Bringing data pipelines to production, with Airflow

Jake Roach

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Jake Roach

- Buffalo, NY
- Data Engineer and Instructor
- 150 rounds of golf with my wife!

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Growing a data team that's manually **building and running data pipelines**, creating analyses, and developing models, but without a tool to centrally manage all these moving parts

Develop and run workflows as code in a centralized platform

Unlock tools to supercharge data pipelines

Monitor and manage data pipeline execution

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Apache Airflow

- Programmatically define data pipelines
  - Dynamic
  - Extensible
  - Flexible
- DAGs
- Schedule, retry, alert
- Monitor data workflows

DAG (directed-acyclic graph)

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https://airflow.apache.org/docs/apache-airflow/stable/index.html

Extracting, transforming, and loading market data

- Pull data from the Polygon API
- Flatten the JSON response
- Transform the flattened response
- Load the transformed DataFrame to a Postgres database

market_data_etl.py

```python
def extract():
    # Pull data from an API for today’s date
    market_date = "2023-12-08"
    raw_response = requests.get(f"https://...{market_date}")
    ...
    return raw_dataset

def transform(raw_dataset):
    # Transform the raw dataset
    ...

...

# Execute the ETL
raw_dataset = extract()
cleaned_dataset = transform(raw_dataset)
load(cleaned_dataset)
```

```
> python3 market_data_etl.py
```

Homegrown data pipelines require additional features to be production-grade

- Schedule
- Policy on retries
- Store sensitive credentials
- Visibility into execution details
- Lots of custom code

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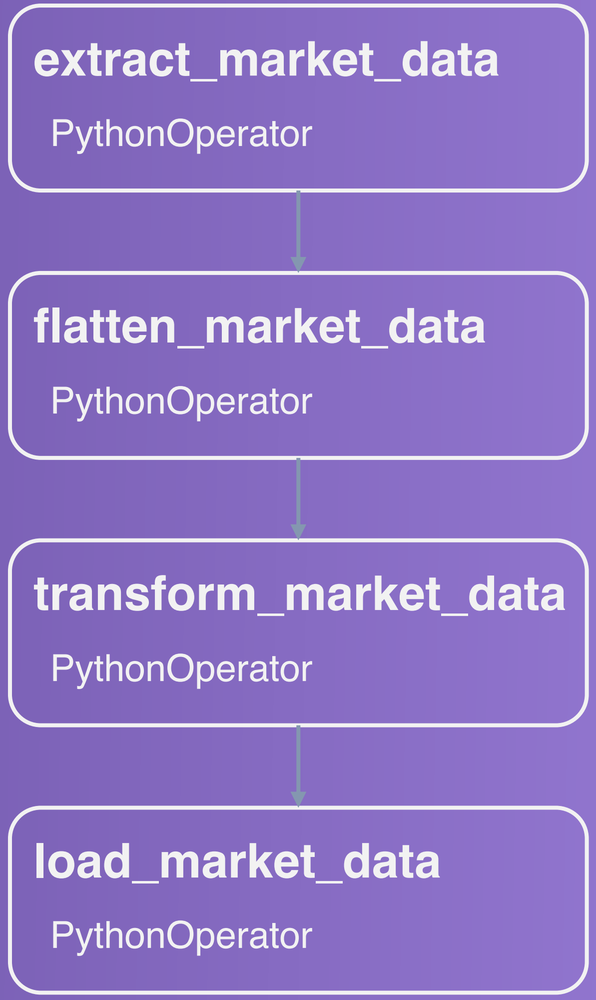
Airflow makes data pipelines production-ready

- Scheduled to run daily, each morning
- Retry on failure
- Securely store and retrieve sensitive credentials
- Persist execution details before run

Use traditional Airflow operators to build a DAG



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Provide a DAG ID, start date, schedule interval

Programmatically define tasks

Set dependencies between tasks

dags/market_etl__traditional.py

```python
# Instantiate the DAG
with DAG(
    dag_id="market_etl__traditional",
    start_date=datetime(2023, 8, 1),
    end_date=datetime(2023, 8, 31),
    schedule="0 9 * * 1-5"
    ...
) as dag:
    # Create tasks using traditional operators
    extract_market_data = PythonOperator(
        dag=dag,
        task_id="extract_market_data",
        python_callable=extract_market_data__callable
    )

    ...

    # Set dependencies between tasks
    extract_market_data >> ... >> load_market_data
```

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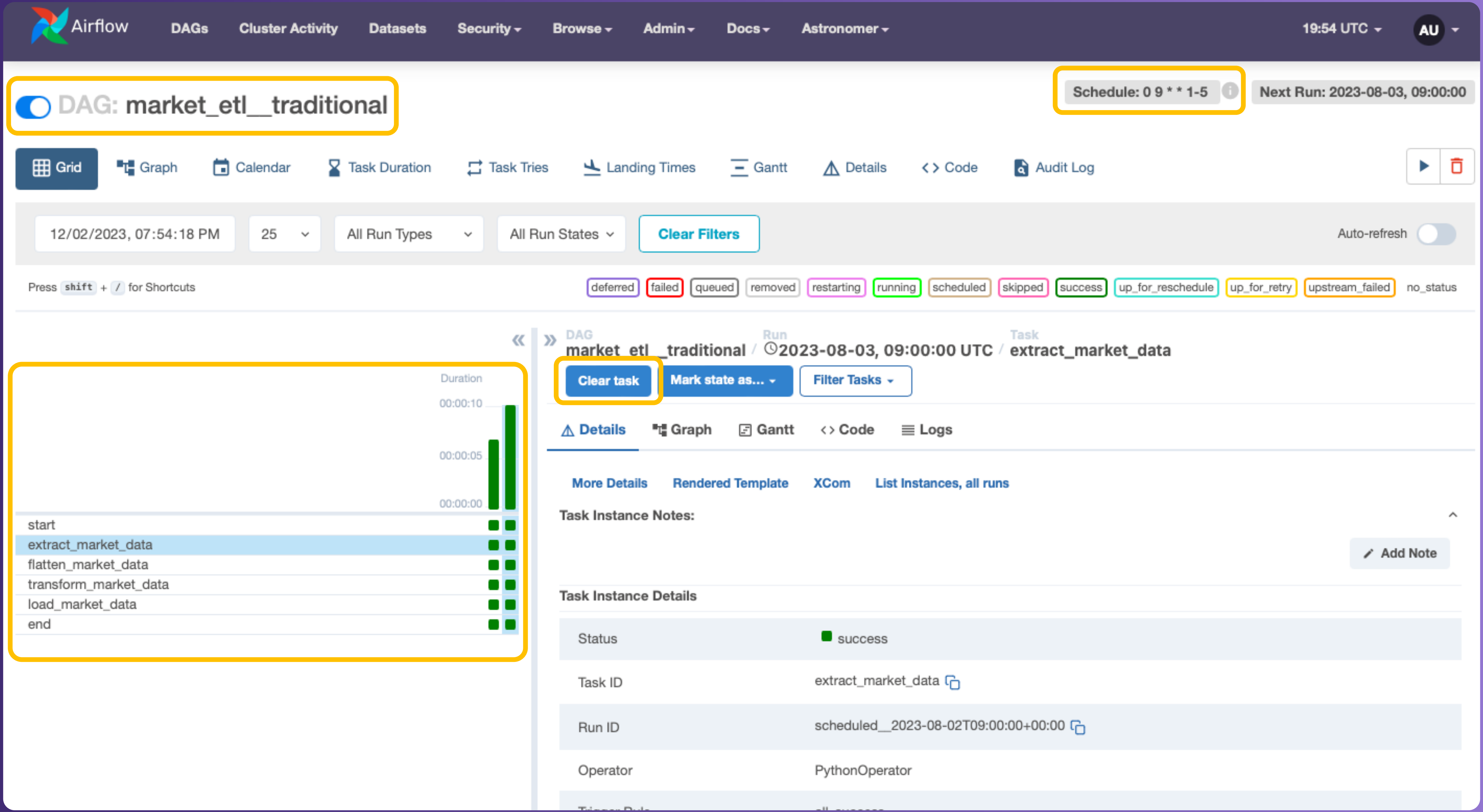
```python
with DAG(
    ...
    default_args={
        "retries": 3,
        "retry_delay": timedelta(minutes=1)
    }
) as dag:
```

```python
polygon_api_key = Variable.get("POLYGON_API_KEY")
```

- Configure custom retry policy
- Securely retrieve variables in code
- Share data between tasks with XComs

```python
flatten_market_data = PythonOperator(
    dag=dag,
    task_id="flatten_market_data",
    python_callable=flatten_market_data__callable,
    op_kwargs={"raw_dataset": "{{ ti.xcom_pull(task_ids='extract_market_data') }}"}
)
```



Airflow
DAGs
Cluster Activity
Datasets
Security
Browse
Admin
Docs
Astronomer
19:54 UTC
AU
DAG: market_etl__traditional
Schedule: 0 9 * * 1-5
Next Run: 2023-08-03, 09:00:00
Grid
Graph
Calendar
Task Duration
Task Tries
Landing Times
Gantt
Details
Code
Audit Log
12/02/2023, 07:54:18 PM
25
All Run Types
All Run States
Clear Filters
Auto-refresh
Press shift + / for Shortcuts
deferred
failed
queued
removed
restarting
running
scheduled
skipped
success
up_for_reschedule
up_for_retry
upstream_failed
no_status
Duration
00:00:10
00:00:05
00:00:00
start
extract_market_data
flatten_market_data
transform_market_data
load_market_data
end
DAG
market_etl__traditional
Run
2023-08-03, 09:00:00 UTC
Task
extract_market_data
Clear task
Mark state as...
Filter Tasks
Details
Graph
Gantt
Code
Logs
More Details
Rendered Template
XCom
List Instances, all runs
Task Instance Notes:
Add Note
Task Instance Details
Status
success
Task ID
extract_market_data
Run ID
scheduled__2023-08-02T09:00:00+00:00
Operator
PythonOperator

Airflow makes writing production-ready data pipelines a breeze

- Schedule DAG runs
- Ability to retry on failure
- Securely interact with source systems and destinations
- Single "pane of glass" into pipeline execution details

TaskFlow API makes getting started with Airflow even easier

The TaskFlow API makes writing DAGs more intuitive for data teams

`@dag`
`@task`

DAGs and tasks defined as functions

Useful when passing information between tasks

Makes Airflow more accessible to data scientists and analysts

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Same parameters as traditional DAG definition

Intuitive process to create tasks

Easy to share data between tasks and set dependencies

dags/market_etl__taskflow_api.py

```
@dag(
    start_date=datetime(2023, 8, 1),
    end_date=datetime(2023, 8, 31),
    schedule="0 9 * * 1-5”,
    ...
)
def market_etl__taskflow_api():
    @task()
    def extract_market_data():
        ...
        return raw_dataset

    @task()
    def flatten_market_data(raw_dataset, **context):
        ...

    raw_data = extract_market_data()
    flattened_data = flatten_market_data(raw_data)
    transformed_data =   transform_market_data(flattened_data)
    load_market_data(transformed_data)

market_etl__taskflow_api()
```

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The TaskFlow API helps data teams provide immediate business value with Airflow

- Easier to port Python ETL logic to Airflow DAGs
- Make Airflow more accessible
- Maintaining the best functionality of DAGs and tasks
- Astro Python SDK extends this functionality

Airflow reduces the code needed to integrate your data stack

- TaskFlow API
- Variables and Connections
- Jinja templating at run-time

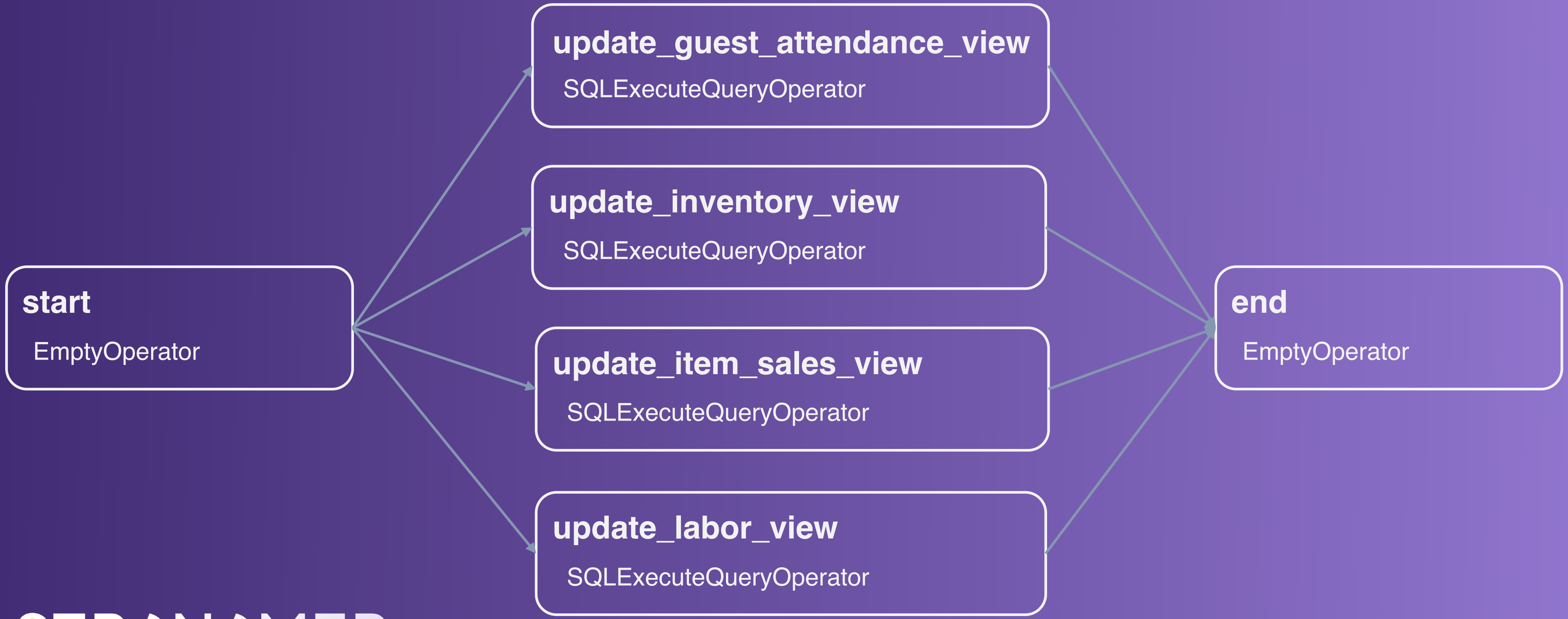
Ever-growing number of pre-built operators to help orchestrate workflows

amazon S3

snowflake

PostgreSQL

Automating analytics workflows



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dags/daily_operations_view_update.py

```python
...

# Define tasks using SQLExecuteQueryOperator
update_guest_attendance_view = SQLExecuteQueryOperator(
    dag=dag,
    task_id="update_guest_attendance_view",
    postgres_conn_id="postgres_daily_operational_conn",
    sql="""
    CREATE OR REPLACE VIEW admissions_by_entrance AS (
        SELECT
            ...
        WHERE admission_date = '{{ ds }}'
        ...
    );"""
)

...

# Set dependencies between tasks
start >> [update_guest_attendance_view, update_labor_view, ...] >> end
```

SQLExecuteQuery-Opeartor

Easily connect to data sources and destinations

Use Jinja templating to render runtime

Allow view updates to run in parallel

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Add a templated path to store SQL files

```
with DAG(
    ...
    template_searchpath="include/sql"
    ...
) as dag:

...

    update_inventory_view = SQLExecuteQueryOperator(
        dag=dag,
        task_id="update_inventory_view",
        postgres_conn_id="postgres_daily_operational_conn",
        sql="update_inventory_view.sql"
    )

...
```

Provide path to SQL file in operator call

Create connection with Astro CLI

```
> astro dev run connections add ... <connection-name>
```

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Using pre-built operators streamlines data pipeline data development

Reduces custom code to build a DAG

Workflows are easier to read and troubleshoot

Leverage Jinja template engine

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Airflow makes complex data pipeline development simple

- Pulling from disparate sources
- Mix of traditional operators and TaskFlow API
- Task groups and branching logic
- Custom operators

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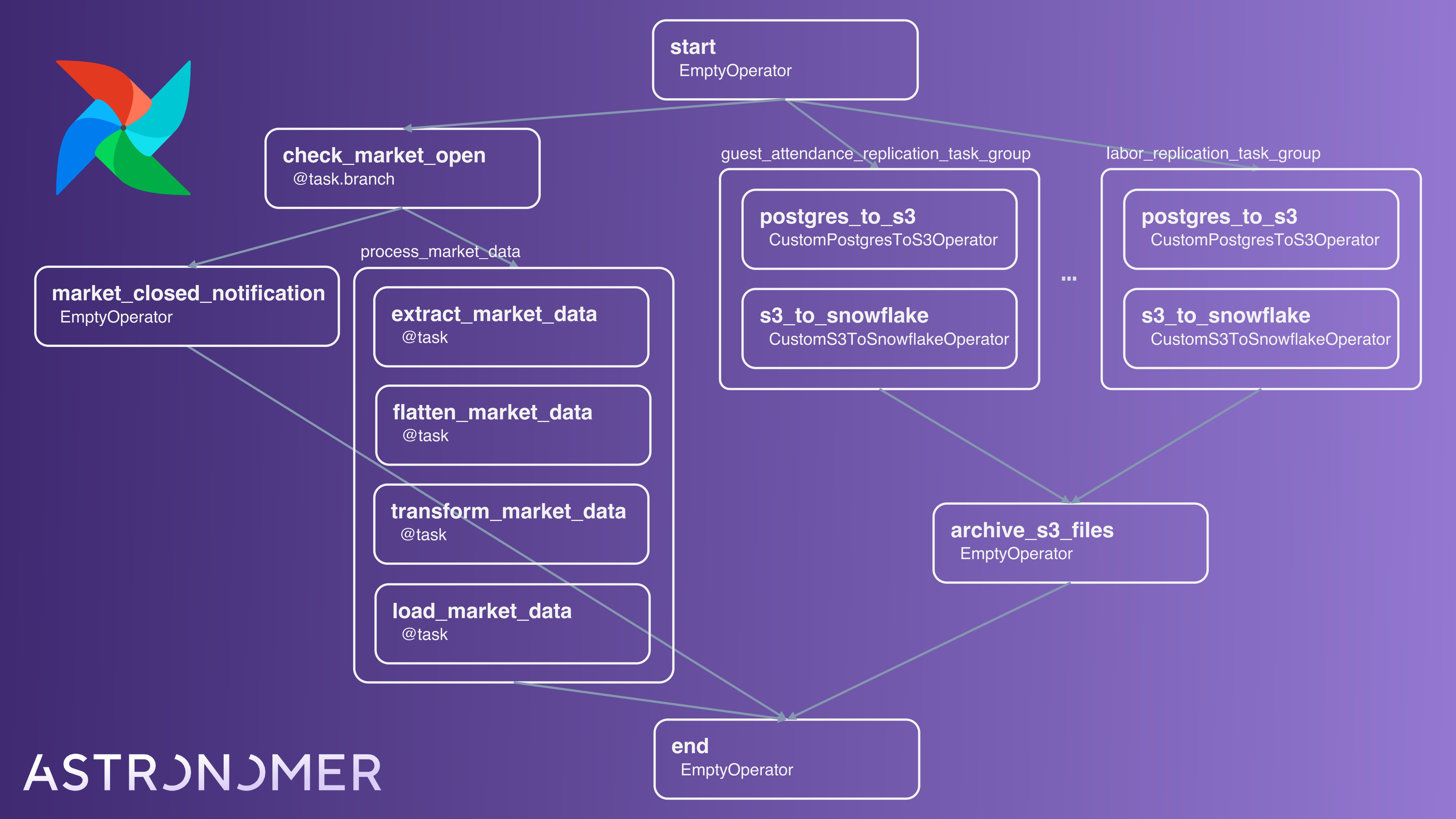
start
EmptyOperator
check_market_open
@task.branch
guest_attendance_replication_task_group
labor_replication_task_group
postgres_to_s3
CustomPostgresToS3Operator
s3_to_snowflake
CustomS3ToSnowflakeOperator
...
postgres_to_s3
CustomPostgresToS3Operator
s3_to_snowflake
CustomS3ToSnowflakeOperator
market_closed_notification
EmptyOperator
process_market_data
extract_market_data
@task
flatten_market_data
@task
transform_market_data
@task
load_market_data
@task
archive_s3_files
EmptyOperator
end
EmptyOperator
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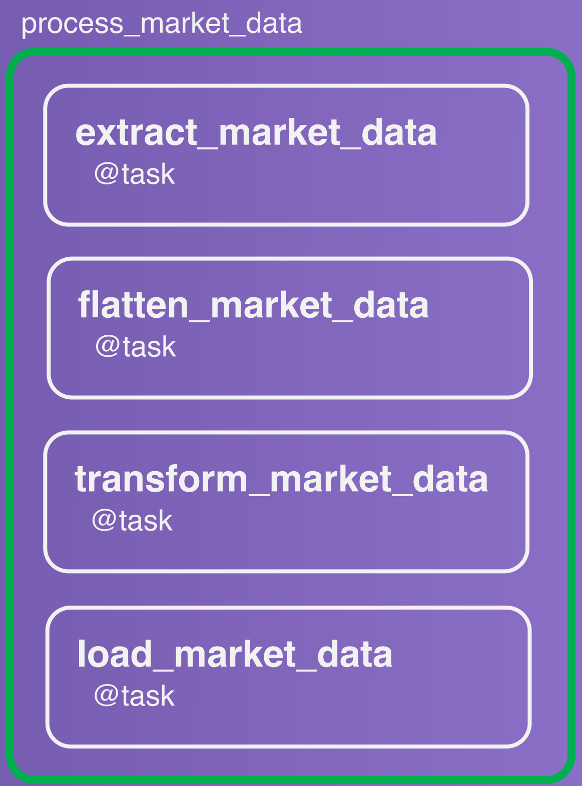
Task groups help to delineate similar tasks within a DAG

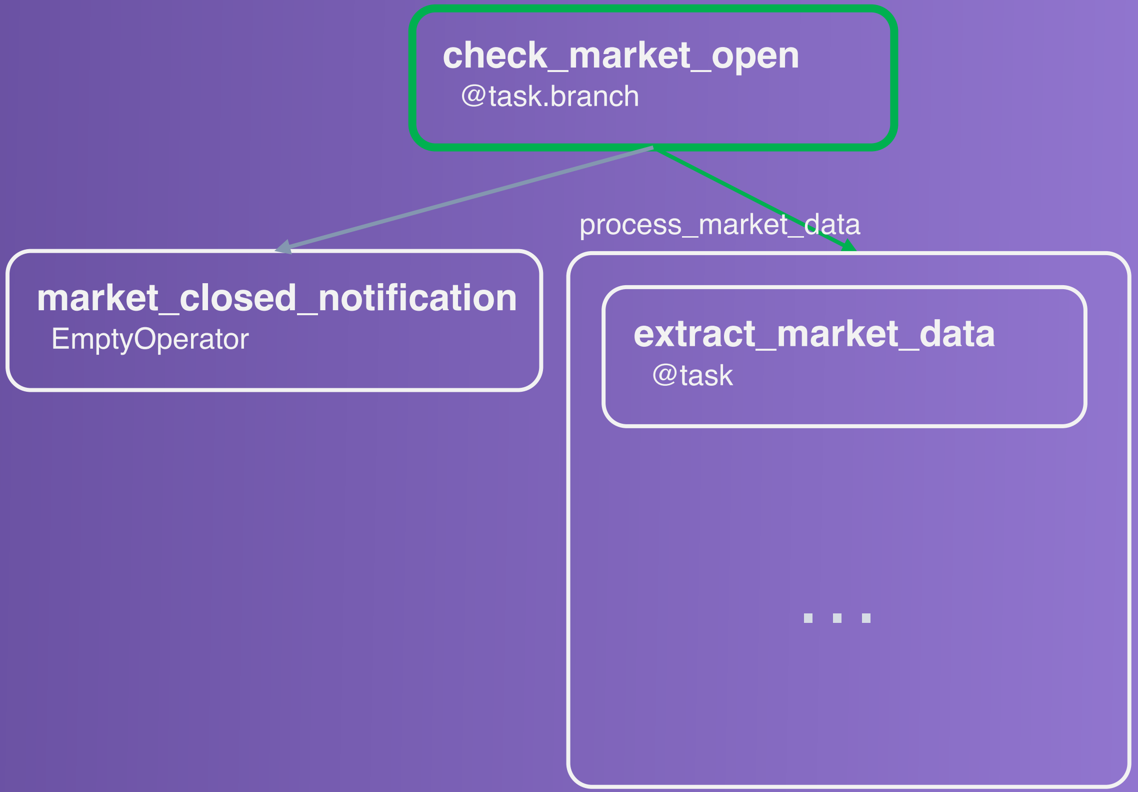
```python
@task_group(group_id="process_market_data")
def process_market_data():
    # Add tasks to task group
    ...
```

```python
with TaskGroup(
    group_id="process_market_data"
) as task_group:
    # Add tasks to task group
    ...
```



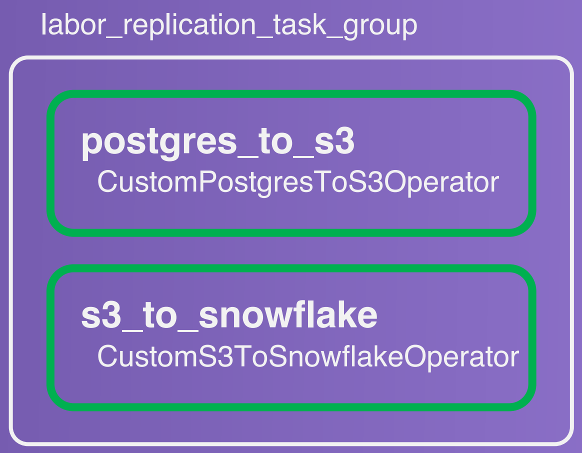
Branching allows for complex logic to be implemented in pipelines

```
@task.branch
def check_market_open(**context):
    ...

    # Branch between two options
    if is_weekend or is_market_holiday:
        return ["market_closed_notification"]

    return ["process_market_data.<task-name>"]

...
```



Custom operators leverage Airflow's extensibility meet to your data team's needs

- Implement custom logic
- Extends existing functionality
- Easy to reuse across DAGs



Airflow simplifies developing and maintaining data workflows of all types

Programmatically define data pipelines

Single-pane of glass into orchestration environment

Leverage tools to supercharge your data pipelines

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Astronomer provides out-of-the-box tools to run Airflow in production

- The leading managed service provider for Airflow
- Easy to create and maintain Airflow environments, without managing the infrastructure
- Astro CLI, Registry, Astro Python SDK

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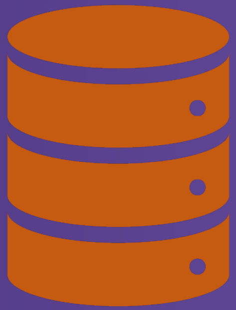
https://www.astronomer.io/product/

Obstacles



Creating a complex data with a limited stack

Enable Airflow to make the biggest impact

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Appendix

https://github.com/jroachgolf84/astronomer-panel-interview

https://airflow.apache.org

https://airflow.apache.org/docs/apache-airflow/stable/index.html

https://www.astronomer.io

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