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

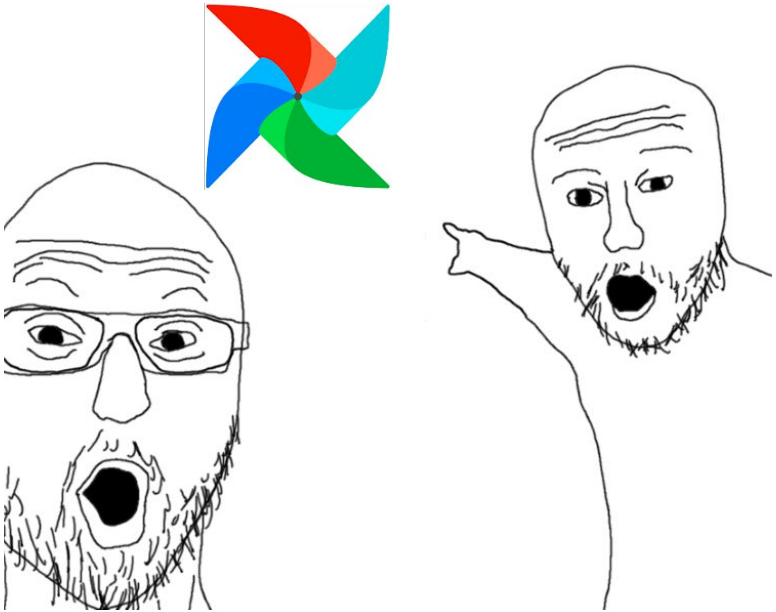
- From 0 to 4 Data Engineers in 2 years
- Google Cloud Platform
- Apache Airflow (Cloud Composer) at its core

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

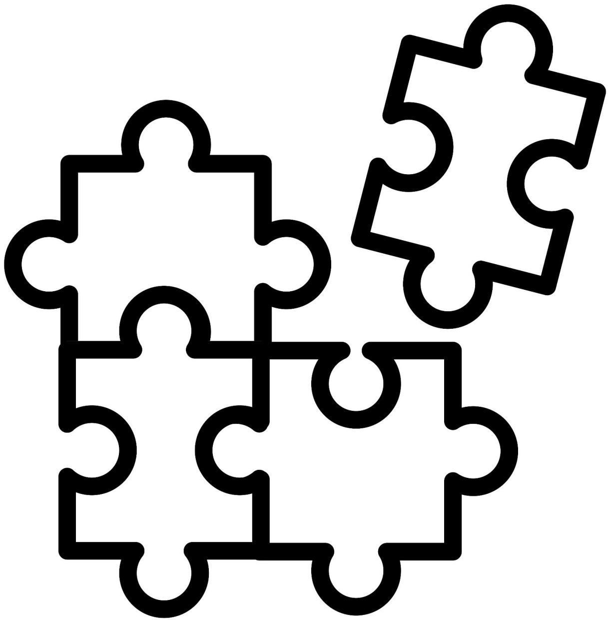
- At the core of Mets Data Platform
- ~ 150 DAGs
- Managed by Google as Cloud Composer
- Extensive integrations
  - 3rd party API
  - MLB



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

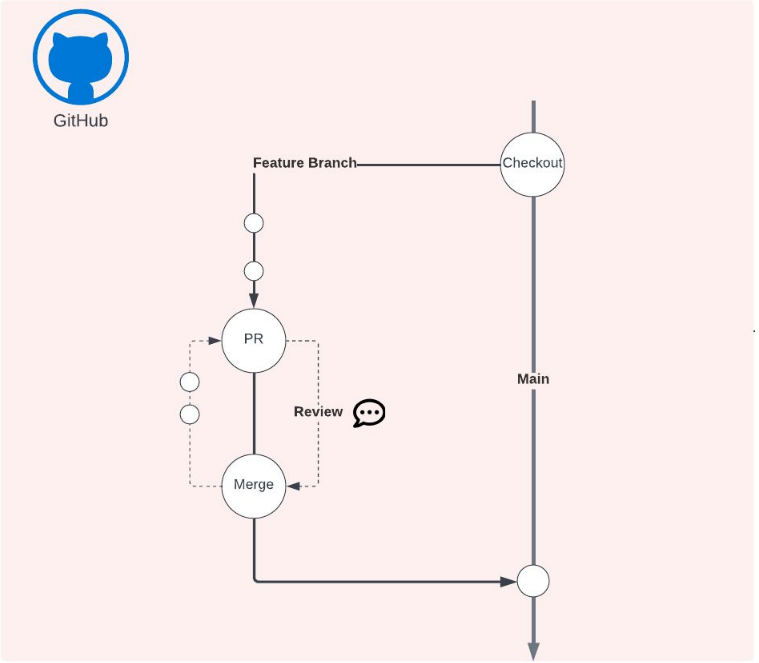


Solution: Data Workflows

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

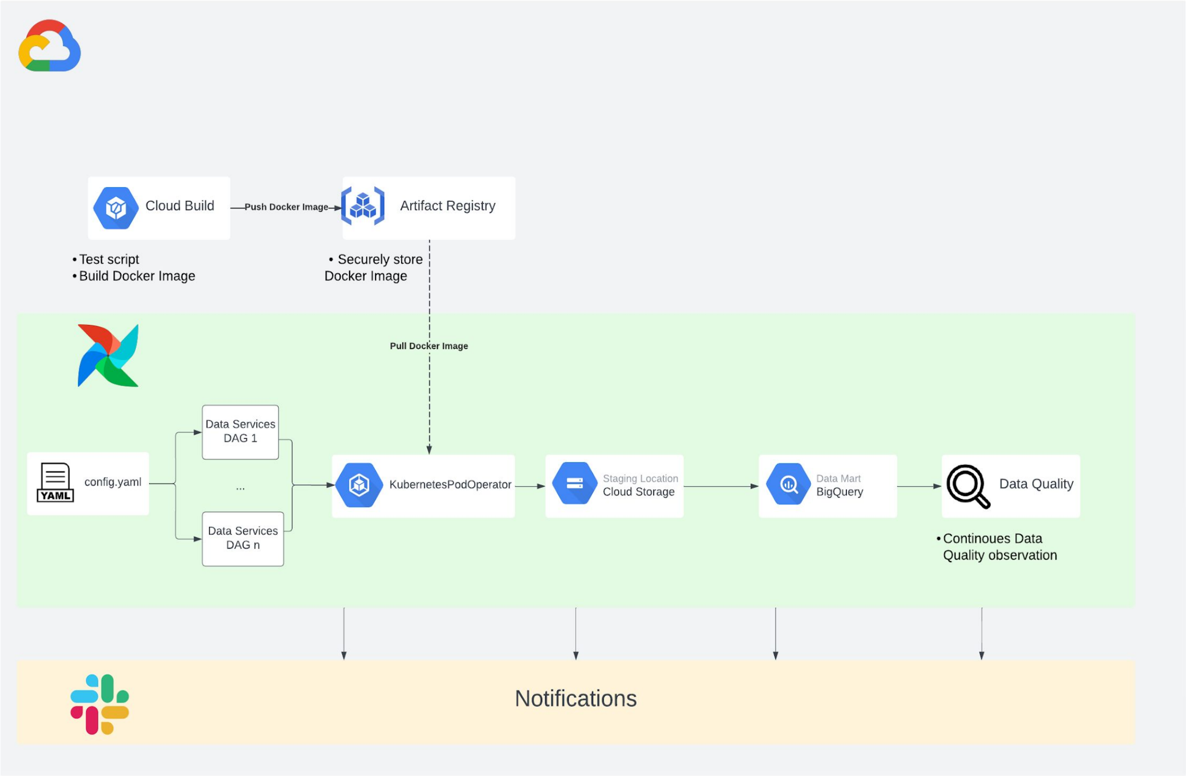
Kubernetes

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

```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"
```

Parse

pydantic_model.py

```python
class Process(BaseModel):  # pylint: disable=R0903
    """
    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[BQOutput, GCSOutput]] = 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="DAG's documentation to be displayed in Airflow UI")
    schedule_interval: Optional[str] = Field(None, description="Schedule Interval for Airflow DAG")
    resources: Resources = Field(..., description="Memory and CPU limits for running pod")
    models_to_materialize: List[str] = Field(
        [], description="dbt models to materialize after the process is run"
    )
    quality_checs: 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

```python
globals()[dag_id] = create_dag(**params)
```

Questions?

Thank you!

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