Empowering Collaborative Data Workflows with Airflow and Cloud Services

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Data Engineering at the New York Mets
Data Engineering at NYM - Overview

- From 0 to 4 Data Engineers in 2 years
- Google Cloud Platform
- Apache Airflow (Cloud Composer) at its core
Data Engineering at NYM - Baseball Data

- Biomechanical joint data
  - Position of every player
- > 45k games a year
- > 7 million pitches a year
- > 30k active players a year
Data Engineering at NYM - Apache Airflow

- At the core of Mets Data Platform
- ~ 150 DAGs
- Managed by Google as Cloud Composer
- Extensive integrations
  - 3rd party API
  - MLB
Data Workflows
Working with Others: Challenges

- Many processes are running locally without monitoring
- Code is developed individually: lacking code review and best practices
- Silos: Data management is decentralized, some people know some processes
Solution: Data Workflows

A *simple* way of running *any* workflow on a schedule, which would let the DE team more easily manage the fun (Airflow) part, and allow all parties to collaborate.
Code collaboration

- Perfect way to learn from each others
- Build reusable components and share with others
  - Python/R
- Each PR requires review from Data Engineer and Data Scientist before merge
- Flexible yet controlled deployments
Data Workflows: Airflow

Established monitoring practices

Loosely-coupled DAGs
Interdependent processes

Config-based dynamic DAGs
Fits all workflows

Kubernetes
Easy and fast scaling
Data Workflows: Process

- Script in any language submitted into Git along with templated documentation
  - Documentation is used for process discovery and sharing value with other departments
- Common shared libraries
  - Stress the importance of common interface
- Tests to be run pre-deployment and after scheduled processes finish
  - Data quality and observability at the core
- Monitoring
  - Shared Slack channel
Data Workflows: Process
Adding new Data Workflow

```
config.yaml

image: "\{region\}-docker.pkg.dev/\{project\}/\{name\}:v1.1"
cmds:
  - "Rscript"
  - "\{home\}/script_name.R"
staging_bucket: "bucket_name"
output:
  - type: "bq"
    location: "\{project_name\}.dataset_name.table_name"
    file: "output_file.csv"

doc_md:
  
  DAG Documentation
schedule_interval: "@daily"
resources:
  limit_cpu: "2"
  limit_memory: "4G"
quality_checks:
  - collection_name: "\{project_name\}: Process Name"
dependents:
  - "dag1"
  - "dag2"
```

```
pydantic_model.py

class Process(BaseModel):
  
  Building blocks for a single process running within Data Workflows

 cmds: List[str] = Field(..., description="Command to start the process in Docker image")
staging_bucket: str = Field("bucket-name", description="Bucket where outputs are staged")
output: List[Union[None, Output, GSOutput]] = Field([])

  description="Where to output the files produced by this service. Currently BQ or GCS are supported")
params: Dict[str, Dict[str, Any]] = Field({}, description="Parameters to DAG")

doc_md: str = Field("", description="Documentation to be displayed in Airflow UI")
schedule_interval: Optional[str] = Field(None, description="Schedule Interval for Airflow DAG")
resources: Resources = Field(...)...,

models to materialize: List[Dict] = Field([])

  description="dbt models to materialize after the process is run"

quality_checks: List[Check] = Field([], description="Data Quality checks to be run after the process is run")

dependents: List[Dependent] = Field([], description="List of dependents of this process")
```

dag.py

```
globals()[\{dag_id\}] = create_dag(**params)
```
Questions?

Thank you!
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