

Building a true data platform

Beyond the Modern Data Stack

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**Join us on Slack: dagster.io/slack in
the #dagster-deep-dives channel**



Agenda

The Unkept Promise of the Modern Data Stack

The Rise of the Data Platform Engineer

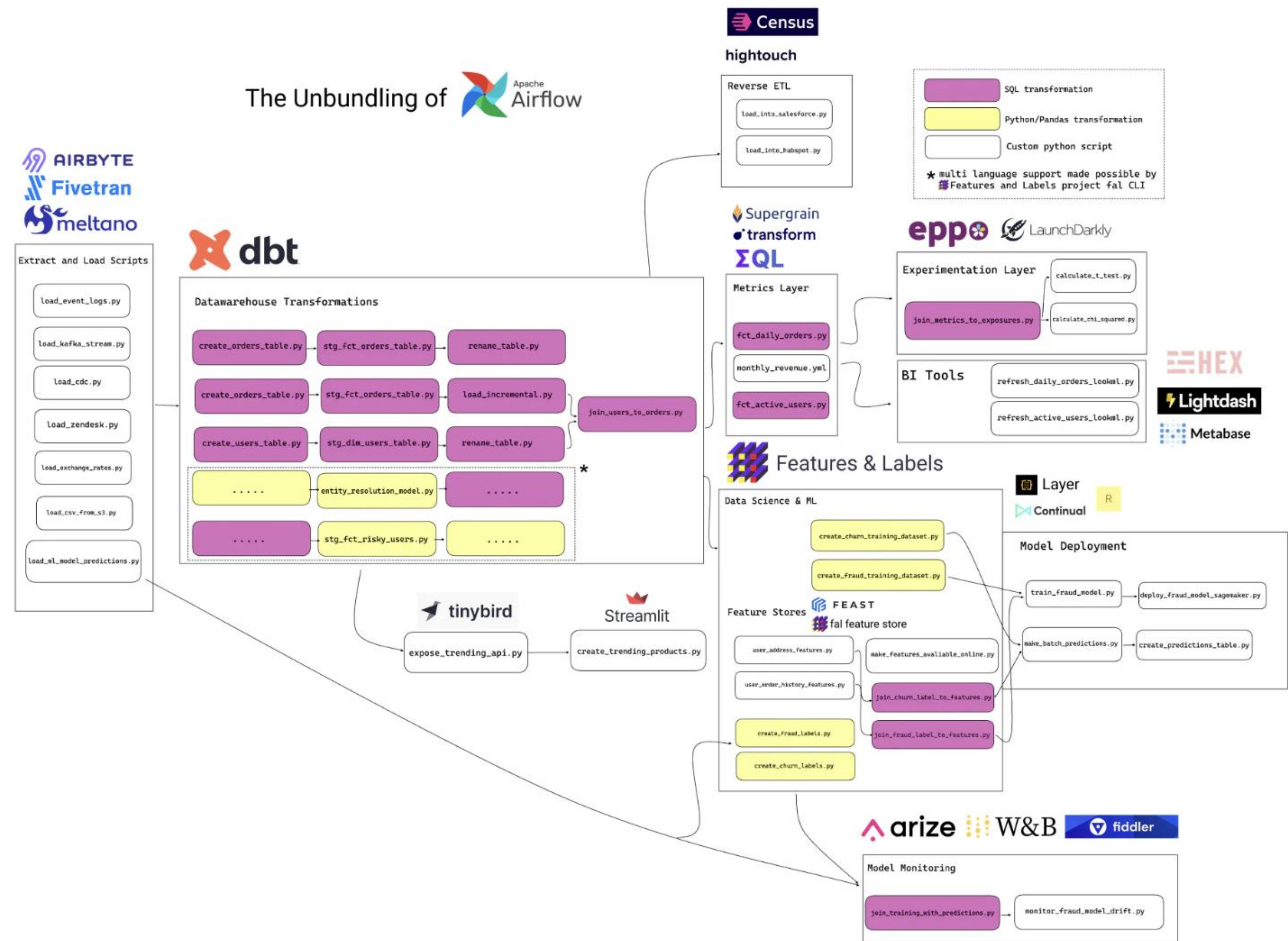
Building a Unified Data Platform

The Unkept Promise of the Modern Data Stack

“The modern data stack saves time, money and effort...leaving your analysts, data scientists and data engineers free to pursue higher-value analytics and data science projects.” -Fivetran Blog



The Unbundling of Airflow



“Benefits” of the unbundled data stack



Sarah Krasnik Bedell  · Jan 5, 2022
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How do you define the modern data stack and if you're using one?



Ananth Packkildurai
[@ananthdurai](#) · [Follow](#)

MDS is a set of vendor tools that solve niche data problems (lineage, orchestration, quality) with the side effect of creating a disjointed data workflow that makes data folks lives more complicated.

7:23 AM · Jan 6, 2022

 18  Share

No Observability

To know the state of your data platform, you need to login to every application, click through a UI, and hope you can find what you need

No orchestration

Insufficient integrations between the stack means you rely on cron-jobs with buffer time that you only hope will complete in time

Expensive and sticky

Difficult to migrate from one solution to another, meaning vendor lock-in, tough negotiations, and skyrocketing bills

The Rise of the Data Platform Engineer



The Unkept Promise of not writing ETL

“Data Engineers are coming back to the original sin of Data Engineering: building bespoke custom pipelines for your downstream consumers, and they’re solving it the same way we were trying to solve it 10 years ago: building platforms, frameworks, and services.”

<https://databased.pedramnavid.com/p/the-rise-of-the-data-platform-engineer>



The Data Platform Engineer

“The next evolution of the role is more akin to a Data Platform Engineer: someone who is tasked not with building ETL pipelines, but with making it possible for their various consumers to build any pipeline they need without having to resort to a complex higher language.”

**Every organization that
has data has a data
platform.**

Three Goals of a Data Platform

Scalability + Maintainability

A Data Platform must scale with your data maturity, while remaining maintainable, reliable, and a pleasure to work with. Not just scaling data, but scaling teams

Data Quality + Governance

Your data platform must be testable, alertable, and part of a software development lifecycle

Data Observability + Insights

Your Data Platform must allow you to observe the state of your pipelines across tools, while also introspecting the underlying data and metadata and enabling discoverability

Qualities of a Data Platform

Encompass the Software Development lifecycle

Testing, version control, branching, and local development

Support heterogeneous use cases

A data platform needs to accommodate a variety of storage and compute tools

Monolithic, unified data plane

Must not be siloed singular platform per team

Declarative workflows

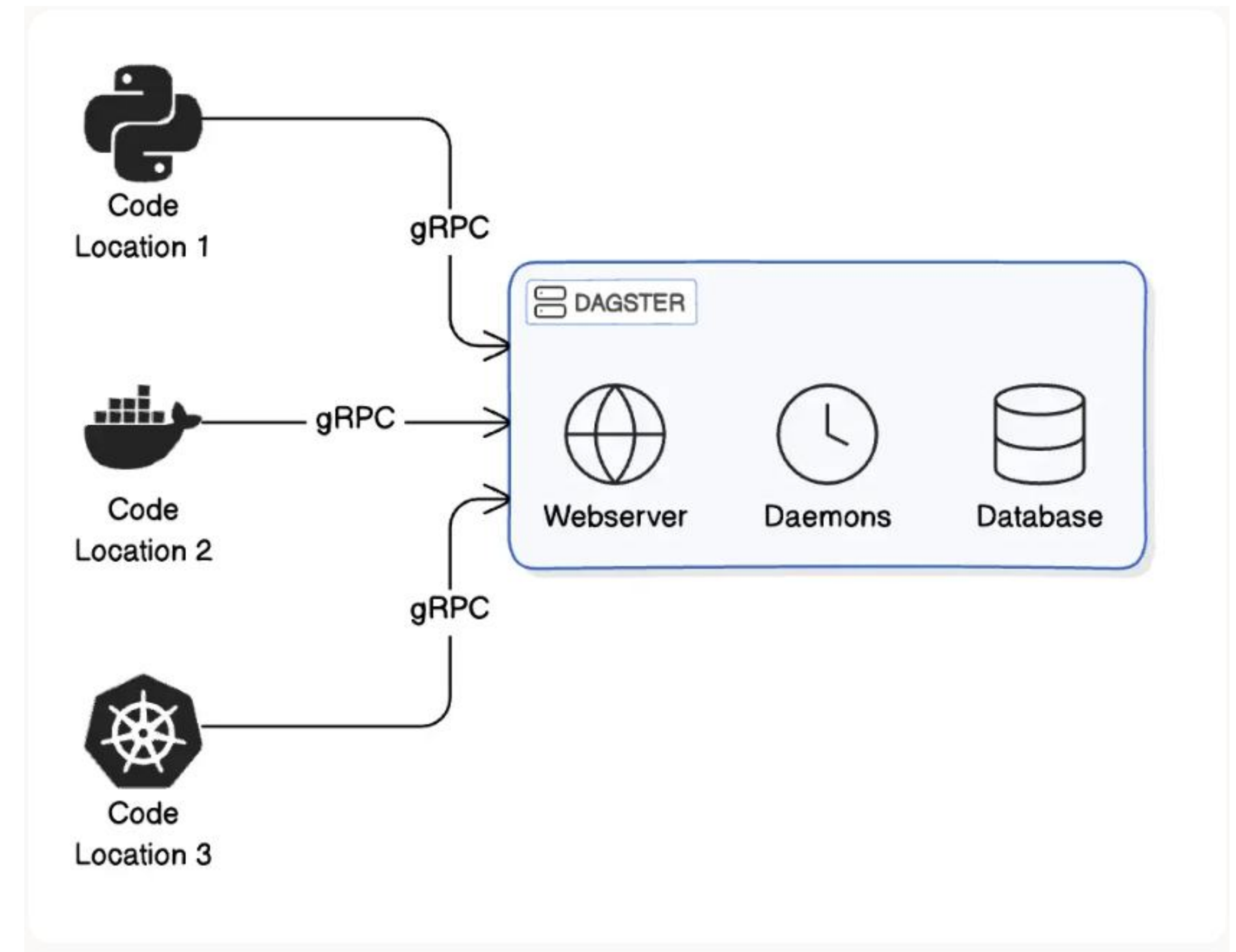
Must allow for both imperative and declarative workflows to simplify maintenance

Building a Data Platform with Dagster

Scalability + Maintainability

Code Locations

A code location helps in organizing and managing the code that defines your data assets and pipelines. It encapsulates your data assets, jobs, schedules, and sensors.



Scalability + Maintainability

Pipelines as Code

Data Engineering is Software Engineering. Data pipelines are expressed as code, and checked into a shared version control system like git.

```
@asset(
    compute_kind="github",
    group_name="support_bot",
    partitions_def=daily_partition,
    op_tags={"team": "devrel"},
    backfill_policy=BackfillPolicy.single_run(),
)
def github_issues(
    context: AssetExecutionContext, github: GithubResource, scoutos: ScoutosResource
) -> MaterializeResult:
    """Fetch Github Issues and Discussions and feed into Scout Support Bot.

    Since the Github API limits search results to 1000, we partition by updated at
    month, which should be enough to get all the issues and discussions. We use
    updated_at to ensure we don't miss any issues that are updated after the
    partition month. The underlying auto-materialize policy runs this asset every
    day to refresh all data for the current month.
    """

    start, end = context.partition_time_window
    context.log.info(f"Finding issues from {start} to {end}")


    issues = github.get_issues(
        start_date=start.strftime("%Y-%m-%d"), end_date=end.strftime("%Y-%m-%d")
    )
    context.log.info(f"Found {len(issues)} issues")

    parsed_issues = [parse_issue(i) for i in issues]
    context.log.info(f"Found {len(parsed_issues)} parsed issues")

    discussions = github.get_discussions(
        start_date=start.strftime("%Y-%m-%d"), end_date=end.strftime("%Y-%m-%d")
    )
    context.log.info(f"Found {len(discussions)} discussions")
    parsed_discussions = [parse_discussion(d) for d in discussions]
    context.log.info(f"Found {len(parsed_discussions)} parsed discussions")
    collection = os.getenv("SCOUTOS_COLLECTION_ID", "")
    context.log.info(f"Using Collection ID: {collection}")
    scoutos.write_documents(collection, parsed_issues)
    scoutos.write_documents(collection, parsed_discussions)
    return MaterializeResult()
```

Data Quality + Governance

Asset Checks + Health

 Overview Runs Catalog Jobs Automation Insights Deployment

🔍

P prod

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Overview

🔄 Reload definitions

Timeline Asset health Auto-materialize Resources Backfills

🌐 All assets

🔍 Filter

Filter asset keys...

Group by Asset Group

⚠️ Execution failures
23 assets

⊗ Check failure errors
0 assets

⚠️ Check failure warning
1 asset

🔄 Executing
22 assets

| Asset | Code location | Group | Checks | Actions |
|-----------------------------------|---------------|--------------------|----------------------|------------|
| 📁 billing_platform in purina (1) | | | | |
| 📄 self_serve_customer_attribution | 📁 purina | 📄 billing_platform | ⚠️ self_se...titions | View asset |

Catch data quality issues and schema changes early using Python-based logic.

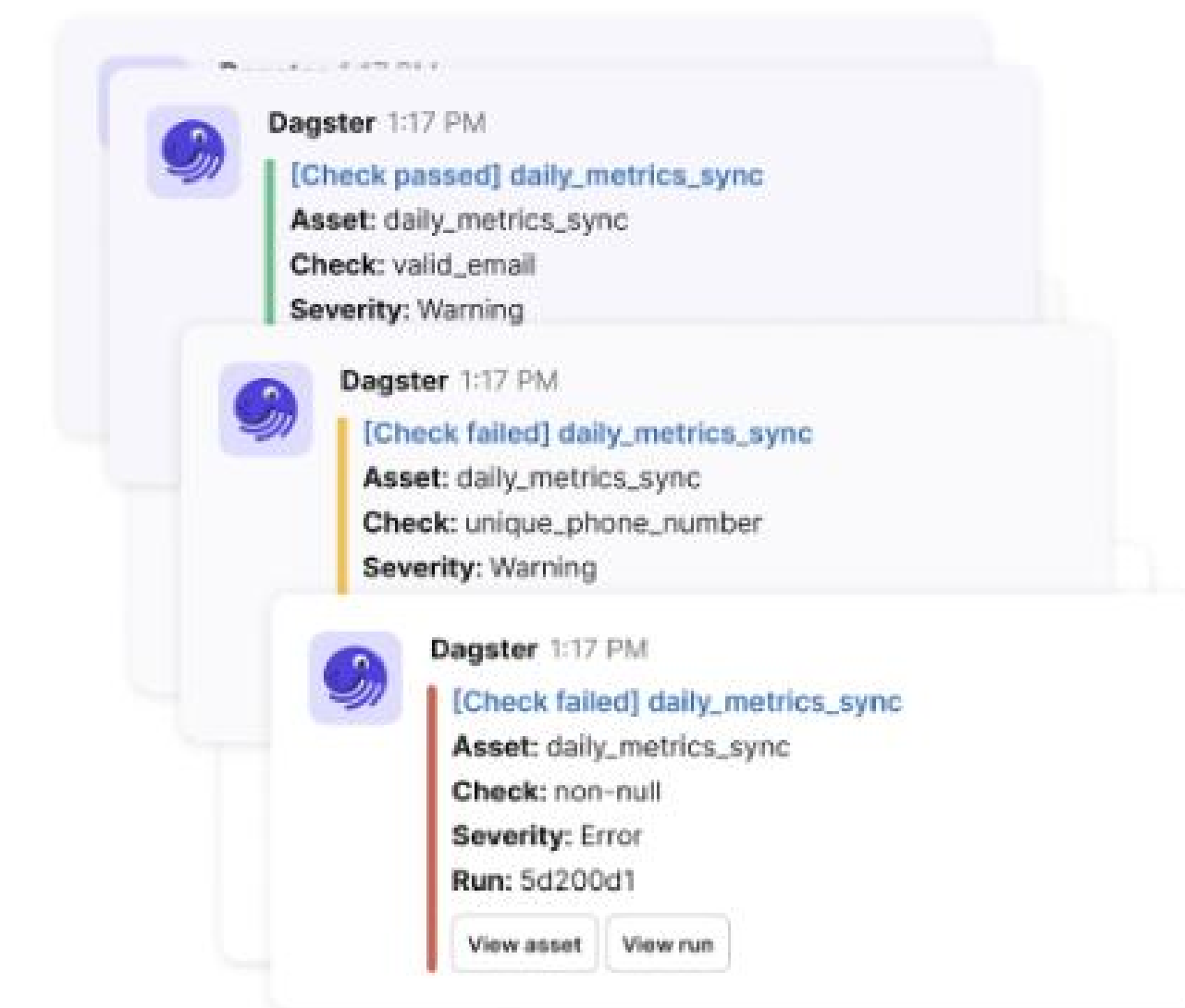
Data Quality + Governance

Data Freshness

```
@dg.asset
def hourly_sales(context: dg.AssetExecutionContext):
    context.log.info("Fetching and emitting hourly sales data")
    ...

hourly_sales_freshness_check = dg.build_last_update_freshness_checks(
    assets=[hourly_sales], lower_bound_delta=timedelta(hours=1)
)
freshness_checks_sensor = dg.build_sensor_for_freshness_checks(
    freshness_checks=hourly_sales_freshness_check
)
```

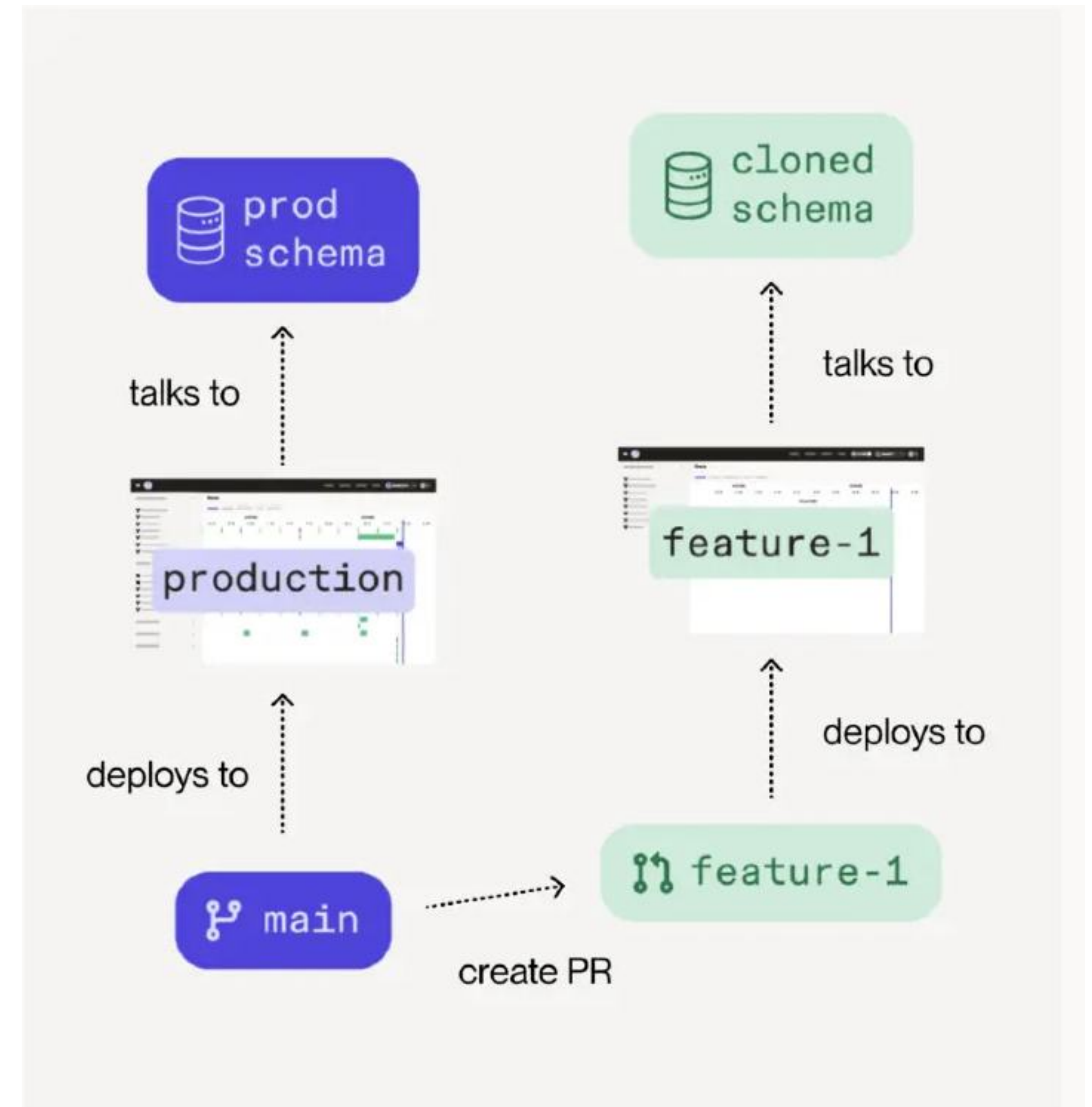
Freshness checks provide a way to identify data assets that are overdue for an update.



Data Quality + Governance

Change Management

Branch Deployments automatically create staging environments of your Dagster code, right in Dagster+. For every push to a branch in your git repository, Dagster+ will create a unique deployment, allowing you to preview the changes in the branch in real-time.



Data Observability + Insights

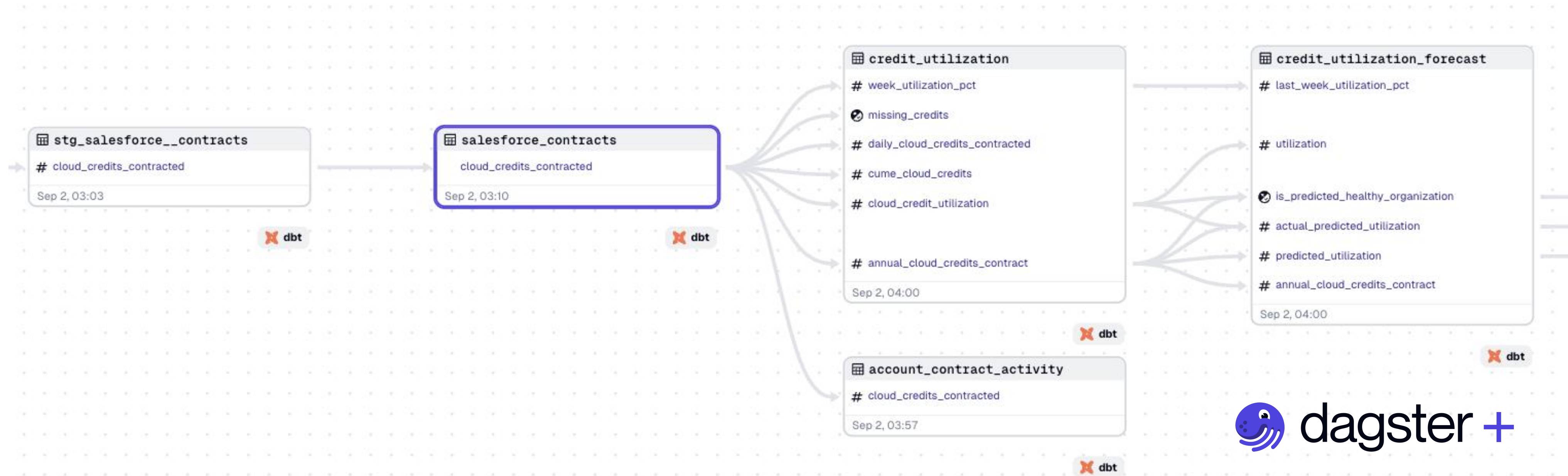
Asset-based pipelines

The Asset Graph is a **map of your data platform**.
Dagster is the only data orchestrator that centers
your pipelines on the assets you create rather than
the tasks that create them



Data Observability + Insights

Column Level Lineage



Data Engineering is Software Engineering. Data pipelines are expressed as code, and checked into a shared version control system like git.

Data Observability + Insights

Data Catalog

Search by asset name, compute kind, group, owner, tag and more.

All assets Catalog

Reload definitions

Good evening, Pedram

View all assetsView lineage

Search assets

Recently visited assets

Owners

Ben Pankow

Nicklaus Roach

dagster-plus

Rex Ledesma

data

Compute kinds

Airtable

fivetran

Slack

dbt

github

sling

dlt

hightouch

Snowflake

Storage kinds

snowflake

Tags

insights

model

seed

Wrapping Up

The Unkept Promise

The Modern Data Stack promised scalability, flexibility, and cost savings, but in reality, it often leaves us with a fragmented and complex ecosystem. This unkept promise has led to operational fragility, lack of observability, and expensive vendor lock-ins.

What We Believe

At Dagster, we believe in building a monolithic, unified data plane that supports heterogeneous use cases and declarative workflows. Our approach ensures that your data platform is not just a collection of disjointed tools but a cohesive, scalable, and maintainable system.

What You Can Accomplish

By leveraging Dagster, you can transform your modern data mess into a streamlined, efficient, and reliable data platform. Remember, the goal is not just to have a data platform but to have one that is truly effective and aligned with your organizational needs.

Q&A