LECTURE 23a

Data Ops and Pipelines

April 17, 2024

Data 101, Fall 2024 @ UC Berkeley

Aditya Parameswaran https://data101.org/sp24

Automating Data Operations

Lecture 23, Data 101/Info 258 Spring 2024

Automating Data Operations
dbt Overview
dbt Models
dbt Tests
Spark as a Workflow System
Pub-Sub and MQs
Workflow Systems

A very pragmatic topic: Automating Data Processing

In the “real world” you don’t deal with data sets, you deal with **data feeds**, or **data streams**.

- Data “arrives” on a regular basis.
- When data arrives, you need to “do the right thing.”

Things to consider when designing **data pipelines** to automate data processing:

1. How does data “arrive”?
2. What kinds of things do you need do upon arrival?
3. How do you automate the work?
4. How do you maintain quality and handle exceptions?

1. How does data “arrive”?

Push: To some location

- Files appear in a staging folder, e.g. in AWS S3; or
- Tables get populated in a data warehouse, e.g. in BigQuery; or
- A software system API provides the data
  - E.g. publish-subscribe (**pub-sub**) or **message queueing** systems (more later)

Pull: Extract data from some source

- Via scheduling software; or
- On receipt of an event, e.g. from pub-sub or MQ systems
  - Or slack or email or … really anything

2. What do you do upon data arrival?

Many possible options, and you should do all of them:

- Run **data quality** (**DQ**) tests
  - E.g. check the new data has expected schema, integrity constraints, data cleaning checks
- Load into “the right place” (a data warehouse or a curated set of directories)
- Run transformation logic
- Log Metadata (**Data Lineage**): track what arrived from whom, where, when…
- Pass along info/control to humans
  - e.g., when there are immediate errors, send a “beeper message” to someone who can approve and continue automation.

2b. Isn't this all Data Transformation? A: Yes, but…

Yes: Data Engineering is largely automated data transformation

…**But**: In many contexts, this involves tasks across many software systems.

Our SQL-centric ELT this semester has been **very clean**.

- Not unrealistic -- some places do this for their main operations.

However, many pipelines involve different systems for some/all pieces of the puzzle:

- **Derived data**: Preparation/Cleaning/Transformation systems, Entity Resolution/Standardization systems
- **Data Structure Maintenance**: Indexes, Materialized View updates, Data Cube updates
- **Data Security/Compliance Systems**: "masking" private data, encryption
  - See: EU's GDPR, or California's CCPA for privacy regulations
- **Metadata storage**: catalogs, data lineage (tracking where data came from and what happened)
- And so on, and so on.

We need to automate these many tasks/systems and their handoffs

- **And** deal with exceptions, human interventions/approvals, etc.

3. How do we automate the work?

Data pipelines are automated with more kinds of systems! 🙃

Workflow Systems: manage processes (human or software)

- With process dependencies (order of activity)
- Activiti, Airflow, BPL, Luigi, …

Dataflow Systems: manage data movement through operations (software)

- Handle data dependencies (inputs/outputs)
- Spark
- dbt + SQL
- Flink, Dataflow, etc.

Messaging/Queueing/Eventing: hand off data reliably from one system to another

- Kafka, RabbitMQ, AWS SQS, MSMQ, MQSeries, …

Practically: Many times you will use combinations of these, and it can be a matter of taste/experience which to use where.

- You'll learn it "on the street…"
- Or, you'll subscribe to company "religion" and be part of many debates

4. How do you maintain quality and handle exceptions?

Data Quality and **Software Quality** share similarities, but also have many differences.

The notion of a "**test**" is now **data-centric**:

- logical (schemas, constraints, etc)
- statistical (outliers, distributional drift)
- etc. Quite different from software debugging!

However, SW Eng DevOps principles are getting more play in DataOps pipelines.

- Test-driven development
- **Continuous Integration** / Continuous Deployment

We'll look at `dbt` as an emerging example.

dbt Overview

Lecture 23, Data 101/Info 258 Spring 2024

Automating Data Operations
dbt Overview
dbt Models
dbt Tests
Spark as a Workflow System
Pub-Sub and MQs
Workflow Systems

3. How do we automate the work?

Data pipelines are automated with more kinds of systems! 🙃

Workflow Systems: manage processes (human or software)

- With process dependencies (order of activity)
- Activiti, Airflow, BPL, Luigi, …

Dataflow Systems: manage data movement through operations (software)

- Handle data dependencies (inputs/outputs)
- Spark
- dbt + SQL
- Flink, Dataflow, etc.

(more later)

Messaging/Queueing/Eventing: hand off data reliably from one system to another

- Kafka, RabbitMQ, AWS SQS, MSMQ, MQSeries, …

Practically: Many times you will use combinations of these, and it can be a matter of taste/experience which to use where.

- You'll learn it "on the street…"
- Or, you'll subscribe to company "religion" and be part of many debates

dbt (data build tool) for ELT pipelines and data quality

dbt (the “data build tool”) is a *commercial open-source* project.

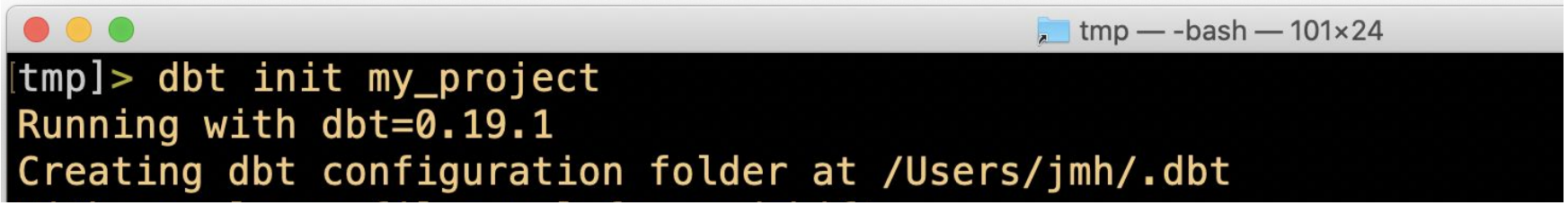
- *free* to use the CLI (command-line interface, i.e., terminal) version
- pay *dbt labs* for cloud-based scheduling, CI-git integration, GUI

A **declarative specification** framework for:

- **pipelines of ELT-style SQL** transformations
- **data quality tests**

dbt Core and Cloud are composed of different moving parts working harmoniously. All of them are important to what dbt does — transforming data—the 'T' in ELT. When you execute `dbt run`, you are running a model that will transform your data without that data ever leaving your warehouse.

[dbt docs]



The expectation is that you connect this to an existing Data Warehouse (i.e., SQL database)..

dbt (data build tool) for ELT pipelines and data quality

dbt (the "data build tool") is a *commercial open-source* project.

- *free* to use the CLI (command-line interface, i.e., terminal) version
- pay *dbt labs* for cloud-based scheduling, CI-git integration, GUI

A **declarative specification** framework for:

- **pipelines of ELT-style SQL** transformations
- **data quality tests**

This tool is very recent!

- ≤v0.X in 2016, then v1.0 in 2021
- various other companies standardize on dbt format

We'll do a quick tour of dbt today! There is no associated project, but instead you will get a sense of how these tools work.

dbt

Developer(s)	dbt-Labs
Initial release	December 3, 2021; 23 months ago
Stable release	1.6.5 / October 2, 2023; 35 days ago [1]
Repository	github.com/dbt-labs/dbt-core
Written in	Python
Operating system	Microsoft Windows, macOS, Linux
Available in	Python
Type	Data analytics, data management
License	Apache License 2.0
Website	docs.getdbt.com

[wikipedia]

a dbt project

A dbt project has several key components.

models: SQL transformations

- `models/*.sql`: 1 query per file

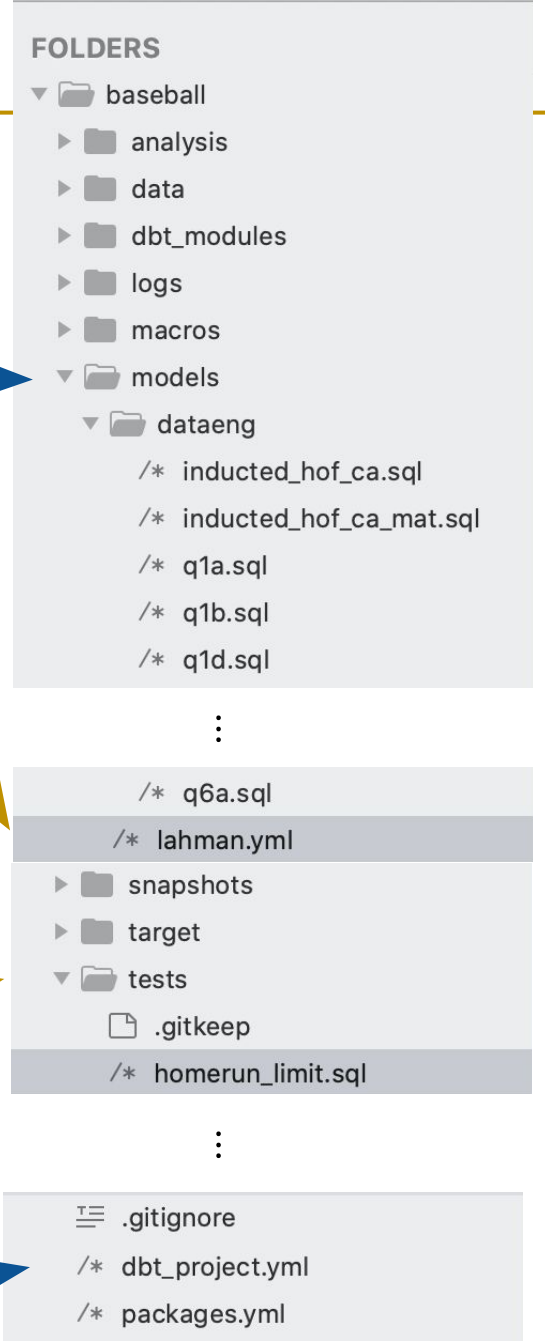
tests

- `models/*.yml` schema integrity tests
  - specified in YAML (JSON analog, but more readable)
- `tests/*.sql`: 1 query per file
  - Passes if it returns 0 rows

`dbt_project.yml`

- required project configuration file, with lots of boilerplate

`models/*.yml` also contains optional metadata

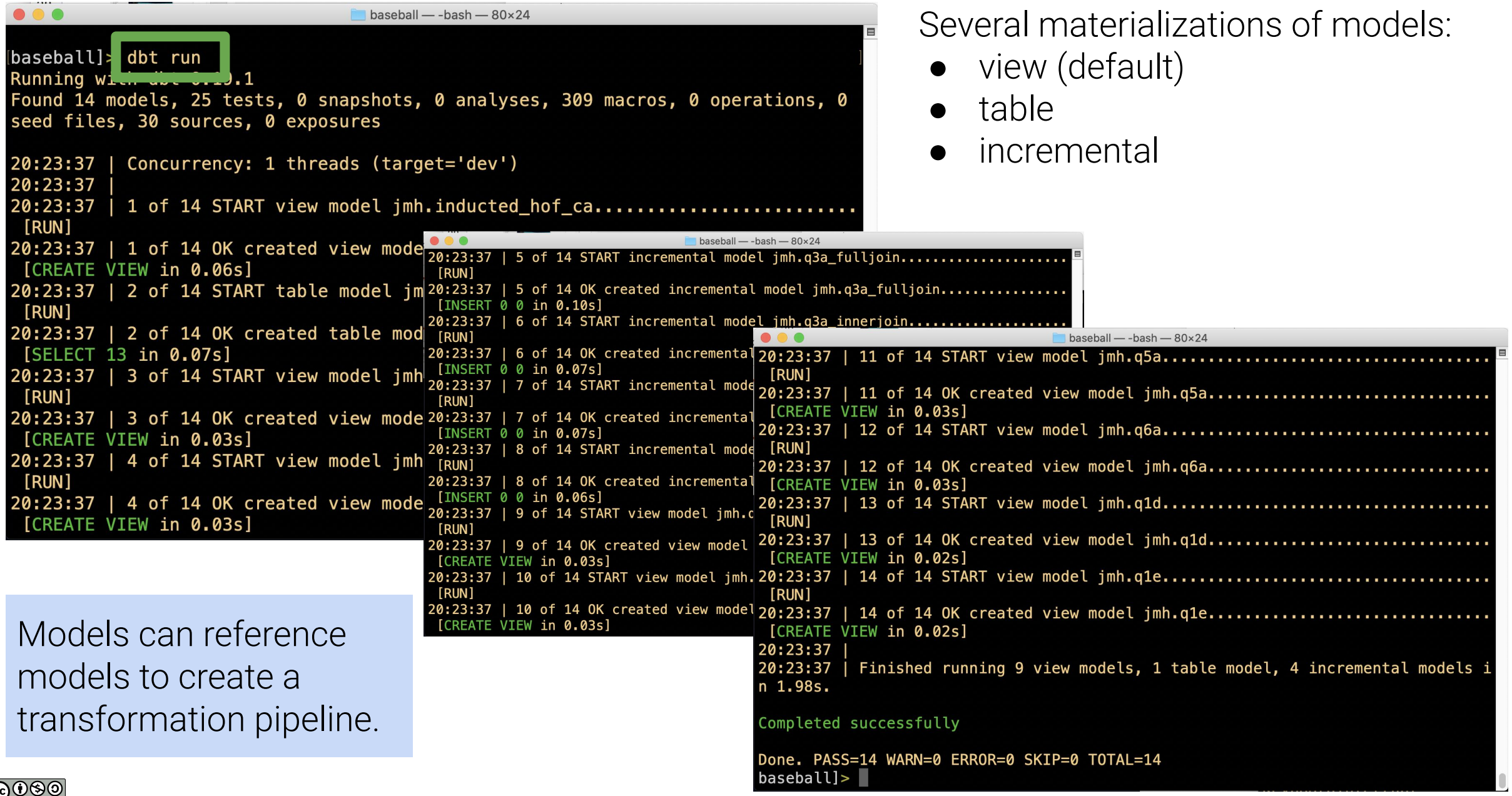


dbt Models

Lecture 23, Data 101/Info 258 Spring 2024

Automating Data Operations
dbt Overview
dbt Models
dbt Tests
Spark as a Workflow System
Pub-Sub and MQs
Workflow Systems

Running models in dbt is `dbt run`



Several materializations of models:

- view (default)
- table
- incremental

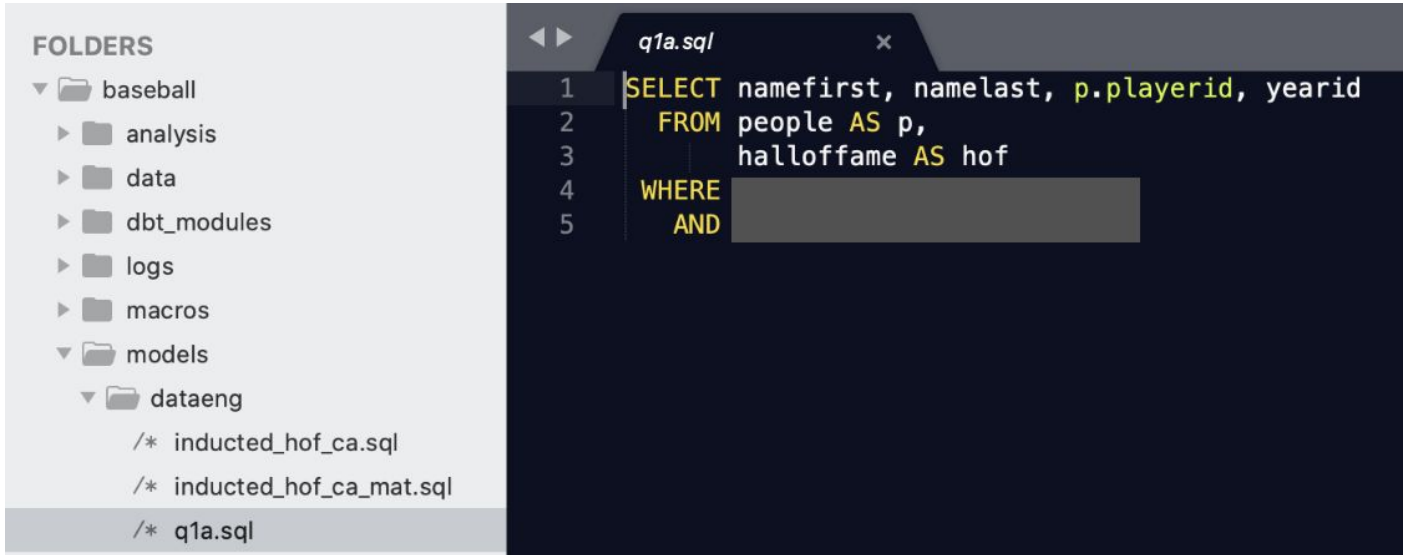
Models can reference models to create a transformation pipeline.

(1/2) Model Materialization: View

Simple model in `q1a.sql`

- Specifies a derived result named `q1a`

Note: By default, results are materialized as **views** (b/c transformations pipelined)

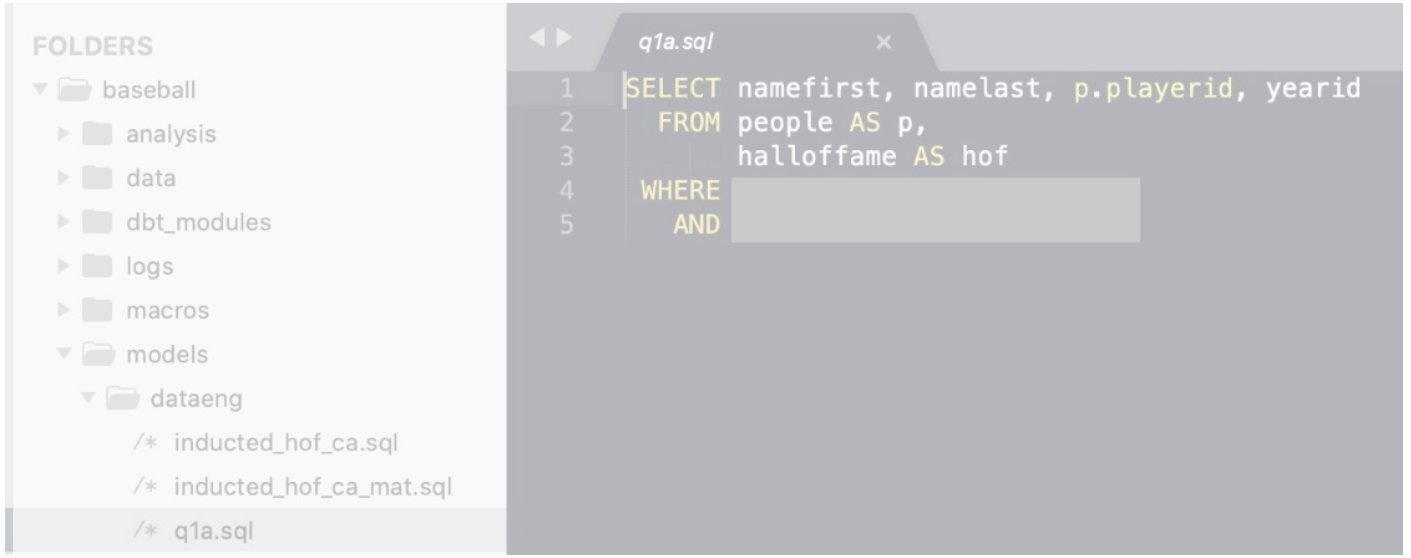


(2/2) Model Materialization: View

Simple model in `q1a.sql`

- Specifies a derived result named `q1a`

Note: By default, results are materialized as **views** (b/c transformations pipelined)



Source references in `q1a.sql`

- Specifies a derived result named `q1b` (a view, by default)

Note the jinja macro in curly braces!

```
{{ source('baseball', 'people') }}
```

- This still references the `people` table.
- However, now it references whatever people table is specified in model/*.yaml configs.

Source references provide nice hygiene via a **level of indirection** so that these models can be retargeted to other databases or schemas as needed.

Side note: the yaml file

```
{{ source('baseball', 'people') }}
```

Source references in `q1a.sql`

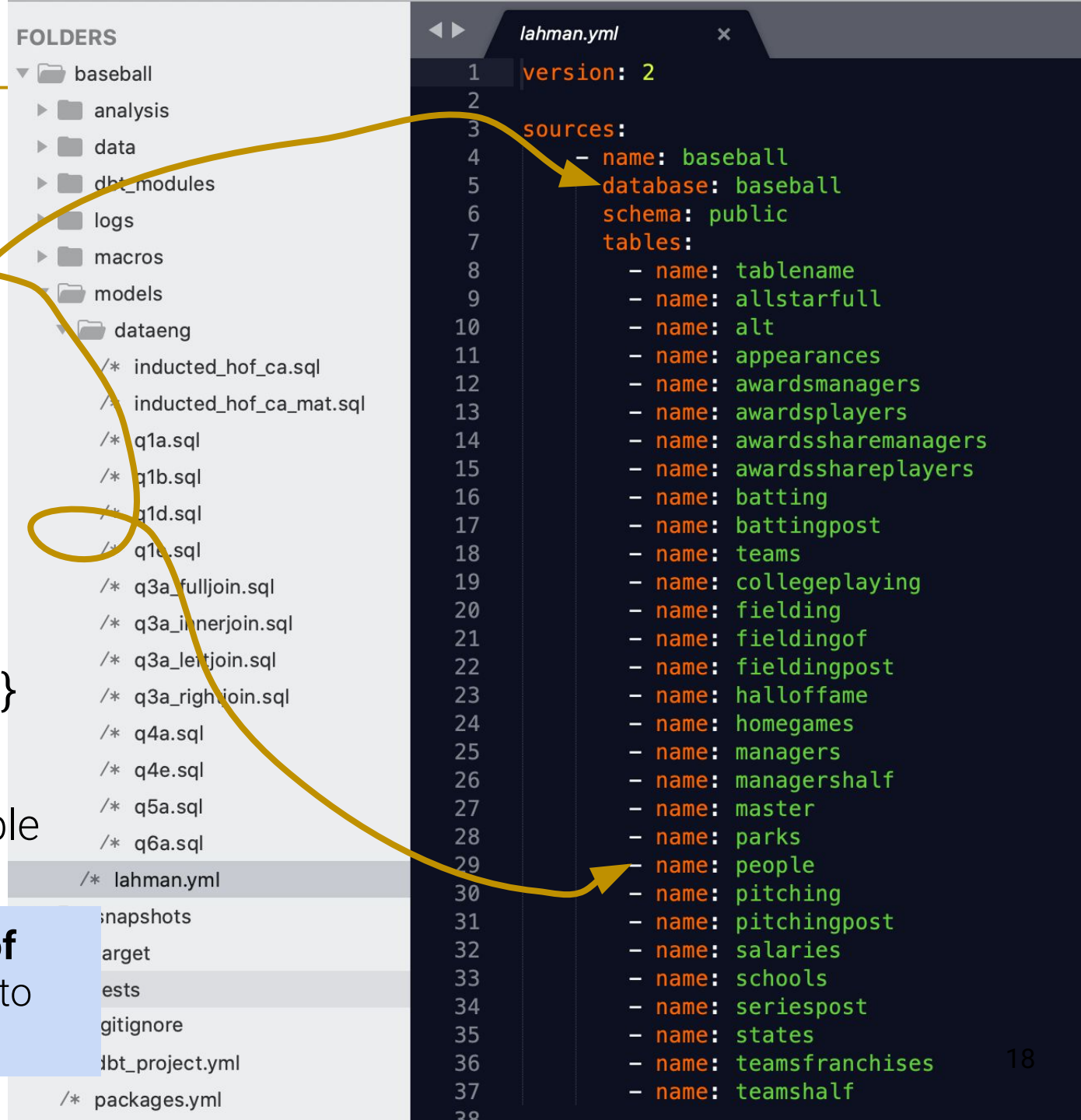
- Specifies a derived result named `q1b` (a view, by default)

Note the jinja macro in curly braces!

```
{{ source('baseball', 'people') }}
```

- This still references the **`people`** table.
- However, now it references whatever people table is specified in model/*.yaml configs.

Source references provide nice hygiene via a **level of indirection** so that these models can be retargeted to other databases or schemas as needed.



Model Materialization: Table

Sometimes, we may want to specify that results are materialized as **tables**.

- Also specify this as Jinja macros!

When we dbt run this project:

- `inducted_hof_ca_mat` becomes a table, not a view.
- Note: tables are **recomputed** every time we dbt run the project!

```
q1a.sql
1  SELECT namefirst, namelast, p.playerid, yearid
2    FROM people AS p,
3         halloffame AS hof
4   WHERE
5     AND
```

simple model in `q1a.sql`, materialized as a view by default

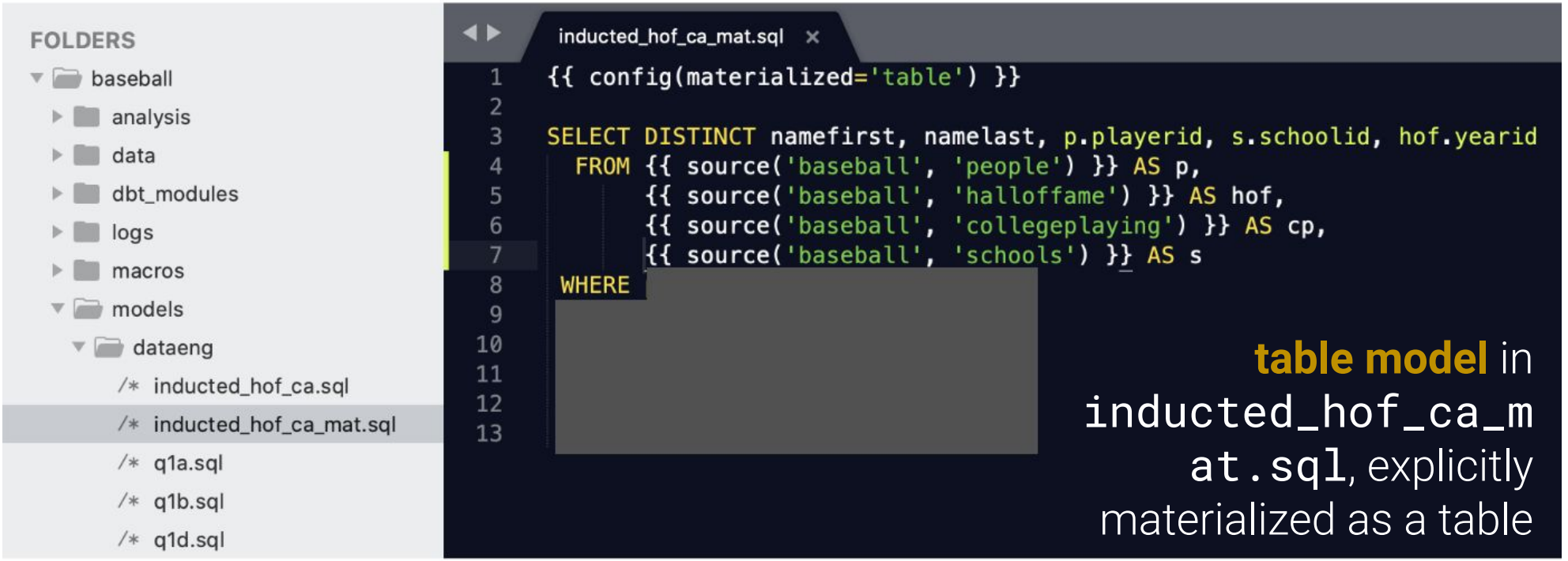


table model in `inducted_hof_ca_mat.sql`, explicitly materialized as a table

Model materialization: Incremental

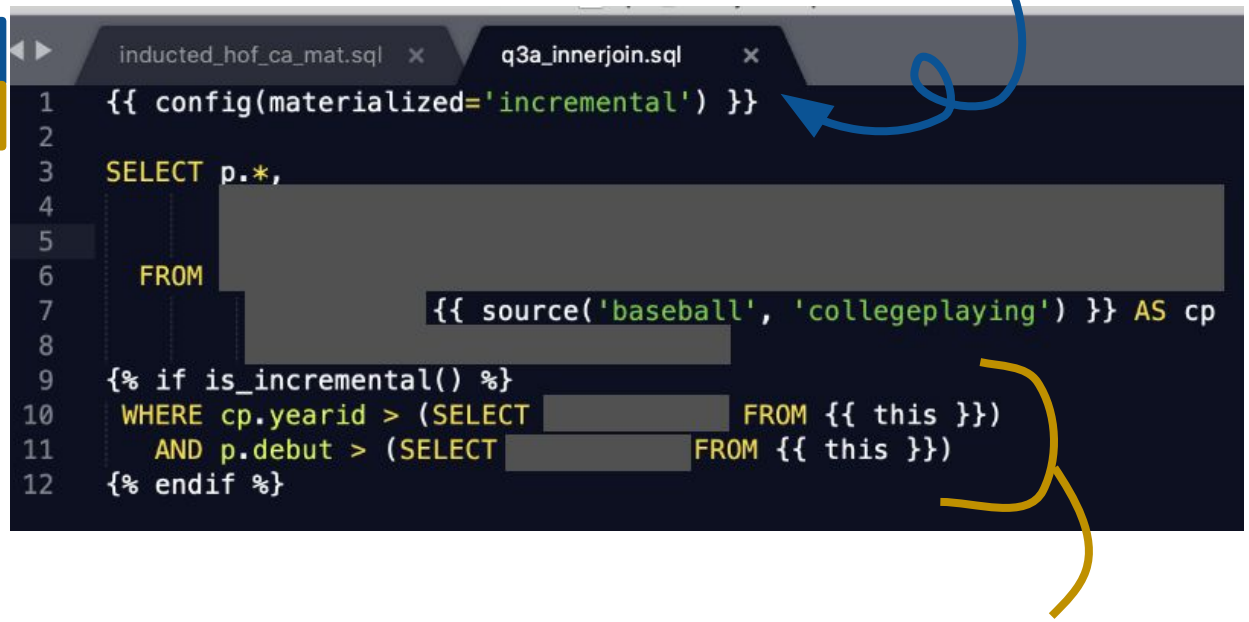
[dbt docs]

`q3a_innerjoin` becomes a table on first run

Incremental models are built as tables in your data warehouse. The first time a model is run, the table is built by transforming *all* rows of source data. On subsequent runs, dbt transforms *only* the rows in your source data that you tell dbt to filter for, inserting them into the target table which is the table that has already been built.

Often, the rows you filter for on an incremental run will be the rows in your source data that have been created or updated since the last time dbt ran. As such, on each dbt run, your model gets built incrementally.

Using an incremental model limits the amount of data that needs to be transformed, vastly reducing the runtime of your transformations. This improves warehouse performance and reduces compute costs.



On subsequent runs, lines 10 & 11 are added to limit the work

Incremental models provide a facility for simple "**materialized view maintenance**" **outside** the database.

Model materialization: Incremental

[dbt docs]

`q3a_innerjoin` becomes a table on first run

Incremental models are built as tables in your data warehouse. The first time a model is run, the table is built by transforming *all* rows of source data. On subsequent runs, dbt transforms *only* the rows in your source data that you tell dbt to filter for, inserting them into the target table which is the table that has already been built.

Often, the rows you filter for on an incremental run will be the rows in your source data that have been created or updated since the last time dbt ran. As such, on each dbt run, your model gets built incrementally.

Using an incremental model limits the amount of data that needs to be transformed, vastly reducing the runtime of your transformations. This improves warehouse performance and reduces compute costs.

inducted_hof_ca_mat.sql | q3a_innerjoin.sql

```
1  {{ config(materialized='incremental') }}
2
3  SELECT p.*,
4
5
6    FROM
7                    {{ source('baseball', 'collegeplaying') }} AS cp
8
9  {% if is_incremental() %}
10  WHERE cp.yearid > (SELECT            FROM {{ this }})
11    AND p.debut > (SELECT            FROM {{ this }})
12 {% endif %}
```

On subsequent runs, lines 10 & 11 are added to limit the work

Incremental models provide a facility for simple "**materialized view maintenance**" **outside** the database.

- Only handles inserts and "upserts" (i.e., replace tuples using unique key)
- No delete handling, no general update handling

Principle from early lectures: "**selection pushdown** is good"...!!

- ...But it depends on the DBMS you're using (docs: When should I use an incremental model?)
- Up to you to figure out if it's a performance win 🙃

Yes, with `ref`, pipelines are that easy!

[dbt docs]

We've seen how with `{{ source('baseball', 'people') }}` models can reference other tables with a layer of indirection.

Models can also **reference other models** with `ref`:

```
{{ ref('induced_hof_ca') }}
```

The most important function in dbt is `ref()`; it's impossible to build even moderately complex models without it. `ref()` is how you reference one model within another. This is a very common behavior, as typically models are built to be "stacked" on top of one another. Here is how this looks in practice:

Specifying `ref` dependencies is how dbt models **implicitly specify a pipeline of models** querying models.

Note: cannot have cycles of ref dependencies, i.e., the graph representing all refs must be a DAG

dbt Tests

Lecture 23, Data 101/Info 258 Spring 2024

Automating Data Operations

dbt Overview

dbt Models

dbt Tests

Spark as a Workflow System

Pub-Sub and MQs

Workflow Systems

a dbt project

A dbt project has several key components.

models: SQL transformations

- `models/*.sql`: 1 query per file

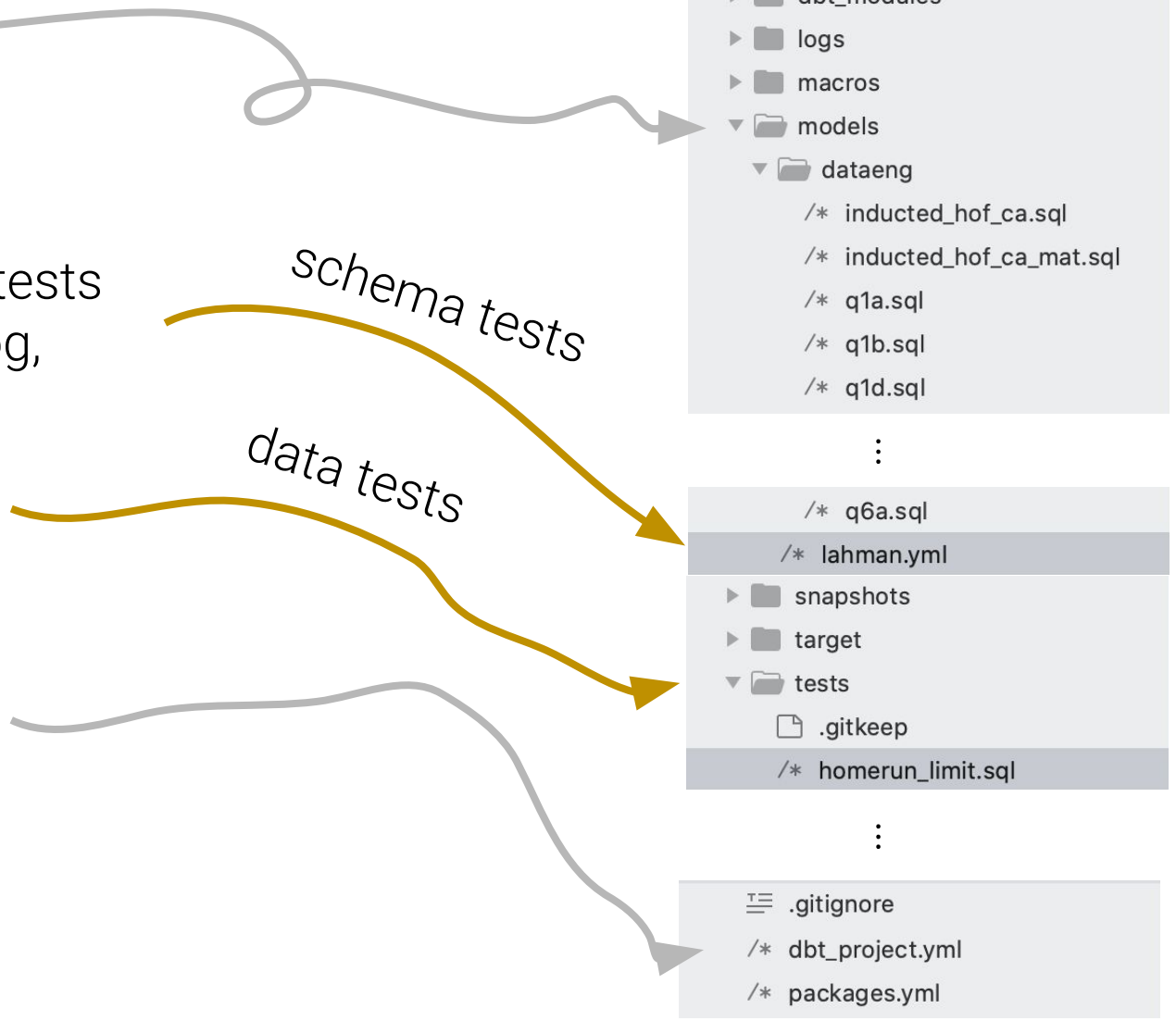
tests

- `models/*.yml` schema integrity tests
  - specified in YAML (JSON analog, but more readable)
- `tests/*.sql`: 1 query per file
  - Passes if it returns 0 rows

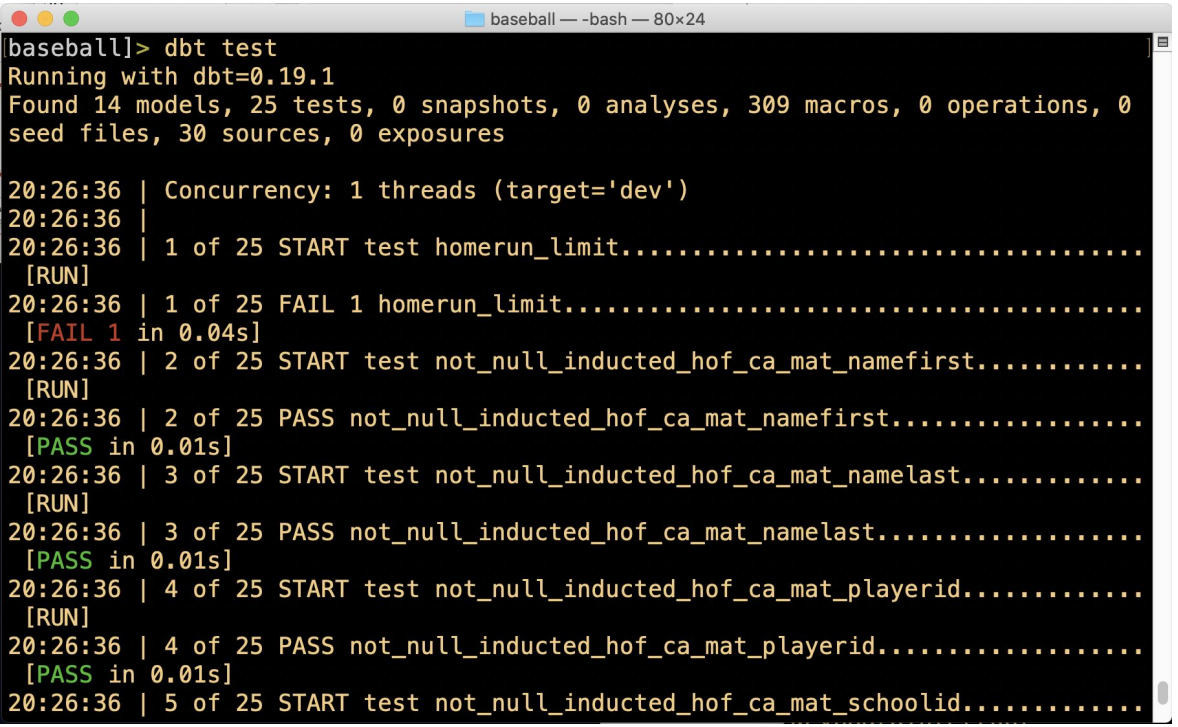
`dbt_project.yml`

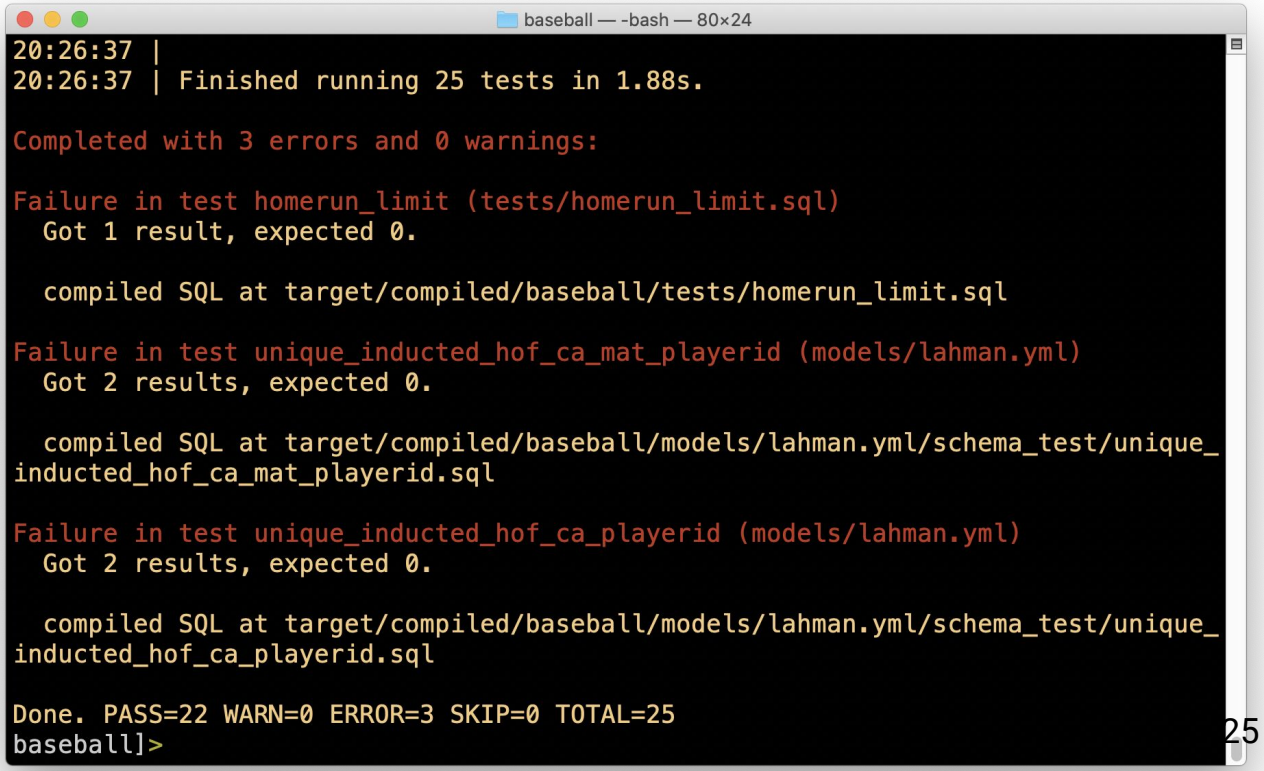
- required project configuration file, with lots of boilerplate

`models/*.yml` also contains optional metadata

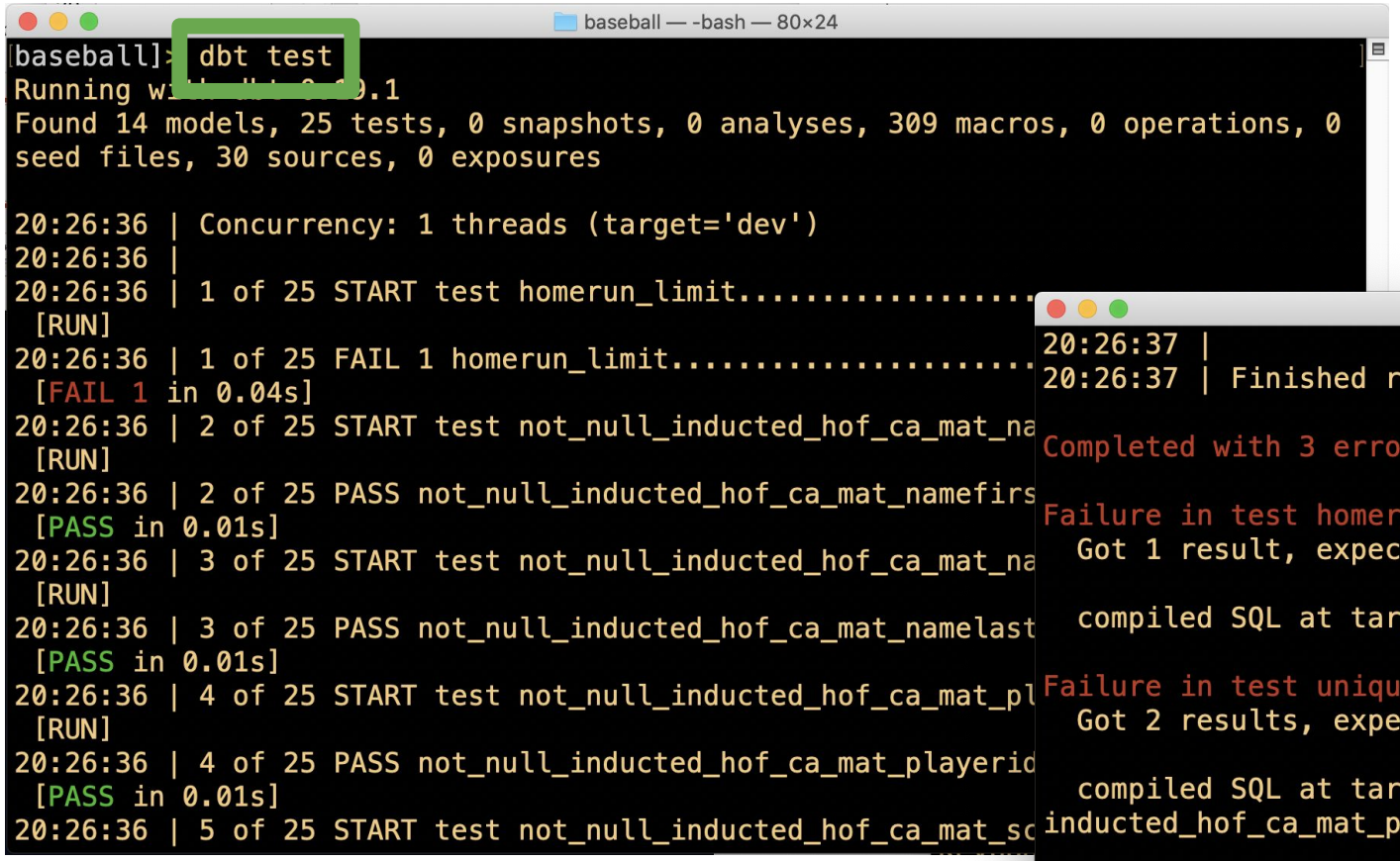


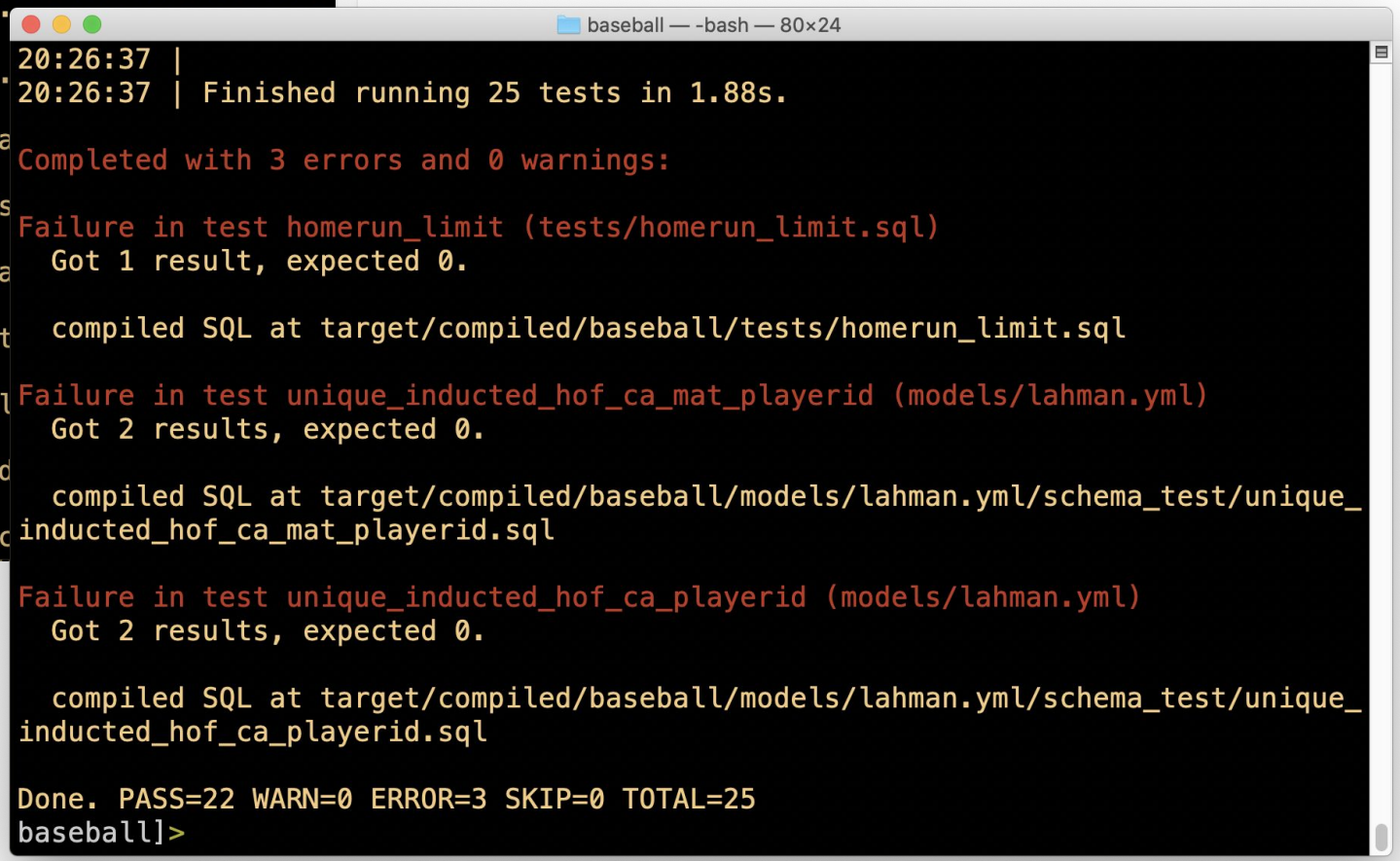
Running Tests





Running tests in dbt is `dbt test`





Schema Tests

`models/*.yml` schema integrity tests

- specified in YAML (JSON analog, but more readable)

Like SQL DDL constraints, but mid-pipeline!

- `unique`, `not_null`
- `accepted_values`
- `relationships`

Caveats:

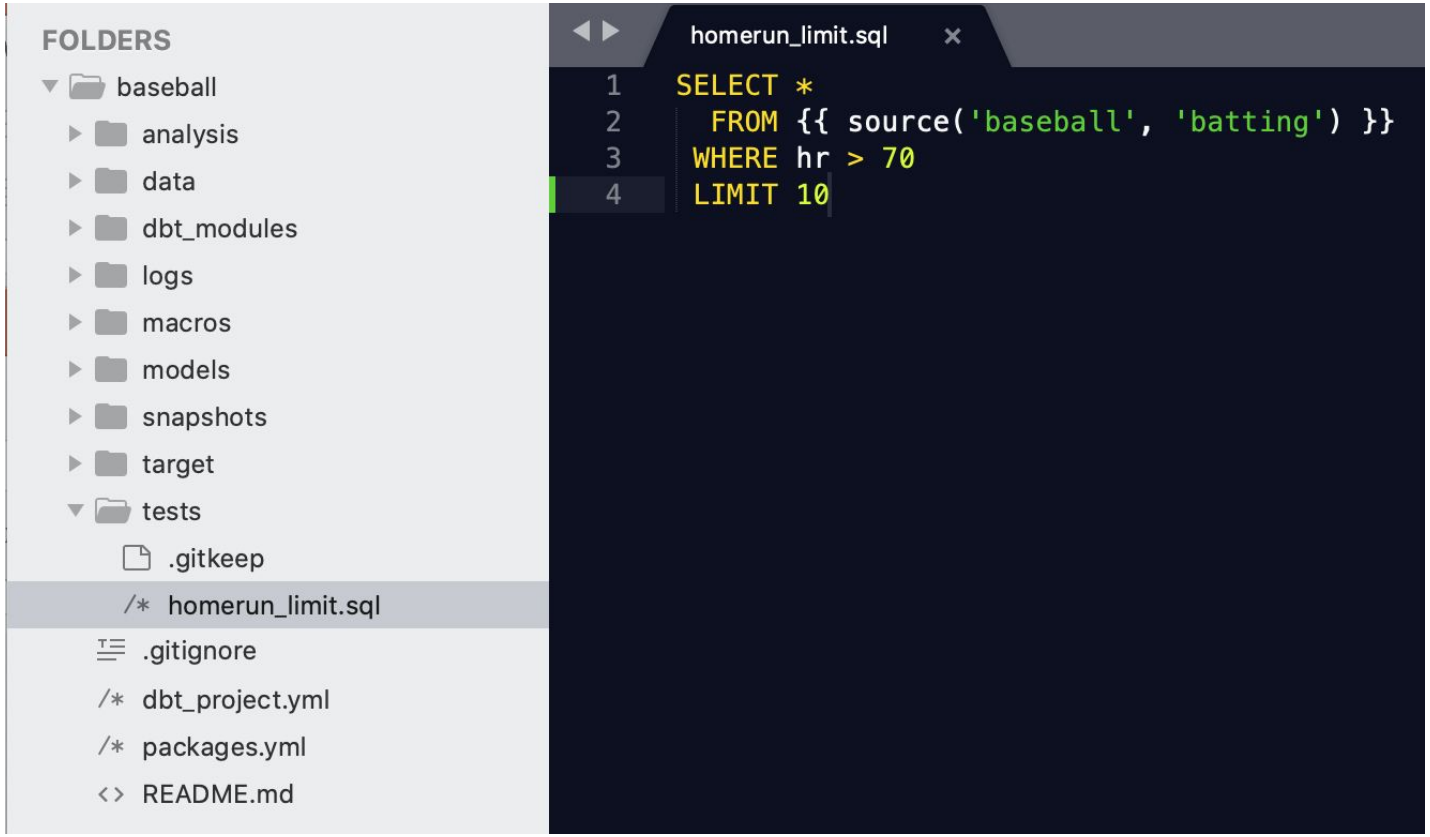
- Single-column by default!
- …but side approaches available to test composite columns
  - "Can I test the uniqueness of two columns?" docs

Data Tests

`tests/*.sql`: 1 query per file

Yes—these are just plain old .sql files.

- Any check you like!
- But keep it quickish.
  It's supposed to be a quick test!
- **Pass: return 0 rows**
- **Fail**: return something "small"
  (of your own design)



`dbt test` in DataOps/CI Testing

Continuous Integration (CI): the practice of merging all developers' working copies to a shared mainline several times a day [wikipedia]

Make sure every code checkin forces **`dbt test`** to run! Example workflows:

- Force a test at client prior to github commit with commit hooks [link]
- Or, pay for dbt labs CI integration of dbt with github
- Or, you can use a github-integrated CI tool like Travis/Jenkins

In all cases, you need to ensure database connectivity.

`dbt test` in DataOps/CI Testing

Continuous Integration (CI): the practice of merging all developers' working copies to a shared mainline several times a day [wikipedia]

Make sure every code checkin forces `dbt test` to run! Example workflows:

- Force a test at client prior to github commit with commit hooks [link]
- Or, pay for dbt labs CI integration of dbt with github
- Or, you can use a github-integrated CI tool like Travis/Jenkins

In all cases, you need to ensure database connectivity.

Standard CI/CD (continuous development) has code go through 2 or 3 different deployments.

- **Dev** (Development) → **Test** (or CI) → **Prod** (Production)

In a **data warehouse**, typically done with different schemas or databases for each stage.

- Specified via outputs and target in the `~/.dbt/profiles.yml` file.
- Queries then source and generate outputs in the appropriate schema/database
- Need to keep track of which version of the code (git tag) is associated with each deployment.

Two Slides on Spark/Algebra

Lecture 23, Data 101/Info 258 Spring 2024

Automating Data Operations

dbt Overview

dbt Models

dbt Tests

Spark as a Workflow System

Pub-Sub and MQs

Workflow Systems

3. How do we automate the work?

Data pipelines are automated with more kinds of systems! 🙃

Workflow Systems: manage processes (human or software)

- With process dependencies (order of activity)
- Activiti, Airflow, BPL, Luigi, …

Dataflow Systems: manage data movement through operations (software)

- Handle data dependencies (inputs/outputs)
- Spark
- dbt + SQL
- Flink, Dataflow, etc.

Messaging/Queueing/Eventing: hand off data reliably from one system to another

- Kafka, RabbitMQ, AWS SQS, MSMQ, MQSeries, …

Practically: Many times you will use combinations of these, and it can be a matter of taste/experience which to use where.

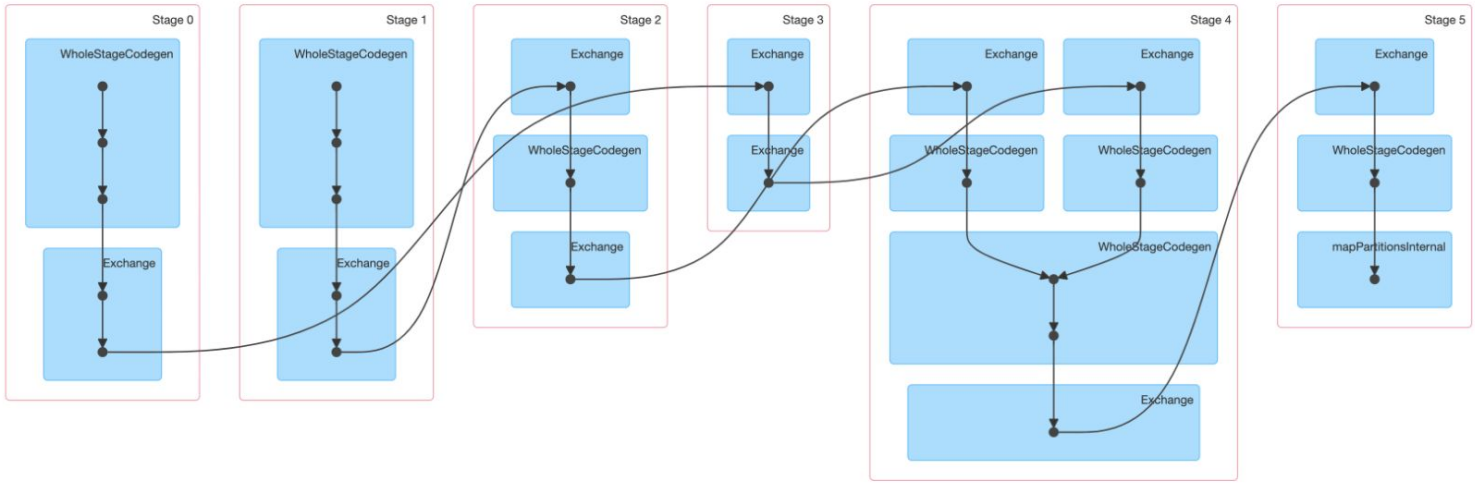
- You'll learn it "on the street…"
- Or, you'll subscribe to company "religion" and be part of many debates

Dataflow: Spark, Google Dataflow, etc.

Like Pandas, lets you define dataflows functionally.

Scala

```scala
val ds1 = spark.range(1, 10000000)
val ds2 = spark.range(1, 10000000, 2)
val ds3 = ds1.repartition(7)
val ds4 = ds2.repartition(9)
val ds5 = ds3.selectExpr("id * 5 as id")
val joined = ds5.join(ds4, "id")
val sum = joined.selectExpr("sum(id)")
sum.show()
```



Spark “RDDs” are akin to Database Views.

- A record of the code needed to compute results from data on demand
- But in a dataflow format akin to a query plan in a database
  - I.e., `EXPLAIN` in Postgres

Cloud
DataFlow

Why choose imperative/algebraic forms over SQL? Or why not?

These is an **incremental** process to writing code in algebraic forms (Rel Alg, Spark, Pandas).

- Build up your complex transformation pipelines one step at a time.
- Good for exploratory thinking, debugging, incremental complexity.

By contrast, SQL wants us to "**declare**" our outputs.

- Stepwise reasoning is harder, though CTEs/WITH and views do help.
- But syntax is unwieldy and CTEs are inconvenient to debug.

However, we'll claim that these distinctions are **form, not function**.

- SQL can do about anything that algebras can do!
- Standard, clean semantics, portable—even compared with modern Spark
- Also: Transactional support, lots of SQL tools, etc.

dbt is a tool to build in SQL "ergonomics" for writing complex Transformation scripts.

Three Slides on Pub-Sub and Message Queues

Lecture 23, Data 101/Info 258 Spring 2024

Automating Data Operations

dbt Overview

dbt Models

dbt Tests

Spark as a Workflow System

Pub-Sub and MQs

Workflow Systems

3. How do we automate the work?

Data pipelines are automated with more kinds of systems! 🙃

Workflow Systems: manage processes (human or software)

- With process dependencies (order of activity)
- Activiti, Airflow, BPL, Luigi, …

Dataflow Systems: manage data movement through operations (software)

- Handle data dependencies (inputs/outputs)
- Spark
- dbt + SQL
- Flink, Dataflow, etc.

These systems address Q1: How data arrives.

Messaging/Queueing/Eventing: hand off data reliably from one system to another

- Kafka, RabbitMQ, AWS SQS, MSMQ, MQSeries, …

Practically: Many times you will use combinations of these, and it can be a matter of taste/experience which to use where.

- You'll learn it "on the street…"
- Or, you'll subscribe to company "religion" and be part of many debates

(1/3) Pub-Sub (publish-subscribe) and Message Queue Software Systems

Software solutions to the data handoff b/t **producer** and **consumer processes** in a pipeline.

e.g., **transactional database** behind a website

- Needs to quickly handle customer/user access

e.g., **data warehouse** for monthly analytics

- Needs high-capacity and durable storage

e.g., **employee "beeper" system** for emergencies

- Needs low latency for QA alerts

(2/3) Pub-Sub (publish-subscribe) and Message Queue Software Systems

Software solutions to the data handoff b/t **producer** and **consumer processes** in a pipeline.

- **Asynchronous management** (analogy: checking mail in a mailbox)
  - A data storage problem: asynchrony requires persistent storage to buffer unprocessed msgs
    - **Producer**: needs persistent storage; **Consumer**: needs ability to check at any time
- **Reliability**
  - **Producer**: make sure that message has been queued **durably**
  - **Consumer**: receive every message, and handle it to completion **atomically**

These requirements translates into an ideal: **exactly-once delivery**.

- Atomic enqueue, Atomic dequeue-and-process
- Queue ACK: durable receipt from producer
- Client ACK: commit of message-handling transaction

} see: distributed transactions (not covered)

Realistically, in many cases: **at least-once delivery**

- Consumer (client) takes responsibility to ensure **idempotent** message handling (i.e., that doing something multiple times is the same as doing it once)

(2/3) Pub-Sub (publish-subscribe) and Message Queue Software Systems

Publish-Subscribe (aka message bus)

- Apache **Kafka** (originally dev'ed @LinkedIn), now owned/managed by Confluent
- even earlier: TIBCO, 1997 (The Information Bus Company)

- Consumers declare persistent **subscriptions** to topics like "Updates-to-table-X"
- SW handles A **stream of messages**, each labeled with ≥1 topics, which are published to subscribers

- Kafka: stores a **durable log** of a window of past events
- Optimized for **high-throughput data volumes**, e.g., web server data

Persistent Message Queue

- RabbitMQ

- Register "**routes**" for forwarding messages to consumers
- **Stream** of messages to be routed
- Consumers acknowledge handoff
- "Exactly once" delivery

- **No big log** – each message deleted
- Optimized for **low-latency** (speed per message)

Two Slides on Workflow Systems

Lecture 23, Data 101/Info 258 Spring 2024

Automating Data Operations

dbt Overview

dbt Models

dbt Tests

Spark as a Workflow System

Pub-Sub and MQs

Workflow Systems

3. How do we automate the work?

Data pipelines are automated with more kinds of systems! 🙃

Workflow Systems: manage processes (human or software)

- With process dependencies (order of activity)
- Activiti, Airflow, BPL, Luigi, …

Dataflow Systems: manage data movement through operations (software)

- Handle data dependencies (inputs/outputs)
- Spark
- dbt + SQL
- Flink, Dataflow, etc.

Messaging/Queueing/Eventing: hand off data reliably from one system to another

- Kafka, RabbitMQ, AWS SQS, MSMQ, MQSeries, …

Practically: Many times you will use combinations of these, and it can be a matter of taste/experience which to use where.

- You'll learn it "on the street…"
- Or, you'll subscribe to company "religion" and be part of many debates

(1/2) Workflow Systems

Workflow systems orchestrate a bunch of separate processes or API calls, including but not limited to:

- Control order of invocation
- Programming constructs like conditionals (IF) and loops over system
- Handle (potentially long) asynchrony in request/response
- Allow for steps that involve humans!
- Run reliably over long periods of time, despite failures of components or the workflow machines
  - Often storing the state of the workflow in a SQL DBMS
  - Sometimes guaranteeing transition between steps transactionally
- Provide features to schedule and monitor progress

(1/2) Workflow System: Apache Airflow

A **DAG (directed acyclic graph)** of (ideally idempotent) **tasks** passing small amounts of data.

- DAGs are constructed programmatically in Python
  - Simple syntax for defining tasks and setting up “edges” between them
  - DAG “shape” can be dynamic at runtime
  - Exception logic to fail, skip, reschedule a task

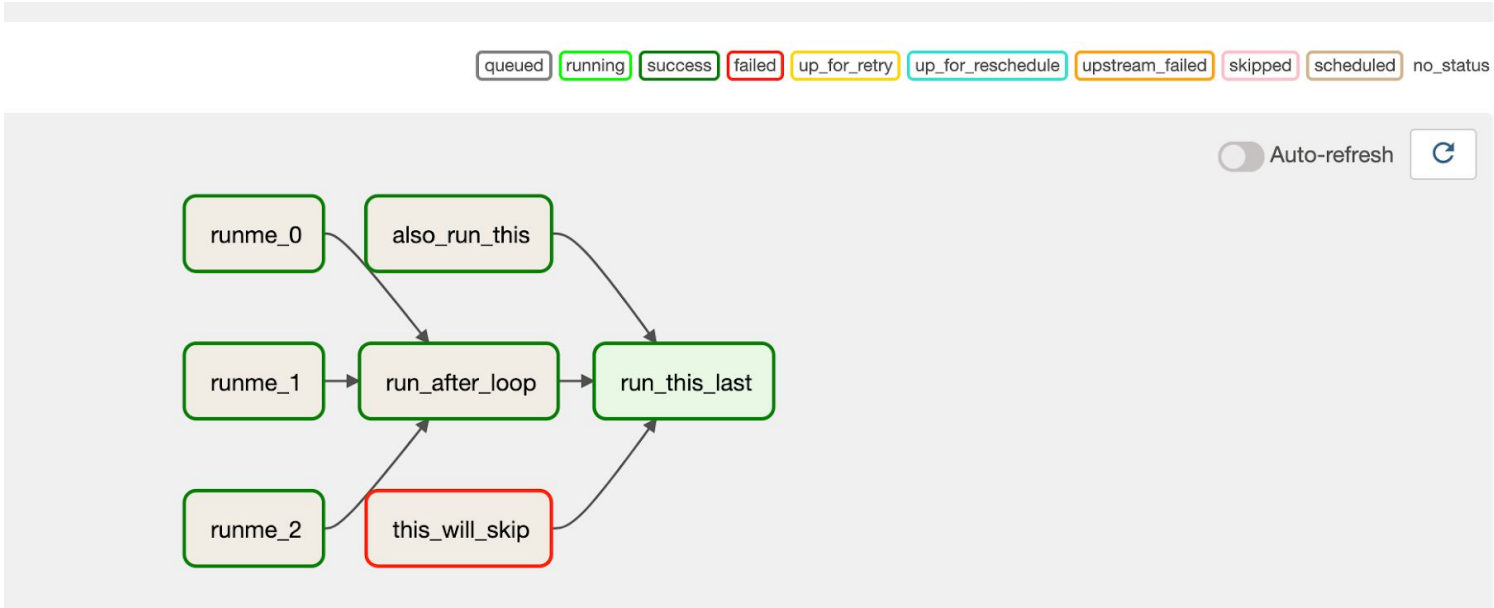
Tasks (Nodes) in the DAG are user-defined.

- Python code, bash calls,
- emails, Slack msgs, API calls, etc.

Scales up via use of message queues

Schedules and tracks Runs

- “Sensors” to check for time passing or data arriving in filesystem or database



[Extra] dbt Essentials

Lecture 23, Data 101/Info 258 Spring 2024

[Extra] dbt essentials

We don’t have an associated project this semester on dbt, so these slides are here for your reference in case you do want to build your own dbt project.

These slides cover essential components of dbt that are needed for a functional project.

dbt_project.yml

- Lines 5-7 configure handy metadata
- Line 10 specifies the connection in `~/.dbt/profiles.yml`
- Lines 12-25 are boilerplate for the standard directory hierarchy generated by `dbt init`
- Lines 34-39 provide defaults for our models
  - contained in a database named “baseball”
  - by default, model results are views, and not materialized

dbt_project.yml

```
1
2   # Name your project! Project names should contain only lowercase characters
3   # and underscores. A good package name should reflect your organization's
4   # name or the intended use of these models
5   name: 'baseball'
6   version: '1.0.0'
7   config-version: 2
8
9   # This setting configures which "profile" dbt uses for this project.
10  profile: 'baseball'
11
12  # These configurations specify where dbt should look for different types of files.
13  # The `source-paths` config, for example, states that models in this project can be
14  # found in the "models/" directory. You probably won't need to change these!
15  source-paths: ["models"]
16  analysis-paths: ["analysis"]
17  test-paths: ["tests"]
18  data-paths: ["data"]
19  macro-paths: ["macros"]
20  snapshot-paths: ["snapshots"]
21
22  target-path: "target"  # directory which will store compiled SQL files
23  clean-targets:         # directories to be removed by `dbt clean`
24      - "target"
25      - "dbt_modules"
26
27
28  # Configuring models
29  # Full documentation: https://docs.getdbt.com/docs/configuring-models
30
31  # In this config, we tell dbt to build all models in the baseball/ directory
32  # as views. These settings can be overridden in the individual model files
33  # using the `{{ config(...) }}` macro.
34  models:
35    baseball:
36      +database: baseball
37      # Applies to all files under models/dataeng/
38      dataeng:
39          materialized: view
40
```

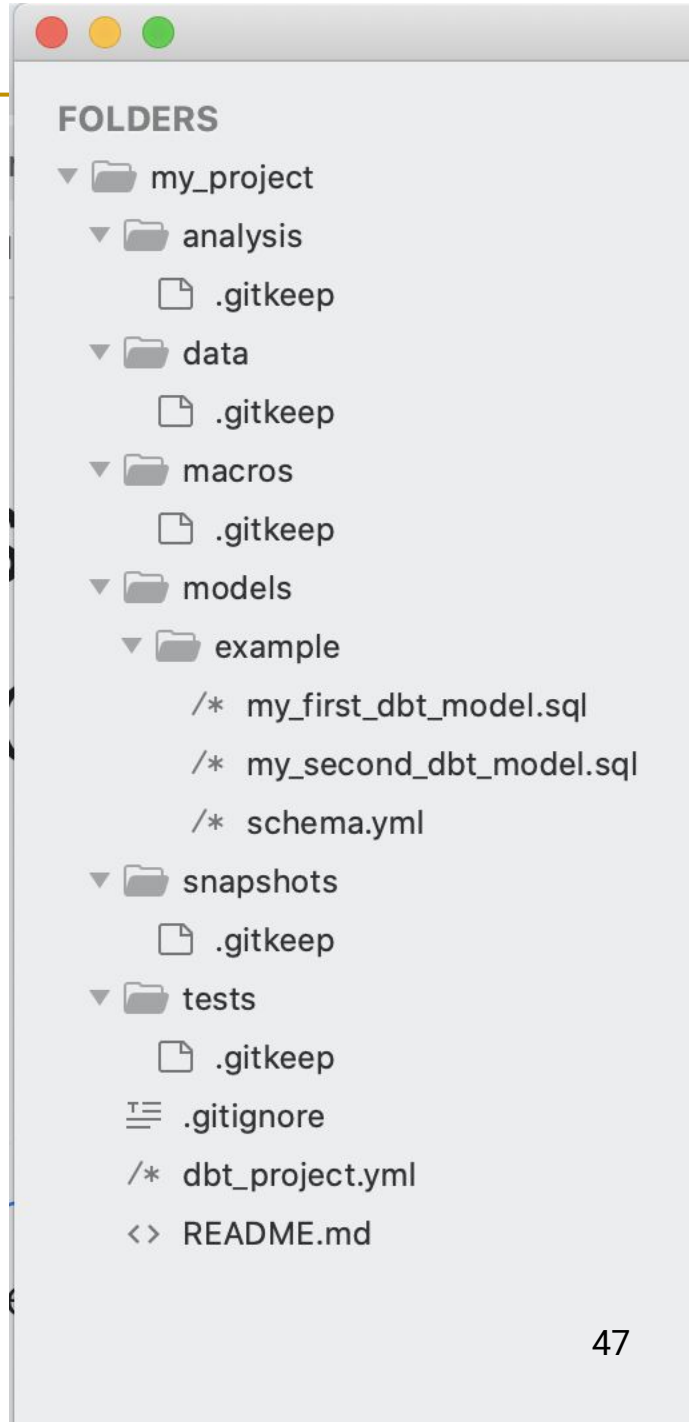
A Basic dbt Repo 3/4

Data: Csv's for "seed data" (e.g. static lookup tables)

Analysis: Extra SQL queries you don't need to run

Macros: String-based macros in the Jinja language

Snapshots: SQL queries to materialize historical data as it's being updated



A Basic dbt Repo 4/4

Also `~/.dbt/profiles.yml`

- DB connectivity information
- Per dbt “profile”
  - Matches your `dbt_project.yml`

profiles.yml

```yaml
default:
  outputs:
    dev:
      type: postgres
      host: localhost
      user: jmh
      password: jmh
      port: 5432
      dbname: dbttest_dev
      schema: jmh
      threads: 1
      keepalives_idle: 0 # default 0, indicating the system default
      # search_path: [optional, override the default postgres search_path]
      # role: [optional, set the role dbt assumes when executing queries]
      # sslmode: [optional, set the sslmode used to connect to the database]

    prod:
      type: postgres
      host: localhost
      user: jmh
      password: jmh
      port: 5432
      dbname: dbttest_prod
      schema: jmh
      threads: 1
      keepalives_idle: 0 # default 0, indicating the system default
      # search_path: [optional, override the default postgres search_path]
      # role: [optional, set the role dbt assumes when executing queries]
      # sslmode: [optional, set the sslmode used to connect to the database]

  target: dev

baseball: # this needs to match the profile: in your dbt_project.yml file
  target: dev
  outputs:
    dev:
      type: postgres
      host: localhost
      user: jmh
      password: jmh
      port: 5432
      dbname: baseball
      schema: jmh
      threads: 1
      keepalives_idle: 0 # default 0, indicating the system default
      # search_path: [optional, override the default postgres search_path]
      # role: [optional, set the role dbt assumes when executing queries]
      # sslmode: [optional, set the sslmode used to connect to the database]
```

Lineage DAG in dbt docs

```
dbt docs generate
dbt docs serve
```

Note that there's no notion of "tasks" here, just **data lineage** (data "dependencies")

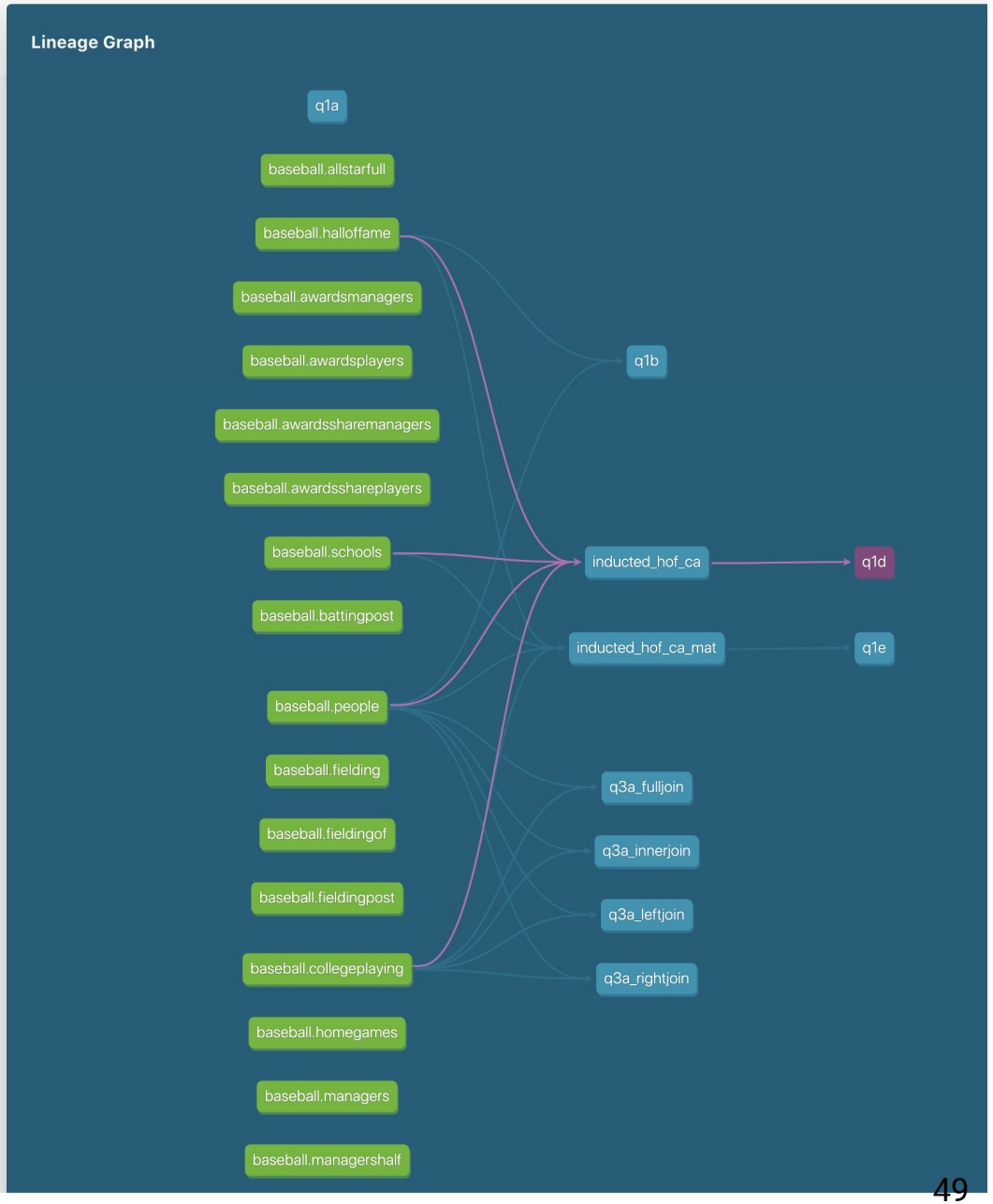
- We `dbt run` the whole DAG

All non-incremental models are rebuilt from scratch each time

Incremental models capture the notion of "change propagation"

- Though fairly primitive in dbt
- There are custom products that are better at "Change Data Capture" and materialized view maintenance

Other nice stuff in dbt docs, poke around!



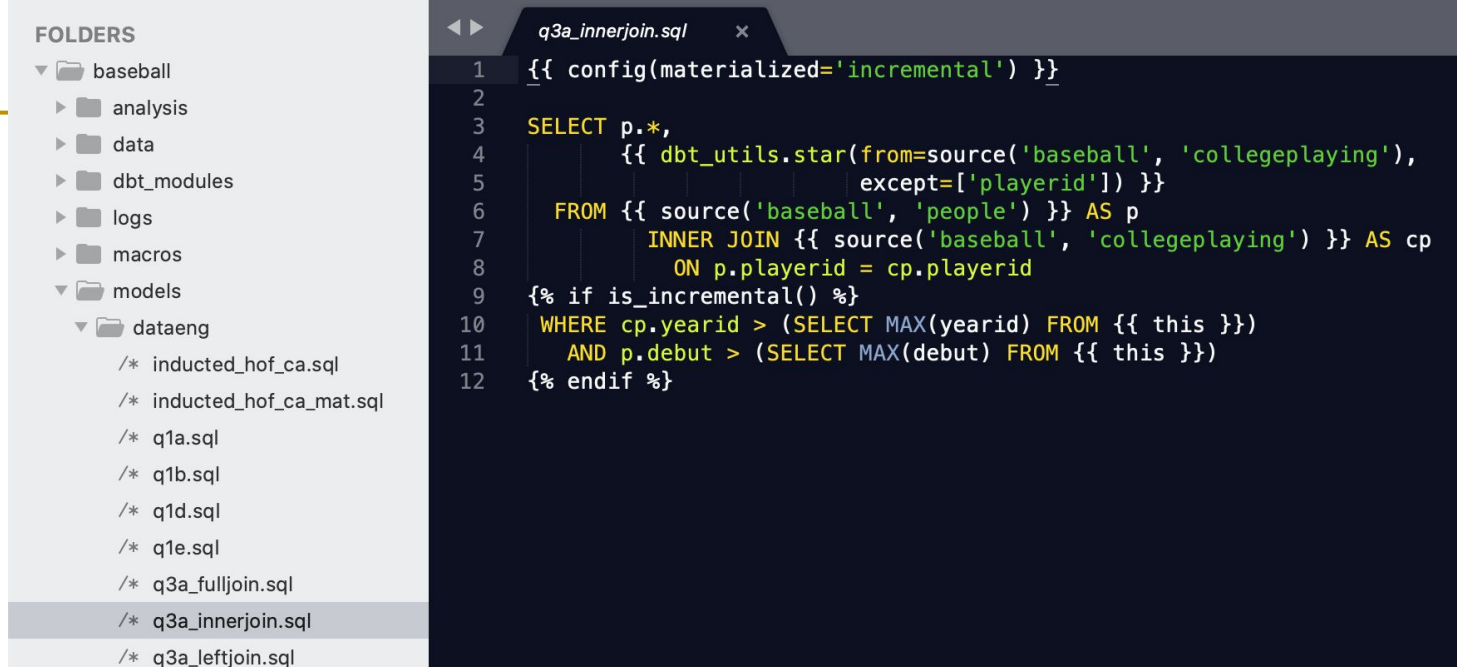
Jinja Macros

Recall that SQL only lets you query rows

- SELECT and FROM lists are “hard-wired”, not dynamic

Jinja can help

- Essentially, parameterized queries via string macros

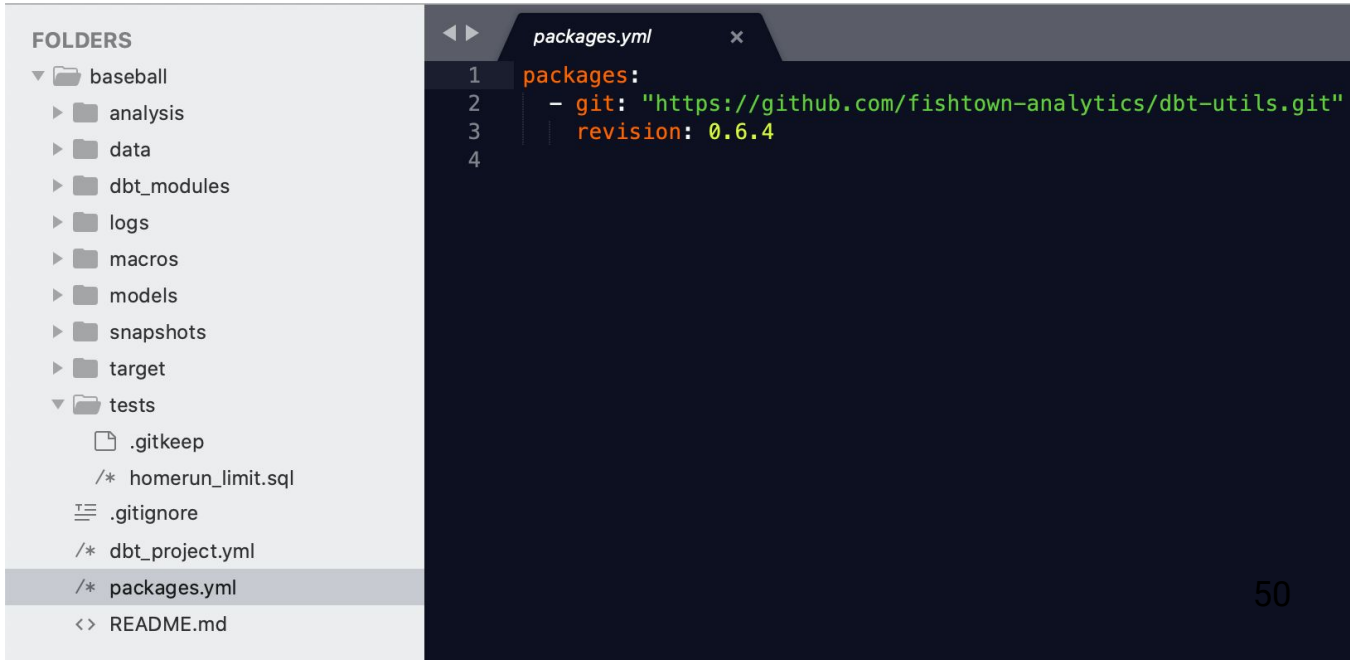


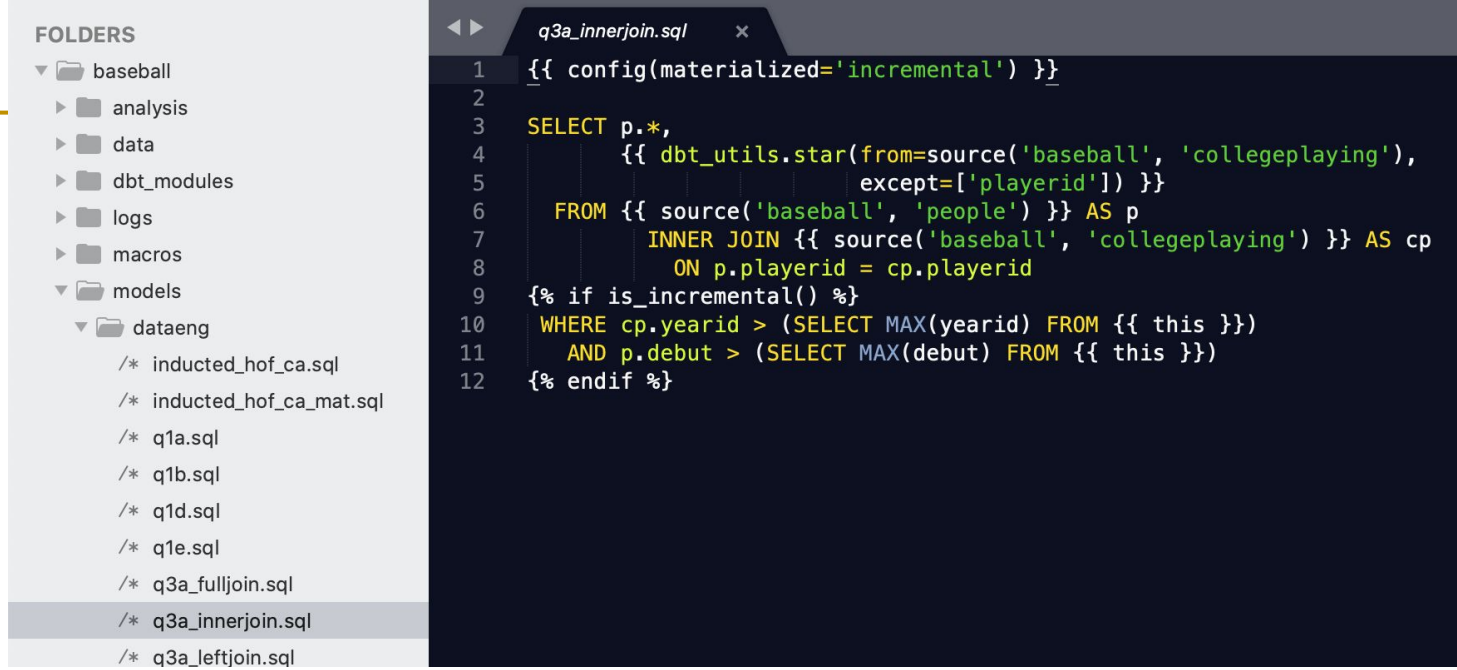
A blunt instrument

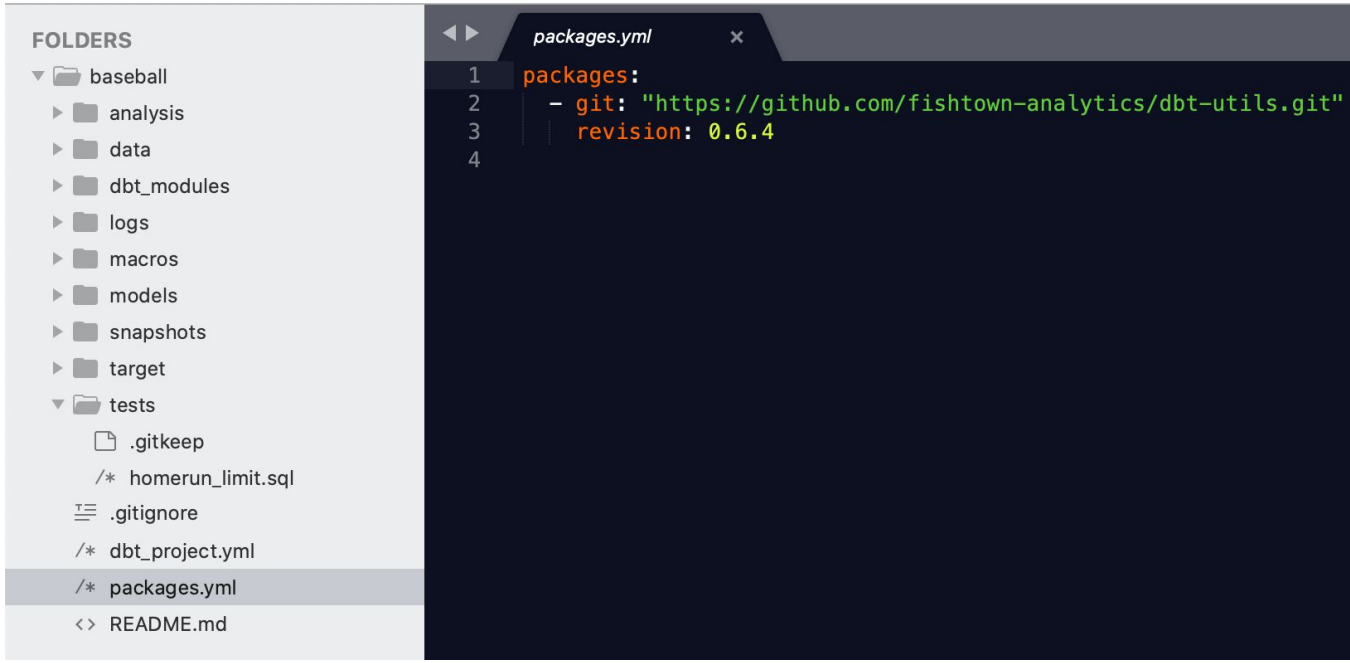
- Easy to write queries that don’t work or are undesirable
- Keep it simple

Can pull in libraries like dbt_utils from git

- packages.yml at top level
- E.g. star command in the upper right lets you choose which columns you want in the SELECT list more flexibly




FOLDERS
baseball
analysis
data
dbt_modules
logs
macros
models
dataeng
inducted_hof_ca.sql
inducted_hof_ca_mat.sql
q1a.sql
q1b.sql
q1d.sql
q1e.sql
q3a_fulljoin.sql
q3a_innerjoin.sql
q3a_leftjoin.sql
q3a_innerjoin.sql
{{ config(materialized='incremental') }}
SELECT p.*,
{{ dbt_utils.star(from=source('baseball', 'collegeplaying'),
except=['playerid']) }}
FROM {{ source('baseball', 'people') }} AS p
INNER JOIN {{ source('baseball', 'collegeplaying') }} AS cp
ON p.playerid = cp.playerid
{% if is_incremental() %}
WHERE cp.yearid > (SELECT MAX(yearid) FROM {{ this }})
AND p.debut > (SELECT MAX(debut) FROM {{ this }})
{% endif %}


FOLDERS
baseball
analysis
data
dbt_modules
logs
macros
models
snapshots
target
tests
.gitkeep
homerun_limit.sql
.gitignore
dbt_project.yml
packages.yml
README.md
packages.yml
packages:
- git: "https://github.com/fishtown-analytics/dbt-utils.git"
revision: 0.6.4

How to Debug Models & Tests

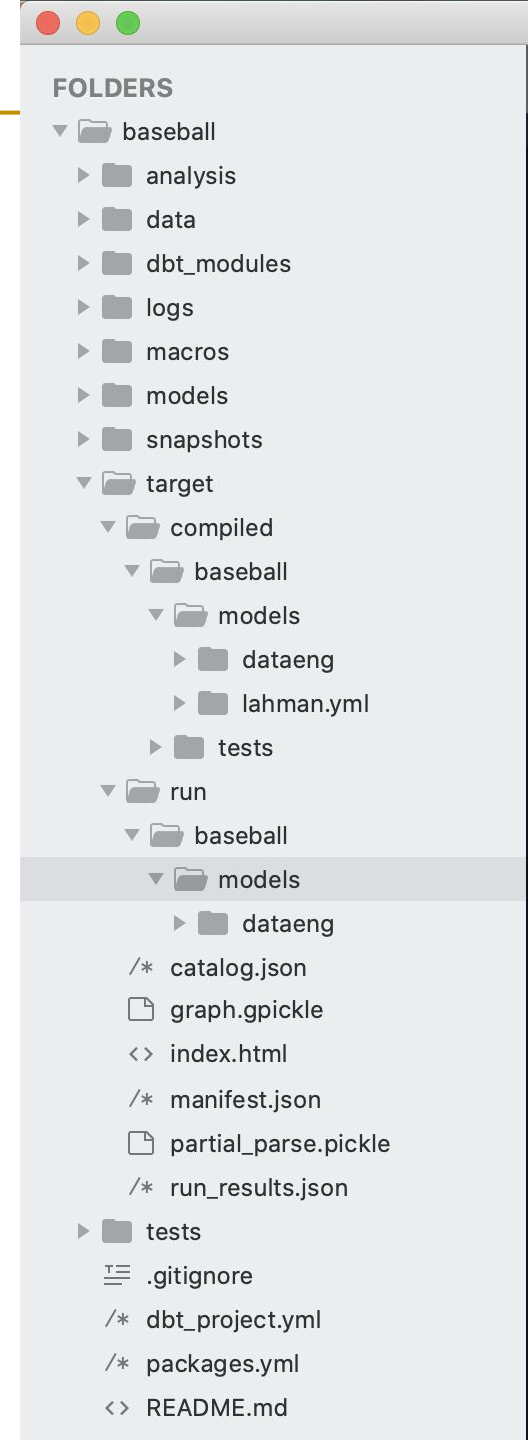
`target/compiled`

- models and tests after Jinja processing complete

`run`

- the DDL that runs to build the models

Can clean this all up with `dbt clean`



[Extra] Transactional Concerns in dbt

By default, **each model execution is a transaction**.

- But the DBMS computes views inside whatever query uses them.
- So materialization **via view** (vs table/incremental) affects transaction boundaries.

Note: Can specify pre-/post-“hooks” on models to run more SQL statements before/after

- And can specify each hook as outside or inside the model’s transaction

[Review] dbt

`dbt` is a declarative specification framework for:

- **pipelines of ELT-style SQL** transformations
- **data quality tests**.

True or False?

homerun_limit.sql

```
SELECT *
  FROM {{ source('baseball', 'batting') }}
 WHERE hr > 70
 LIMIT 10
```

q1a.sql

```
SELECT namefirst, namelast, p.playerid, yearid
  FROM people AS p,
       halloffame AS hof
 WHERE
   AND
```

inducted_hof_ca_mat.sql

```
{{ config(materialized='table') }}

SELECT DISTINCT namefirst, namelast, p.playerid, s.schoolid, hof.yearid
  FROM {{ source('baseball', 'people') }} AS p,
       {{ source('baseball', 'halloffame') }} AS hof,
       {{ source('baseball', 'collegeplaying') }} AS cp,
       {{ source('baseball', 'schools') }} AS s
 WHERE
```

1. The `homerun_limit.sql` test passes if it returns 0 rows.

2. The `q1a.sql` model materializes a table called q1a in the database.

3. The `q1a.sql` model materializes a table called induced_hof_ca_mat.sql in the database.

[Review] dbt

`dbt` is a declarative specification framework for:

- **pipelines of ELT-style SQL** transformations
- **data quality tests**.

True or False?

homerun_limit.sql

```sql
SELECT *
  FROM {{ source('baseball', 'batting') }}
 WHERE hr > 70
 LIMIT 10
```

1. The `homerun_limit.sql` test passes if it returns 0 rows.

True! If test fails, return rows for debugging

q1a.sql

```sql
SELECT namefirst, namelast, p.playerid, yearid
  FROM people AS p,
       halloffame AS hof
 WHERE
   AND
```

2. The `q1a.sql` model materializes a table called q1a in the database.

False! dbt models are views by default. Views computed on every `dbt run`

inducted_hof_ca_mat.sql

```sql
{{ config(materialized='table') }}

SELECT DISTINCT namefirst, namelast, p.playerid, s.schoolid, hof.yearid
  FROM {{ source('baseball', 'people') }} AS p,
       {{ source('baseball', 'halloffame') }} AS hof,
       {{ source('baseball', 'collegeplaying') }} AS cp,
       {{ source('baseball', 'schools') }} AS s
 WHERE
```

3. The `q1a.sql` model materializes a table called induced_hof_ca_mat.sql in the database.

True! use curly braces (Jinja macros) to explicitly materialize tables or reference other tables.