
# Manage Data Pipelines with Cloud Data Fusion and Cloud Composer

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01

Building batch data pipelines visually with Cloud Data Fusion

- Components
- UI overview
- Building a pipeline
- Exploring data using Wrangler

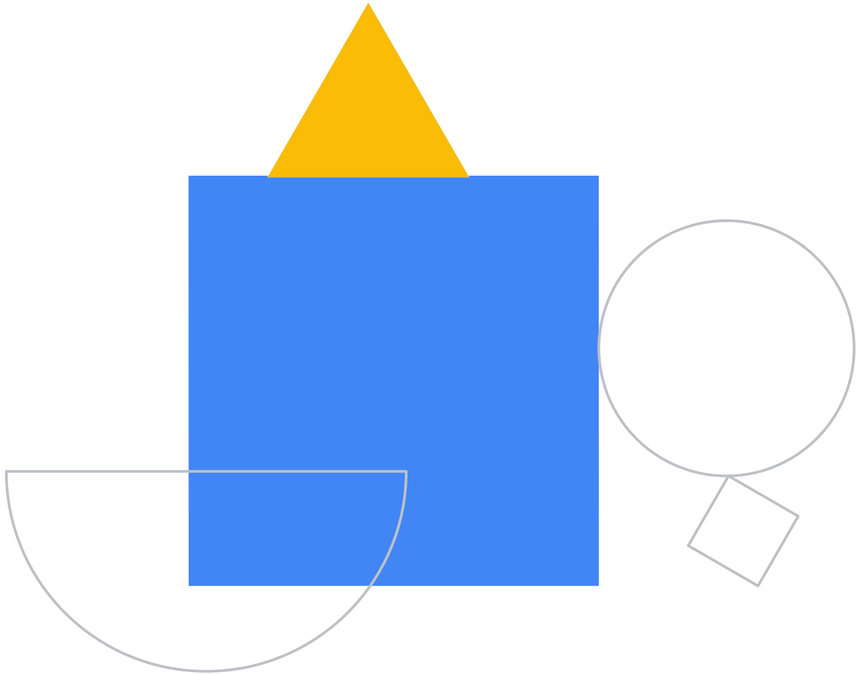
02

Orchestrating work between Google Cloud services with Cloud Composer

- Apache Airflow environment
- DAGs and Operators
- Workflow Scheduling
- Monitoring and Logging

# Lab Startup

Building and Executing a Pipeline Graph in Cloud Data Fusion



# Manage Data Pipelines with Cloud Data Fusion and Cloud Composer

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# Cloud Data Fusion

Cloud Data Fusion is a **fully-managed, cloud native, enterprise data integration service** for quickly building and managing data pipelines.

# Developer, data scientist, and business analyst

1

Need to cleanse, match, de-dupe, blend, transform, partition, transfer, standardize, automate, and monitor.

2

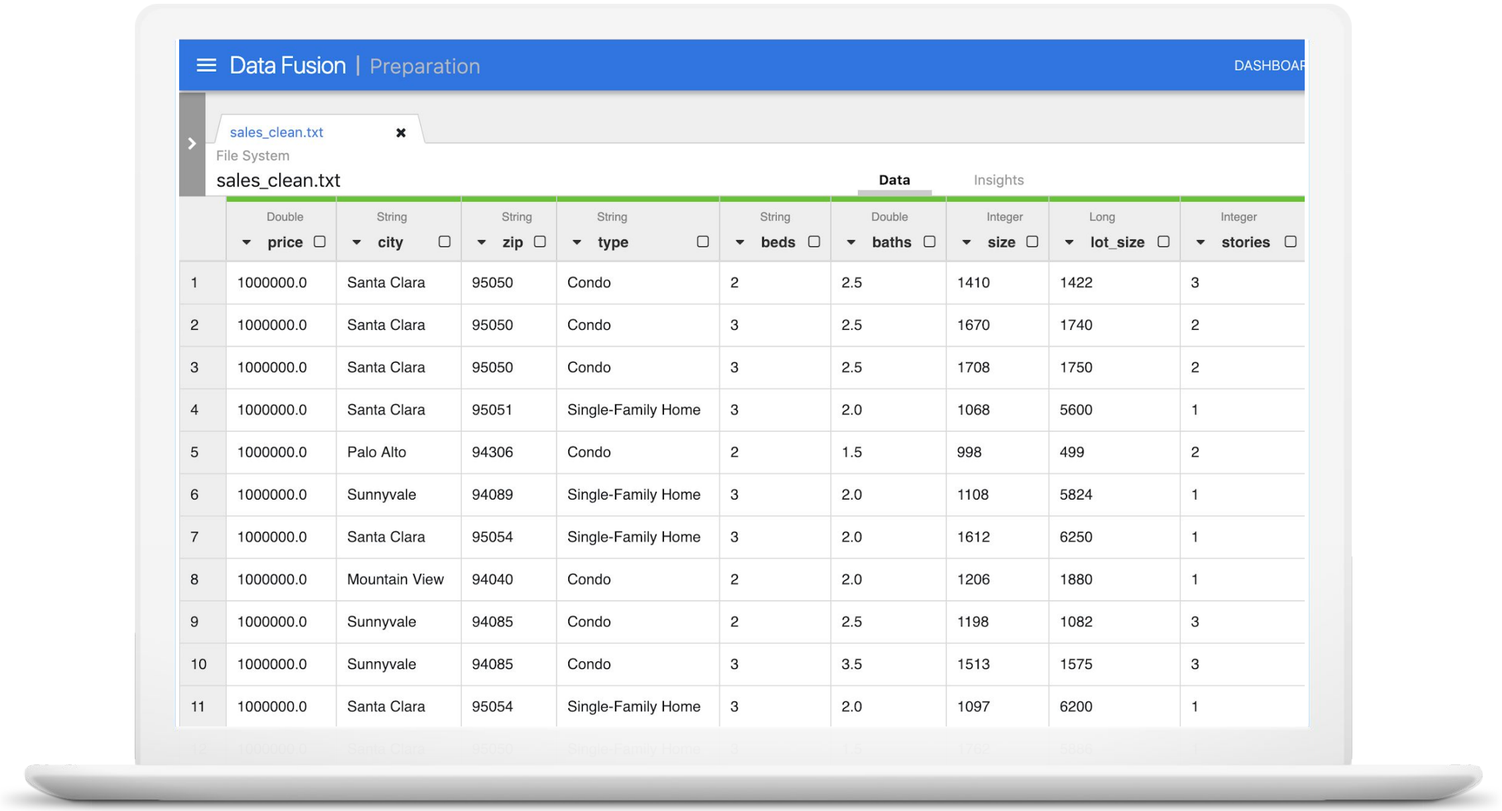
Use Cloud Data Fusion to visually build integration pipeline, test, debug and deploy.

3

Run it at scale on Google Cloud, operationalize (monitor, report) pipelines, inspect rich integration metadata.

# Benefits

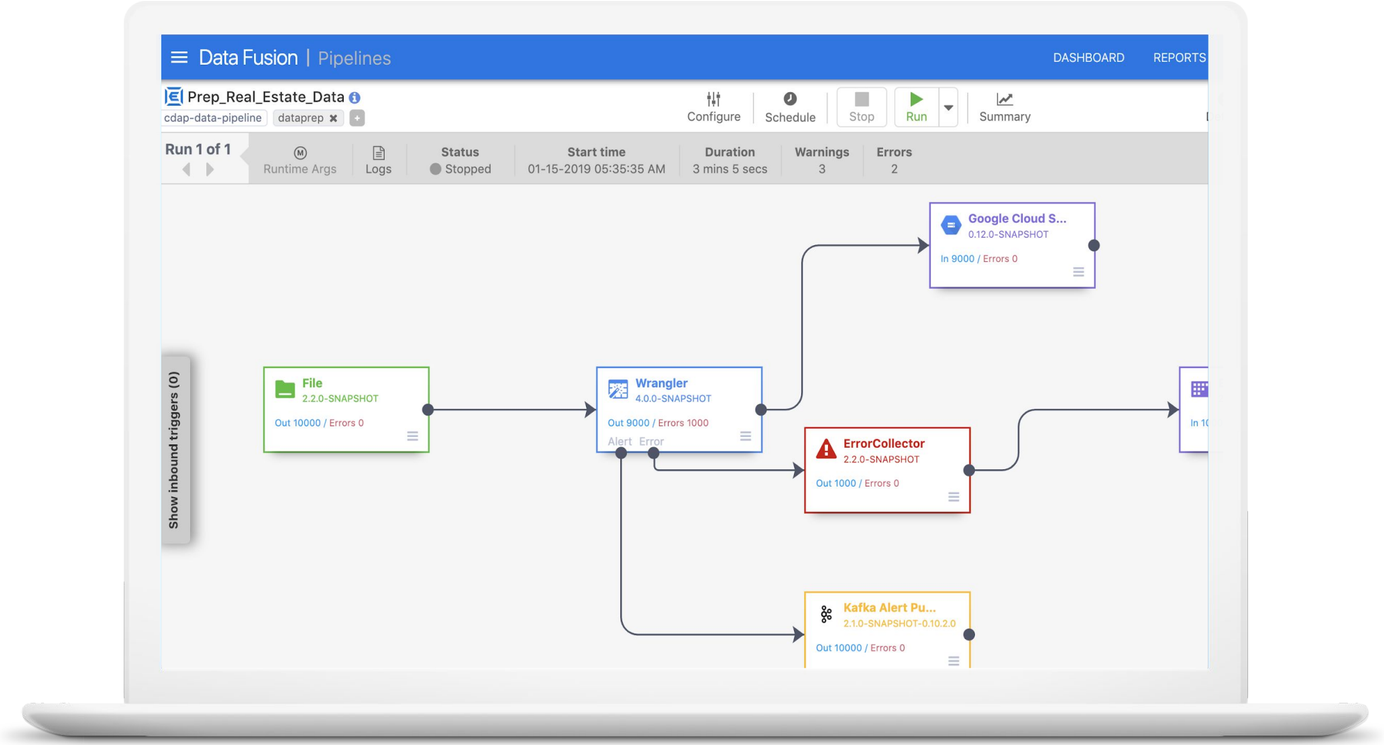
- Integrate with any data
- Increase productivity
- Reduce complexity
- Increase flexibility




| | Double price | String city | String zip | String type | String beds | Double baths | Integer size | Long lot_size | Integer stories |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1000000.0 | Santa Clara | 95050 | Condo | 2 | 2.5 | 1410 | 1422 | 3 |
| 2 | 1000000.0 | Santa Clara | 95050 | Condo | 3 | 2.5 | 1670 | 1740 | 2 |
| 3 | 1000000.0 | Santa Clara | 95050 | Condo | 3 | 2.5 | 1708 | 1750 | 2 |
| 4 | 1000000.0 | Santa Clara | 95051 | Single-Family Home | 3 | 2.0 | 1068 | 5600 | 1 |
| 5 | 1000000.0 | Palo Alto | 94306 | Condo | 2 | 1.5 | 998 | 499 | 2 |
| 6 | 1000000.0 | Sunnyvale | 94089 | Single-Family Home | 3 | 2.0 | 1108 | 5824 | 1 |
| 7 | 1000000.0 | Santa Clara | 95054 | Single-Family Home | 3 | 2.0 | 1612 | 6250 | 1 |
| 8 | 1000000.0 | Mountain View | 94040 | Condo | 2 | 2.0 | 1206 | 1880 | 1 |
| 9 | 1000000.0 | Sunnyvale | 94085 | Condo | 2 | 2.5 | 1198 | 1082 | 3 |
| 10 | 1000000.0 | Sunnyvale | 94085 | Condo | 3 | 3.5 | 1513 | 1575 | 3 |
| 11 | 1000000.0 | Santa Clara | 95054 | Single-Family Home | 3 | 2.0 | 1097 | 6200 | 1 |

# Build data pipelines with a friendly UI

- Rich graphical interface
- 100+ plugins - connectors, transforms, and actions
- Code free visual transformations
- 1000+ transforms, data quality
- Test and debug pipeline
- Pre-built pipelines
- Developer SDK



# Integration metadata

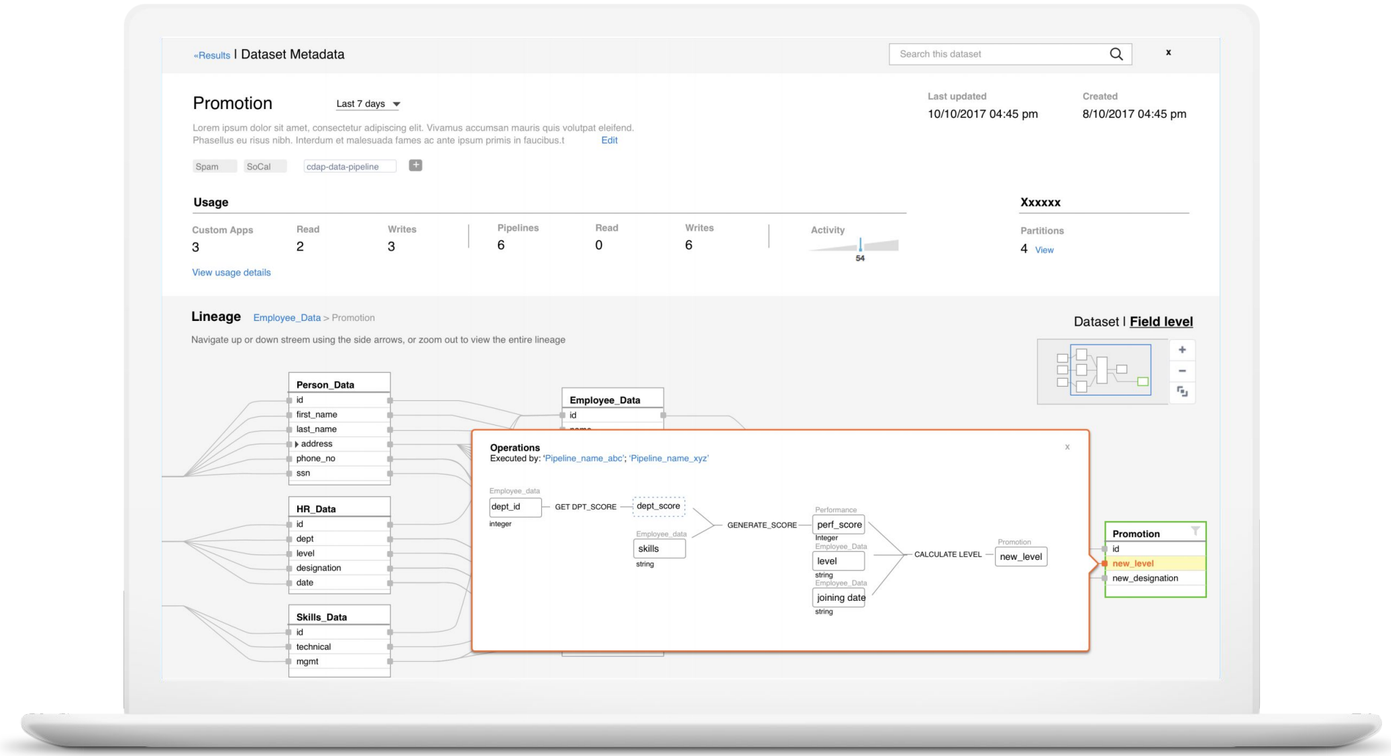
## Tags and Properties support

- Pipeline
- Dataset
- Schema

## Search integrated entities by

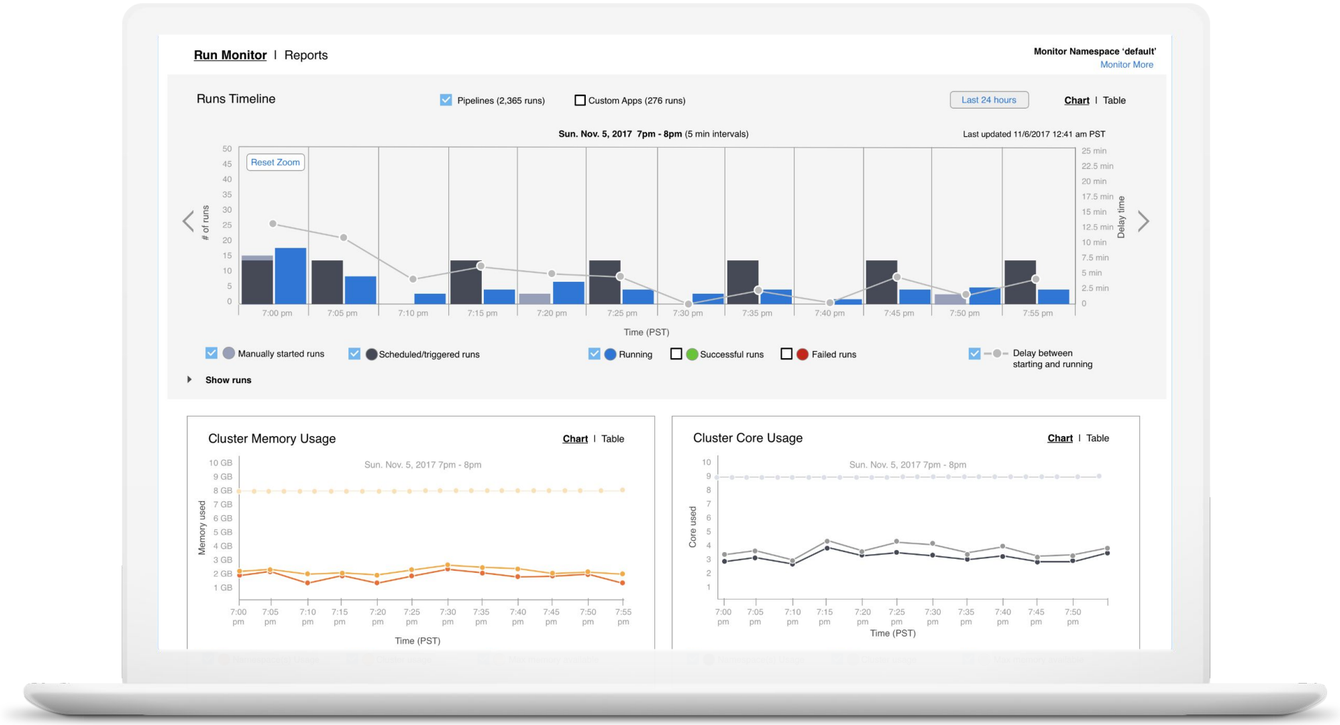
- Keyword
- Schema name and type

## Dataset level and Field level lineage

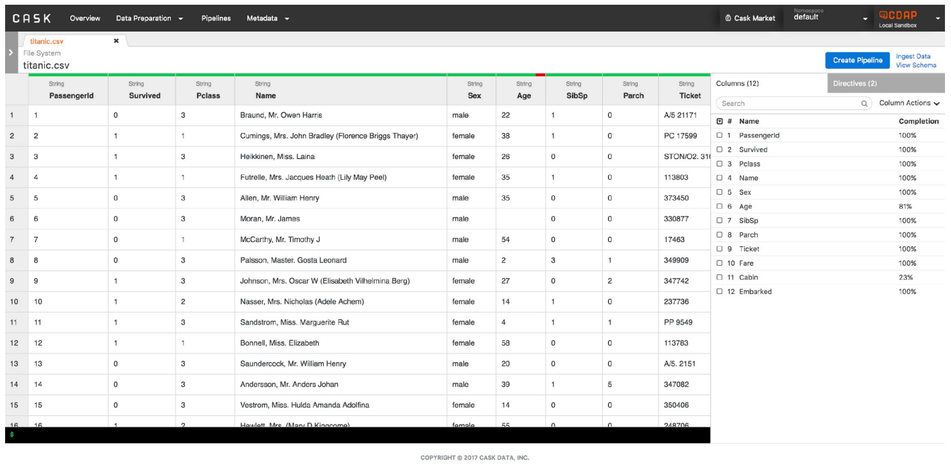


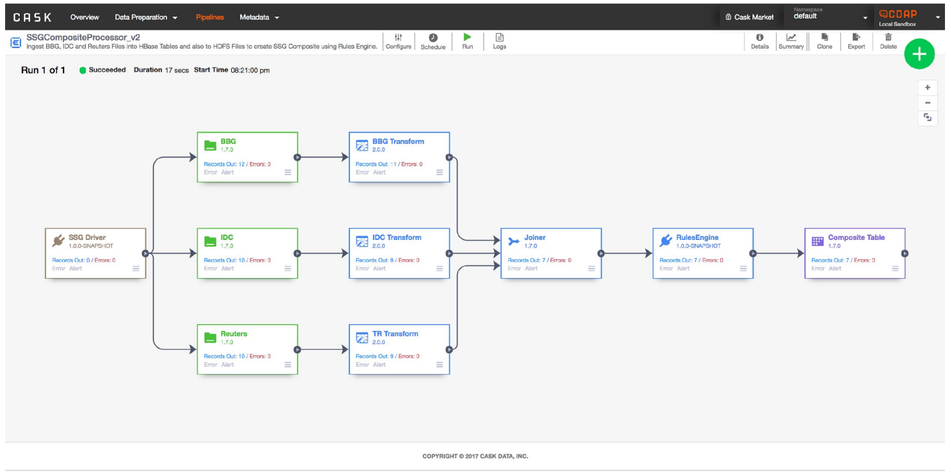
# Extensible

- Pipeline templatization
- Conditional pipeline triggers
- Plugin management
- Plugin templatization
- Plugin UI widget
- Custom provisioners
- Custom compute profiles
- Hub integration



# Components of Cloud Data Fusion




## 01

## Wrangler — Framework

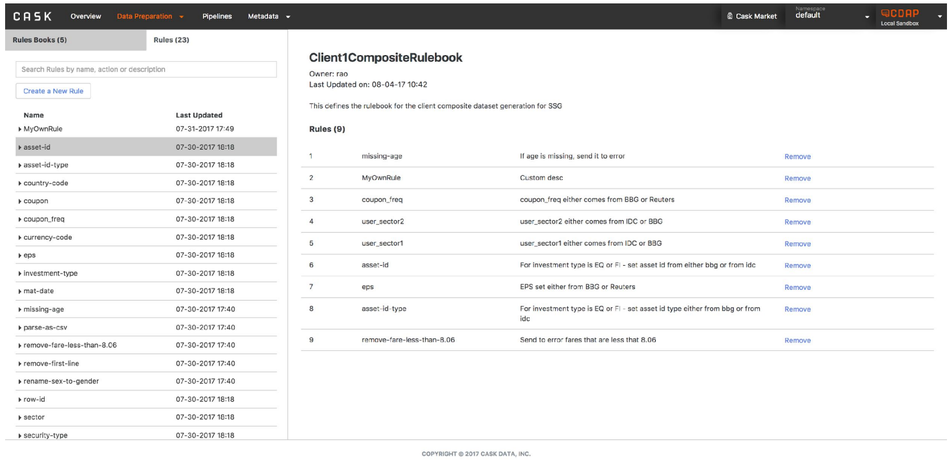
- Data Preparation for on-boarding new sources and datasets.
- Perform Data Transformations, Data Quality checks with visual feedback.
- Extend the Wrangler by building new user defined directives.
- **Integrates with Data Pipeline for operationalizing transformations.**

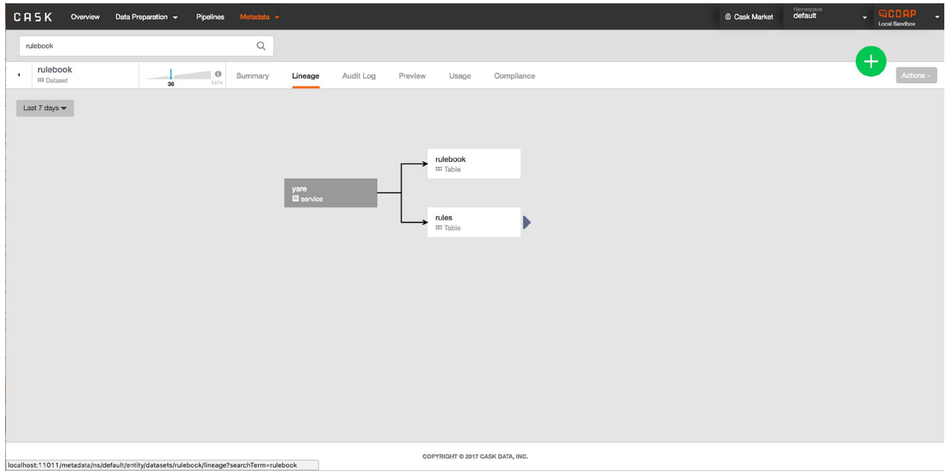
## 02

## Data Pipeline — Framework

- User interface for building complex data workflows.
- Join, Lookup, Aggregate, Filtering data in-flight.
- Building complex workflows with 100s of connectors.
- Extend Data Pipeline using simple APIs.
- **Integrates with Dataprep, Rule Engine and Metadata Aggregator.**

# Components of Cloud Data Fusion




## 03

## Rules Engine — Tool

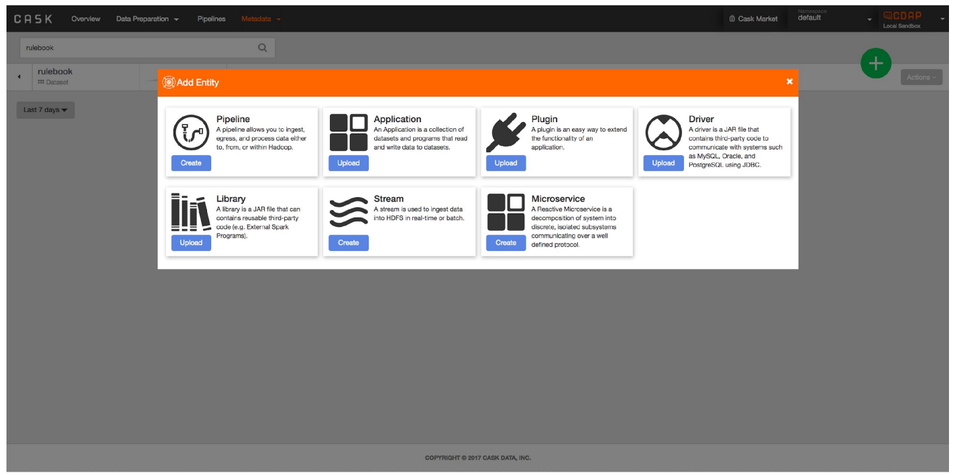
- Business Data Transformations and checks codified for business users.
- Define Complex rules using intuitive and simple to use user interface.
- Logically group Rules in Rulebook and trigger or schedule processing.
- Integrates with Data Pipeline for operationalizing Rules.

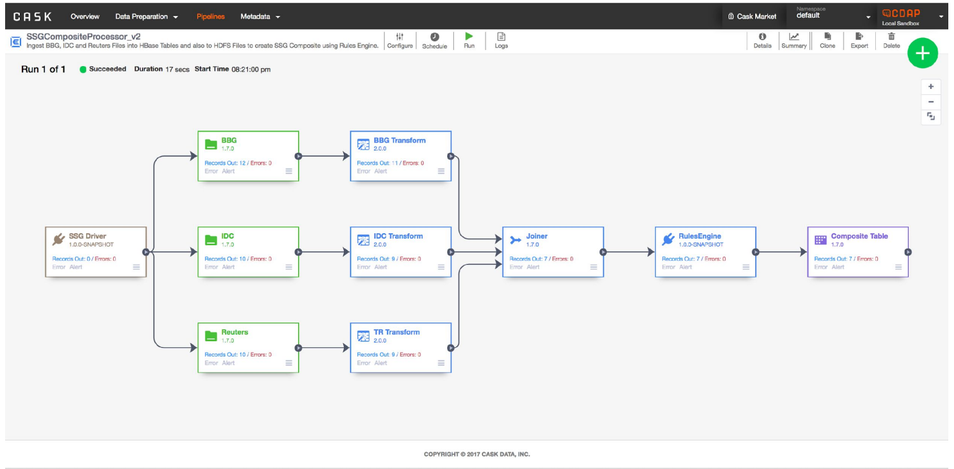
## 04

## Metadata Aggregator — Tool

- Aggregate Business, Technical and Operational Metadata.
- Track the flow of data (Lineage) for richer data needed for governance.
- Create Data Dictionary and Metadata Repository.
- Integrate with enterprise MDM solutions.
- Integrates with Data Pipeline, Rules Engine.

# Components of Cloud Data Fusion




## 05

## Microservice — Framework

- Build specialized logic for processing data.
- Create loosely coupled network for processing events.
- Bind processing to varied set of queues.

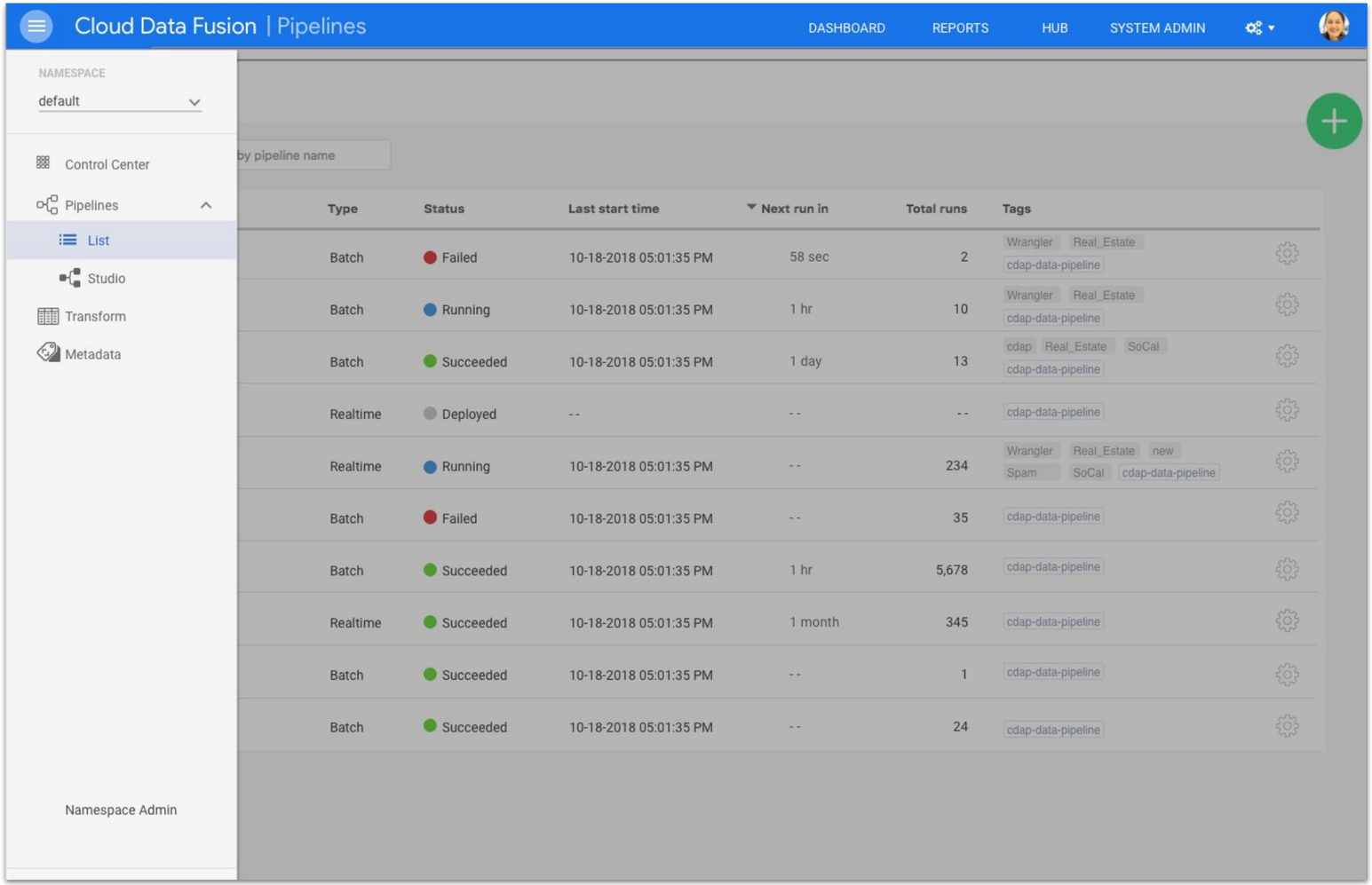
## 06

## Event Condition Action (ECA) — Application

- Delivers a specialized solutions for IoT event processing.
- Parses any events, triggers conditions and executes Action.
- Real-time notification system, with easy-to-use user interface for configuring event parsing, condition and actions.

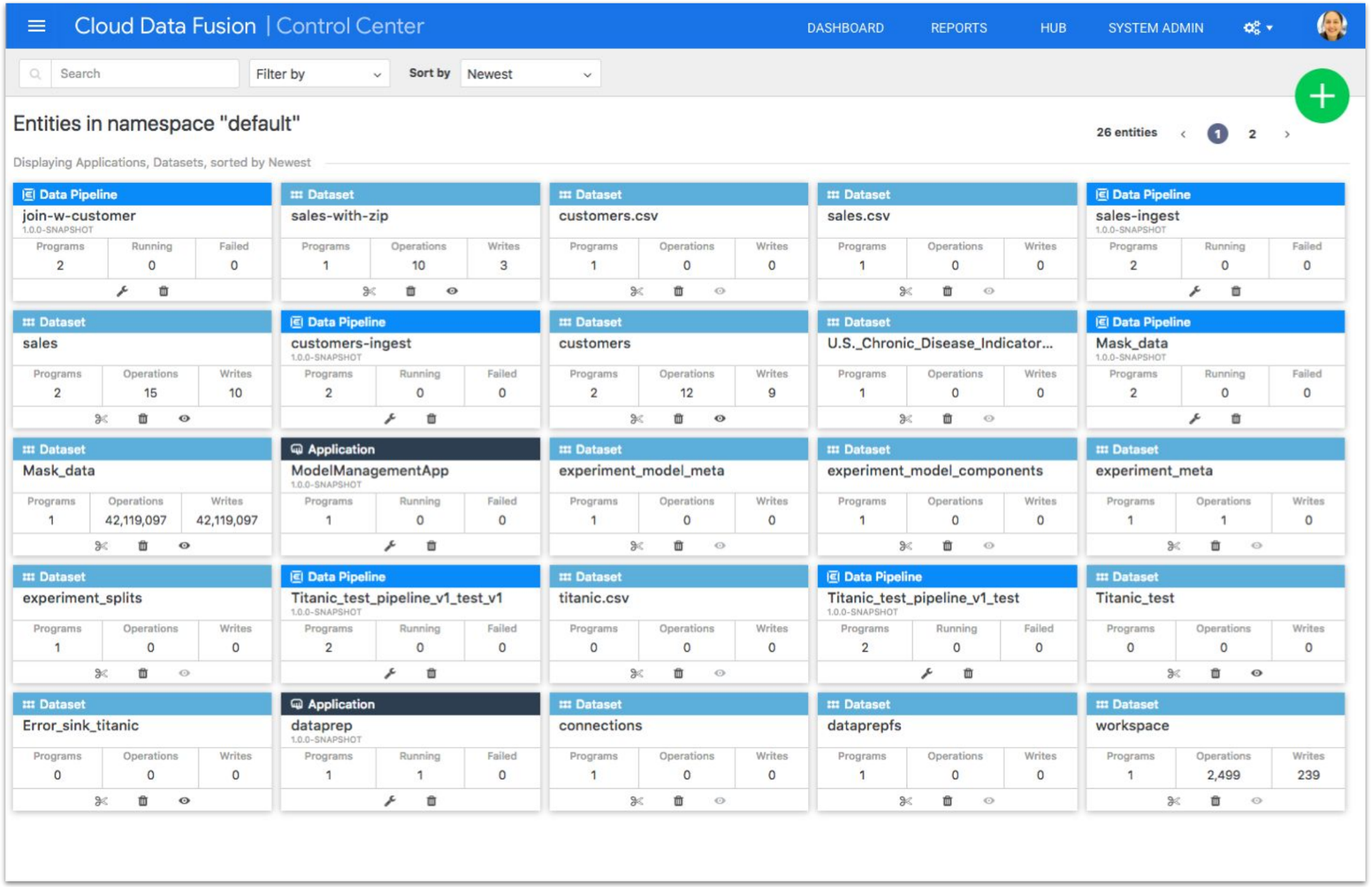
# Cloud Data Fusion - UI overview

- Control Center
- Pipelines
- Wrangler
- Metadata
- Hub
- Entities
- Administration



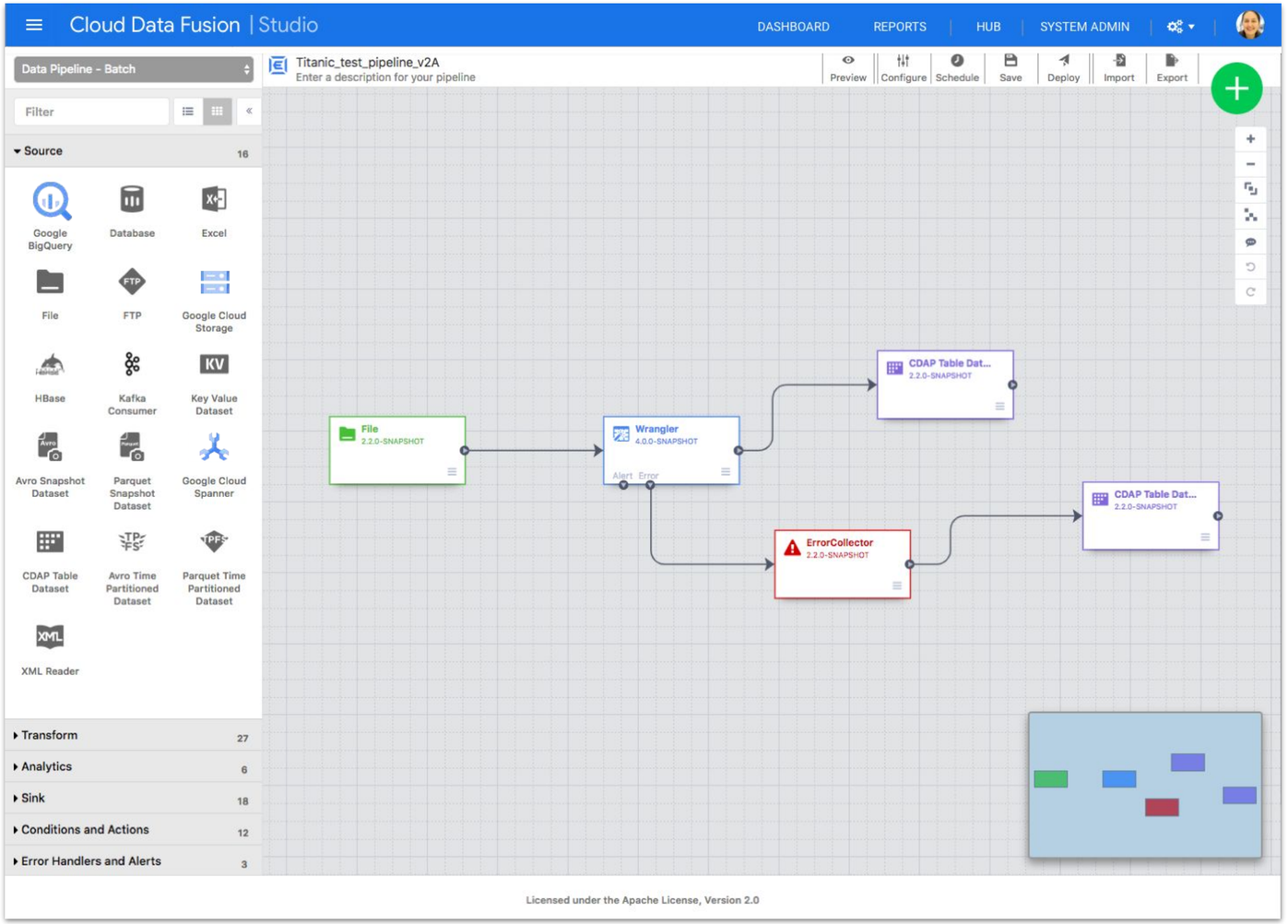
# Control Center

- Application
- Artifact
- Dataset



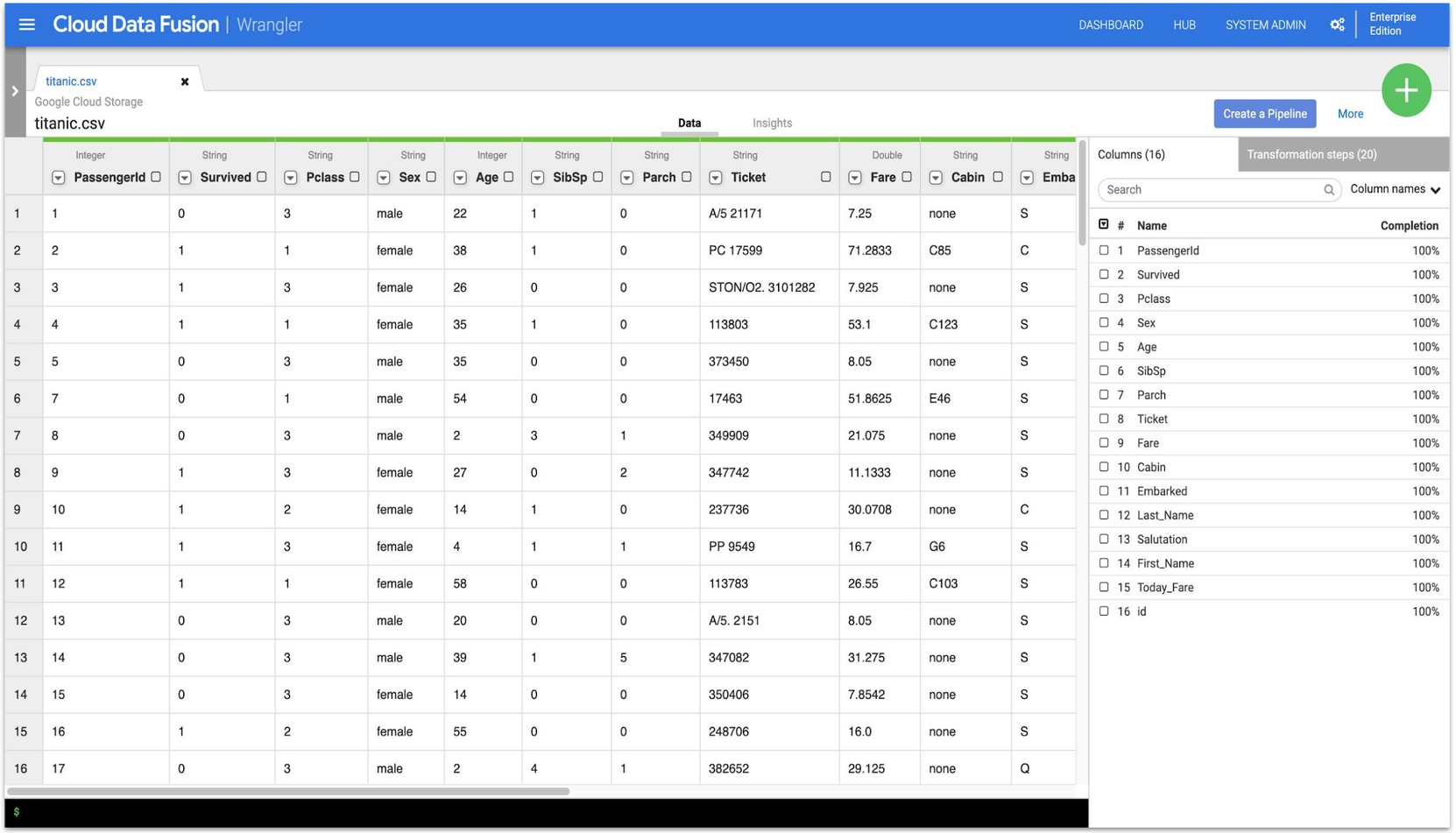
# Pipelines

- Developer Studio
- Preview
- Export
- Schedule
- Connector and function palette
- Navigation



# Wrangler

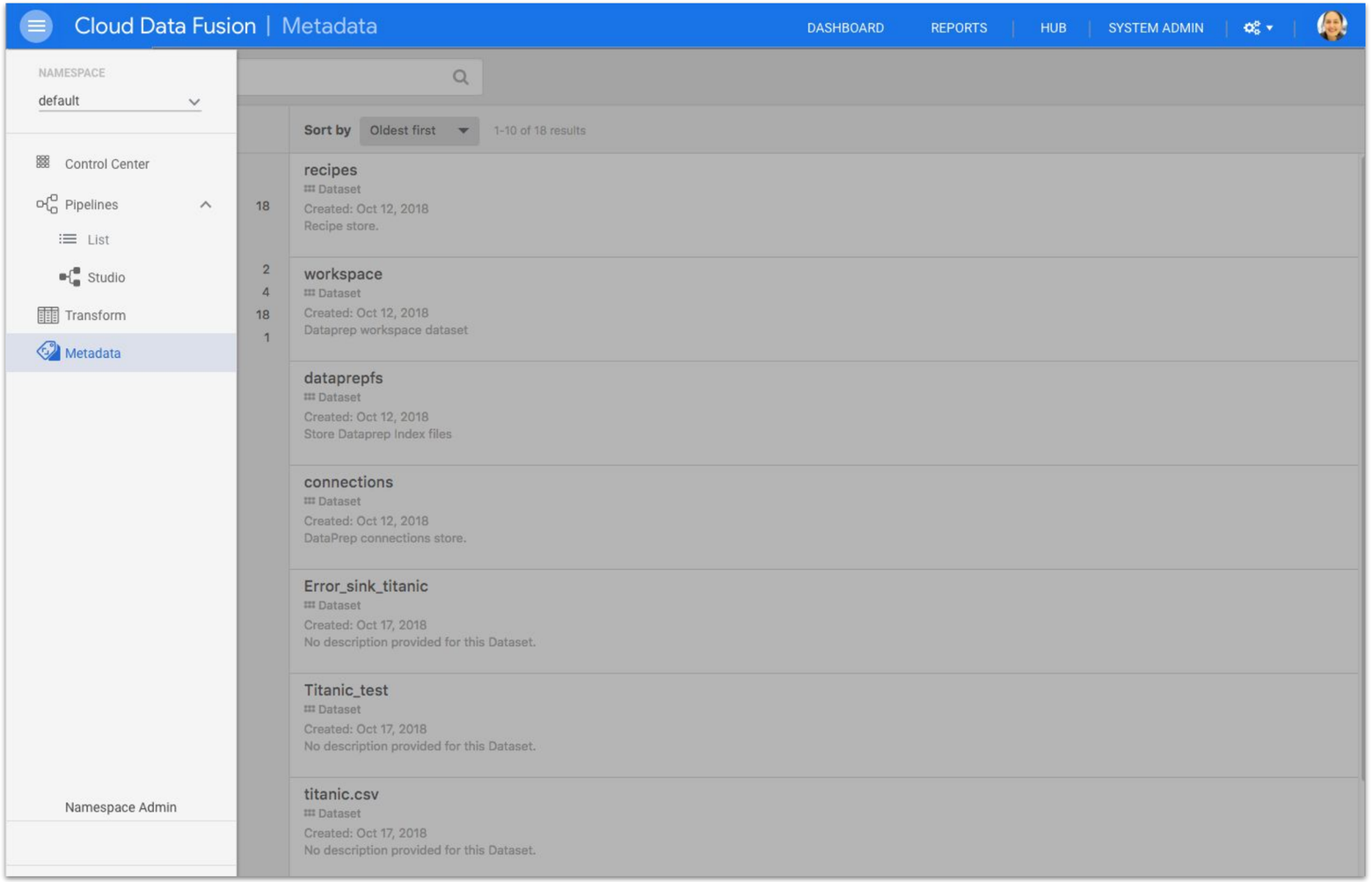
- Connections
- Transforms
- Data Quality
- Insights
- Functions




| | PassengerId | Survived | Pclass | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Emba |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Integer | String | String | String | Integer | String | String | String | Double | String | String |
| 1 | 1 | 0 | 3 | male | 22 | 1 | 0 | A/5 21171 | 7.25 | none | S |
| 2 | 2 | 1 | 1 | female | 38 | 1 | 0 | PC 17599 | 71.2833 | C85 | C |
| 3 | 3 | 1 | 3 | female | 26 | 0 | 0 | STON/O2. 3101282 | 7.925 | none | S |
| 4 | 4 | 1 | 1 | female | 35 | 1 | 0 | 113803 | 53.1 | C123 | S |
| 5 | 5 | 0 | 3 | male | 35 | 0 | 0 | 373450 | 8.05 | none | S |
| 6 | 7 | 0 | 1 | male | 54 | 0 | 0 | 17463 | 51.8625 | E46 | S |
| 7 | 8 | 0 | 3 | male | 2 | 3 | 1 | 349909 | 21.075 | none | S |
| 8 | 9 | 1 | 3 | female | 27 | 0 | 2 | 347742 | 11.1333 | none | S |
| 9 | 10 | 1 | 2 | female | 14 | 1 | 0 | 237736 | 30.0708 | none | C |
| 10 | 11 | 1 | 3 | female | 4 | 1 | 1 | PP 9549 | 16.7 | G6 | S |
| 11 | 12 | 1 | 1 | female | 58 | 0 | 0 | 113783 | 26.55 | C103 | S |
| 12 | 13 | 0 | 3 | male | 20 | 0 | 0 | A/5. 2151 | 8.05 | none | S |
| 13 | 14 | 0 | 3 | male | 39 | 1 | 5 | 347082 | 31.275 | none | S |
| 14 | 15 | 0 | 3 | female | 14 | 0 | 0 | 350406 | 7.8542 | none | S |
| 15 | 16 | 1 | 2 | female | 55 | 0 | 0 | 248706 | 16.0 | none | S |
| 16 | 17 | 0 | 3 | male | 2 | 4 | 1 | 382652 | 29.125 | none | Q |

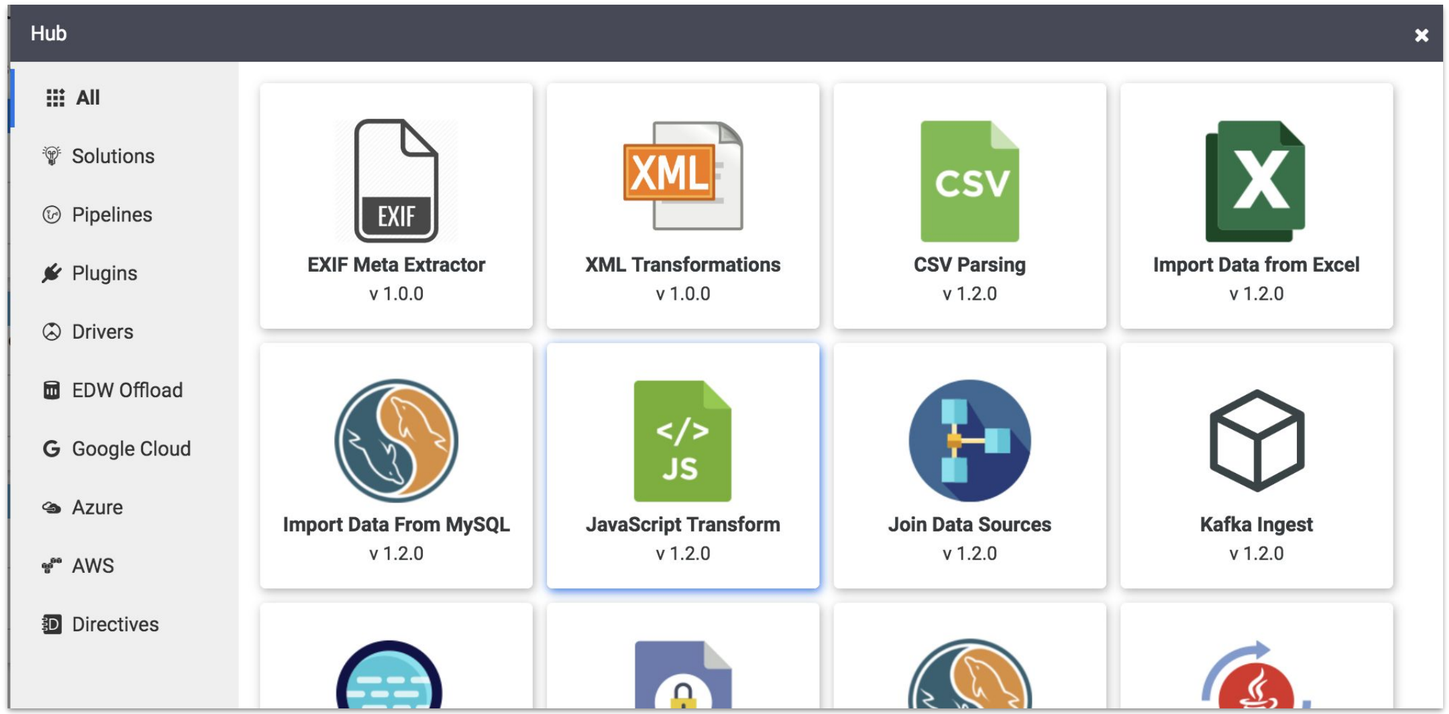
# Integration metadata

- Search
- Tags and Properties
- Lineage - Field and Data



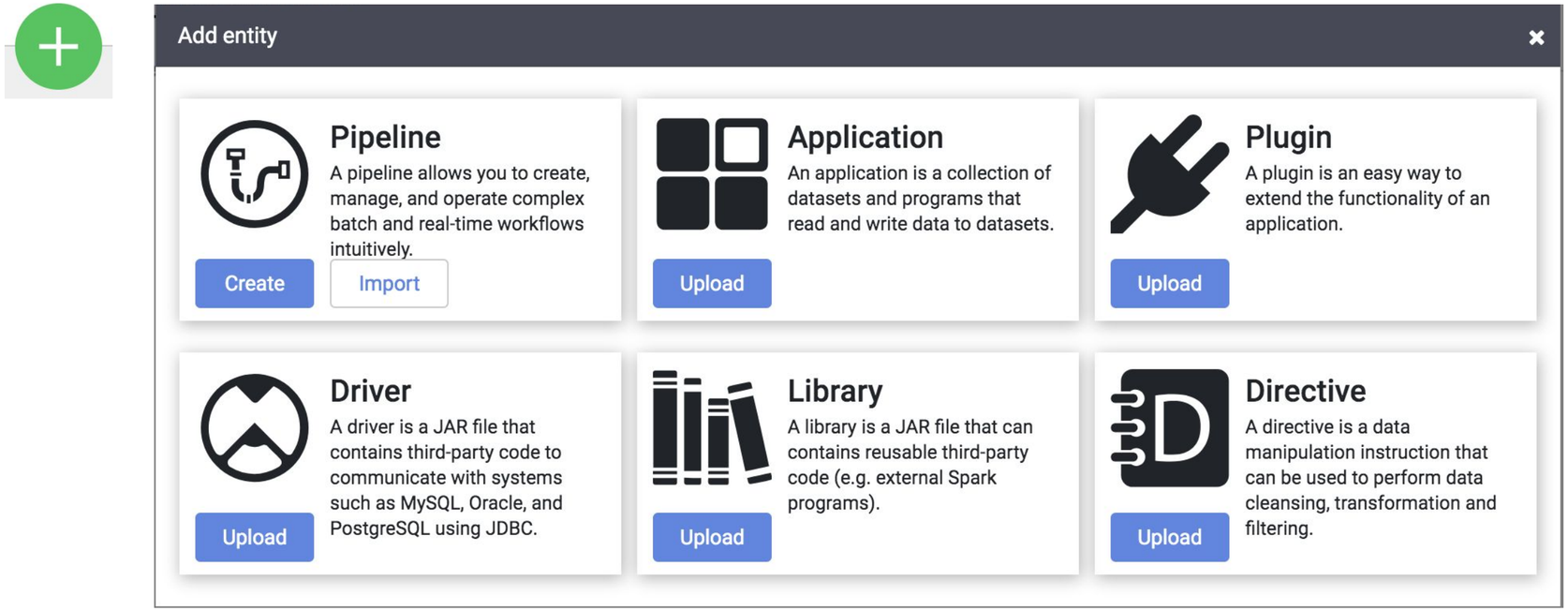
# Hub

- Plugins
- Use cases
- Pre-built pipelines



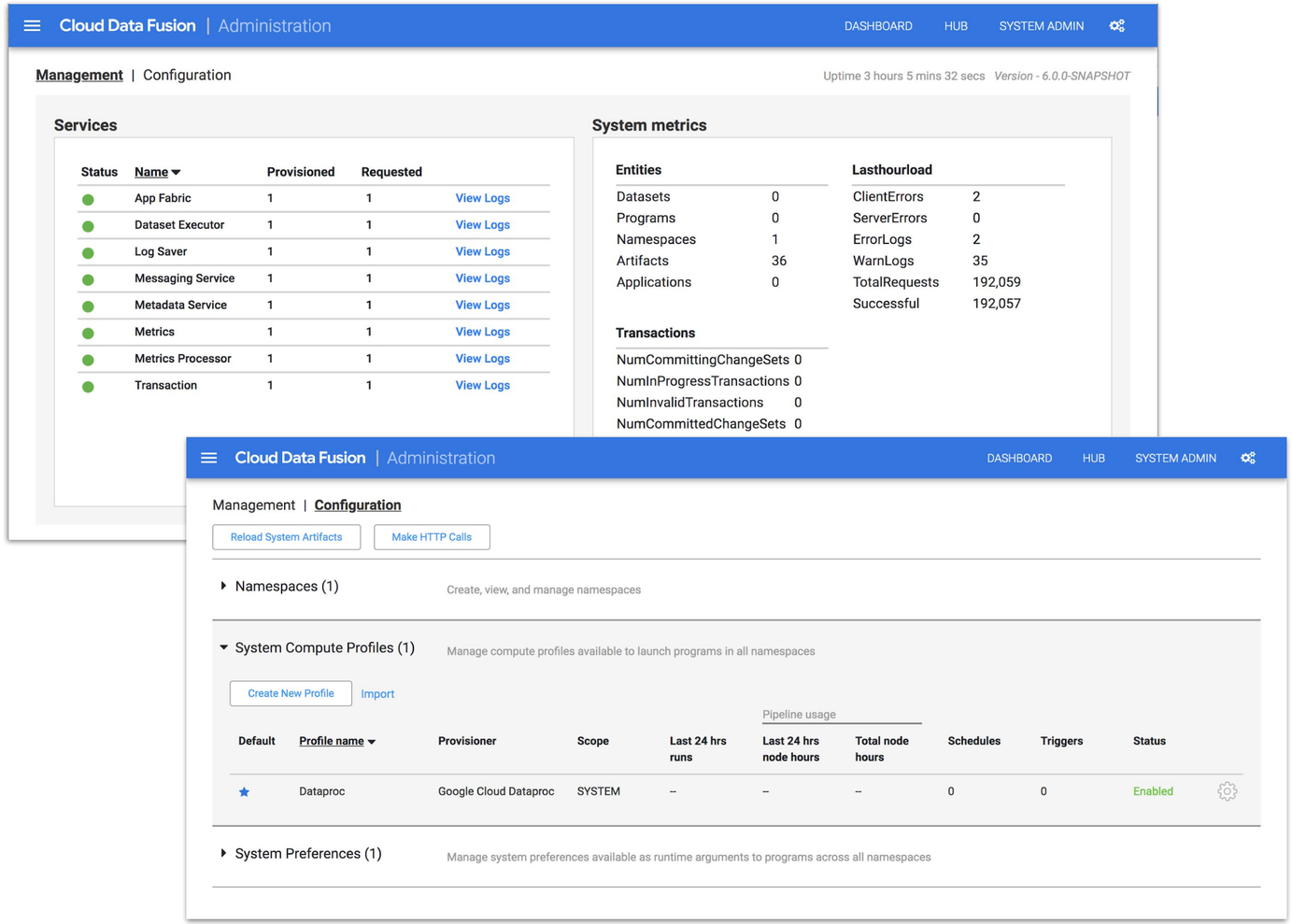
# Entities

- Pipeline
- Application
- Plugin
- Driver
- Library
- Directive

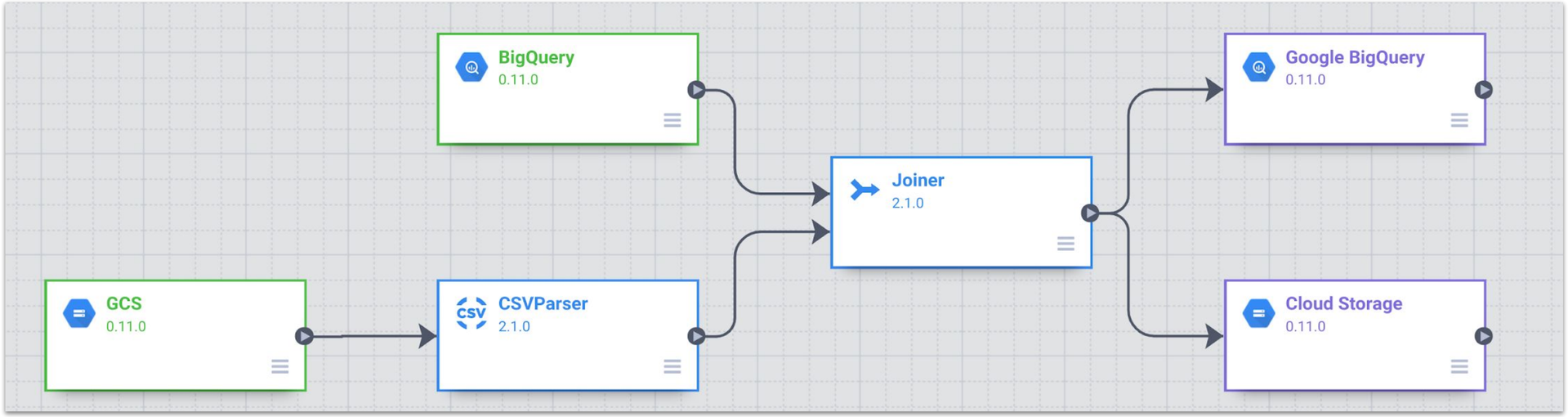


# Administration

- Management
  - Services
  - Metrics
- Configuration
  - Namespace
  - Compute Profiles
  - Preferences
  - System Artifacts
  - REST Client



# Data Pipeline | Directed Acyclic Graph (DAG)

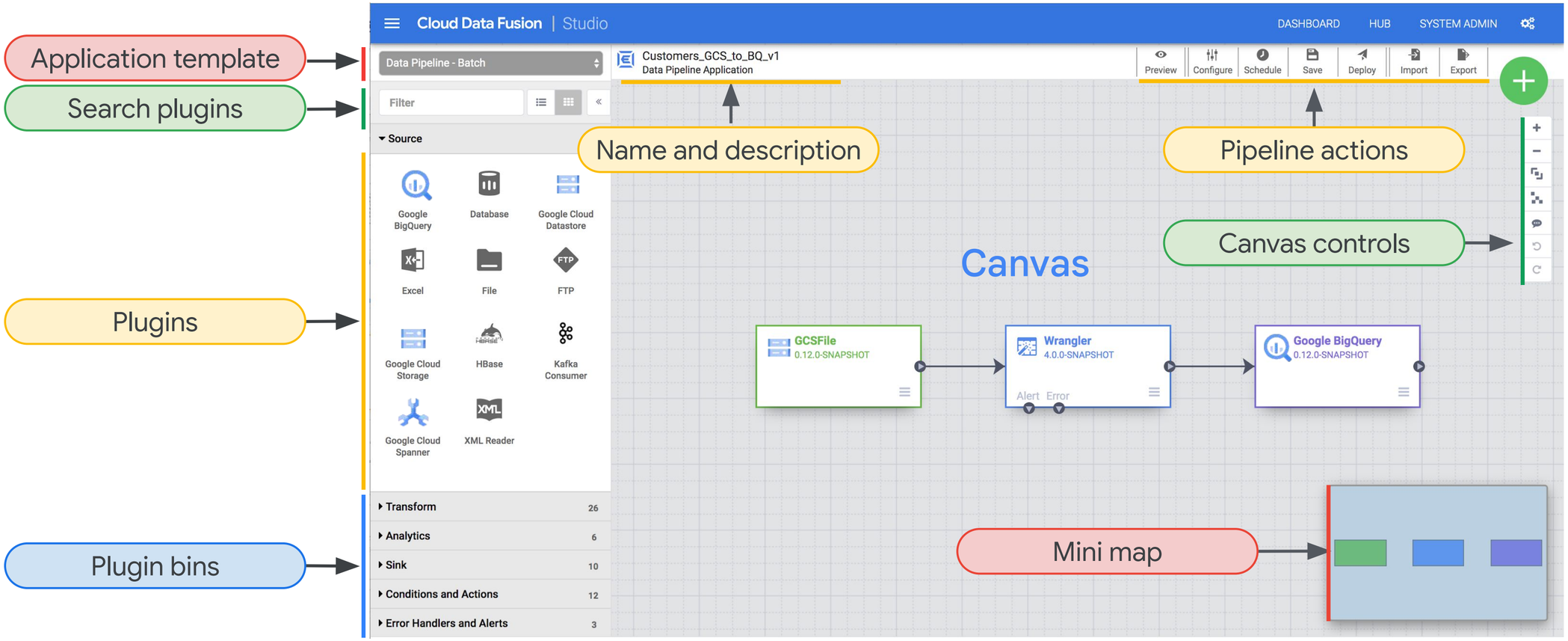



- Represented by a series of stages arranged in a DAG. This forms a one-way pipeline.
- Stages, which are the "nodes" in the pipeline graph, can be of different types.

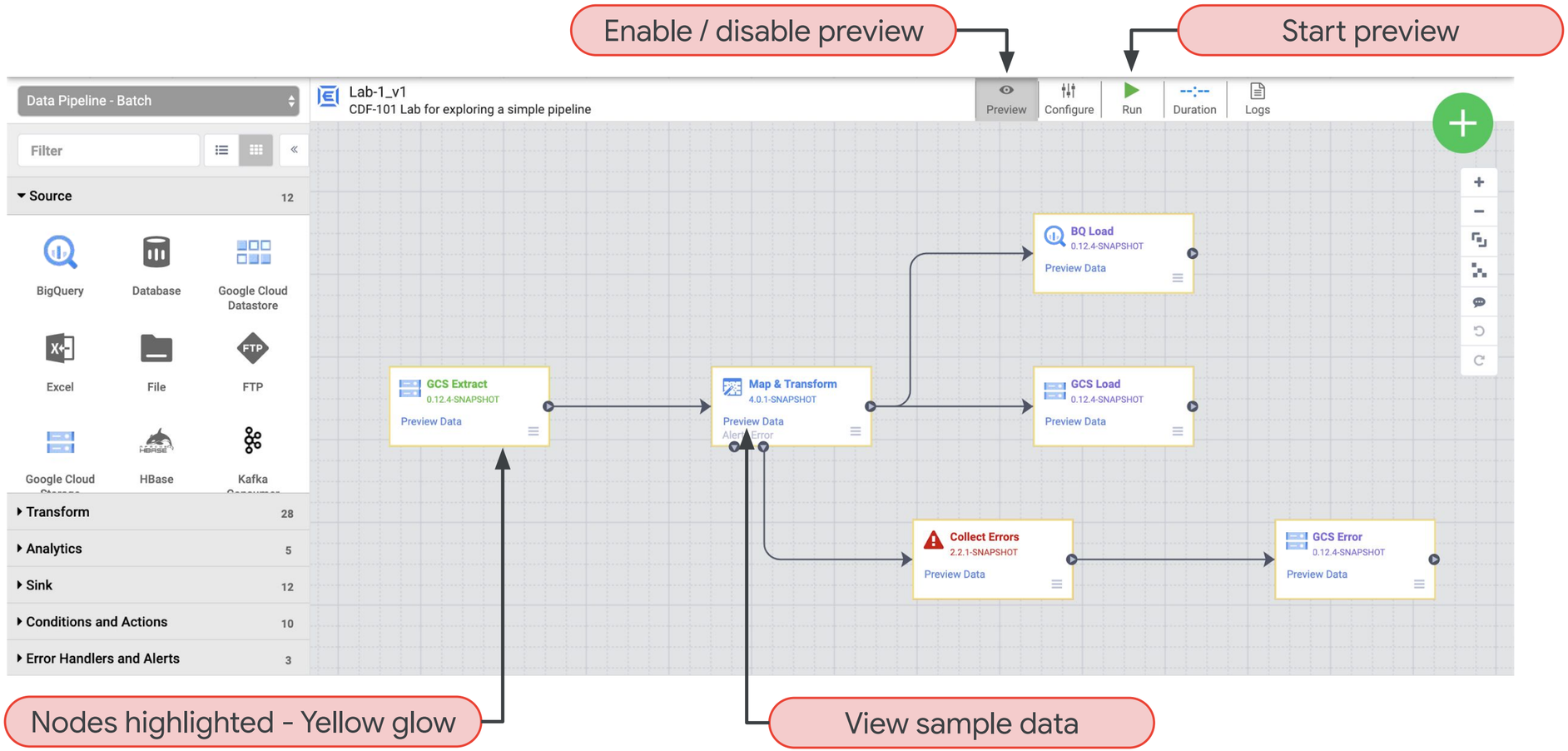
# Data pipeline

- Allows non-linear pipelines.
- Can fork from a node, where output from a node can be sent to two or more stages.
- Two or more forked nodes can merge at a transform or a sink node.

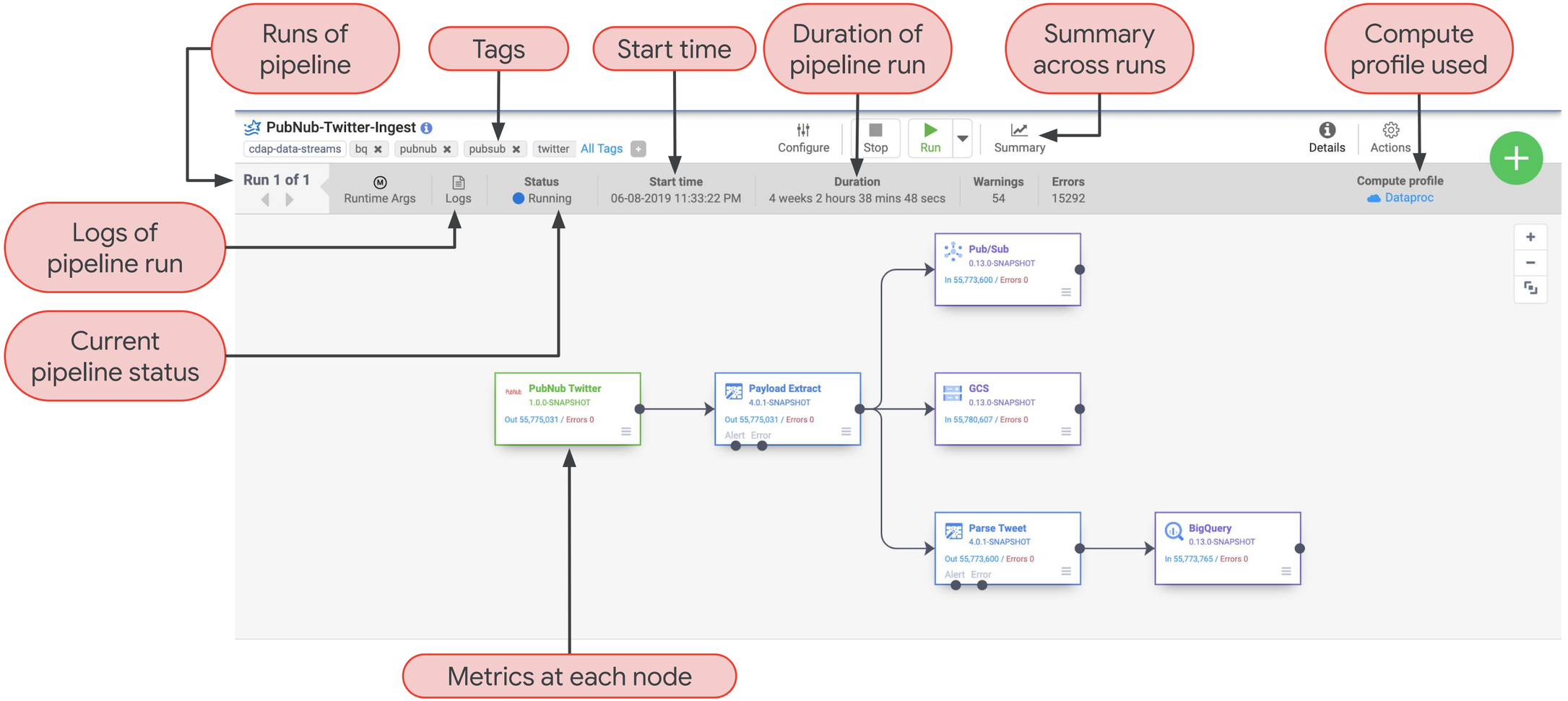
# Studio is the UI where you create new pipelines



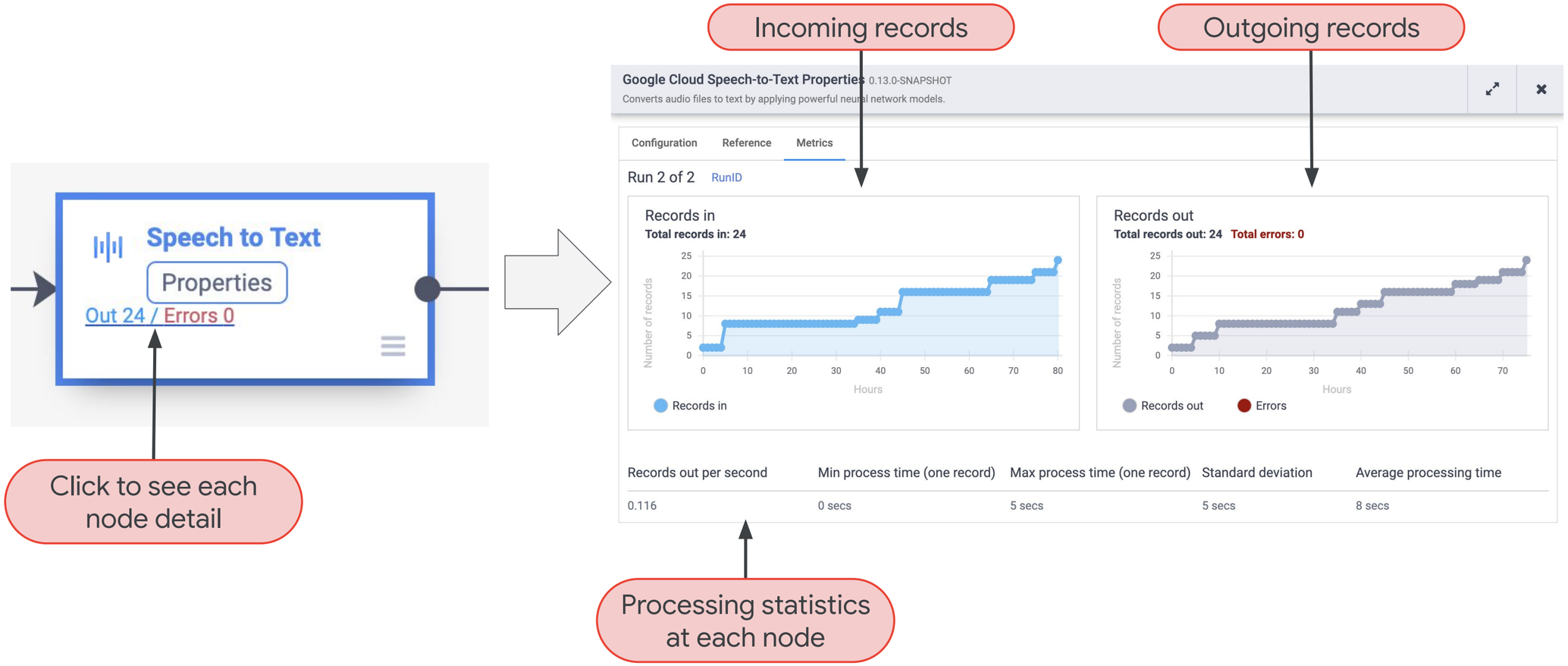
# Use Preview Mode to see how the pipeline will run



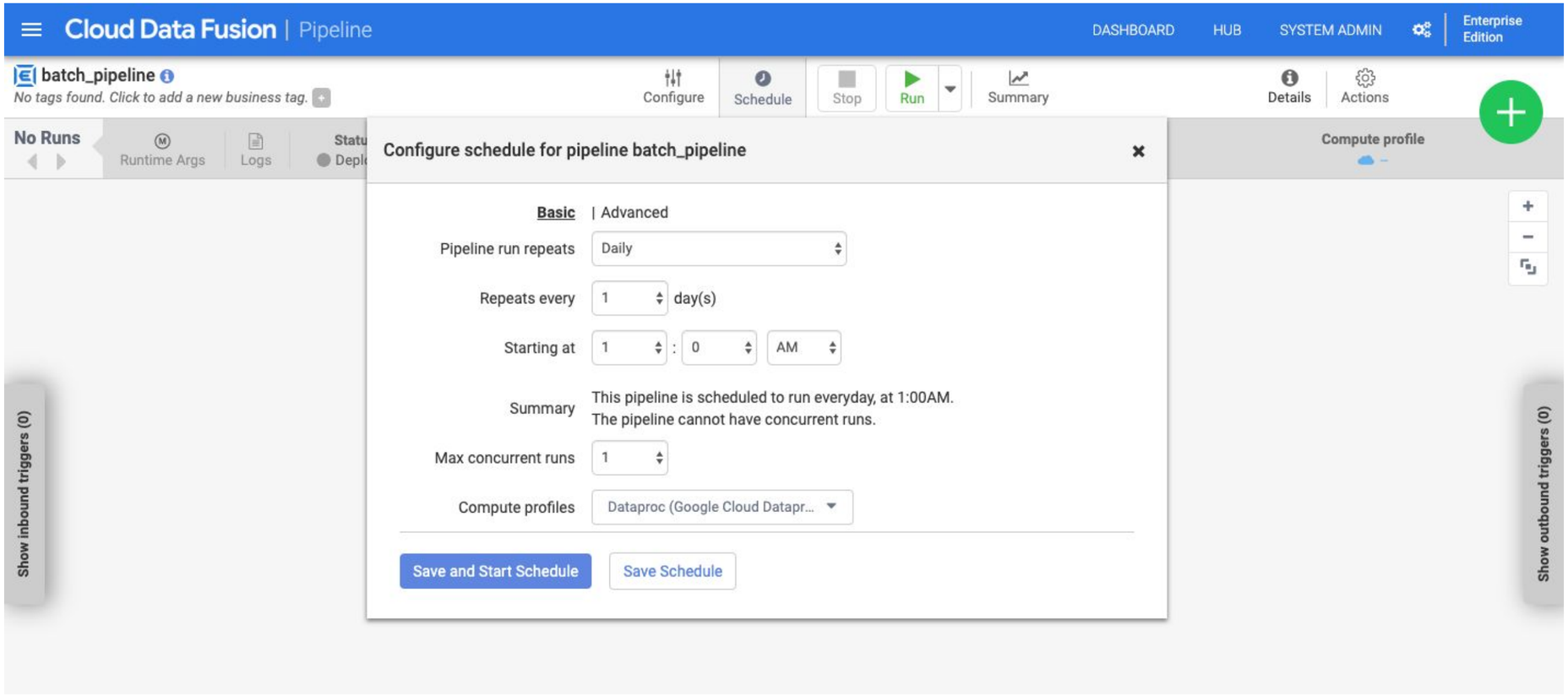
# Monitor the health of the entire pipeline



# Monitor the health of a single node

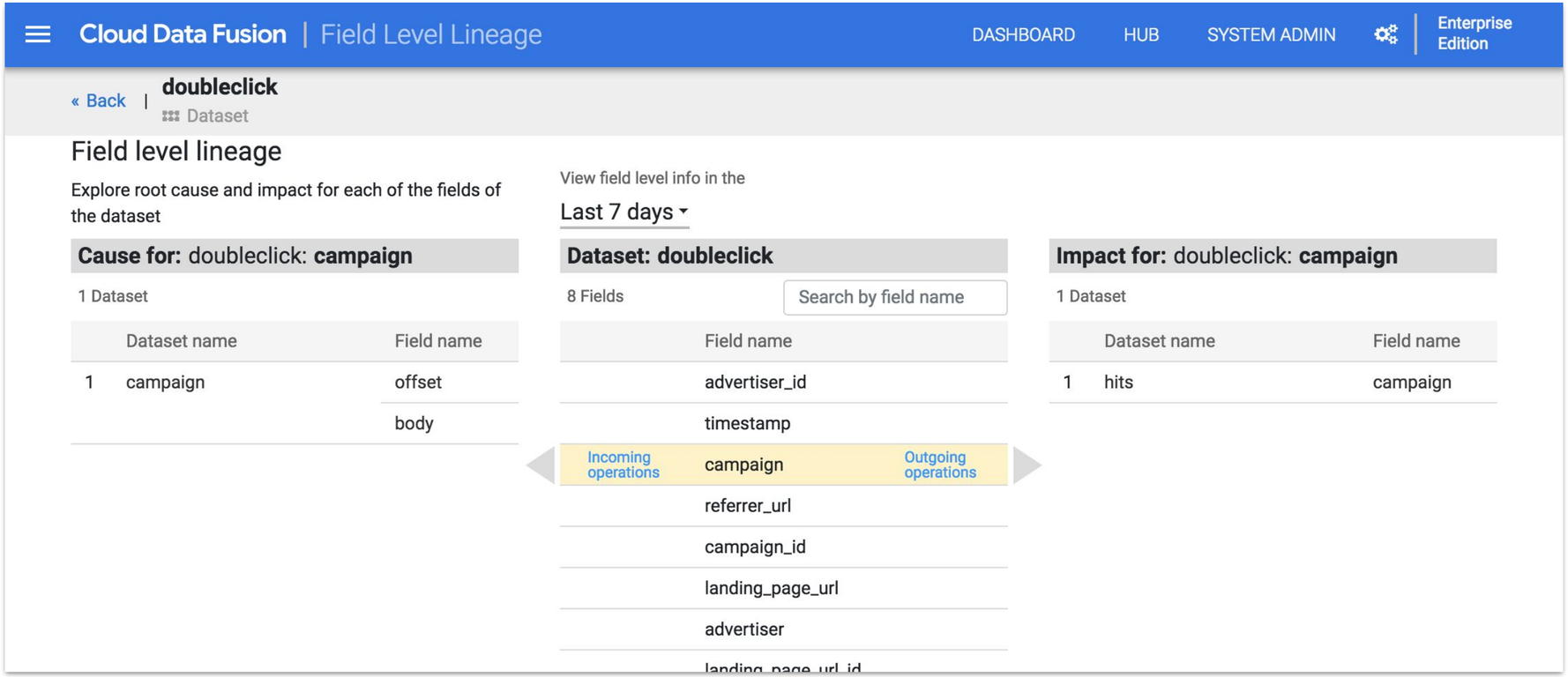


# You can schedule batch pipelines



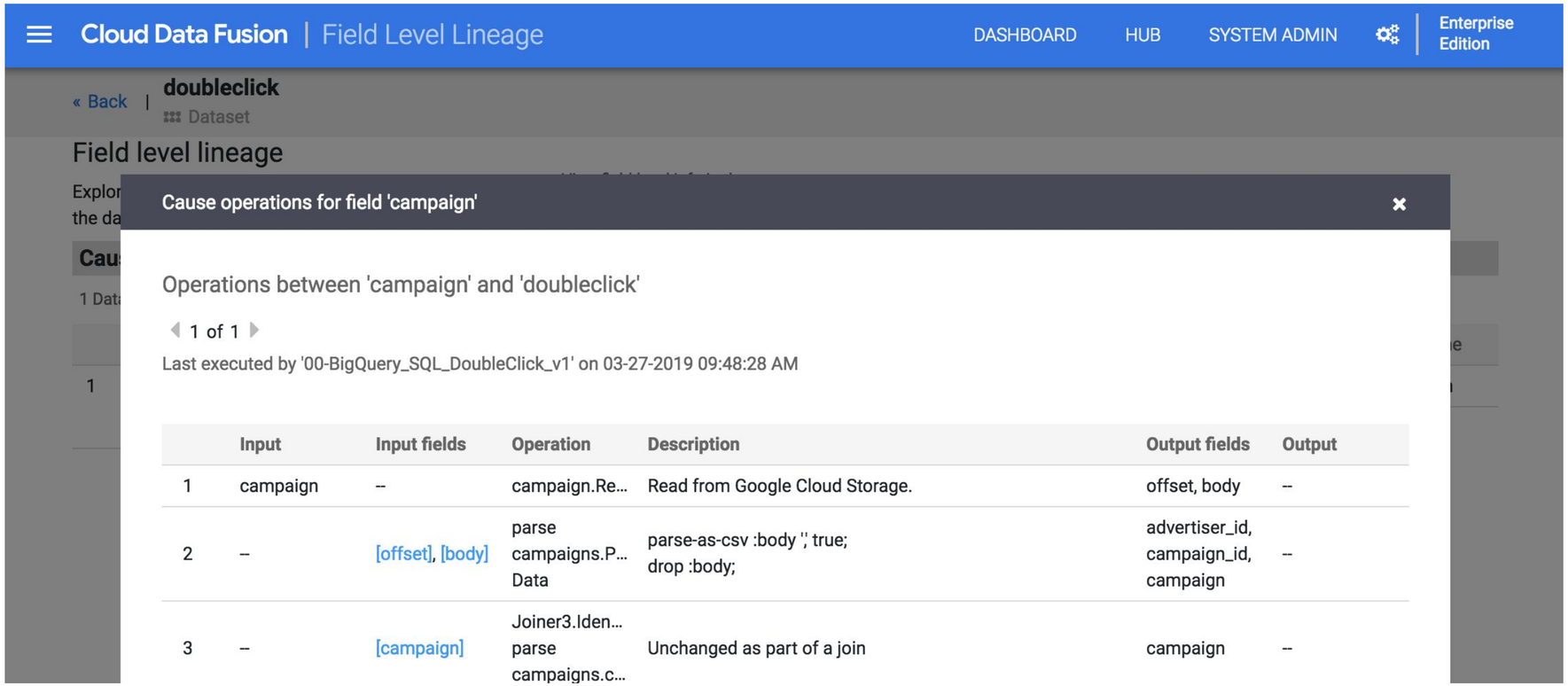
# After data is transformed, you can track field-level lineage

## Relationship between fields of datasets: Provenance, Impact



# See every operation that is made on a field

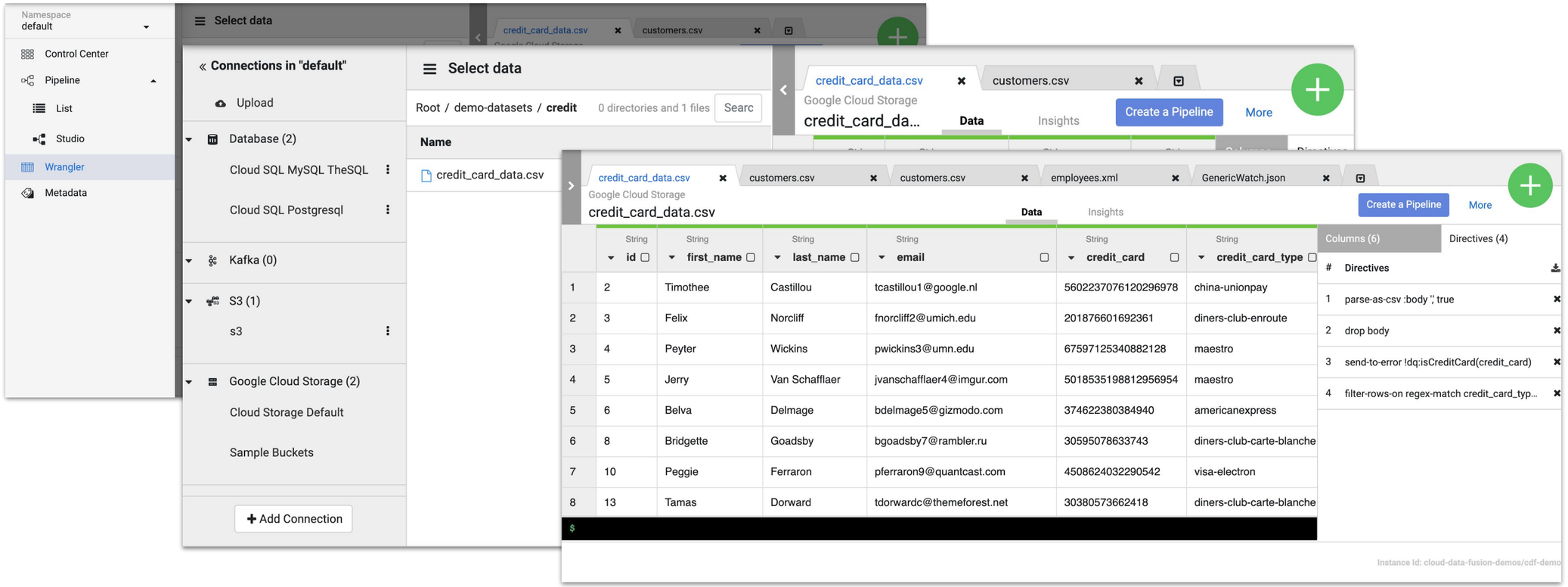
## Operations applied to a field



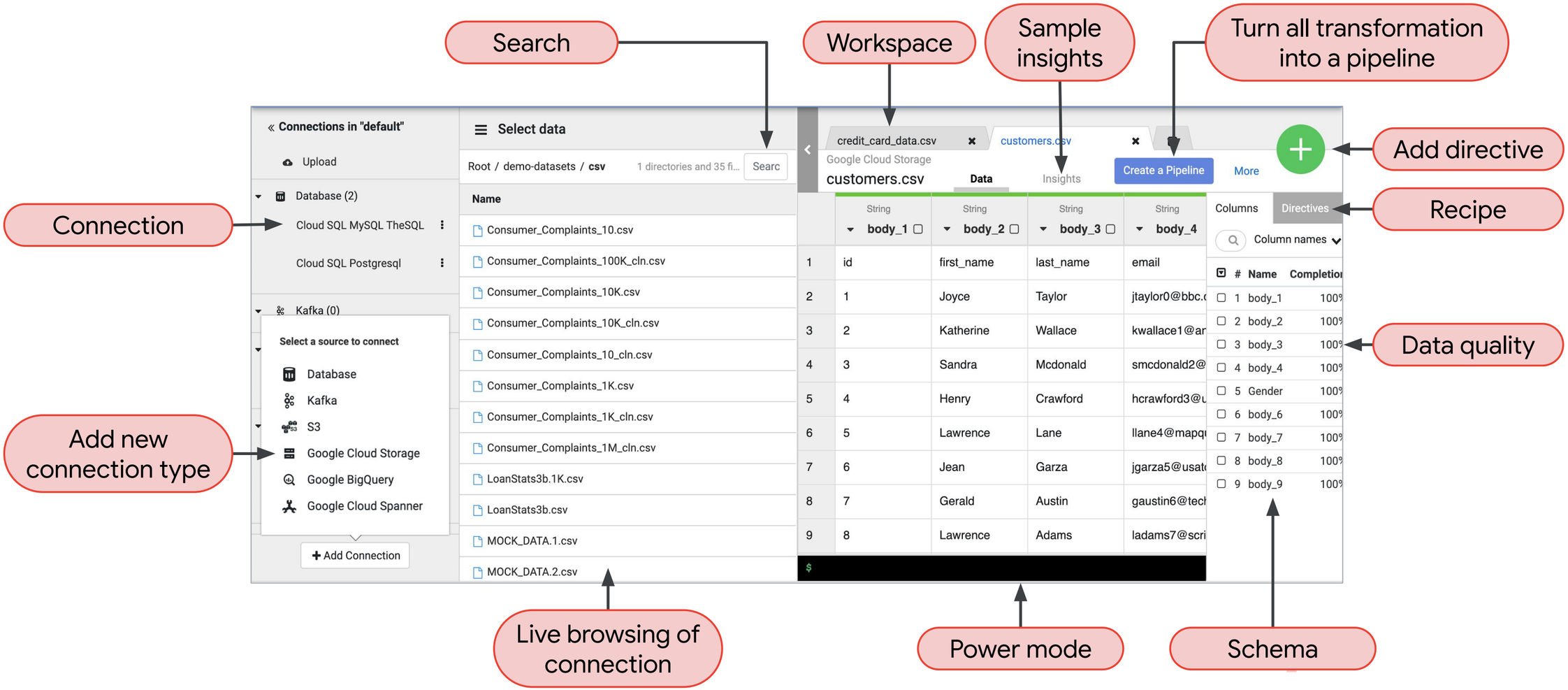

| | Input | Input fields | Operation | Description | Output fields | Output |
|---|---|---|---|---|---|---|
| 1 | campaign | -- | campaign.Re... | Read from Google Cloud Storage. | offset, body | -- |
| 2 | -- | [offset], [body] | parse campaigns.P... Data | parse-as-csv :body '' true; drop :body; | advertiser_id, campaign_id, campaign | -- |
| 3 | -- | [campaign] | Joiner3.Iden... parse campaigns.c... | Unchanged as part of a join | campaign | -- |

# Data analysts can explore datasets in the Wrangler

Wrangler is a code-free, visual environment for transforming data in data pipelines.

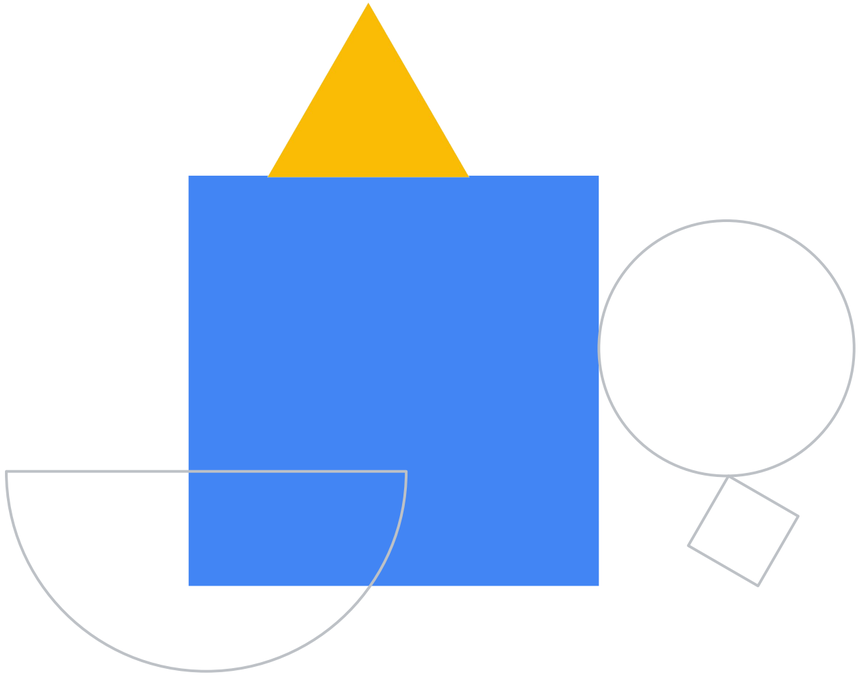


# Wrangler UI overview for exploring datasets



# Lab Intro

Building and Executing a Pipeline Graph in Cloud Data Fusion



# Lab objectives

01 Connect Cloud Data Fusion to a couple of data sources

02 Apply basic transformations

03 Join two data sources

04 Write data to a sink

# Manage Data Pipelines with Cloud Data Fusion and Cloud Composer

01

Building batch data pipelines visually with Cloud Data Fusion

- Components
- UI overview
- Building a pipeline
- Exploring data using Wrangler

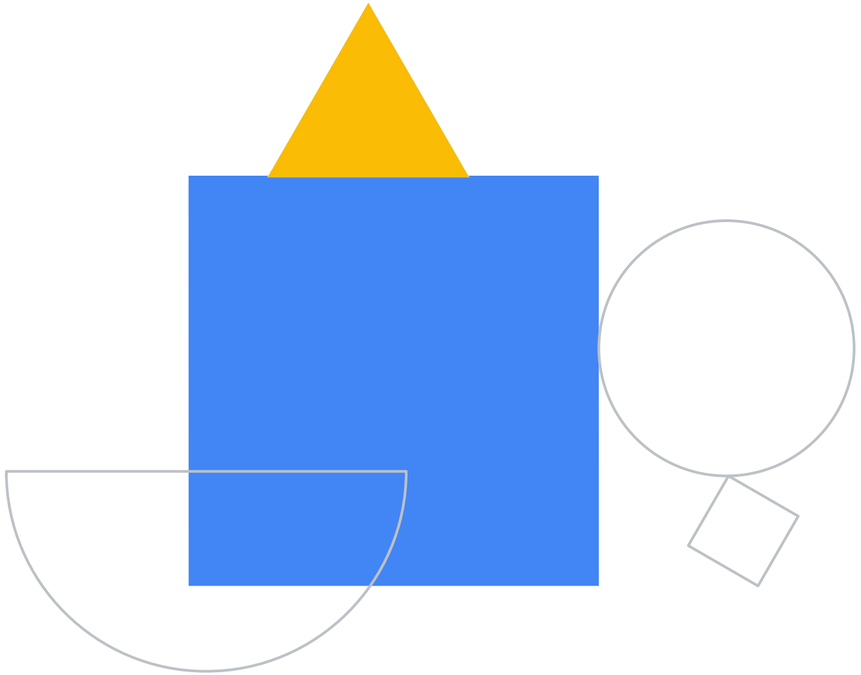
02

Orchestrating work between Google Cloud services with Cloud Composer

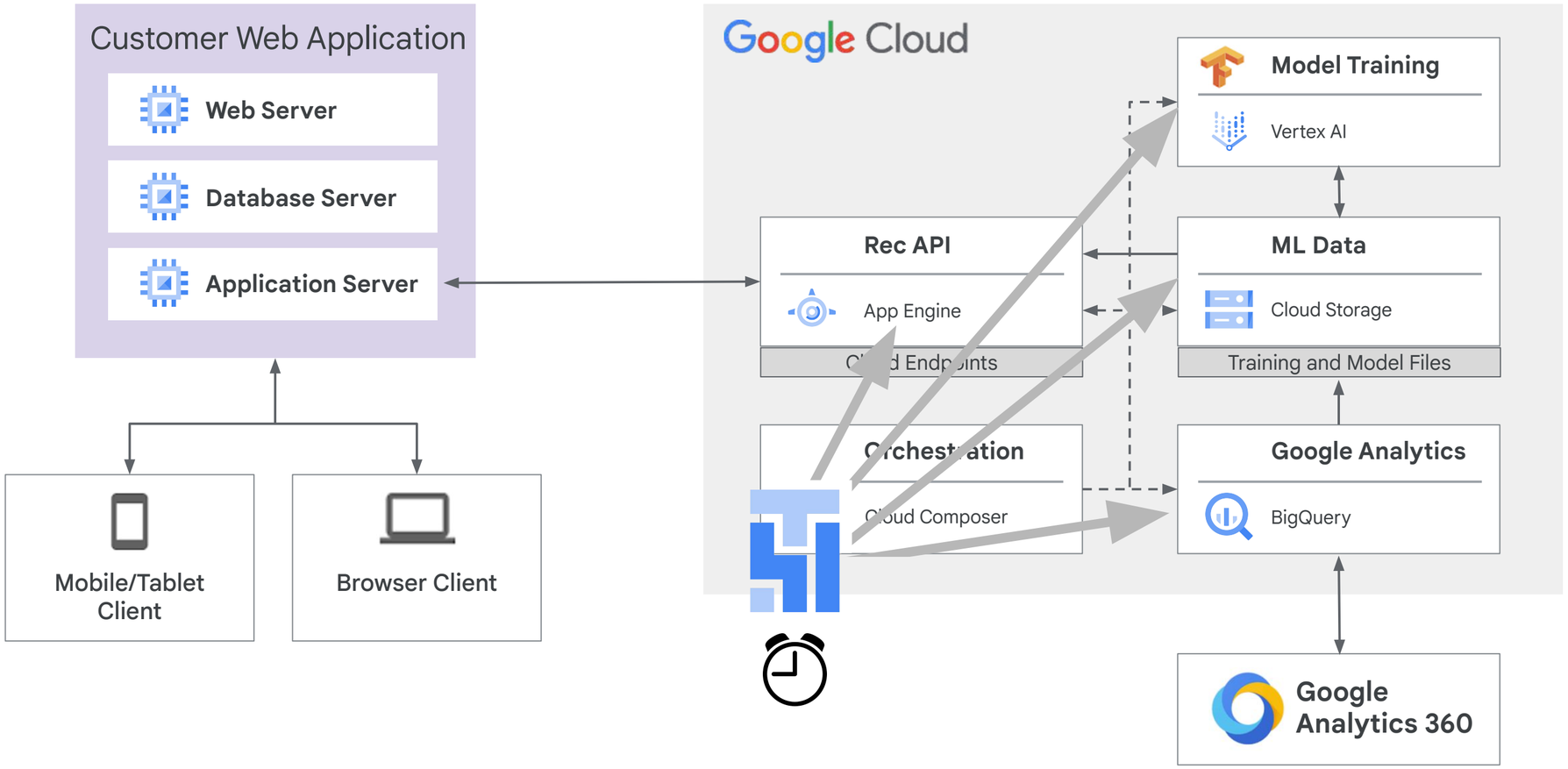
- Apache Airflow environment
- DAGs and Operators
- Workflow Scheduling
- Monitoring and Logging

# Lab Startup

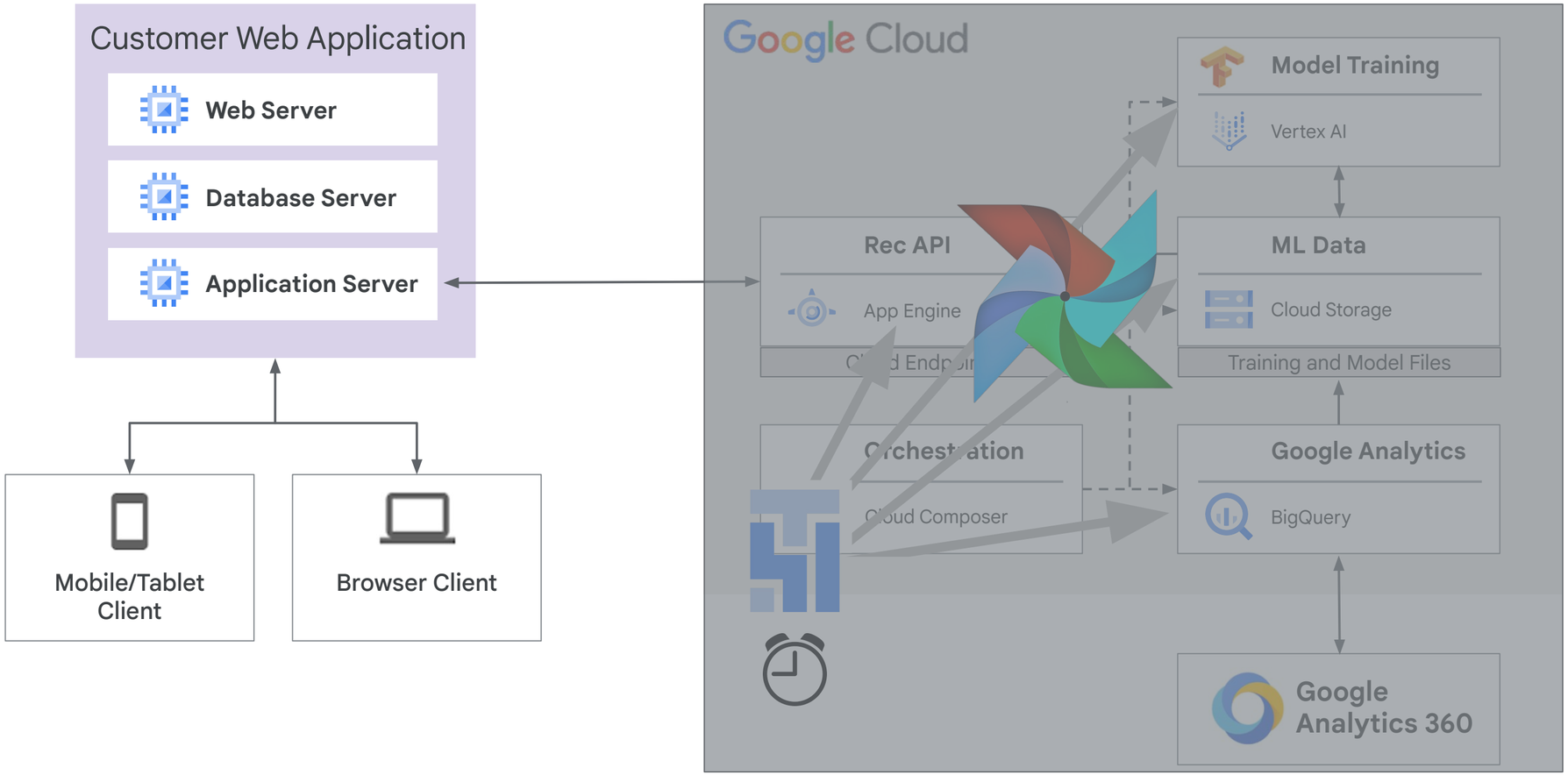
An Introduction to
Cloud Composer



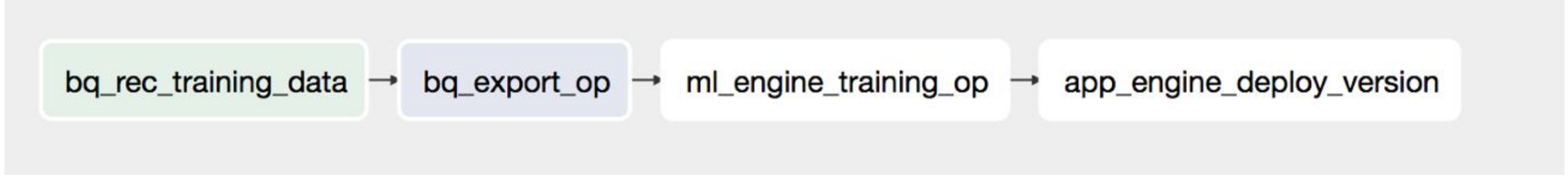
# Cloud Composer orchestrates automatic workflows



# Cloud Composer is managed Apache Airflow

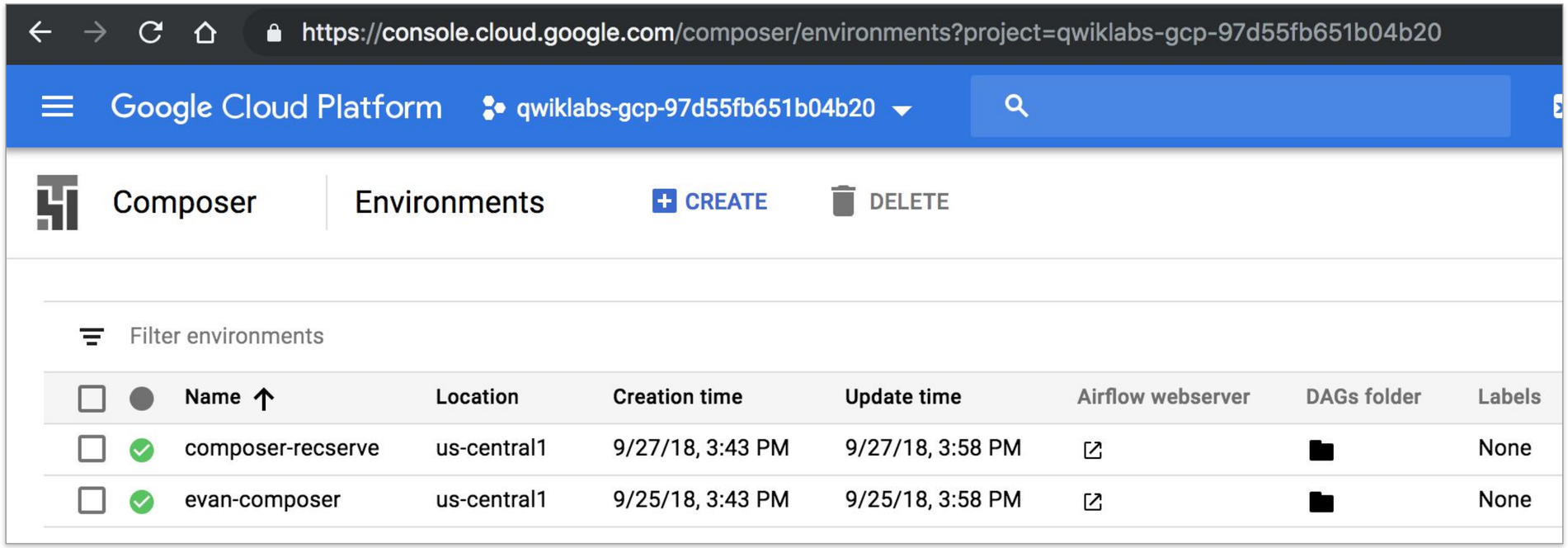


# Use Apache Airflow DAGs to orchestrate Google Cloud services

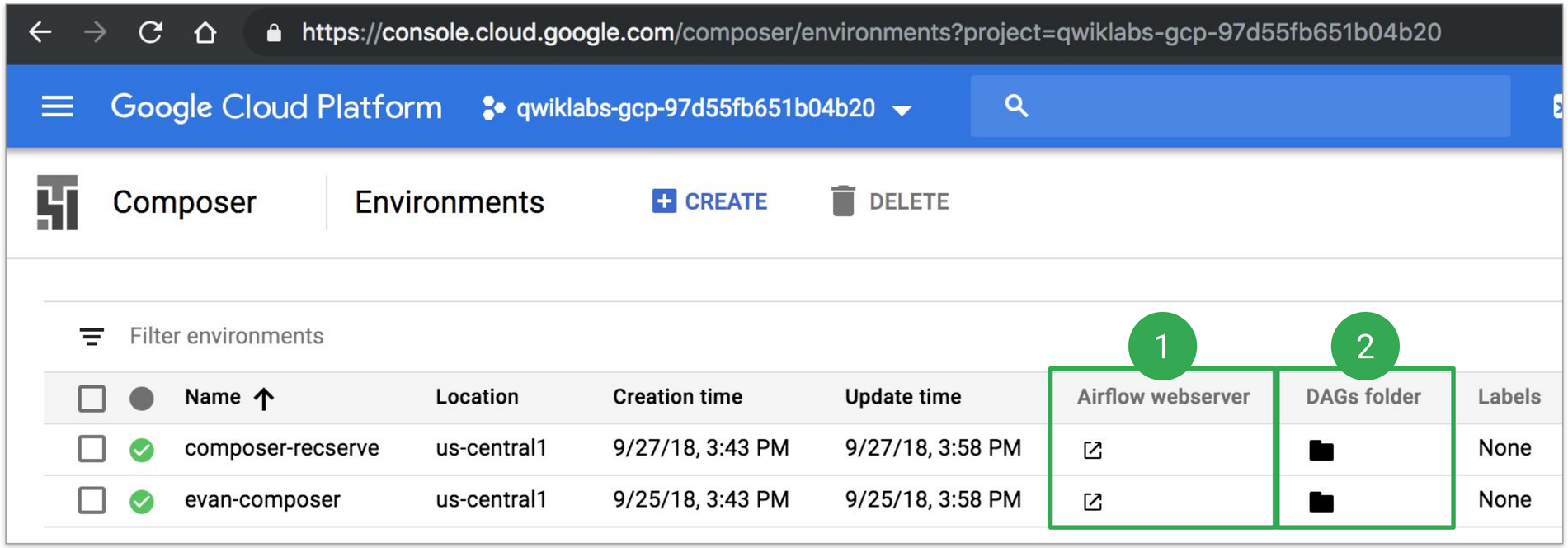



DAG = Directed Acyclic Graph

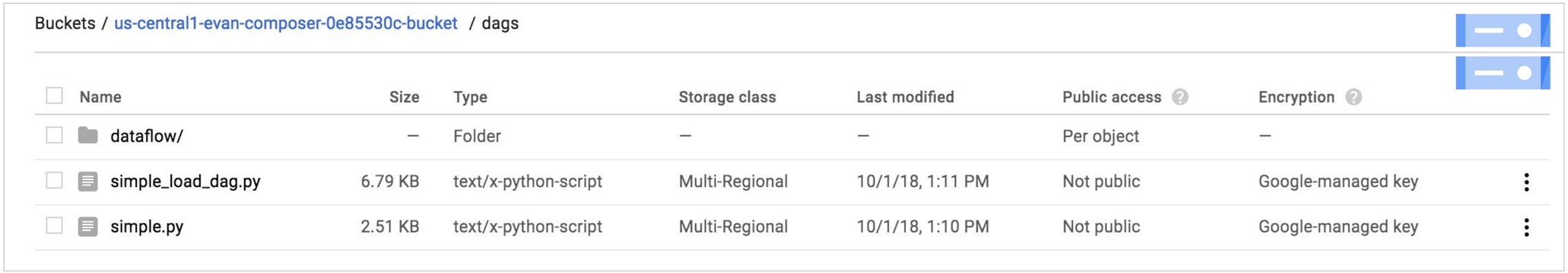
# Cloud Composer creates managed Apache Airflow environments



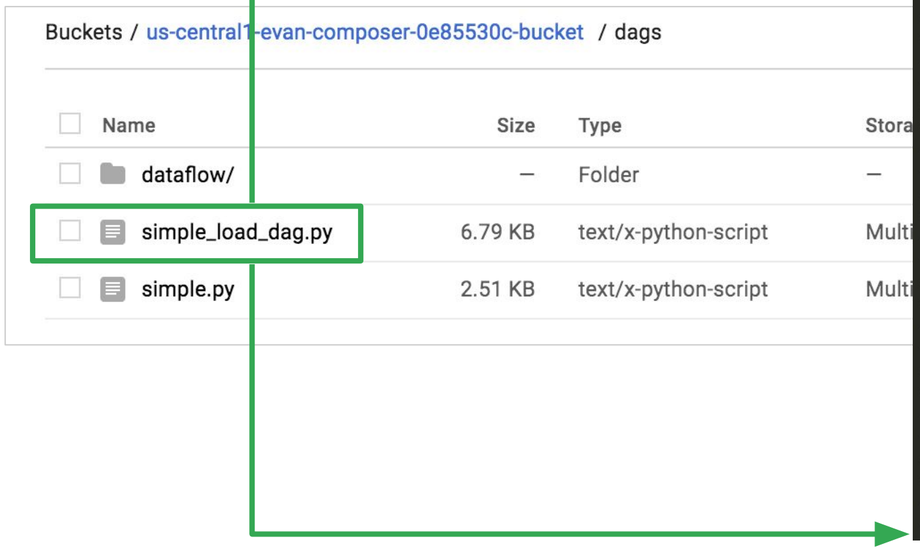
# Each Airflow environment has a separate web server and folder in Cloud Storage for pipeline DAGs



# The DAGs folder is simply a Cloud Storage bucket where you will load your pipeline code



# Airflow workflows are written in Python




```
#                 e.g. state,gender,year,name,number,created_date
with models.DAG(dag_id='GcsToBigQueryTriggered',
                description='A DAG triggered by an external Cloud Function',
                schedule_interval=None, default_args=DEFAULT_DAG_ARGS) as dag:
    # Args required for the Dataflow job.
    job_args = {
        'input': 'gs://{{ dag_run.conf["bucket"] }}/{{ dag_run.conf["name"] }}',
        'output': models.Variable.get('bq_output_table'),
        'fields': models.Variable.get('input_field_names'),
        'load_dt': DS_TAG
    }

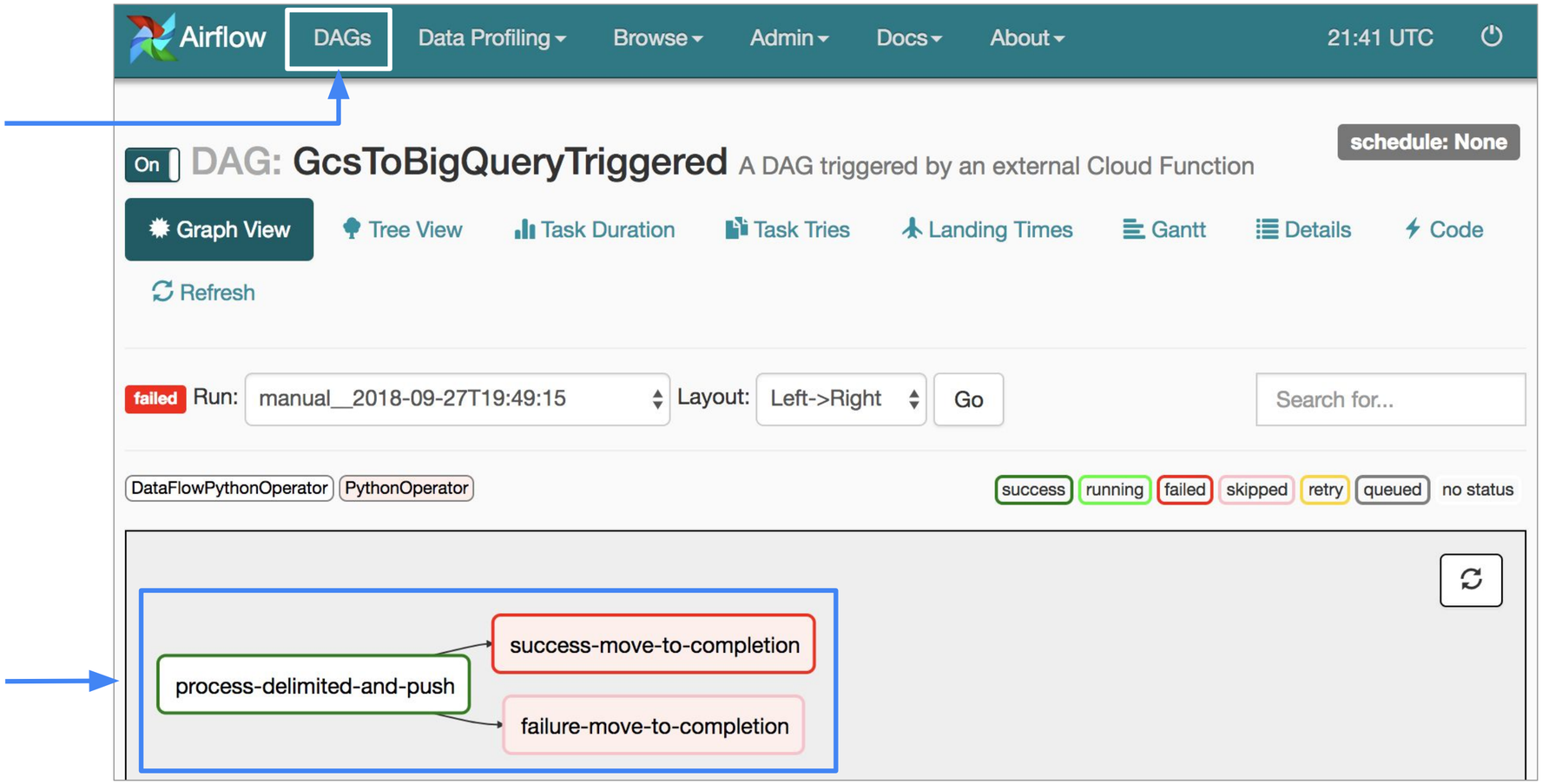
    # Main Dataflow task that will process and load the input delimited file.
    dataflow_task = dataflow_operator.DataFlowPythonOperator(
        task_id="process-delimited-and-push",
        py_file=DATAFLOW_FILE,
        options=job_args)

    # Here we create two conditional tasks, one of which will be executed
    # based on whether the dataflow_task was a success or a failure.
    success_move_task = python_operator.PythonOperator(task_id='success-move-to-completion',
                                                       python_callable=move_to_completion_bucket,
                                                       # A success_tag is used to move
                                                       # the input file to a success
                                                       # prefixed folder.
                                                       op_args=[COMPLETION_BUCKET, SUCCESS_TAG],
                                                       provide_context=True,
                                                       trigger_rule=TriggerRule.ALL_SUCCESS)

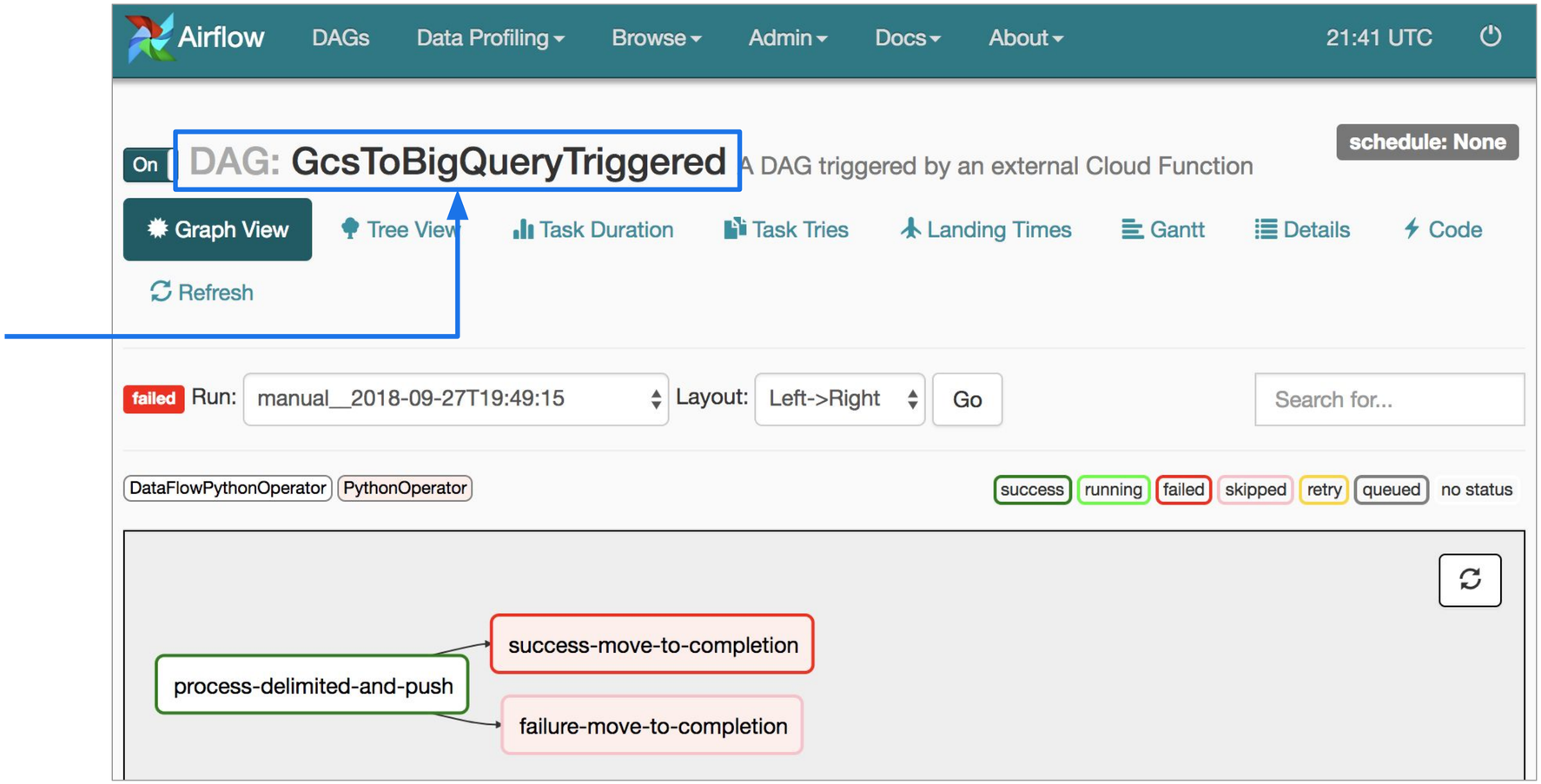
    failure_move_task = python_operator.PythonOperator(task_id='failure-move-to-completion',
                                                       python_callable=move_to_completion_bucket,
                                                       # A failure_tag is used to move
                                                       # the input file to a failure
                                                       # prefixed folder.
                                                       op_args=[COMPLETION_BUCKET, FAILURE_TAG],
                                                       provide_context=True,
                                                       trigger_rule=TriggerRule.ALL_FAILED)

    # The success_move_task and failure_move_task are both downstream from the
    # dataflow_task.
    dataflow_task >> success_move_task
    dataflow_task >> failure_move_task
```

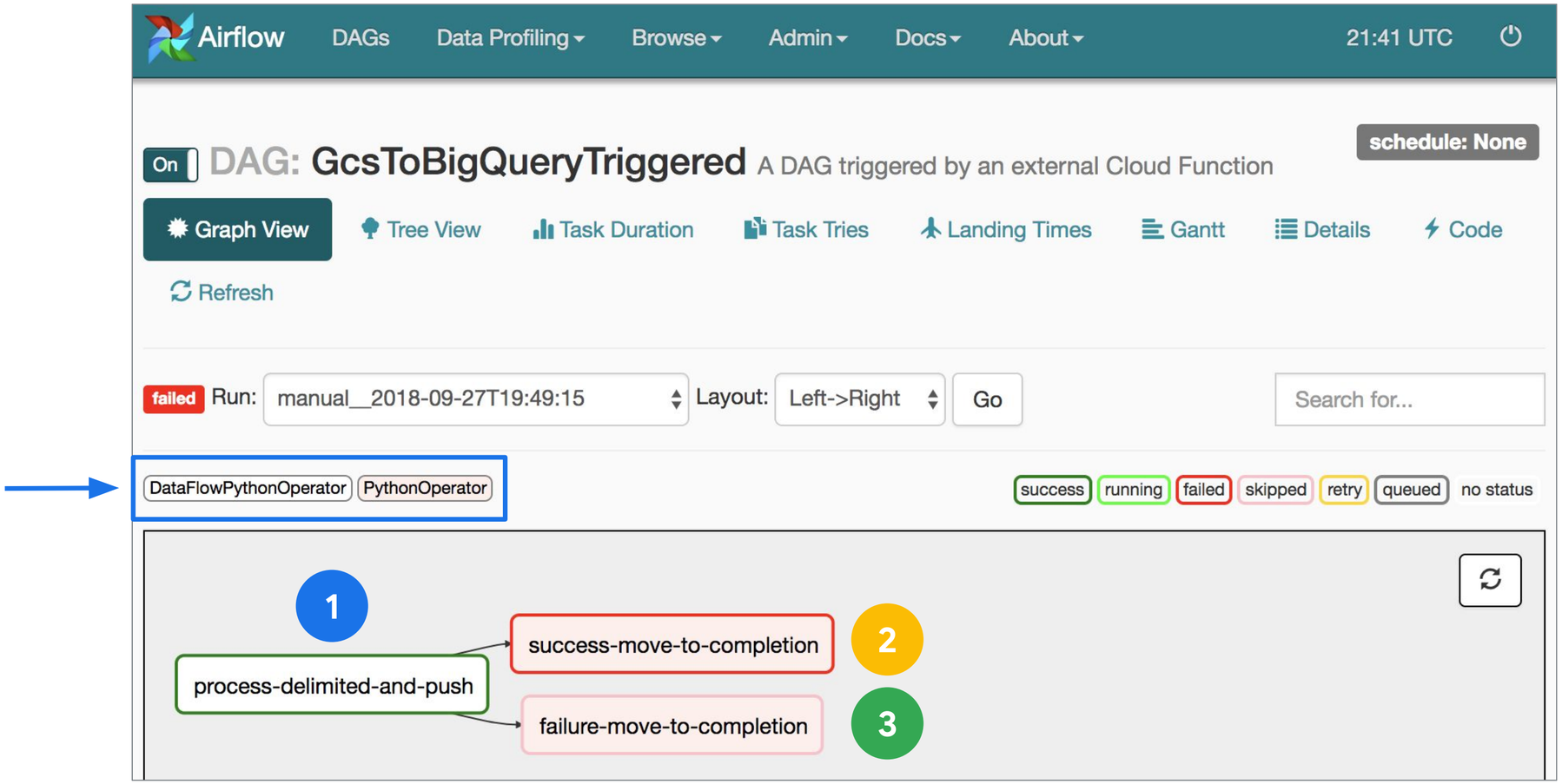
# The Python file creates a DAG



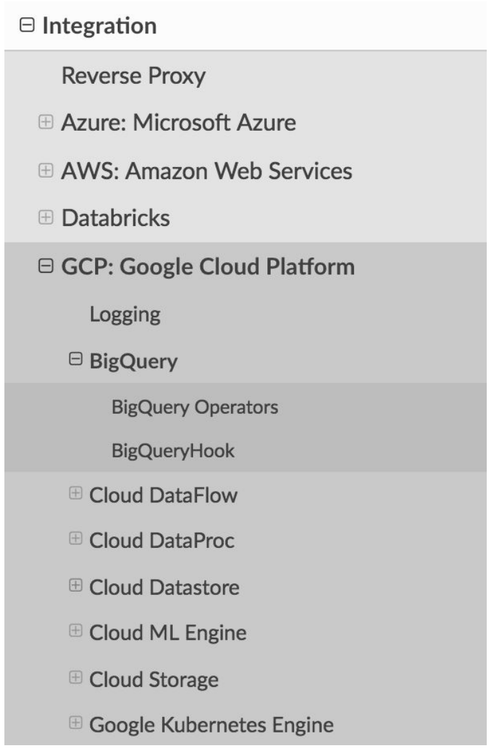
# Airflow web server UI overview



# The Python file creates a DAG



# Airflow uses operators in your DAG to orchestrate other Google Cloud services



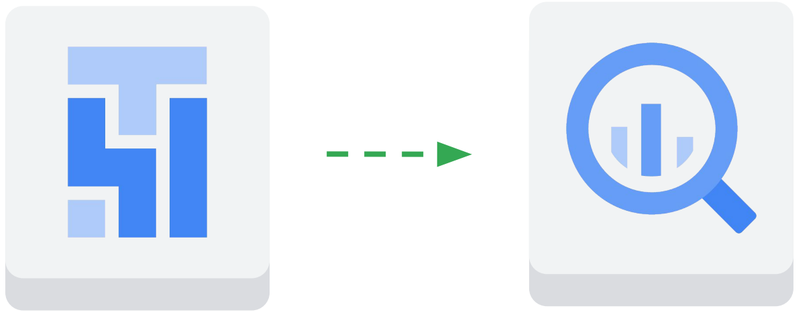

View all Google Cloud services that Airflow can orchestrate:

http://airflow.apache.org/integration.html#gcp

\+ sample code

# BigQuery Operators are popular for updating your ML training dataset

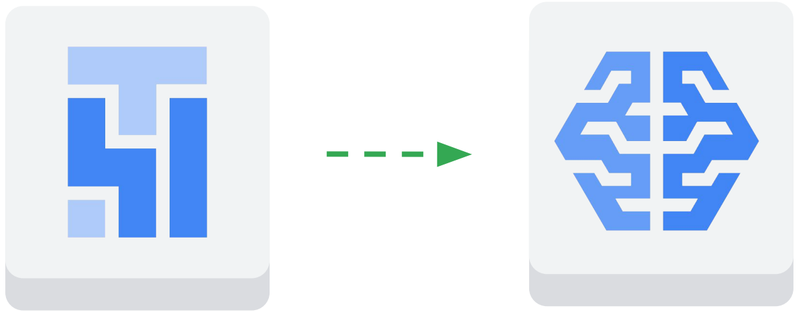
- Integration
  - Reverse Proxy
  - Azure: Microsoft Azure
  - AWS: Amazon Web Services
  - Databricks
  - GCP: Google Cloud Platform
    - Logging
    - BigQuery
      - BigQuery Operators
      - BigQueryHook
    - Cloud DataFlow
    - Cloud DataProc
    - Cloud Datastore
    - Cloud ML Engine
    - Cloud Storage
    - Google Kubernetes Engine



```
BigQueryOperator
BigQueryCheckOperator
BigQueryIntervalCheckOperator
BigQueryCreateEmptyTableOperator
BigQueryCreateExternalTableOperator
BigQueryDeleteDatasetOperator
BigQueryToBigQueryOperator
BigQueryToCloudStorageOperator
```

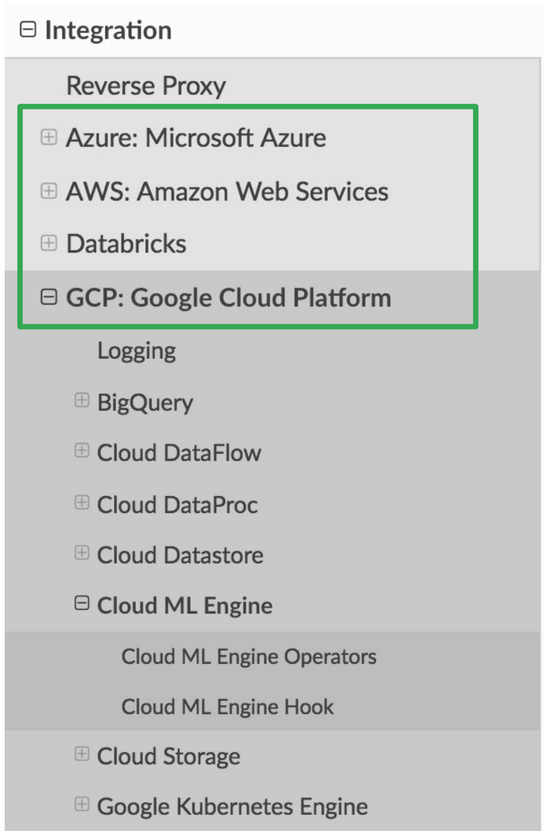
# Vertex AI (formerly Cloud ML Engine) operators can launch training and deployment jobs

- Integration
  - Reverse Proxy
  - Azure: Microsoft Azure
  - AWS: Amazon Web Services
  - Databricks
  - GCP: Google Cloud Platform
    - Logging
    - BigQuery
    - Cloud DataFlow
    - Cloud DataProc
    - Cloud Datastore
    - Cloud ML Engine
      - Cloud ML Engine Operators
      - Cloud ML Engine Hook
    - Cloud Storage
    - Google Kubernetes Engine



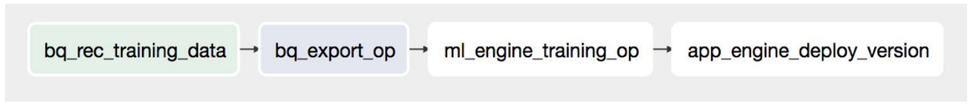
```
MLEngineBatchPredictionOperator
MLEngineModelOperator
MLEngineTrainingOperator
MLEngineVersionOperator
```

# Apache Airflow is open source and cross-platform for hybrid pipelines



# Example: Common Machine Learning workflow

## DAG Operators




```
# update training data
t1 = BigQueryOperator(
)

# BigQuery training data export to GCS
t2 = BigQueryToCloudStorageOperator(
)

# AI Platform training job
t3 = MLEngineTrainingOperator(
)

# App Engine deploy new version
t4 = AppEngineVersionOperator(
)

# DAG dependencies
t2.set_upstream(t1)
t3.set_upstream(t2)
t4.set_upstream(t3)
```

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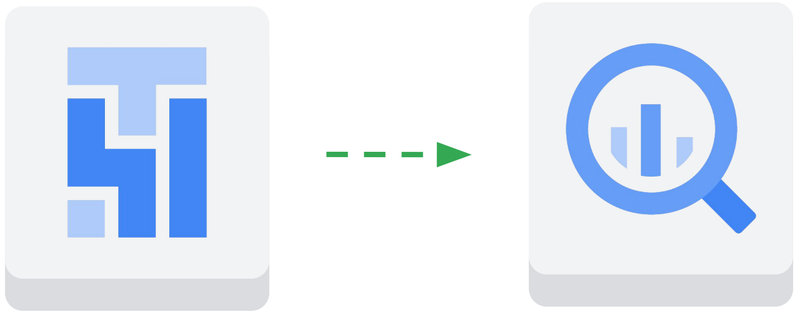
# BigQuery and Cloud Storage operators get us fresh training data



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t2 = BigQueryToCloudStorageOperator(
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# AI Platform training job
t3 = MLEngineTrainingOperator(
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# App Engine deploy new version
t4 = AppEngineVersionOperator(
)

# DAG dependencies
t2.set_upstream(t1)
t3.set_upstream(t2)
t4.set_upstream(t3)
```

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# Use the BigQueryOperator to run SQL

```
from airflow.contrib.operators import bigquery_operator

# constants or can be dynamic based on Airflow macros
max_query_date = '2018-02-01'
min_query_date = '2018-01-01'

    # Query recent StackOverflow questions.
    bq_recent_questions_query = bigquery_operator.BigQueryOperator(

        task_id='bq_recent_questions_query',

        bql="""
        SELECT owner_display_name, title, view_count
        FROM `bigquery-public-data.stackoverflow.posts_questions`
        WHERE creation_date < CAST('{max_date}' AS TIMESTAMP)
            AND creation_date >= CAST('{min_date}' AS TIMESTAMP)
        ORDER BY view_count DESC
        LIMIT 100
        """.format(max_date=max_query_date, min_date=min_query_date),

        use_legacy_sql=False,

        destination_dataset_table=bq_recent_questions_table_id)
```

# SQL commands can hold parameters (from Python)

```
from airflow.contrib.operators import bigquery_operator

# constants or can be dynamic based on Airflow macros
max_query_date = '2018-02-01'
min_query_date = '2018-01-01'

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        WHERE creation_date < CAST('{max_date}' AS TIMESTAMP)
            AND creation_date >= CAST('{min_date}' AS TIMESTAMP)
        ORDER BY view_count DESC
        LIMIT 100
        """.format(max_date=max_query_date, min_date=min_query_date),

        use_legacy_sql=False,

        destination_dataset_table=bq_recent_questions_table_id)
```

# Note the Python constants for a date range here

```
from airflow.contrib.operators import bigquery_operator

# constants or can be dynamic based on Airflow macros
max_query_date = '2018-02-01'
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        WHERE creation_date < CAST('{max_date}' AS TIMESTAMP)
            AND creation_date >= CAST('{min_date}' AS TIMESTAMP)
        ORDER BY view_count DESC
        LIMIT 100
        """.format(max_date=max_query_date, min_date=min_query_date),

        use_legacy_sql=False,

        destination_dataset_table=bq_recent_questions_table_id)
```

# You could even set a rolling window with macros

```
from airflow.contrib.operators import bigquery_operator

# constants or can be dynamic based on Airflow macros
max_query_date = {{ macros.ds_add(ds, -1) }}  # one day prior
min_query_date = {{ macros.ds_add(ds, -7) }}  # seven days prior

    # Query recent StackOverflow questions.
    bq_recent_questions_query = bigquery_operator.BigQueryOperator(

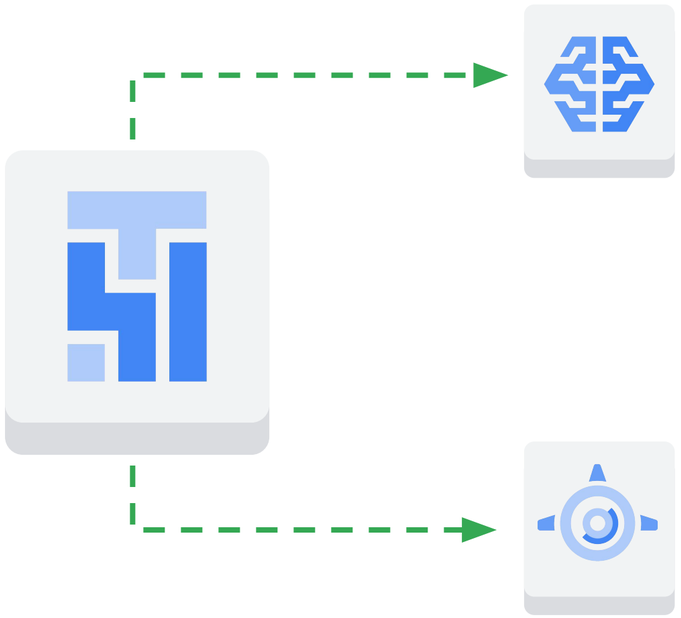
        task_id='bq_recent_questions_query',

        bql="""
        SELECT owner_display_name, title, view_count
        FROM `bigquery-public-data.stackoverflow.posts_questions`
        WHERE creation_date < CAST('{max_date}' AS TIMESTAMP)
            AND creation_date >= CAST('{min_date}' AS TIMESTAMP)
        ORDER BY view_count DESC
        LIMIT 100
        """.format(max_date=max_query_date, min_date=min_query_date),

        use_legacy_sql=False,

        destination_dataset_table=bq_recent_questions_table_id)
```

# Vertex AI and App Engine operators retrain and redeploy our model



```
# update training data                                    1
t1 = BigQueryOperator(
)

# BigQuery training data export to GCS                   2
t2 = BigQueryToCloudStorageOperator(
)

# AI Platform training job                               3
t3 = MLEngineTrainingOperator(
)

# App Engine deploy new version                          4
t4 = AppEngineVersionOperator(
)

# DAG dependencies
t2.set_upstream(t1)
t3.set_upstream(t2)
t4.set_upstream(t3)
```

# Manage pipelines and dependencies as code

```
# update training data
t1 = BigQueryOperator(
)

# BigQuery training data export to GCS
t2 = BigQueryToCloudStorageOperator(
)

# AI Platform training job
t3 = MLEngineTrainingOperator(
)

# App Engine deploy new version
t4 = AppEngineVersionOperator(
)

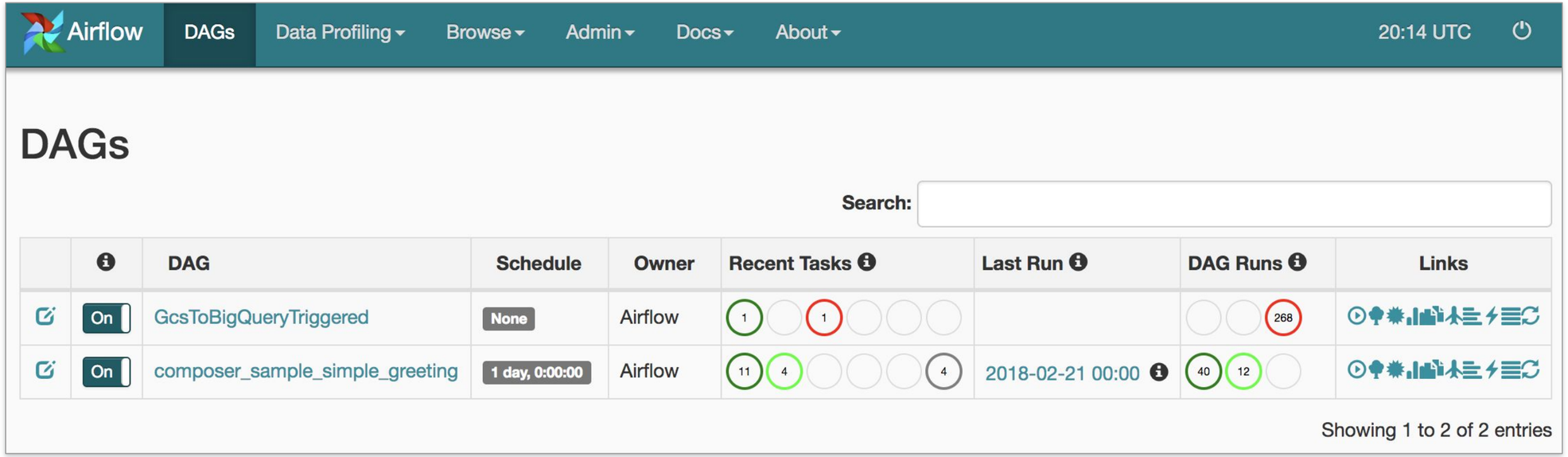
# DAG dependencies
t2.set_upstream(t1)
t3.set_upstream(t2)
t4.set_upstream(t3)
```

# Two scheduling options for Cloud Composer workflows

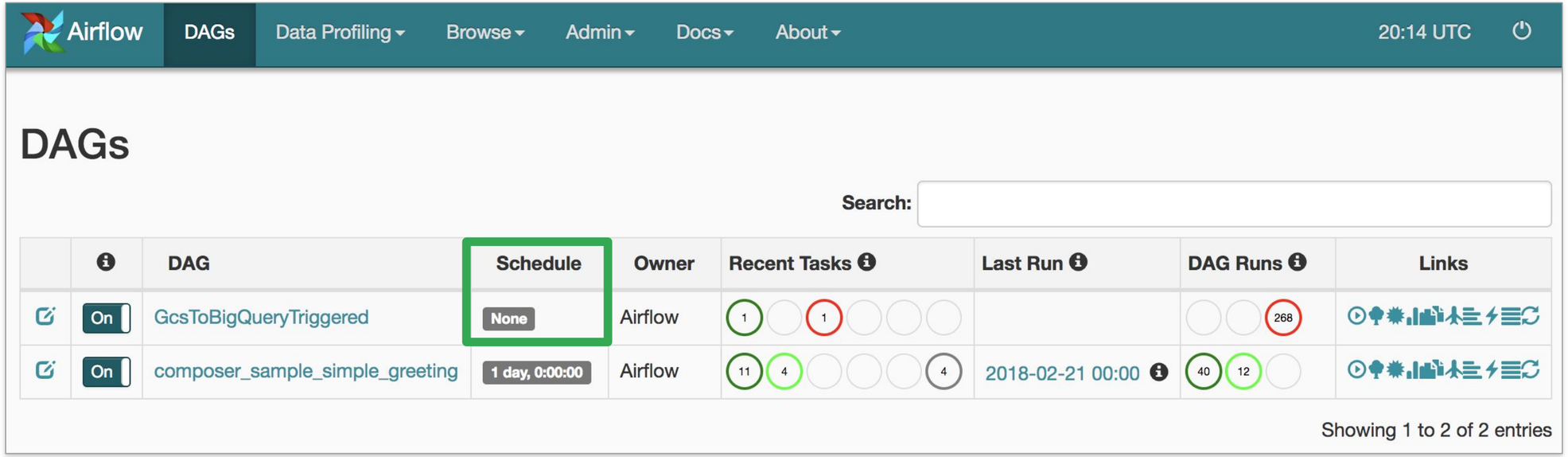
Periodic

Event-driven

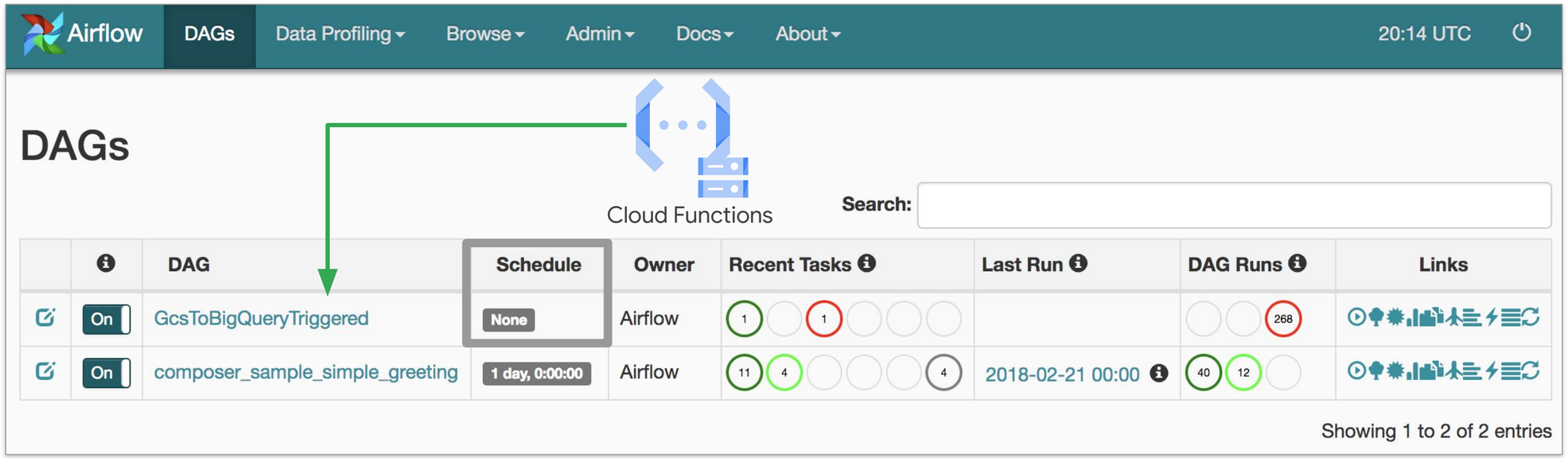
# Airflow scheduling basics



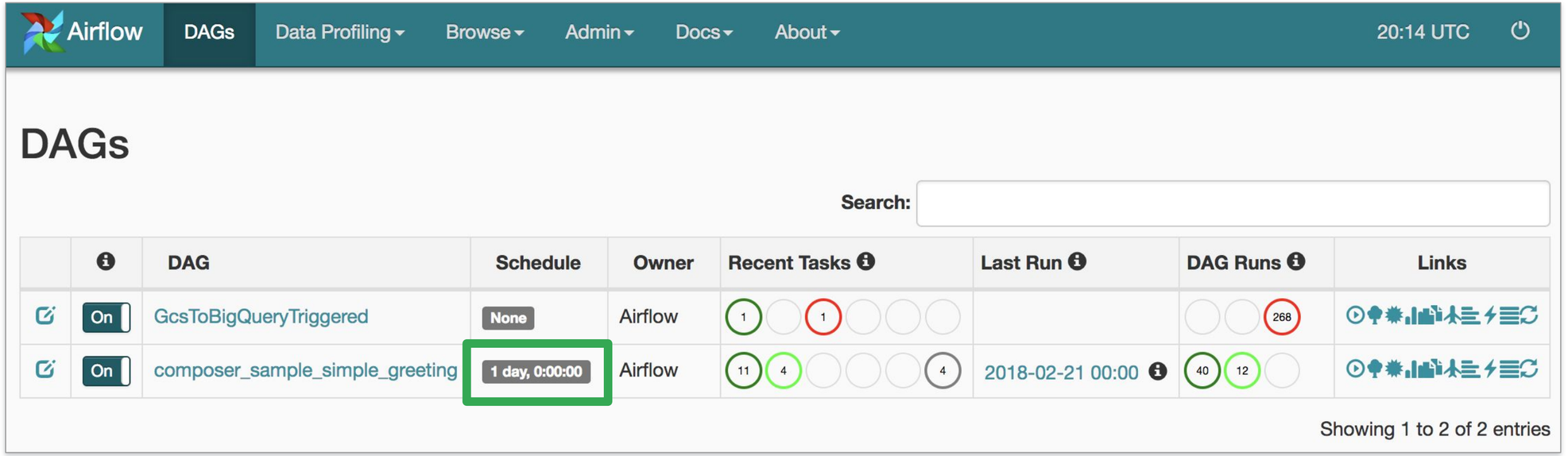
# Why is this DAG missing a schedule?



# Option 1: Event-driven scheduling with Cloud Functions



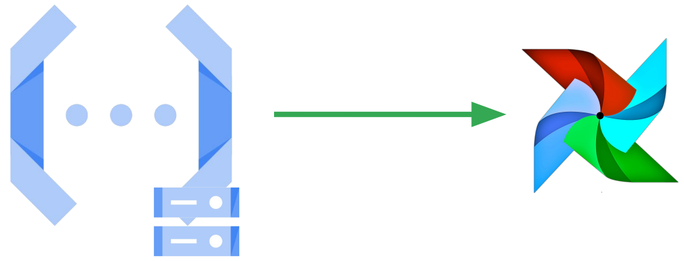
# Option 2: Specify pipeline schedule_interval in your DAG




```
with models.DAG(
        'composer_sample_simple_greeting',
        schedule_interval=datetime.timedelta(days=1),
        default_args=default_dag_args) as dag:
```

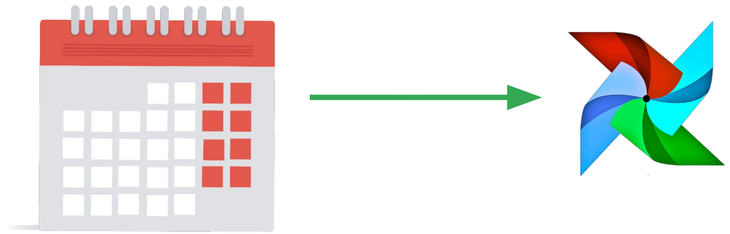
# Two types of workflow ETL patterns

## Push (event-triggered)

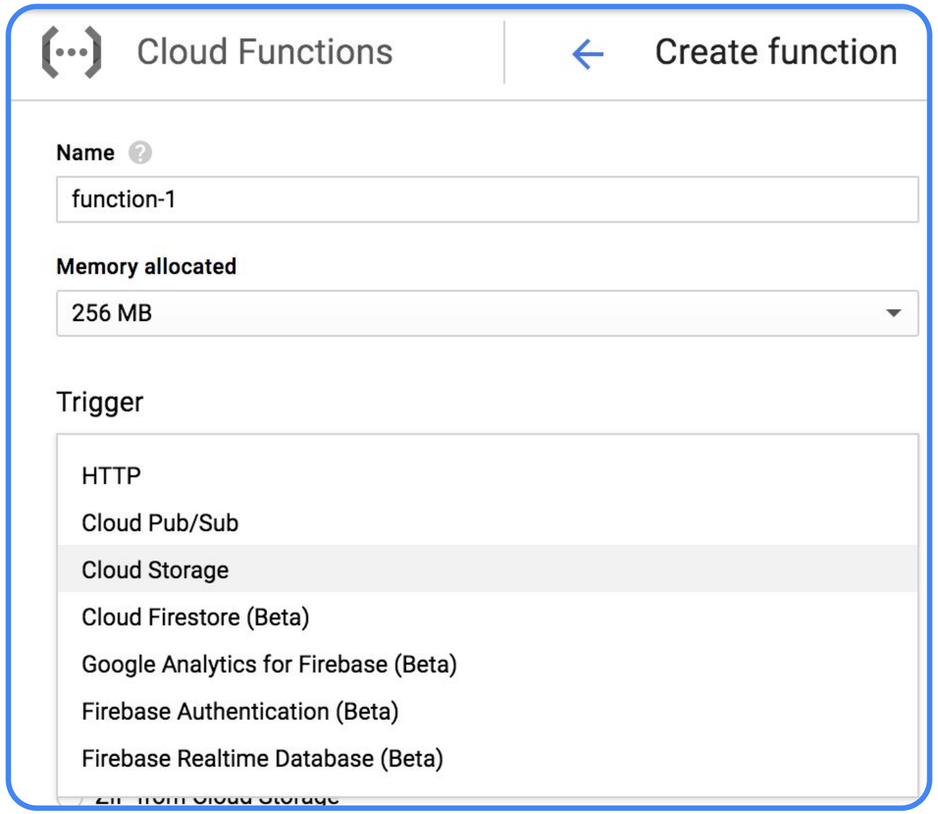


Cloud Functions

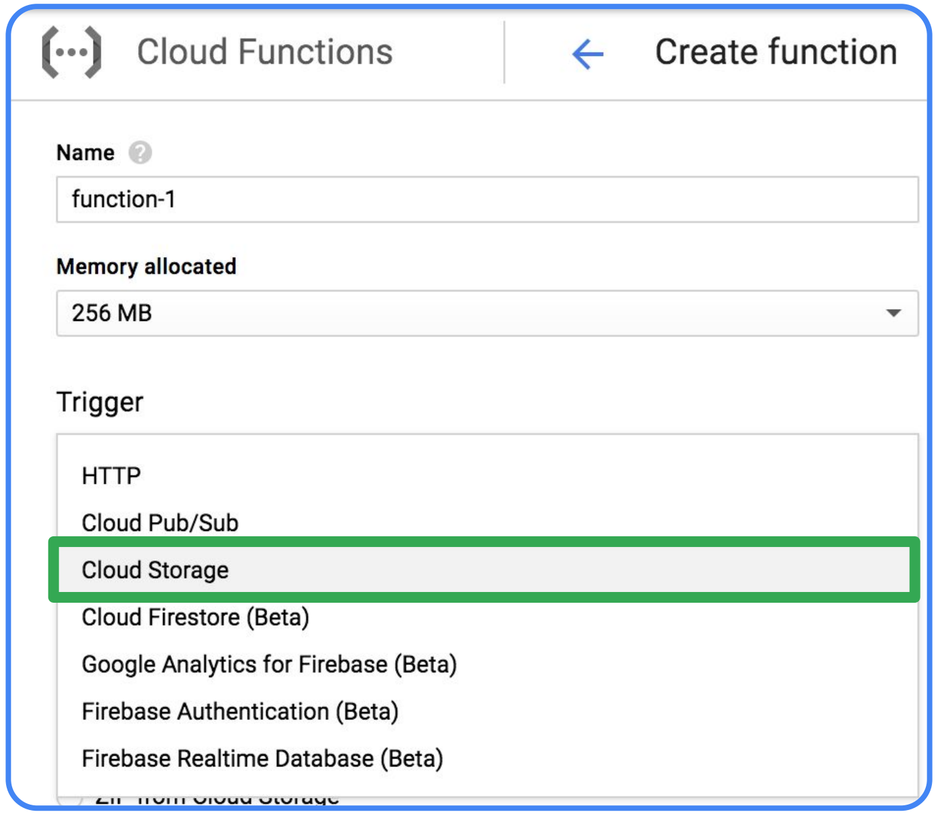
## Pull (scheduled workflow run)



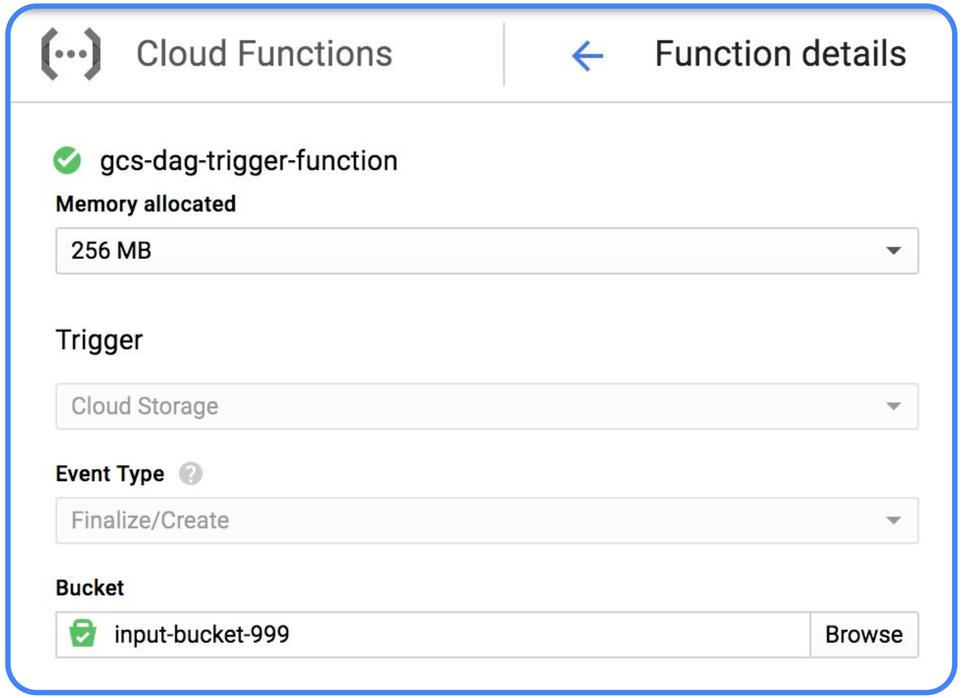
# Use Cloud Functions to create an event-based push architecture



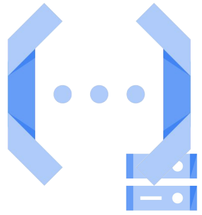
# Example: Trigger an event when new data is loaded to Cloud Storage



# Creating a Cloud Function to trigger an Airflow DAG



# Creating a Cloud Function Cloud Storage trigger an Airflow DAG



Cloud Functions

index.js package.json

```
14  * @param {!Object} event The Cloud Functions event.
15  * @param {!Function} callback The callback function.
16  */
17 exports.triggerDag = function triggerDag (event, callback) {
18   // Fill in your Composer environment information here.
19
20   // The project that holds your function
21   const PROJECT_ID = 'qwiklabs-gcp-                    ';
22   // Navigate to your webserver's login page and get this from the URL
23   const CLIENT_ID = '                                                .apps.googleusercontent.com';
24   // This should be part of your webserver's URL:
25   // {tenant-project-id}.appspot.com
26   const WEBSERVER_ID = 'b9                          -tp';
27   // The name of the DAG you wish to trigger
28   const DAG_NAME = 'GcsToBigQueryTriggered';
29
30   // Other constants
31   const WEBSERVER_URL = `https://${WEBSERVER_ID}.appspot.com/api/experimental/dags/${DAG_NAME}/dag
32   const USER_AGENT = 'gcf-event-trigger';
33   const BODY = {'conf': JSON.stringify(event.data)};
34
35   // Make the request
36   authorizeIap(CLIENT_ID, PROJECT_ID, USER_AGENT)
37     .then(function iapAuthorizationCallback (iap) {
38       makeIapPostRequest(WEBSERVER_URL, BODY, iap.idToken, USER_AGENT, iap.jwt);
39     })
40     .then(_ => callback(null))
41     .catch(callback);
42 };
43
```

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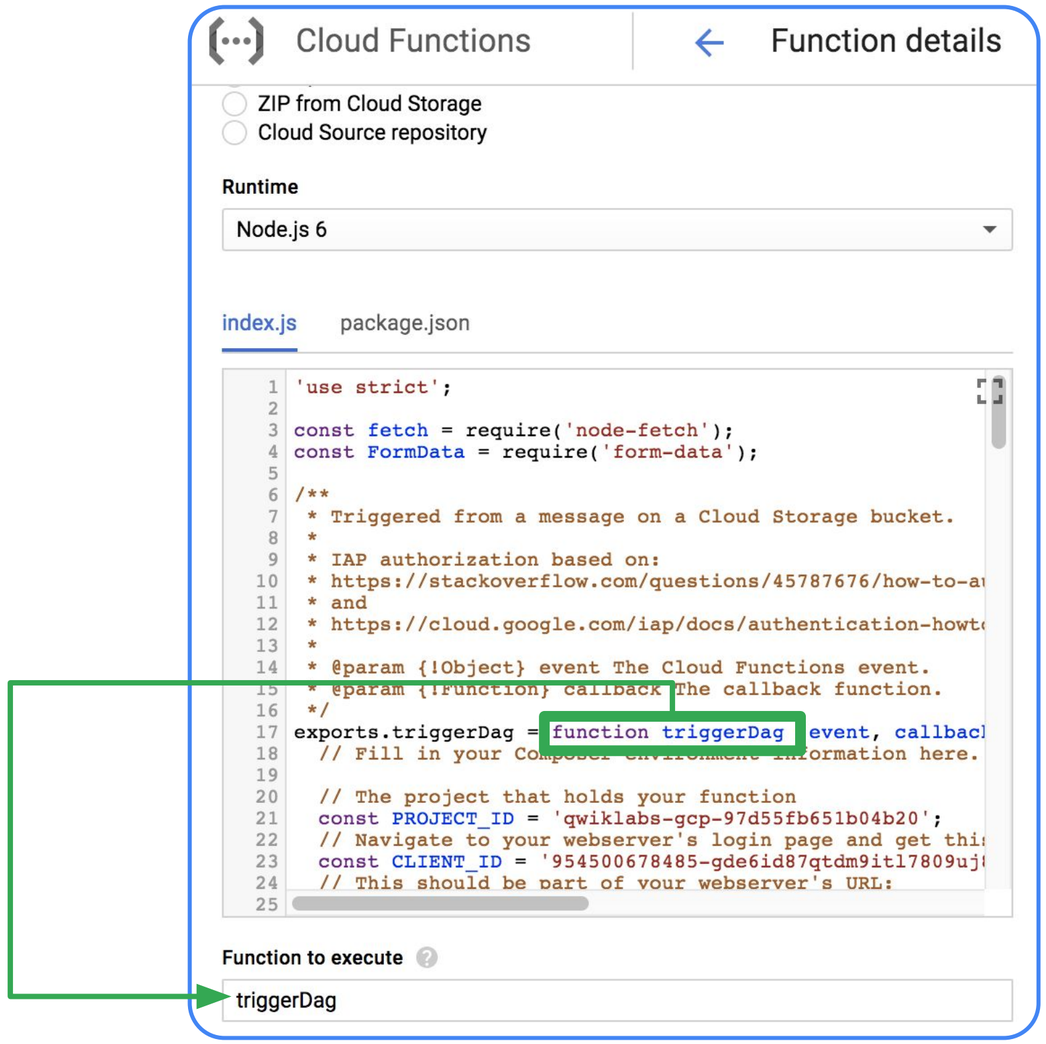
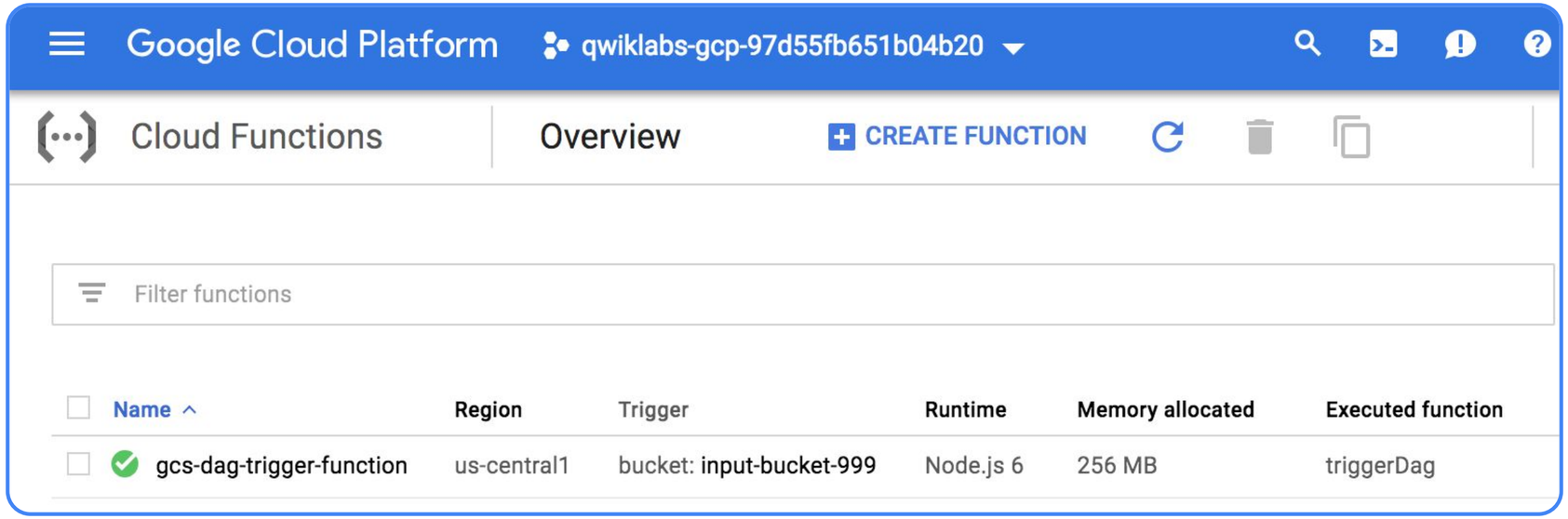
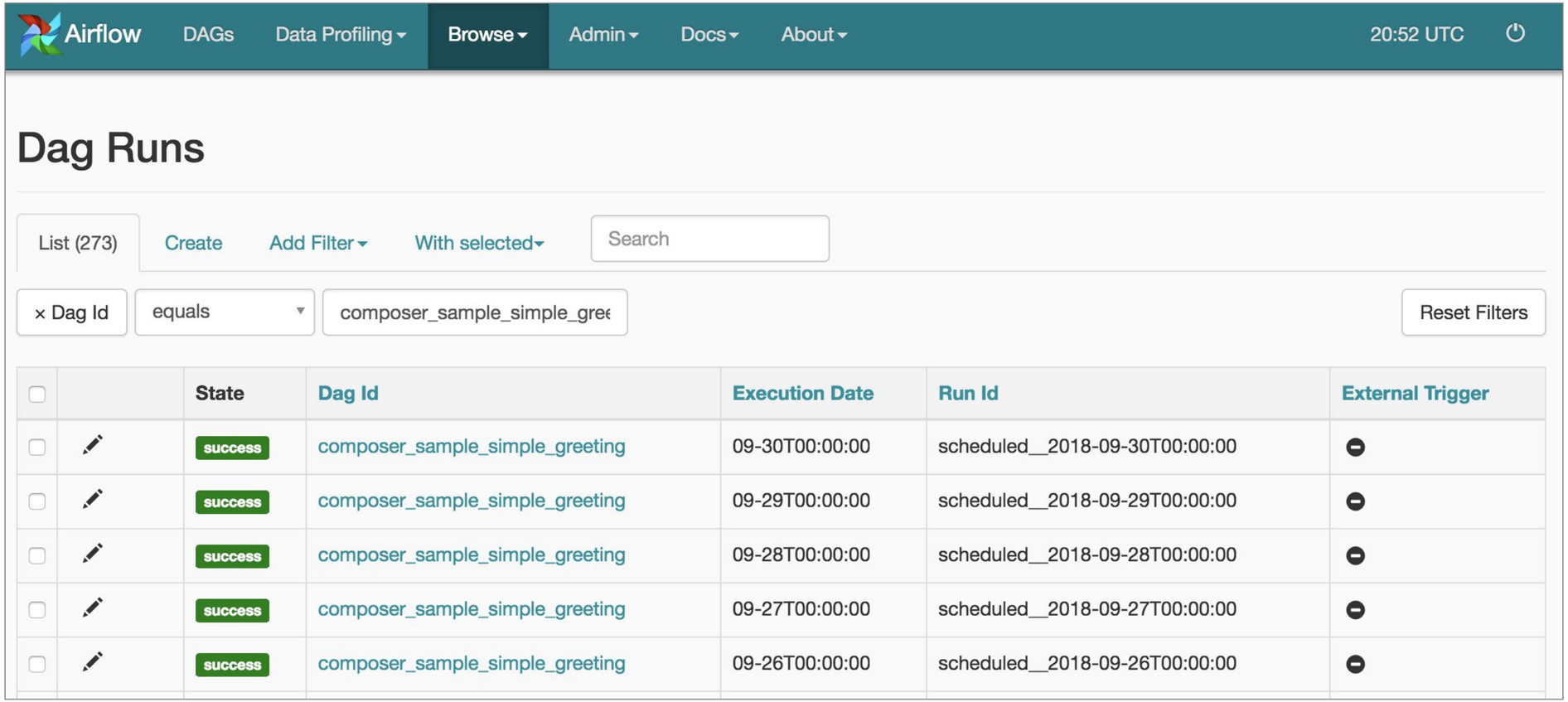
# Be sure to specify the function you want Cloud Functions to call in your script



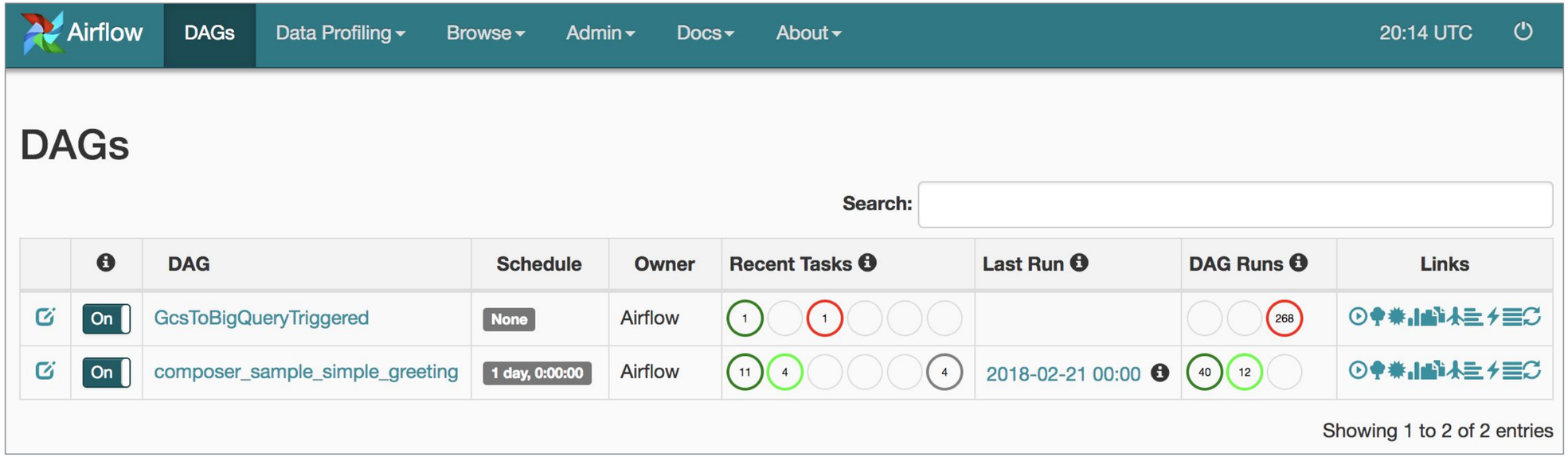
# Cloud Function is triggered whenever a new file is loaded to a specific Cloud Storage bucket



# Monitor current and historical workflow progress

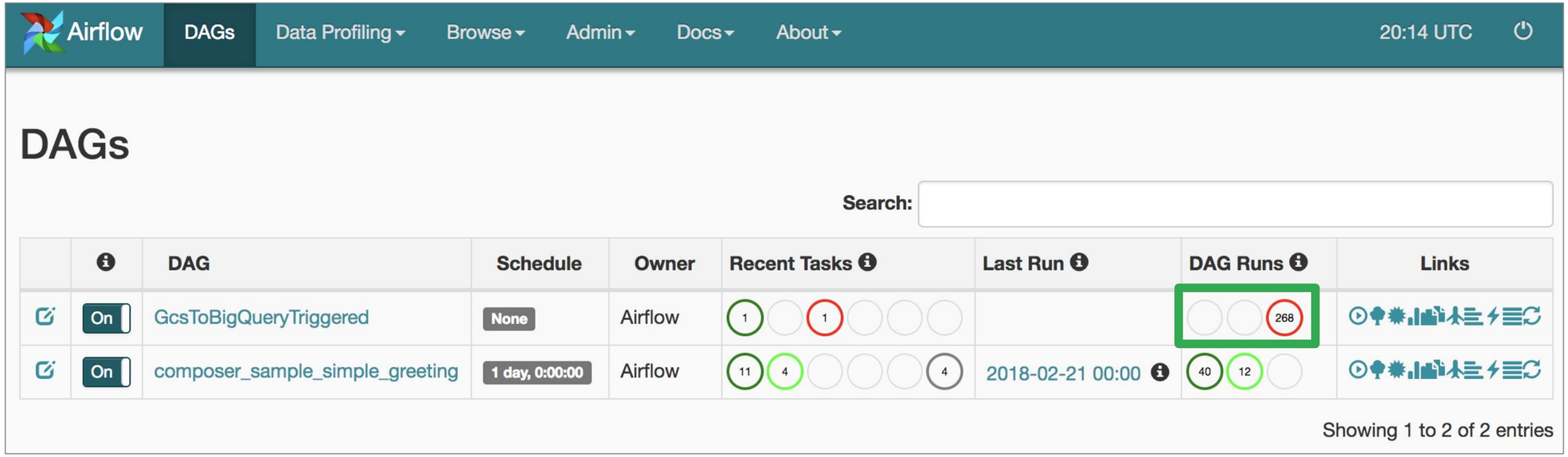


# Quickly gauge pipeline health of DAG runs

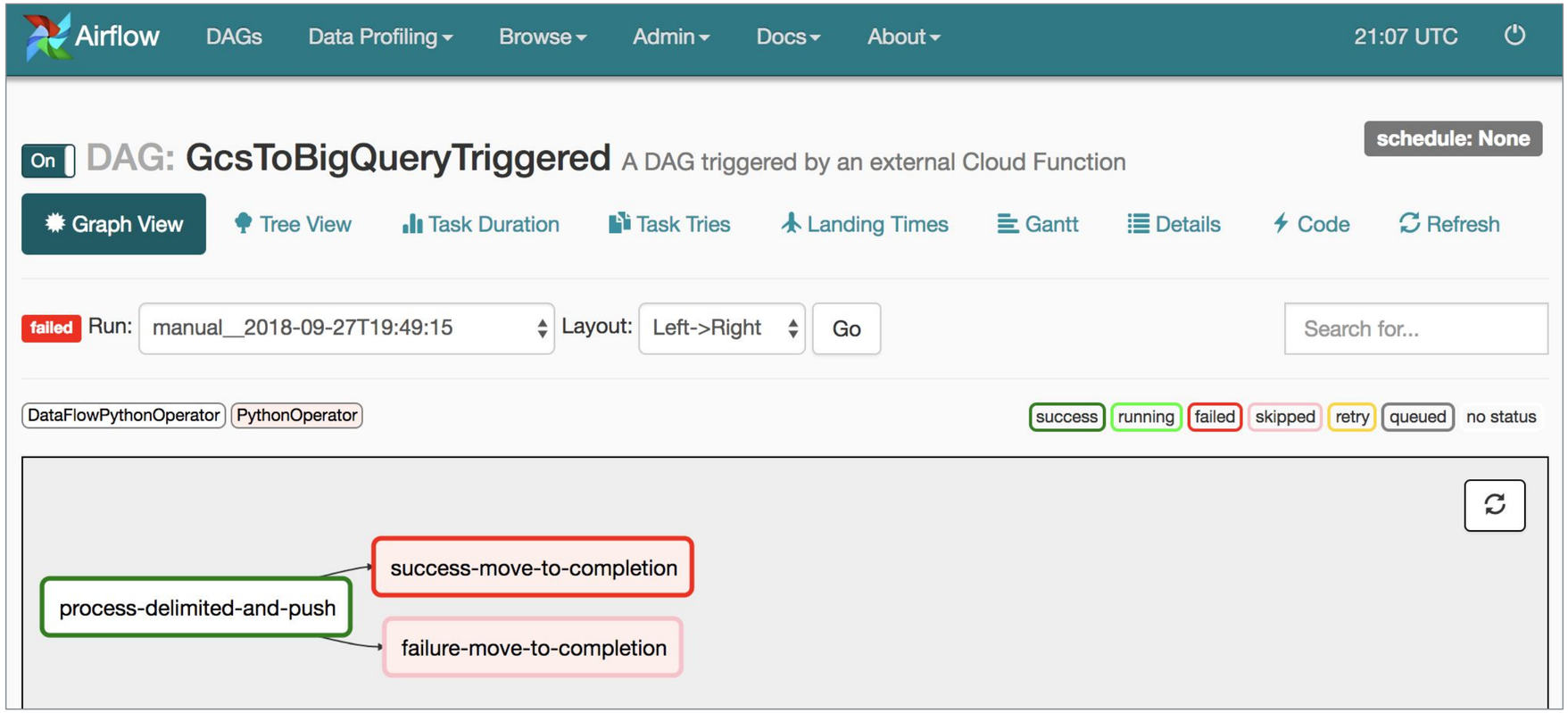



Which pipeline is healthier?

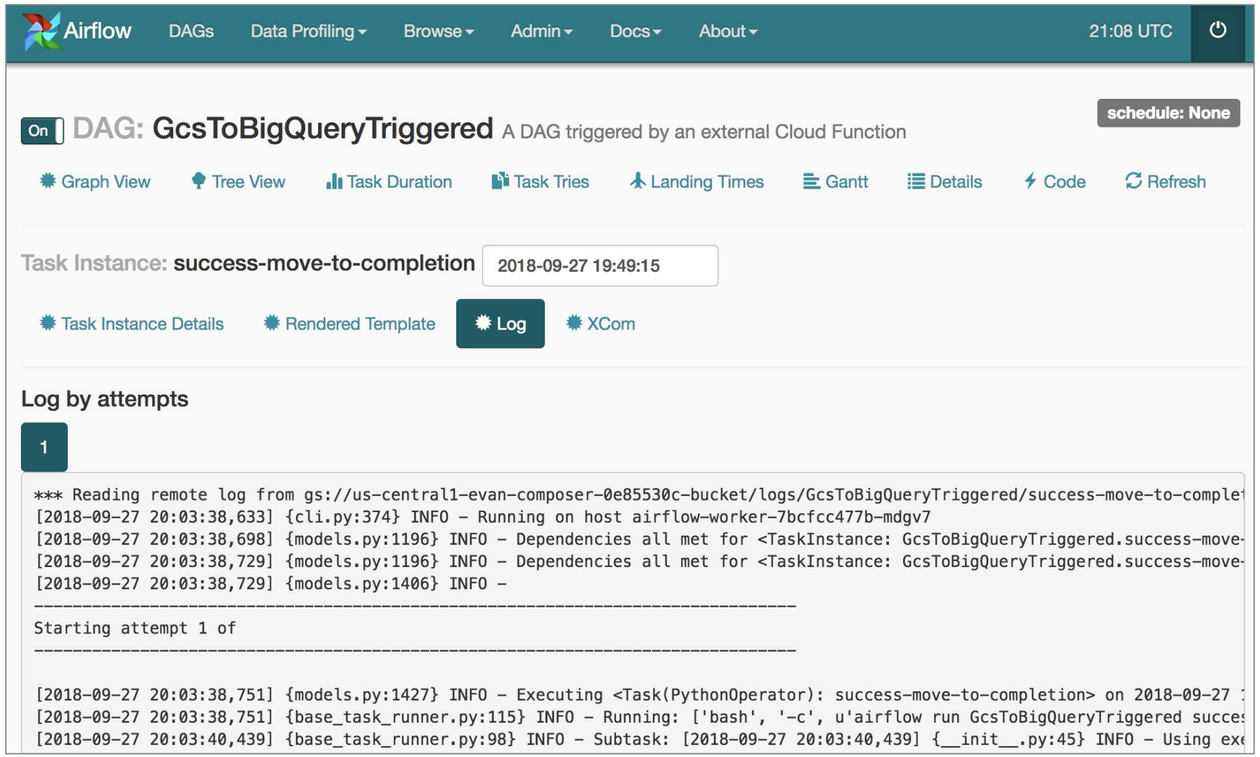
# Quickly gauge pipeline health of DAG runs



# Quickly gauge pipeline health of DAG runs

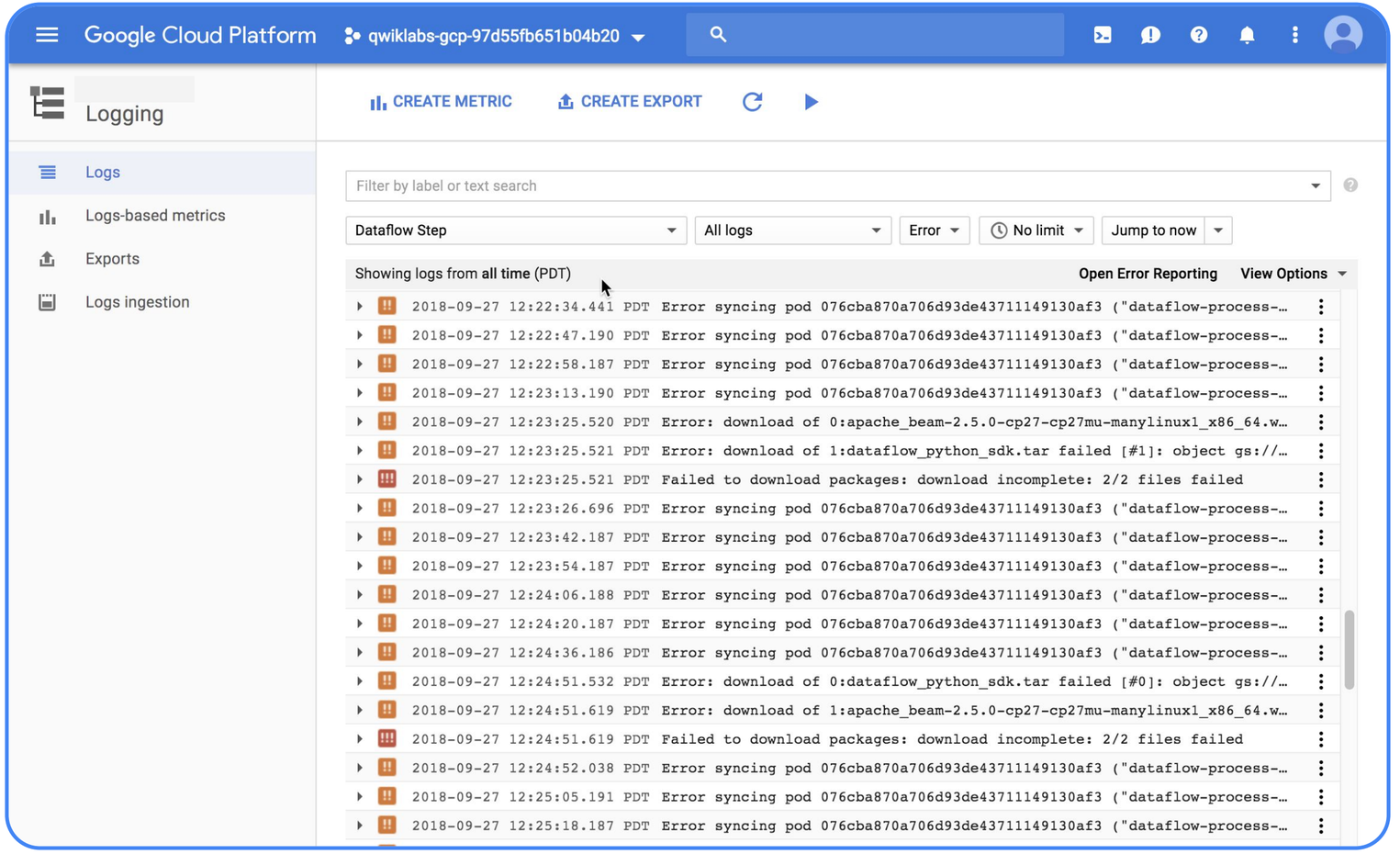


# Monitor and troubleshoot Airflow step errors in logs

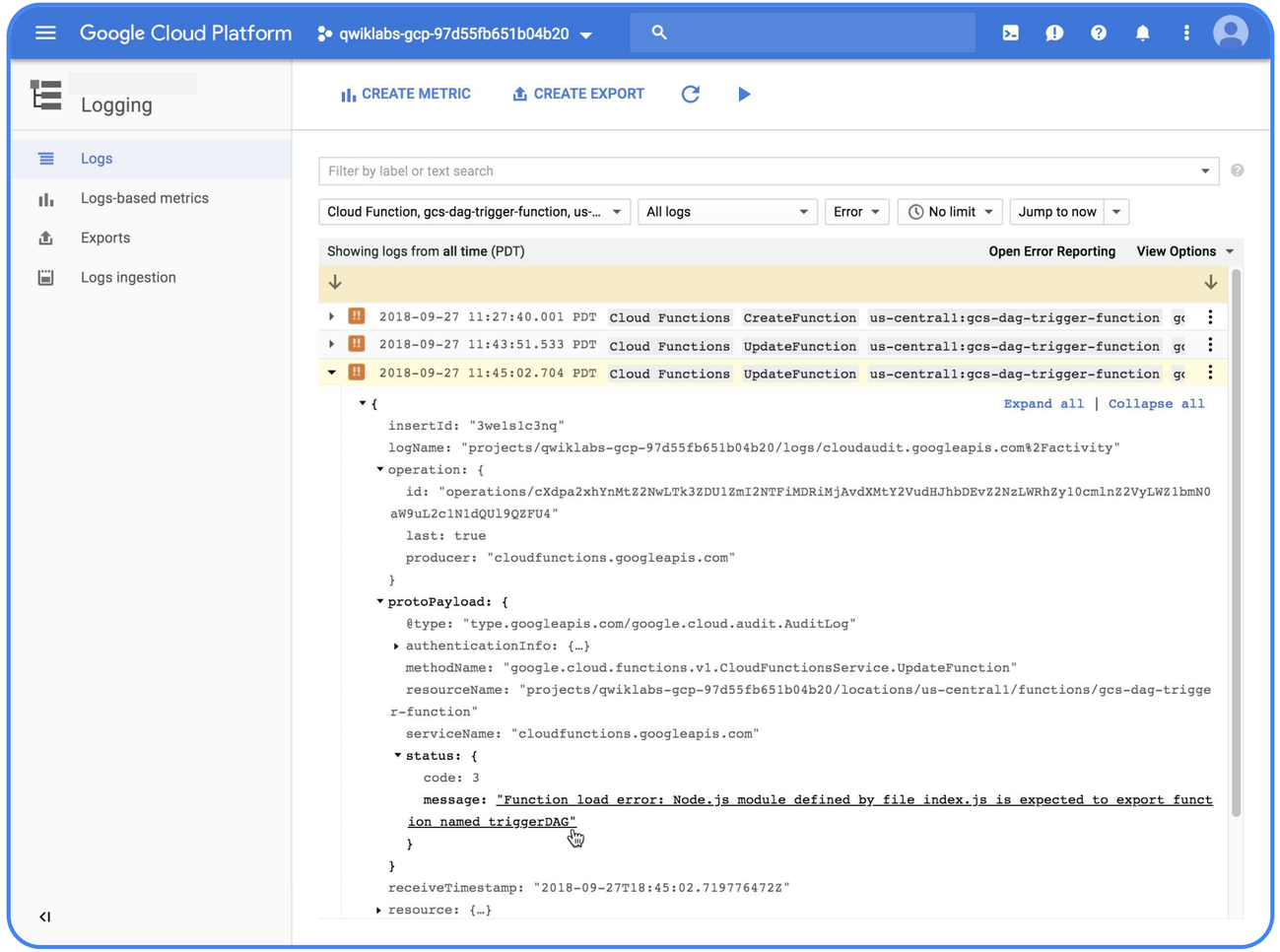



errors.HttpError: <HttpError 400 when requesting https://www.googleapis.com/storage/v1/b/input-bucket-999/o/usa_names.csv/copyTo/b/gs%3A%2F%2Foutput-bucket-999%2F/o/success%2F2018-09-27%2Fusa_names.csv?alt=json returned "Invalid bucket name: 'gs://output-bucket-999/'">

# Monitor Dataflow health in Cloud Logging

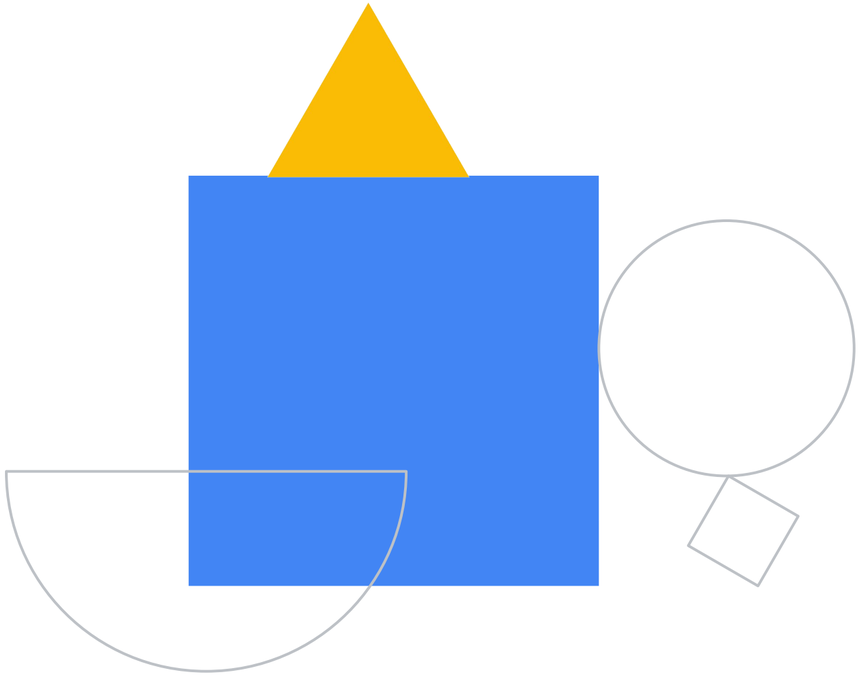


# Monitor Cloud Function health in Cloud Logging



# Lab Intro

An Introduction to Cloud Composer



# Lab objectives

01 Use the Cloud Console to create a Cloud Composer environment

02 View and run a DAG in the Airflow web interface

03 View the results of the wordcount job in storage

# Summary

Cloud Data Fusion for building data pipelines.

Cloud Composer, Cloud Functions and Cloud Scheduler are the glue for your data pipelines.