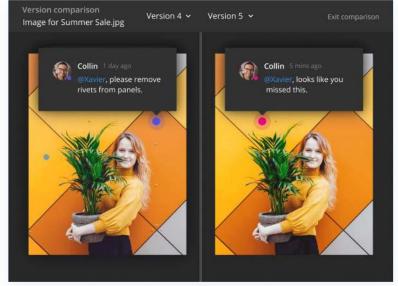


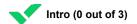


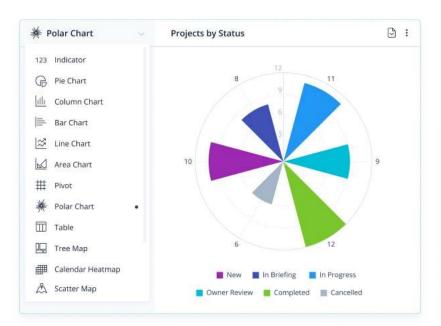


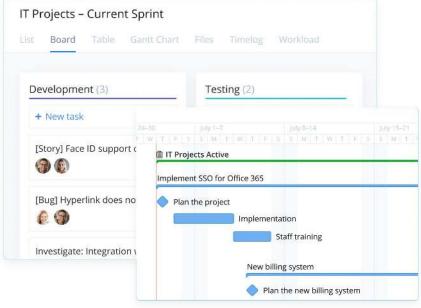


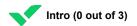


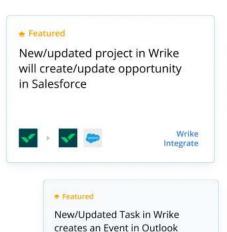


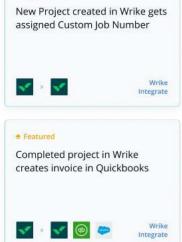








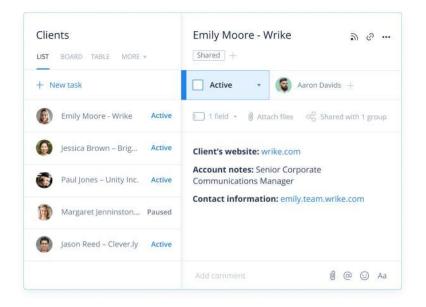




* Featured

Wrike

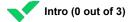
Integrate



Calendar

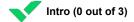
Data Engineering in Wrike

- SaaS means that we
 - Create
 - Support
 - Sell our product, and
 - Attract leads
- Help these teams speak the language of data
- We've got big space for data democratization



Data Engineering Team in Wrike

- 16 data engineers in 4 teams
- We're supporting 250+ DAGs on production
- Up to 1200 tasks
- With median of 13 tasks
- ~10 updates of production or acceptance each day
- Helped 5 other teams to start using Airflow
- ~10-15% of our colleagues are using data engineering infrastructure and sources every month directly (>50% are using analytical reports or through integrations)



We've Started With

- First analysts using new Data Warehouse based on Google BigQuery
- Data provided by a single instance of Airflow
 - A lot of bugs found on production data
 - A lot of changes during review
 - A lot of delays in data
 - Partially available data
 - Lack of the full picture during code review and architecture problems
- And we wanted to start democratization.
 - Reliable production
 - No changes on production, at least unexpected ones
 - No changes in Data Structure
 - No changes in Data Freshness

Acceptance Could Help

DEV

- Quickly run your pipeline on a very small subset of your data
- In our case 0.0025% of all data
- Nothing will make sense, but it's a nice integration test

ACC

- Carbon copy of production
- You can check if you feel comfortable pushing to PRD
- Give access to a Product Owner for them to check

TST

- Select a subset of your data for data that you know
- Immediately see if something is off
- Still quick to run

PRD

- Greenlight procedure for merging from ACC to PRD
- Manual operation
- Great for git blame

<u>Via Data's Inferno</u> by Wholesale Banking Advanced Analytics

Acceptance Environment

- Acceptance is an environment where changes are welcome
- To make sure that we aren't going to need them on production

No Changes on Production, at Least Unexpected Ones

- No Changes in Data Structure
- No Changes in Data Freshness
- No Changes during release from Acceptance to Production

No Changes in Data Structure



Implementation of Acceptance

DEV

- Quickly run your pipeline on a very small subset of your data
- In our case 0.0025% of all data
- Nothing will make sense, but it's a nice integration test

ACC

- Carbon copy of production
- You can check if you feel comfortable pushing to PRD
- Give access to a Product Owner for them to check

TST

- Select a subset of your data for data that you know
- Immediately see if something is off
- Still quick to run

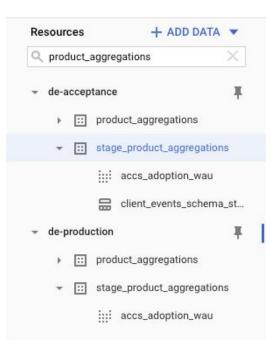
PRD

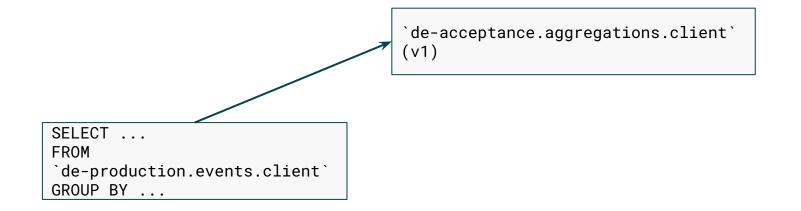
- Greenlight procedure for merging from ACC to PRD
- Manual operation
- Great for git blame

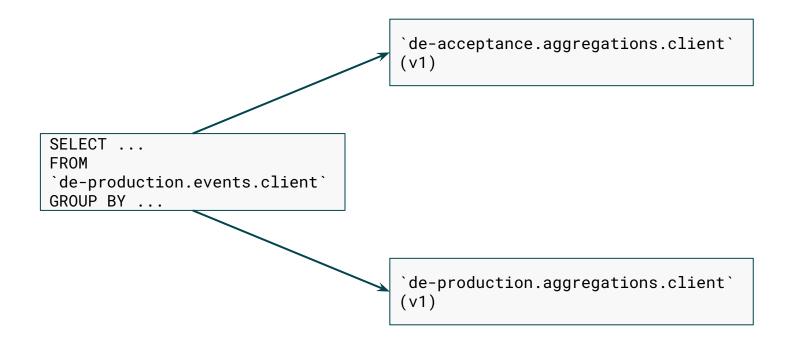
<u>Via Data's Inferno</u> by Wholesale Banking Advanced Analytics

Acceptance on DB Side. BigQuery

- Acceptance and production are different projects in the notation of BigQuery
- Isolated quotas and limits (resources)
- BigQuery allows for cross-project queries
 - So we store on acceptance only changed data
 - And take source data from production.

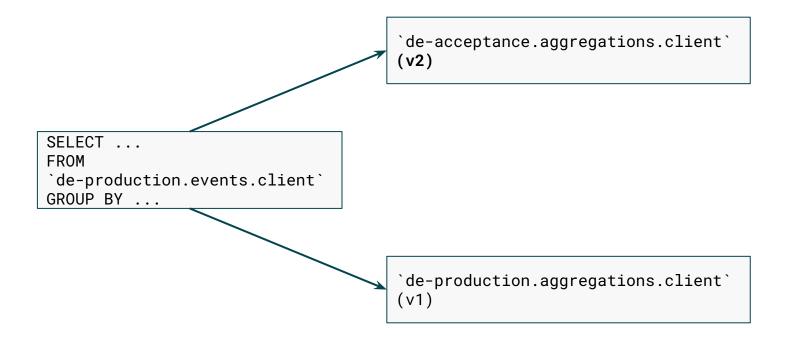


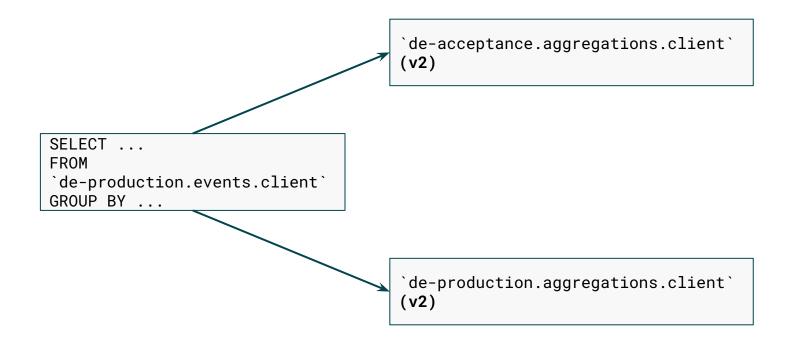




```
SELECT ...
FROM
`de-production.events.client`
GROUP BY ...

`de-production.aggregations.client`
(v1)
```





Interface Separation on Other DBs

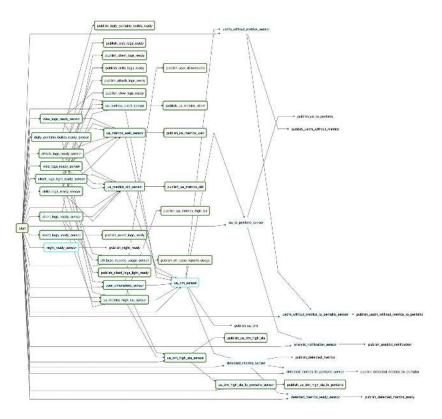
- Look for interface separation and resource isolation
 - And think about cost tradeoffs
- Approaches for interface separation
 - Schemas
 - Base directory name
 - Naming (bucket names for example)
 - Separate DBs
- Approaches for resource isolation (several trade offs with cost)
 - On service layer (separate DBs)
 - On DB side (e.g. roles, connection pools, quotas)
 - Airflow side (e.g. pools, priority, parallelism limit)
 - On monitoring side (e.g. query killer)



No Changes in Data Freshness

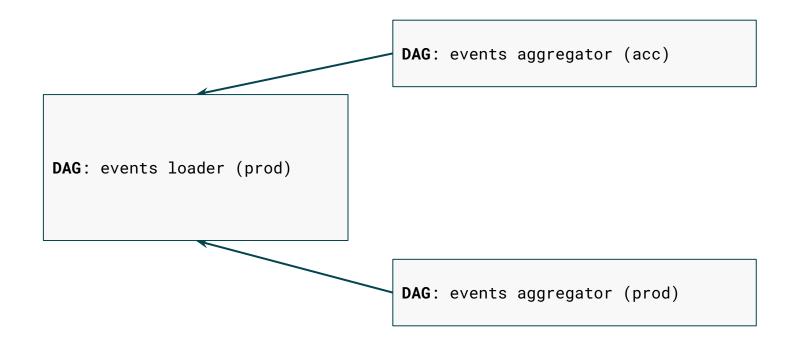


Beautiful DAG with 150 Tasks



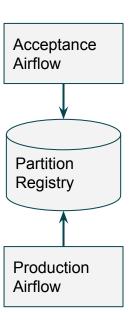
```
`de-acceptance.aggregations.client`
                                     DAG: events aggregator (acc)
SELECT ...
FROM
`de-production.events.client`
GROUP BY ...
DAG: events loader (prod)
                                     `de-production.aggregations.client`
                                     DAG: events aggregator (prod)
```

Execution Example

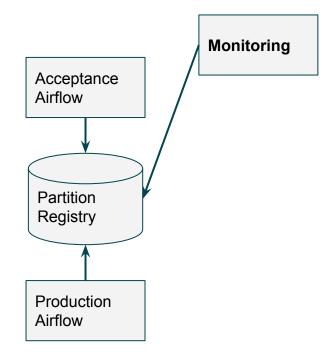


Separate Airflows

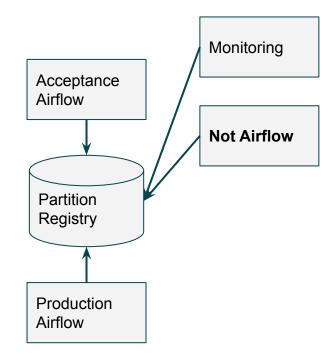
- Coordinated via Postgres database named Partition Registry
 - Inspired by <u>Functional Data Engineering</u> by Maxime Beauchemin
 - Partition unit of work for DAG, typically hour/day/week in a table
- State of partition published using operator
 - Explicitly publish sources
 - After all data validations have passed
- Wait for dependent sources using sensor
 - Automatically identify the strategy for interval
 - Week-on-hour, Month-on-day, custom catch-ups, etc.



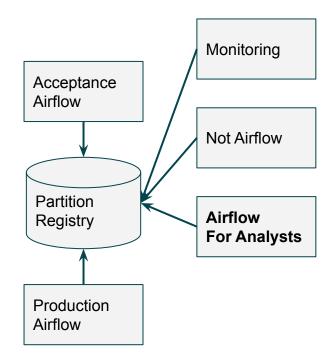
- Custom monitoring and alerts:
 - Severity of delays for partitions (DAG SLAs)
 - Base for data lineage



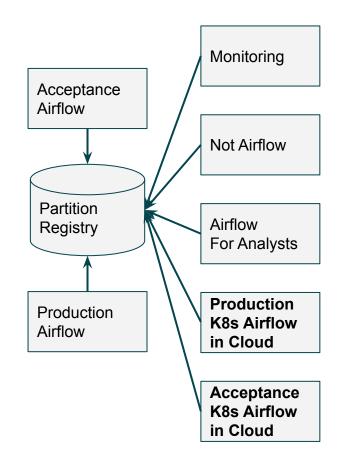
- Custom monitoring and alerts:
 - Severity of delays for partitions (DAG SLAs)
 - Base for data lineage
- Not Airflow: Pentaho DI and Old Jenkins Pipelines



- Custom monitoring and alerts:
 - Severity of delays for partitions (DAG SLAs)
 - Base for data lineage
- Not Airflow: Pentaho DI and Old Jenkins Pipelines
- Airflow for Analysts: isolated resources and credentials

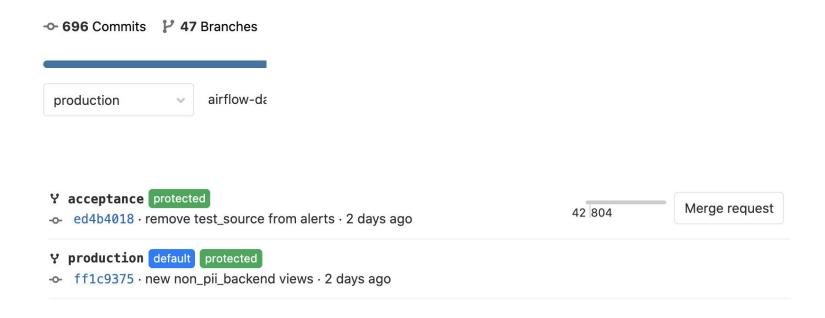


- Custom monitoring and alerts:
 - Severity of delays for partitions (DAG SLAs)
 - Base for data lineage
- Not Airflow: Pentaho DI and Old Jenkins Pipelines
- Airflow for Analysts: isolated resources and credentials
- K8s Airflow in Cloud
 - Easy switch with on-prem
 - Zero downtime migration
 - Data locality



No Changes During Release from Acc to Prod

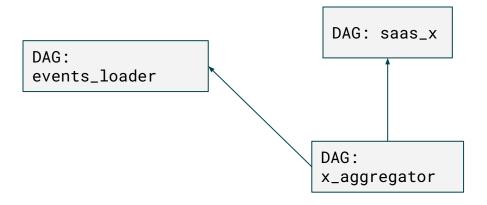
Acceptance Told Us Where We Went Wrong



Fast and Reliable Release

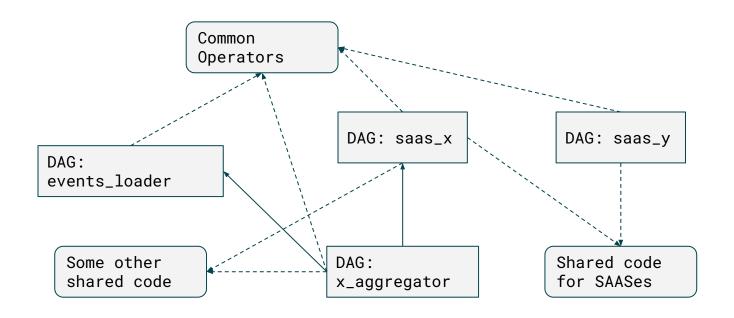
- We need code freeze to test dependent parts
- But we need 10 releases per day
 - So, we need to freeze as little as possible
 - But still review and test every change made

Dependency Scheme



DAG: saas_y

Dependency Scheme with Code



No Changes During Release Process Means

- Good data isolation during release
- Good code isolation during release

Bad Data Isolation Is When

- You recalculate your data and get different results
- Data distribution changes
- Data distribution does not change when it should
- Analytical dashboard starts to focus on the wrong things
- You achieve your results a lot faster :)
- Something else is wrong and you don't know about it.

So if Data Changes

- It's safe to assume
 - Review is no longer valid
 - Manual testing is no longer valid
 - Data sources may be corrupted
- So before the release of data change
 - Notifying all stakeholders of all changed dependent sources
 - Checking that everything works correctly on acceptance
 - Making atomic release
- We're helping to implement recalculation strategies
 - Recalculating everything and keeping it up-to-date
 - Preserving history for metrics in prestaging
 - Supporting and gradual deprecation of old version of metrics

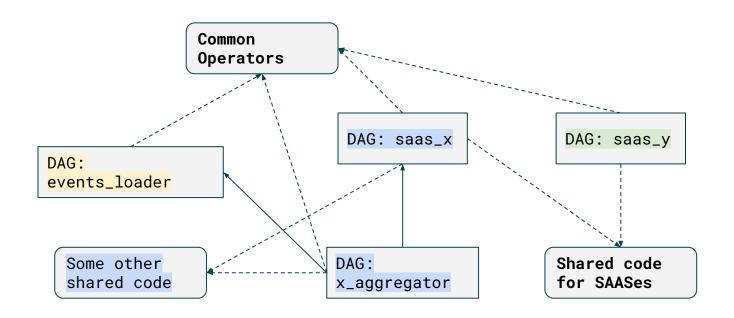
Keeping Track of Data Isolation

- Knowing when dependencies are updated after release to production
 - Notifications from other teams
 - Dependency on exact version of partition
 - Makes it easier to switch between acc and prod in code
 - Validation of data on your side
 - Great Expectations to explicitly specify your assumptions on data nature
 - Anomaly detection
- Finding all dependent sources before release to the production
 - Manual
 - BigQuery history
 - Search in git repository
 - Data Lineage + release process
 - Autotests

Good Code Isolation

- Bad code isolation means you have a bug and your pipeline is not working
- This happens when when 2+ DAGs use the same code
 - You update code or library and other DAG fails
- Two types of failure
 - Scheduler/Web Server appears immediately, hard isolation (fat-zip, boilerplate)
 - Worker visible during execution, easy isolation (k8s, venv)
 - Can be at the end of a 4 hour-long task at the start of the next month :(
- How do we avoid this?
 - There is 20% of code used in 80% of cases
 - We're moving it to the library, test and track backward compatibility
 - We have a shared code that is changed rarely
 - This code should be as private as possible to make sure that we're not reusing it
 - The main reason for DAGs to be included in the single repo or merge request

Dependency Scheme with Code



How Do We Reason About Reliability?

- Our production is very predictable
- All interface changes reviewed on separate environment
 - We keep track of all data dependencies and communicate the change to all stakeholders throughout the pipeline
 - Every source on production is reviewed, supported by several data engineers, have a clear time of readiness and all errors are communicated to all stakeholders
- We're using partition registry
 - To isolate resources of acceptance
 - As little recalculation as possible
 - To integrate Airflow with separate creds and resources to other teams
- Acceptance could be made cheaper



Thank You! Any Questions?

Alexander Eliseev at Airflow Slack

alexander.eliseev@team.wrike.com https://qithub.com/eliseealex

