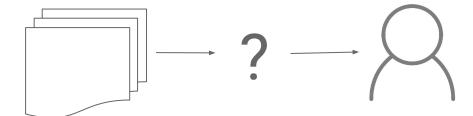
Apache Airflow and Amazon Redshift

Applications to Machine Learning and Analytics

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https://github.com/skirmer/airflow_plus_redshift
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Learning Goals

- What are Airflow and Redshift?
- How can they be used to build and manage a data warehouse?
- How can machine learning workflows employ them?
- What are the risks and pitfalls to avoid?



Toolkit

Data storage solution:



Installation instructions:
 https://docs.aws.amazon.com/redshift/latest/gsg/getting-started.html

Job scheduler:



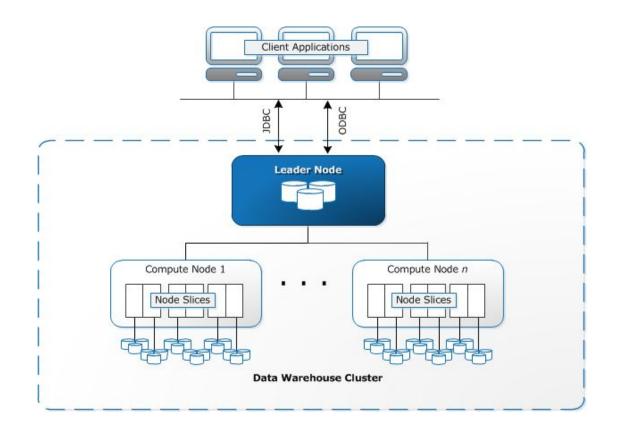
Installation instructions:
 https://airflow.apache.org/docs/stable/start.html

Optional, nice to have: a helpful Ops colleague

Amazon Redshift

Redshift is a data storage product from Amazon.

- Common ancestor with PostgreSQL branched off from PostgreSQL 8.0.2
- Columnar storage, which allows powerful compression
- Gives lots of opportunities for parallelization because of distributed nature, but data manipulation clashes still can happen
- AWS tools allow you to programmatically create and destroy instances/clusters



Architecture Overview

Leader receives queries and develops plans for execution.

Compute Nodes receive instruction from Leader and hand off to Slices to run.

Data is split into **Slices**, divided according to your chosen distribution keys.

https://docs.aws.amazon.com/redshift/latest/dg/chiqhlevelsystem_architecture.html

Take these steps to make Redshift work for you.

Understand the underlying framework

- Relational and distributed
- Distribution key helps Redshift choose what data to store together in nodes.
- Data compression- set encodings that make sense for your data (ANALYZE COMPRESSION).

Plan ahead and be strategic

- It's difficult to change architecture midstream.
- Sort key: what do you usually filter/sort by? This might be it.
- Redshift wants to help you- use EXPLAIN to test how beefy your query is going to be.

A Moment on Schemas

Redshift <u>will</u> allow you to build unkeyed, unlinked tables willy-nilly - *I advise against this!*

Employing a systematic, planned data architecture schema will save you pain and stress in the future.

Redshift does not enforce foreign or primary key restrictions the way other SQL types may - you have to maintain your own discipline.

Using table keys can make choosing highly performant sort keys and dist keys easier too!

Tell Redshift what to expect.

```
CREATE TABLE IF NOT EXISTS public.customer(
    customer_key integer not null IDENTITY(1,1) encode zstd sortkey,
    customer_uuid char(36) encode zstd,
    customer_home_base char(20) encode zstd,
    customer_home_base_key integer encode zstd,
    primary key(customer_key));
```

Protect yourself when inserting data.

```
COPY public.customer(customer_uuid, customer_home_base, customer_home_base_key)
    from 's3://s3_bucket/s3_key_customer.csv'
    iam_role '{self.iam}'
    region 'us-east-1'
    removequotes
    NULL 'None'
    emptyasnull
    blanksasnull
    delimiter ','
;
```

Mistakes I've Made With Redshift

Not optimizing queries to match keys

No query should run for 66 hours.

Making a table for every occasion

- Think about how the table fits with your architecture. You have an architecture, right?
- Don't gunk up your data warehouse with tables that are not documented or reusable. Clean house sometimes!

Making tables without keys or clear relationships

 Optimize, optimize, optimize - you will have more data, and more users, eventually

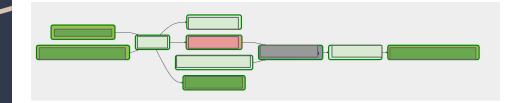
Making tables without compression

This is one of the big advantages of Redshift, so why not use it?

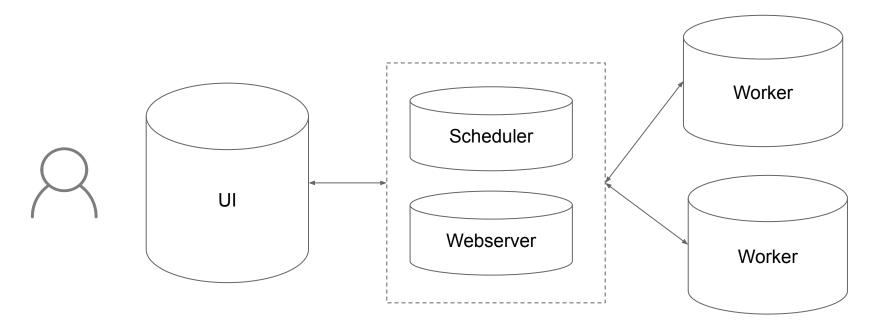
Apache Airflow

Airflow is an open source task management tool.

- Tool for programmatically building, scheduling, and maintaining jobs
- Python based, uses Directed Acyclic Graphs (DAGs)
- Allows testing, versioning, and monitoring
- Open source and free you can contribute!



Airflow is structured in clusters.



You might need a friendly Ops person to help with installation. Note: I have omitted some elements of metadata management and logging here for simplicity's sake.

Airflow wants to know	Write in your DAG definition file	
What tools/resources do you need?	Calls of python libraries, airflow modules and operators, etc	
What information will all your tasks want to know?	Dictionary of default arguments- retry rules, failure notifications, etc	
What is this DAG all about?	Call DAG function with arguments of DAG characteristics- name, run schedule, etc	
What is each task you want to perform?	Call each operator, and define each task with the arguments	
What order should things happen?	Define dependencies (task >> next_task)	

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```
default args = {
   "owner": "airflow",
   "start date": datetime(2020, 4, 5),
   "depends on past": False,
   "email": ["stephanie@stephaniekirmer.com"],
   "email on failure": True,
   "email on retry": False,
   "retries": 3.
   "retry delay": timedelta(minutes=1),
   "on failure callback": partial(trigger pagerduty alert, environ),
   "on success callback": partial(resolve pagerduty alert, environ),
   "provide context": True,
```

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```
dag = DAG(
    dag id="my dag name",
    default args=default args,
    schedule interval="30 3 1 * *",
    catchup=True
```

Note: it accepts the default args here

Scheduling intervals are in CRON syntax: crontab.guru is a big help

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What is this DAG all about?	Call DAG function with arguments of DAG characteristics- name, run schedule, etc	
What is each task you want to perform?	Call each <u>operator</u> , and define each task with the arguments	
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Operators define individual actions for Airflow to complete.

A task in Airflow is asking for an action to happen. An Operator is a class that you call to initialize the action.

What kind of task?

- Run a bash script?
- Run a python script?
- Take data from S3 and drop it in Redshift?
- Run a command on Redshift?
- Something else?

Many operators are already defined, and you can use these off the shelf.

Operators can be customized or written to meet your needs.

If you need a task that has no built-in operator:

- Start with an existing operator, look at the source code.
- Can you adapt it? Copy and paste the source, make your edits, save in your environment.
- If not, use it as a model and write your own from scratch.

Ask Airflow to Initialize an Athena Query.

A built-in Airflow find records = AWSAthenaOperator(macro! Locate within the task id="find records", dag, get all the dag=dag, default args query=hdq.query text.format(datestr="{{ ds }}"), aws conn id="aws default", output location="s3://my bucket/my folder/", database="production", Most arguments are specific to the AWS Athena operator

Take these steps to make Airflow work for you.

Understand Acyclic Graphing (order of tasks)

- What really needs to happen first?
- Think creatively, so you can use the parallelization benefits

Use built in credentials management

Let Airflow manage the creds for database connections

Practice navigating the GUI

Find your logs, read the graphs to debug easily

Mistakes I've Made with Airflow

Lousy memory management

Holding large data volumes in memory is unnecessary expense - your workers may have issues

Too much repetition in DAG code

- Think programmatically, be concise
- Use the default args, try Jinja templating

Sloppy Logging/Failure Tracking

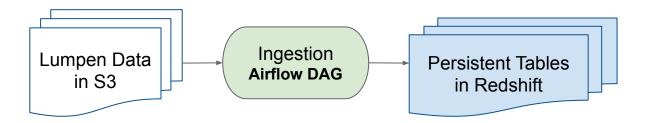
- Quietly record metadata on results of your jobs in case you need to postmortem
- Don't page for every little error, but make sure someone is informed if a job fails

Practical Examples

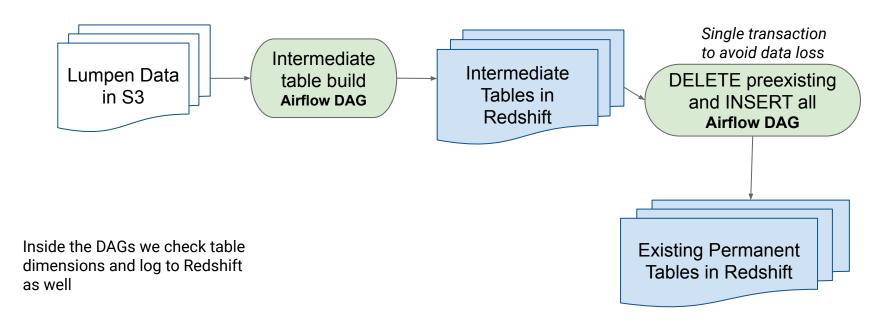
Success can be measured concretely.

Build and populate a data warehouse	Run scheduled data analysis tasks and models	Update and manage data warehouse	Make data warehouse easy to use
Scheduled, transparent jobs Built-in checks for data quality and typing	Train models on a schedule or with one click Store results in Redshift hands-free	Use Redshift features to minimize resource use Monitor and log changes to data warehouse	Redshift <> R/Python Direct querying with SQL from IDE

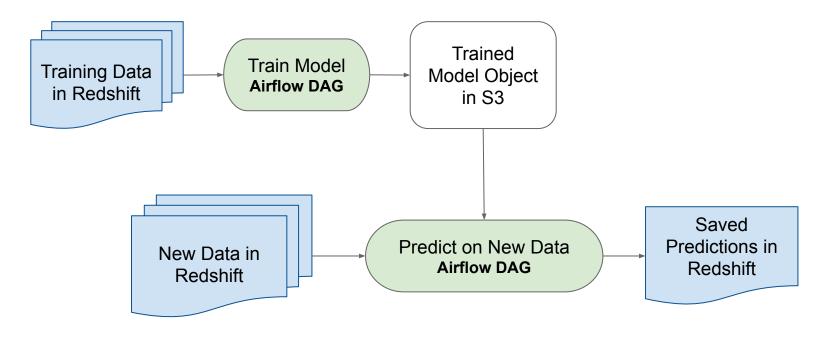
Example New Data Ingestion Workflow



Example Data Updating Workflow

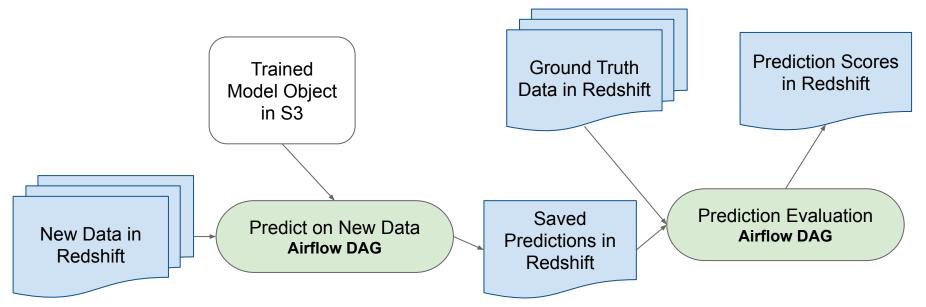


Example ML Workflow



Airflow runs two different jobs to make the pipeline work - training will be less frequent.

Example Prediction Evaluation Workflow



This can be one DAG with many tasks in it, depending on how you get ground truth data.

A Moment on UPDATE

Redshift would rather not

TL;DR: Redshift has to process every column in order to update one row

Long answer:

Compression and columnar data storage means that it's unusually resource intensive to update row by row. The resource intensiveness and slowness is dramatic.

Instead:

- Create Temp Table 1 with the new row values
- Delete any rows from Existing Table that would have been amended
- INSERT rows from Temp Table 1 into Existing Table
- Delete Temp Table 1 as cleanup

INSERT is much easier for Redshift to handle.

Finishing touches to make your life much easier.

Develop **logging and monitoring** processes in the DAGs so that you can catch any problems

- Table size checks
- Data quality checks
- DAG failure monitoring/log review

Teach end users to write their own DAGs - empower users to generate value themselves.

Document, document - make sure you have a data dictionary or API guide.

Additional Links/Resources

Redshift

- Using COPY:
 https://docs.aws.amazon.com/redshift/latest/dg/r_COPY.
 html
- Analyze compression:
 https://docs.aws.amazon.com/redshift/latest/dg/r_ANALY
 ZE COMPRESSION.html
- Sort keys:
 https://docs.aws.amazon.com/redshift/latest/dg/c_best-pr
 actices-sort-key.html
- Dist keys:
 https://docs.aws.amazon.com/redshift/latest/dg/c_best-practices-best-dist-key.html
- Optimizing queries: https://docs.aws.amazon.com/redshift/latest/dg/c_designing-queries-best-practices.html
- https://docs.aws.amazon.com/redshift/latest/dg/r_EXPLA IN.html

Additional Links/Resources

Airflow

- Tutorial:
 https://airflow.apache.org/docs/stable/tutorial.html
- Operators: https://airflow.apache.org/docs/stable/howto/operator/ index.html
- Built in macros:
 https://airflow.apache.org/docs/stable/macros-ref.html
- The codebase! https://github.com/apache/airflow
- Structuring a DAG:
 https://airflow.apache.org/docs/stable/tutorial.html#it-s-a-dag-definition-file

Thank You!

Questions?

Stephanie Kirmer www.stephaniekirmer.com
https://github.com/skirmer/airflow_plus_redshift
google-com/skirmer/airflow_plus_redshift
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```
class RedshiftOperator(BaseOperator):
    template fields = ["sql statement"]
    @apply defaults
    def init (self, redshift conn id, sql statement, *args, **kwargs):
        self.redshift conn id = redshift conn id
        self.sql statement = sql_statement
        super(). init (*args, **kwargs)
    def execute(self, context):
        self.hook = PostgresHook(postgres_conn_id=self.redshift_conn_id)
        conn = self.hook.get conn()
        cursor = conn.cursor()
        log.info("Connected to " + self.redshift conn id)
        cursor.execute(self.sql statement)
        cursor.close()
        conn.commit()
        log.info("Redshift SQL command completed")
        return True
```

This lets us pass Airflow macros inside the query body