Building a robust data pipeline with dbt, Airflow, and Great Expectations

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Hi, I'm Sam!

I'm an engineering director at
Superconductive, the team behind the Great
Expectations open source project. I'm from
Germany, but currently based in NYC.
You can find me on Twitter @spbail



Q: What tools do you use for your data pipelines?

Post in the chat!

Welcome to the "dAG" Stack: dbt, Airflow, Great Expectations

- 1. What are all these tools?
- 2. How do they fit together?
- 3. Why should you test your data?



1: dbt (data build tool)



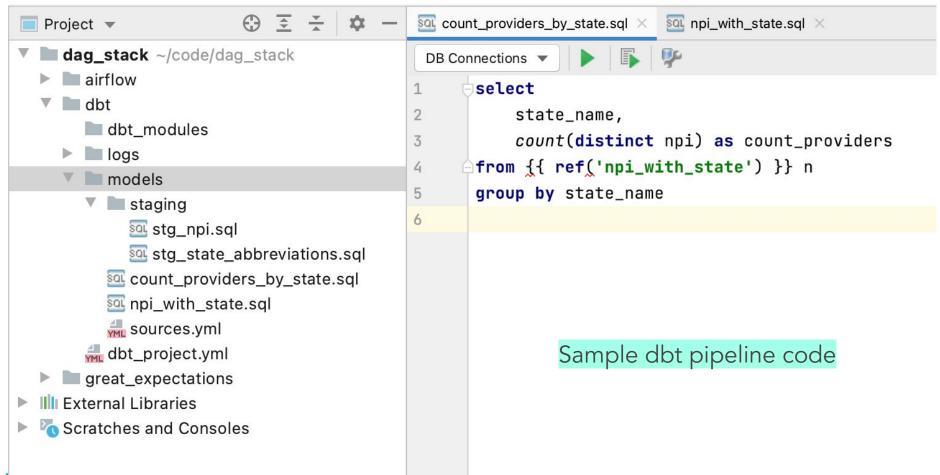
"The T in ELT"

Open source Python package

Write a data pipeline as a series of templated SQL nodes

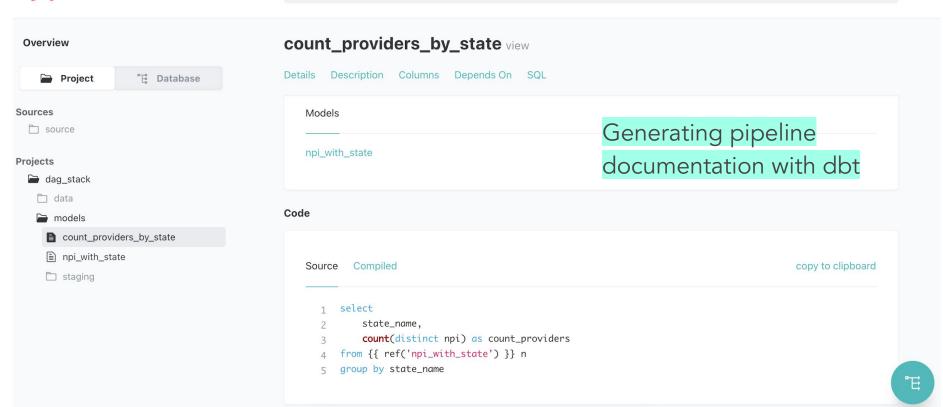
```
source.npi_small
stg_npi
npi_with_state
count_providers_by_state
source.state_abbreviations
```





```
(base) sam@Sams-MacBook-Pro dbt % dbt run
Running with dbt=0.19.0
Found 4 models, 0 tests, 0 snapshots, 0 analyses, 138 macros, 0 operations, 2 seed files, 2 sources,
0 exposures
18:26:47 | Concurrency: 1 threads (target='dev')
18:26:47 I
18:26:48 | 2 of 4 OK created view model public.stq_state_abbreviations...... [CREATE VIEW in 0.58
18:26:49 | 3 of 4 OK created view model public.npi_with_state..... [CREATE VIEW in 0.63
18:26:49 | 4 of 4 START view model public.count_providers_by_state...... [RUN]
18:26:50 | 4 of 4 OK created view model public.count_providers_by_state...... [CREATE VIEW in 0.67
18:26:50
18:26:50 | Finished running 4 view models in 4.70s.
                                          Running a dbt pipeline
Completed successfully
Done. PASS=4 WARN=0 ERROR=0 SKIP=0 TOTAL=4
```







```
(base) sam@Sams-MacBook-Pro dbt % dbt test
Running with dbt=0.19.0
Found 4 models, 2 tests, 0 snapshots, 0 analyses, 138 macros, 0 operations, 2 seed files, 2 sources,
0 exposures
19:11:48 | Concurrency: 1 threads (target='dev')
19:11:48
19:11:49 | 2 of 2 PASS unique_npi_with_state_npi...... [PASS in 0.50s]
19:11:49
19:11:49 | Finished running 2 tests in 2.56s.
Completed successfully
                                     models:
                                      - name: npi_with_state
Done. PASS=2 WARN=0 ERROR=0 SKIP=0 TOTAL=2
                                       columns:
```

Adding tests to a dbt pipeline



- name: npi tests:
 - unique
 - not_null

dbt does not have any built-in scheduling functionality

If you want to run a pipeline periodically, you'll have to schedule that with... something

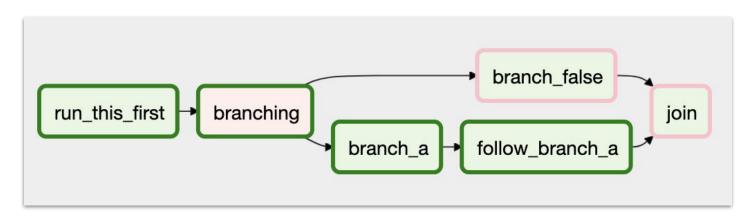


2: Apache Airflow

Workflow orchestration tool

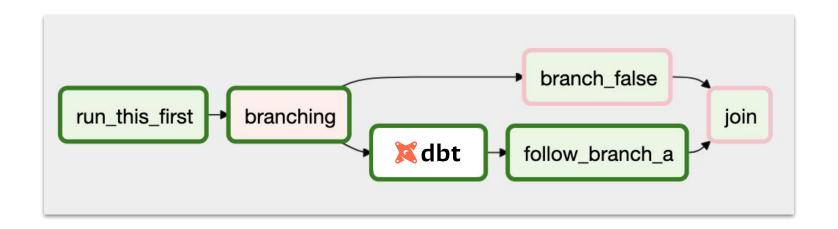
Another open source Python package :)

"Cron on steroids" - scheduling and more





We can run a dbt pipeline as a task in an Airflow DAG



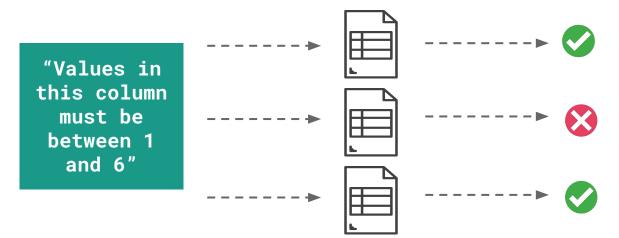


```
import airflow
       from airflow import AirflowException, DAG
2
       from airflow.operators.bash import BashOperator
3
4
       dbt_dag_dir = '/Users/sam/code/dag_stack/dbt'
5
       default_args = {
6
           "owner": "Airflow",
           "start_date": airflow.utils.dates.days_ago(1)
8
                                                                 Running a dbt pipeline in
      _}}
9
                                                                 an Airflow task
10
11
       dag = DAG(
           dag_id='ge_tutorials_dag_with_ge',
12
13
           default_args=default_args,
           schedule_interval=None,
14
15
16
       task_transform_data_in_db = BashOperator(
17
18
           task_id='run_dbt_dag',
           bash_command='dbt run --project-dir {}'.format(dbt_dag_dir),
19
           dag=dag
20
21
```

3: Great Expectations



Open source data validation and documentation tool Let's you express what you *expect* from your data (ha!)





What is an Expectation?

A statement about what we expect from our data, that can be expressed in code

```
{
    "expectation_type": "expect_column_values_to_be_between",
        "kwargs": {
            "column": "passenger_count",
            "min_value": 1,
            "max_value": 6
        },
}
```

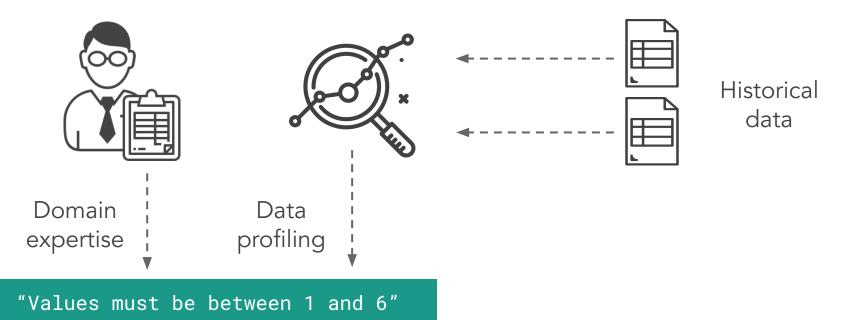
That is stored in JSON

"Values in this column must be between 1 and 6"

And can be translated into a human-readable format

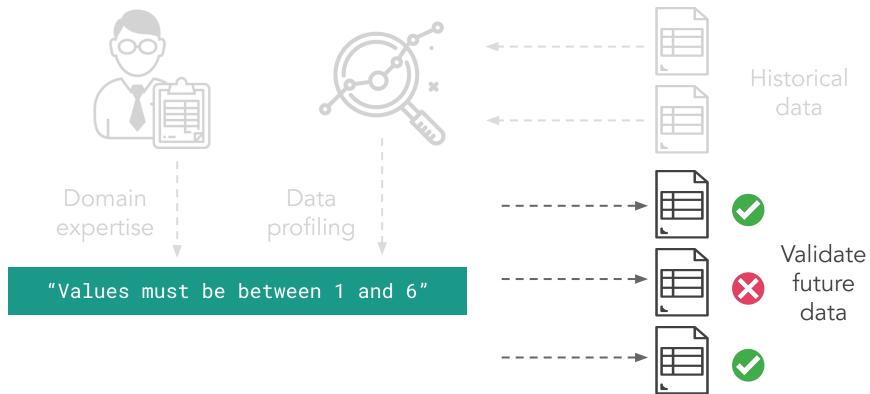


Automated profiling to "scaffold" Expectations

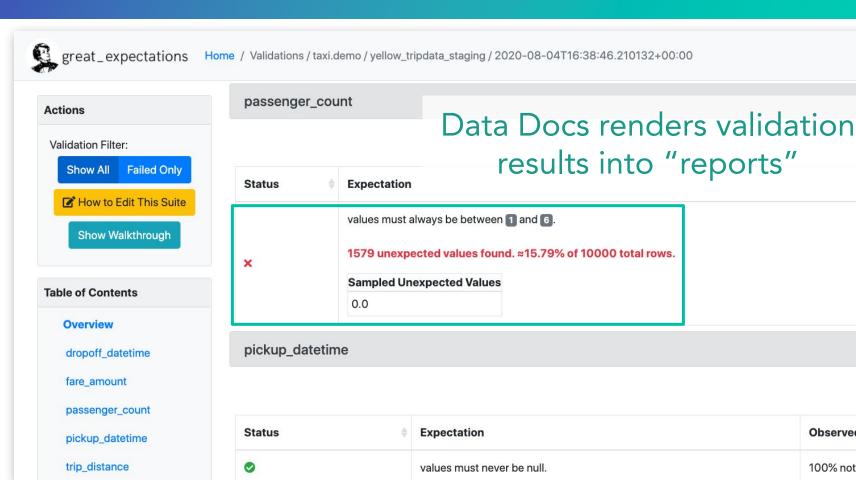


SUPERCONDUCTIVE

Validating your data









Observed Value

100% not null

Observed \

≈15.79% un

Quick live demo of Great Expectations!



Ok, now back to our stack: How does this all fit together?



1: You should test your data.

(No, really.)



Don't believe me?



"Our stakeholders would notice data issues before we did... which really eroded trust in the data and our team."

(A Great Expectations user)



"Re-running our pipelines after finding a data quality issue would incur actual costs for the compute environment."

(A Great Expectations user)



"Remember that one Thanksgiving where we worked all weekend to fix those data issues we only noticed at the last minute? Never again."

(That was me. True #datahorrorstory.)



But... where do we start?

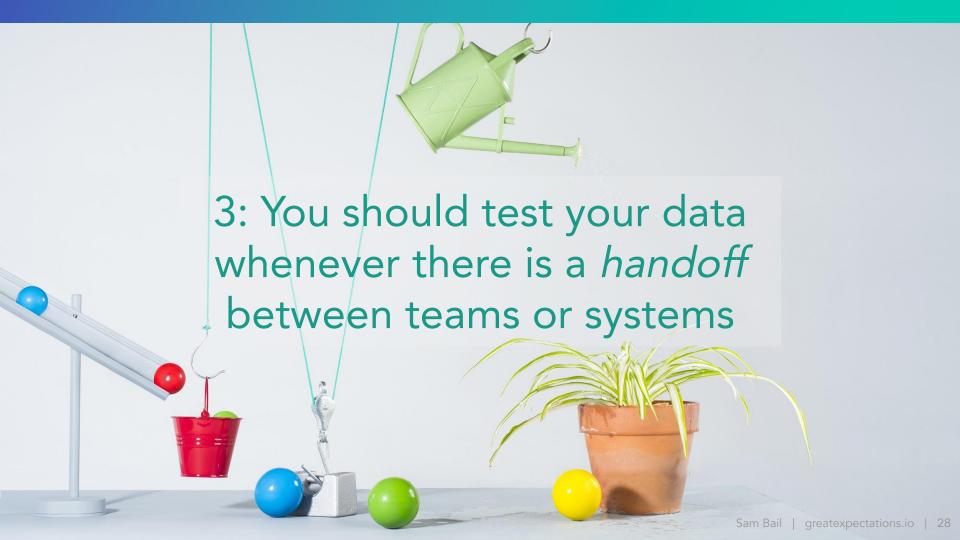
(Which tool should we use? How do we know we're testing the right thing? What do we do when tests fail? Who owns this? How do we keep them up to date? How do our stakeholders find out about the state of the data?)

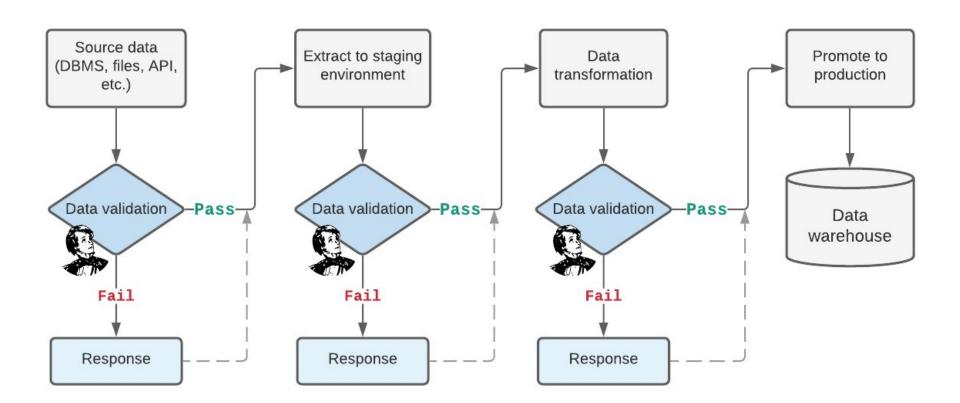


2: Data testing is kinda hard.

(But I can show you how to get started...)









Ok, *now* we're back to the stack.



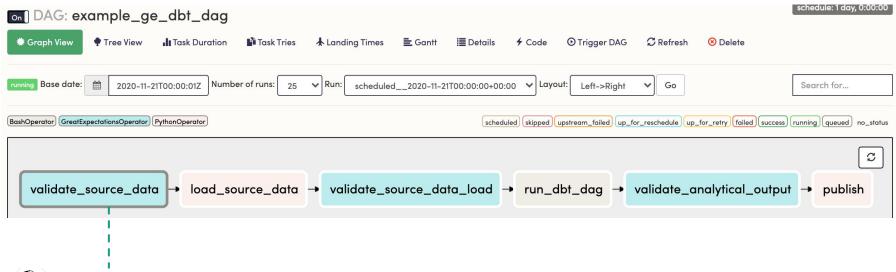


```
task_validate_source_data = GreatExpectationsOperator( ==
airflow
   - my_dag.py -
                                     task_load_files_into_db = PythonOperator( ==
dbt
    dbt_modules
    dbt_project.yml
                                     task_validate_source_data_load = GreatExpectationsOperator( ==
    logs
    models
                                     task_transform_data_in_db = BashOperator( ==
great_expectations
    expectations
                                     task_validate_analytical_output = GreatExpectationsOperator( ==
    great_expectations.yml
    notebooks
                                     task_publish = PythonOperator( ==
    plugins
    uncommitted
```

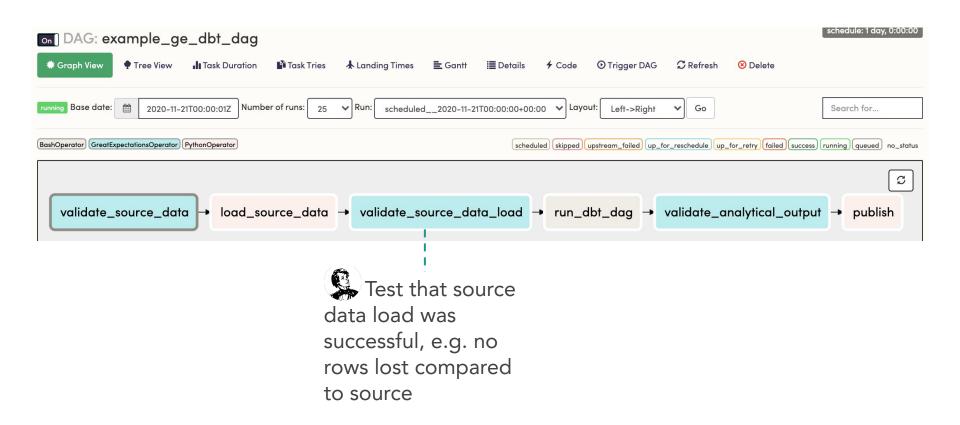






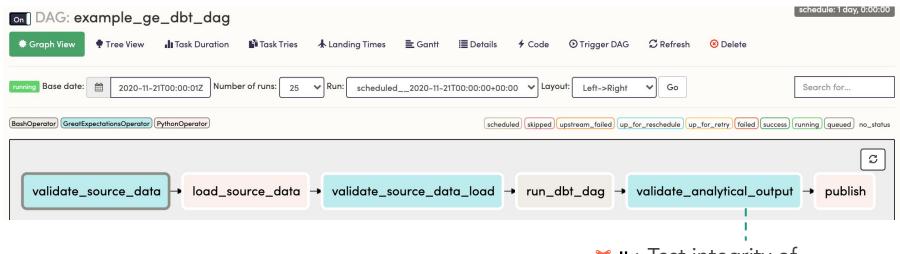


Test that source data matches expected format, e.g. correct number of columns, data types, row count "similar" to last month's, etc.









Mabt Test integrity of transformations, e.g. no fan-out joins, no NULL columns, etc.

Use off-the-shelf methods for complex tests, e.g. distributions of values - and generate Data Docs



Wrap-up!

Airflow, dbt, and Great Expectations = a modern data

pipeline stack with testing capabilities

Test your data whenever there is a handoff between teams

or systems

Use dbt or Great Expectations depending on what you test

and the complexity of your tests



Thank you!



