

Building Trino data pipelines with SQL or Python

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Starburst (the Trino company)



trino

Connection before content



Lester Martin – <https://linktr.ee/lestermartin>

- Developer Relations @ Starburst
 - Blogging & forums
 - Webinars & videos
 - User groups & events
 - Training & tutorials
- 30+ years of technology experience
 - Started journey on TRS-80 Model III
 - Played most roles, but a programmer at my core
 - ½ career in OLTP and ½ in data analytics
 - Decade+ of “big data” experience to include
 - Trino/Starburst, Hadoop, Hive, Spark
 - NiFi, Kafka, Storm, Flink
 - HBase, MongoDB

The rise of big data

Querying large volumes of data was difficult and time consuming

Early 2000s: Data generation and collection has skyrocketed due to the rise of the Internet

2006: Apache Hadoop was designed to meet the needs of large datasets on a scale previously unimaginable

2008: Facebook created Apache Hive to query terabytes of data in Hadoop using a SQL-like interface. Data consumers were limited by the number of queries they could run — often fewer than 10/day

The birth of Trino

A new query engine designed to solve the data accessibility problem

2012: Trino (*formerly known as Presto*) is created by Martin Traverso, Dain Sundstrom, David Phillips and Eric Hwang at Facebook

Trino is an open source query engine that:

- *Harnesses the power of distributed computing*
- *Separates compute from storage*
- *Super fast and performant*
- *Supports pluggable connectors to a variety of data sources*
- *ANSI-SQL BASED!!!! Which means... SQL on anything!*



Trino trusted by industry leaders at PB scale



trino

- ✓ Open-source query engine.
- ✓ Separates compute and storage.
- ✓ Queries across all data sources.
- ✓ Iceberg was designed for Trino.

Proven at exabyte scale/high concurrency:



25PB on S3



1 Exabyte of Data
100PB weekly data
1200 nodes
2.5M queries/week



600PB on S3
1000 nodes



10PB daily read data
250K queries per day



300PB data lake

Trino open source users

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Trino open source users

Thriving
open source
community:

11300+
SLACK
MEMBERS

10,000+
GITHUB STARS

750+
CONTRIBUTORS

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Trino open source users

Starburst is the Trino company:

Bringing
Trino to the
enterprise

Cofounded
by Trino
creators

#1 Trino
committer

Largest team of
Trino experts in
the world

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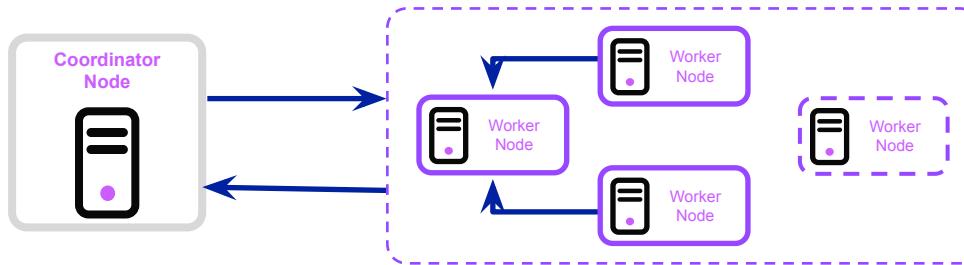
Server stereotypes

Coordinator node

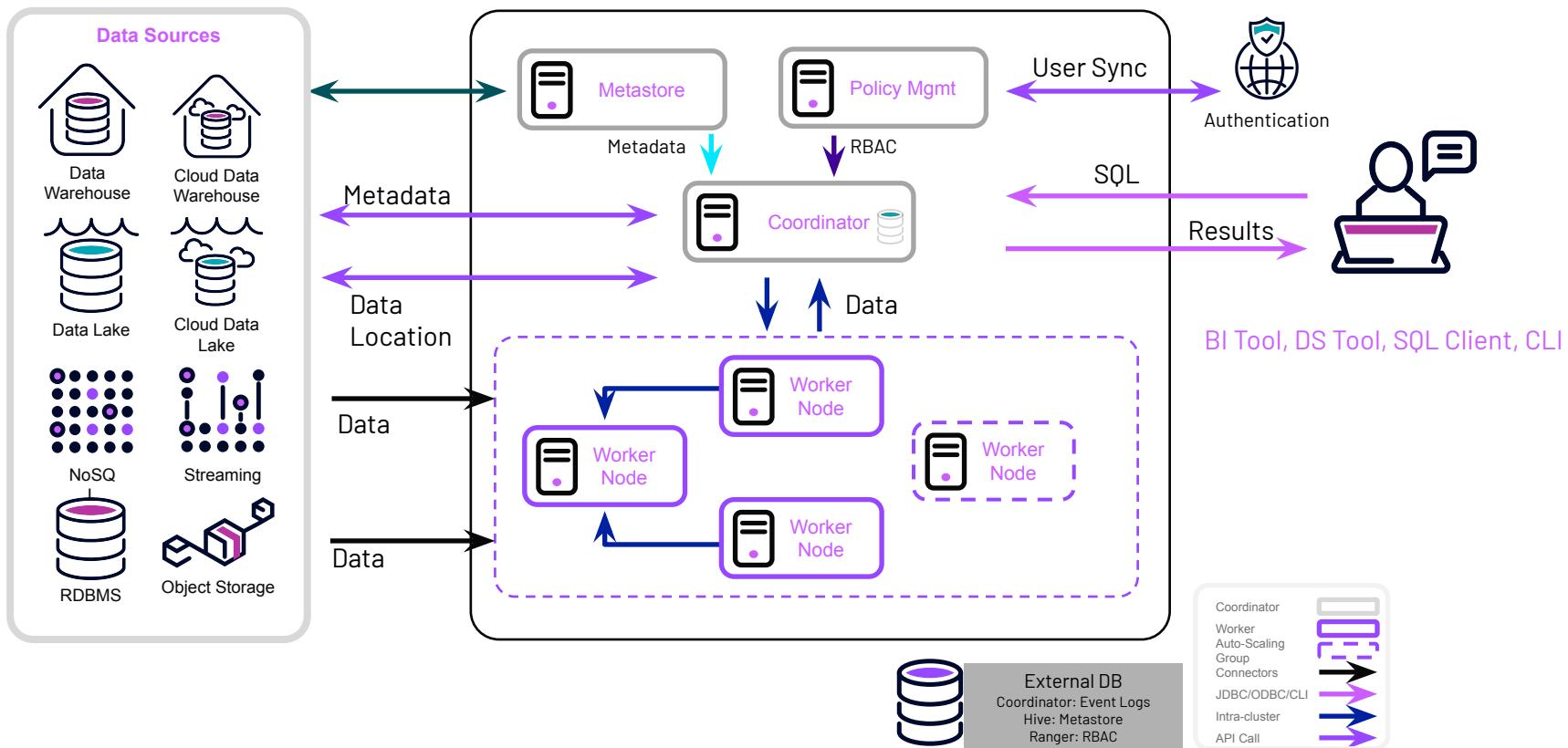
Server that is responsible for parsing statements, planning queries, and managing Trino worker nodes.

Worker nodes

Server which is responsible for executing tasks and processing data. Worker nodes fetch data from connectors and exchange intermediate data with each other.



Logical architecture



Rich ecosystem of data source connectors

Open-source & Starburst Proprietary

Data Source
Connectors

Real-time Analytics



Data Lakes



NoSQL Stores



Applications



Relational DBs



History of Trino - ETL processing

From purely interactive use-cases to multiple workloads

2013: Released into production at Facebook for interactive use cases

2014: Users start scheduling batch/ETL queries with Trino instead of Hive

2018: 50% of existing ETL workloads and 85% of new workloads on Trino

Why?

- *Trino can communicate with disparate data sources to federate data*
- *Trino is a distributed, massively parallel processing system*
- *Faster, Cheaper and ANSI-SQL BASED!*

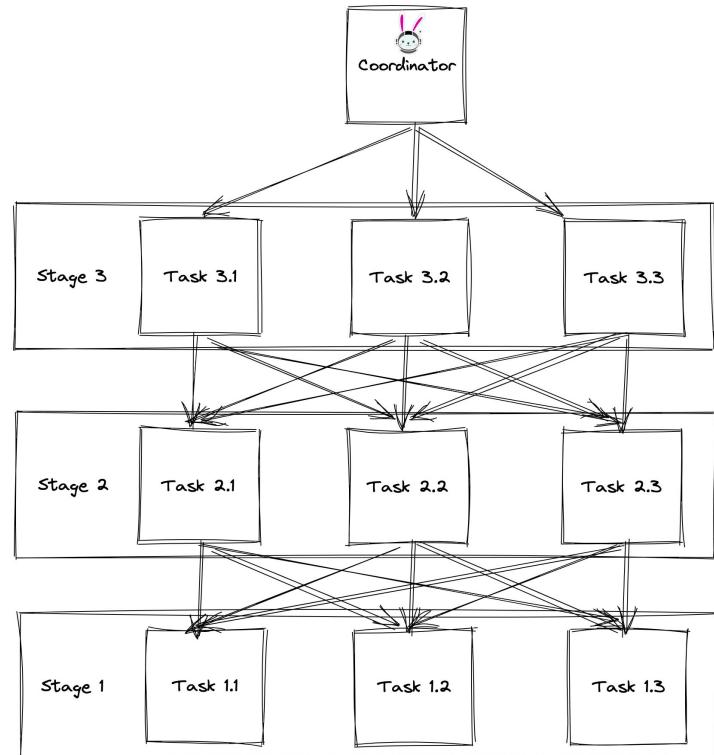
Soon others caught on, and teams like [Salesforce](#) and [Lyft](#) started utilizing Trino for Batch/ETL capabilities.

ETL concerns with the original architecture

The design goals for interactive querying performance did not provide sufficient support for long-running and memory-intensive queries:

- **Long running queries unreliable:** the all-or-nothing architecture makes it really hard to tolerate faults
- **Distributed memory limit:** with streaming shuffle, aggregations and joins have to process all at once

Also, with original architecture, it's really hard to apply classic techniques like adaptive query execution, speculative execution and skew handling, etc.

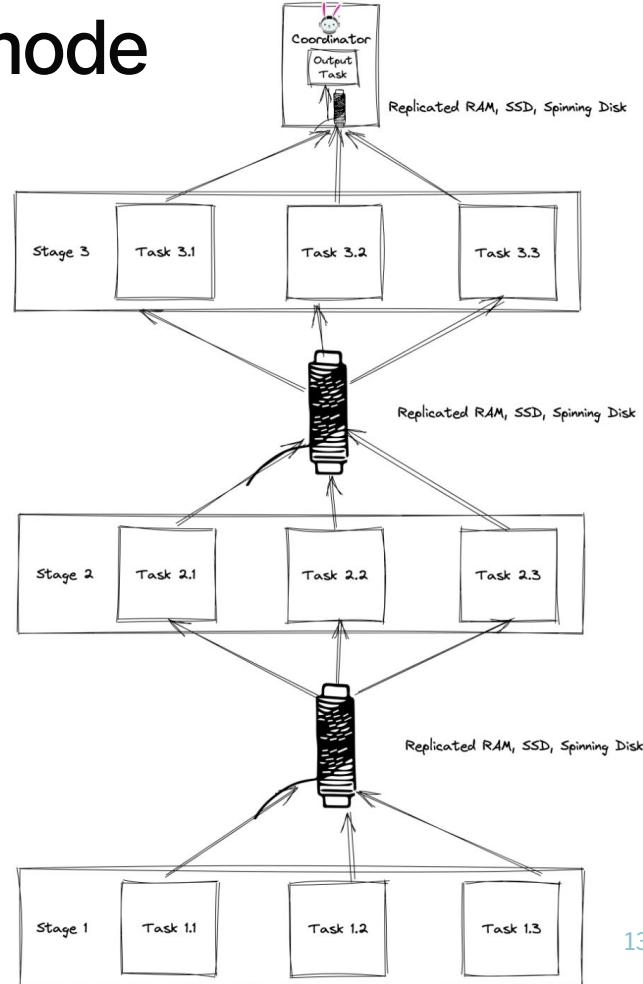


Enter fault-tolerant execution mode

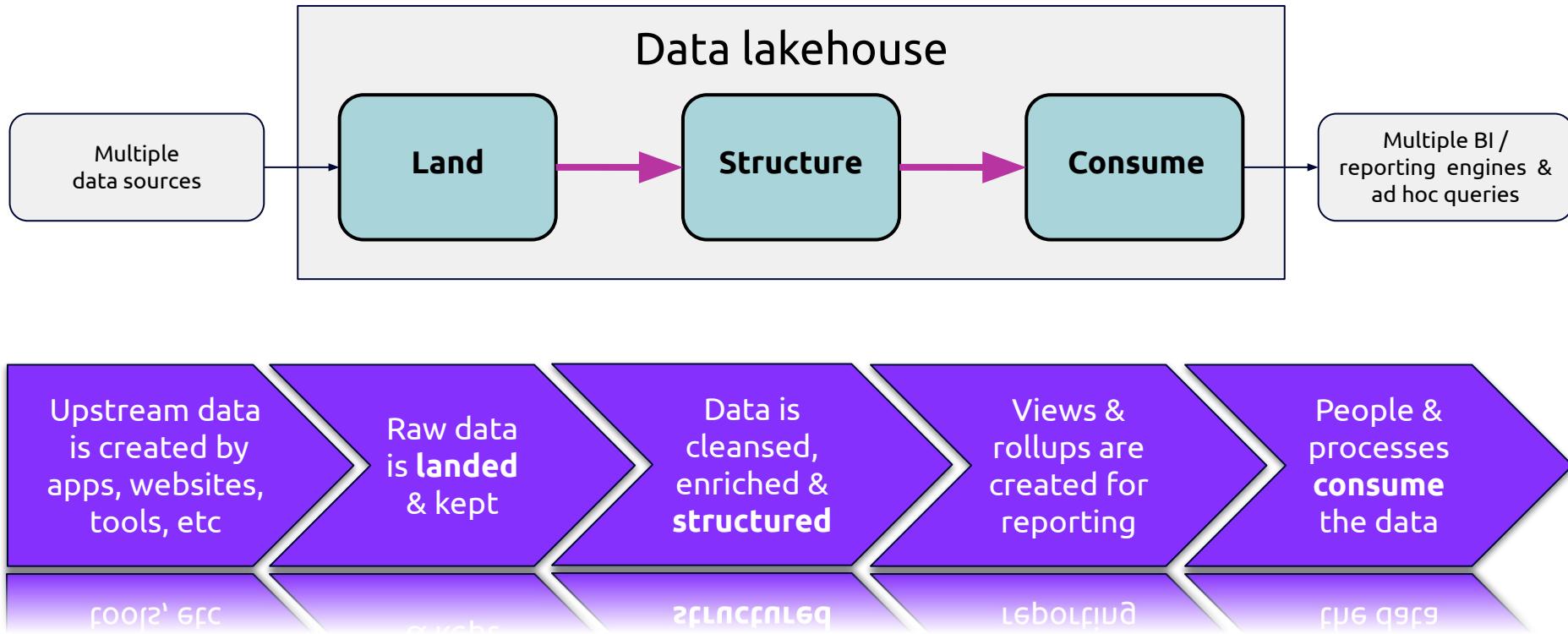
Introduced external exchanges:

- **Independent tasks**
- **Task retries**
- **Resource-aware scheduling**

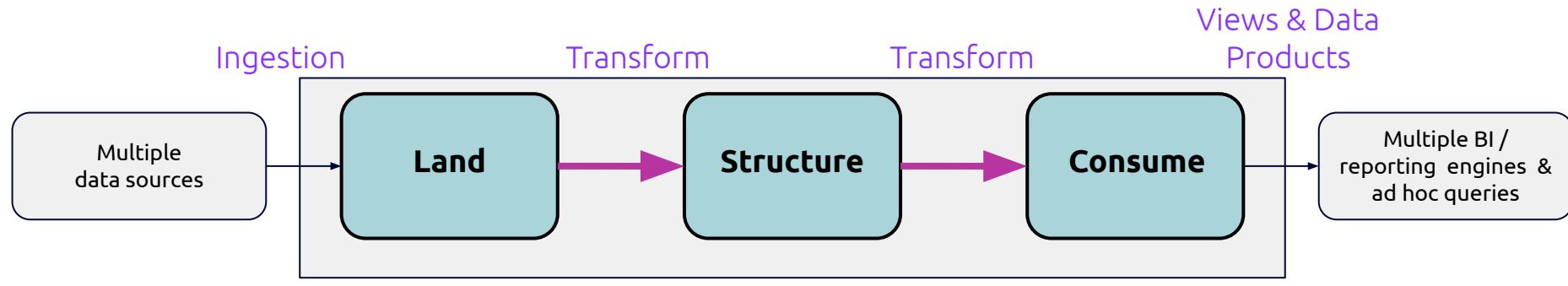
Stage by stage execution



Activities across the medallion architecture



Data pipelines across the medallion architecture



Data pipeline

Extract

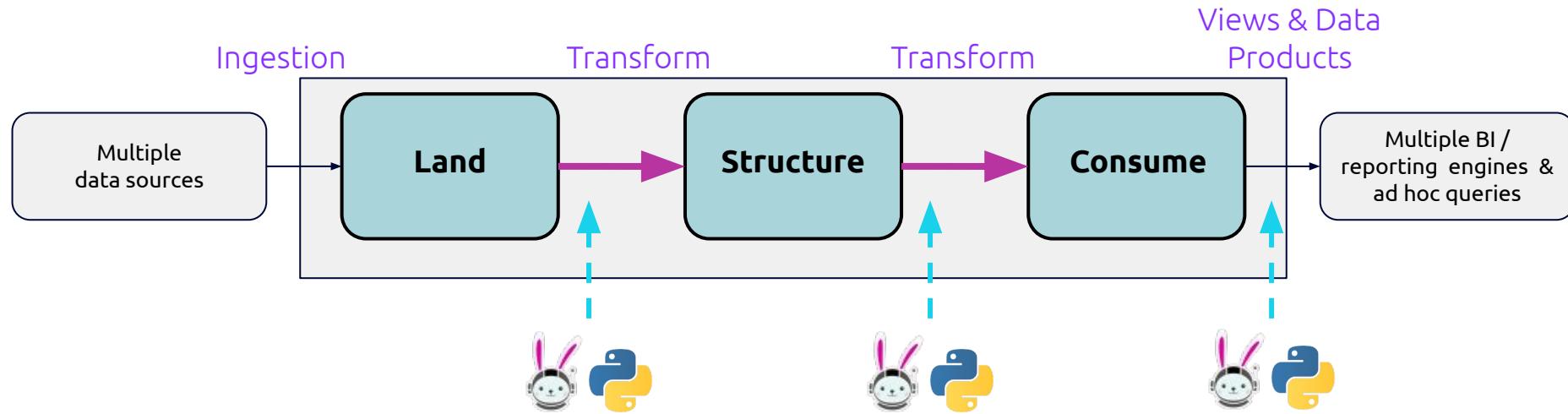
Load

Transform

Transform

Transform

Data pipelines with SQL and/or Python



SQL for transformation processing

```
SELECT
CASE
    WHEN product_id IN (1, 2, 3, 4) THEN 'product_one'
    ELSE 'product_two'
END as product,
SUM(order_amount) as sales
FROM
tmp_sales
GROUP BY
CASE
    WHEN product_id IN (1, 2, 3, 4) THEN 'product_one'
    ELSE 'product_two'
END
```

Pros

- Compact
- Easy to understand for simple logic

Cons

- No real time debugging
- Can't perform other actions on results
- No unit tests
- Version Diffs likely hard to read

Complexity makes SQL even more difficult

```
SELECT
    order_month,
    order_day,
    COUNT(DISTINCT order_id) AS num_orders,
    COUNT(book_id) AS num_books,
    SUM(price) AS total_price,
    SUM(COUNT(book_id)) OVER (
        PARTITION BY
        | order_month
        ORDER BY
        | order_day
    ) AS running_total_num_books
FROM
(
    SELECT
        DATE_FORMAT(co.order_date, '%Y-%m') AS order_month,
        DATE_FORMAT(co.order_date, '%Y-%m-%d') AS order_day,
        co.order_id,
        ol.book_id,
        ol.price
    FROM
        cust_order co
        INNER JOIN order_line ol ON co.order_id = ol.order_id
) sub
GROUP BY
    order_month,
    order_day
ORDER BY
    order_day ASC;
```

As complexity grows

- Schema changes are hard to debug
- Logic errors are difficult to find
- Collaboration and sharing is more difficult

Python Dataframes

PySpark Example

```
1  from pyspark.sql import DataFrame, SparkSession
2  import spark.sql.functions as F
3
4  def read_sales_data(uri: str = 's3a://sales-data/customer-orders/
2021/*') -> DataFrame:
5      df = spark.read.parquet(uri)
6      return df
7
8  def define_product(input_df: DataFrame) -> DataFrame:
9      output_df = input_df.withColumn('product',
10          F.when(
11              F.col('product_id').
12                  isin([1,2,3,4]), F.lit
13                  ('product_one')).otherwise(F.lit
14                  ('product_two'))
15
16      return output_df
17
18  def agg_sales_by_product(input_df: DataFrame, gb: str = 'product',
19      ag: str = 'order_amount') -> DataFrame:
20      output_df = input_df.groupBy(gb).agg(F.sum(F.col(ag)).alias
21          ('sales'))
22      return output_df
23
24
25  df = read_sales_data()
26  products = define_product(df)
27  metrics = agg_sales_by_product(products)
```

A Dataframe is a Python data structure that represents a Table that can be operated on

Pros

- Reusable functions
- Version diffs are easy to read
- Easily create unit tests
- Could combine Python libraries like Numpy, Scipy
- Perform real-time debugging
- Easy to follow complex logic
- Allows for logging

Cons

- A bit verbose

Behind the scenes (1)

SQL Query Human

Query text

```
1   SELECT
2     c.first_name,
3     c.last_name,
4     c.estimated_income,
5     a.products,
6     a.cc_number,
7     a.mortgage_id,
8     cp.customer_segment,
9     pp.cc_type
10  FROM
11    glue.burst_bank.customer c
12    JOIN mysql.burst_bank.account a ON c.custkey = a.custkey
13    JOIN mysql.burst_bank.product_profile pp ON a.custkey = pp.custkey
14    JOIN postgresql.burst_bank.customer_profile cp ON c.custkey = cp.custkey
15 WHERE
16   cp.customer_segment = 'diamond'
17   AND c.estimated_income > 200000
18   AND pp.cc_type = 'basic'
19 LIMIT 10
```

Query text

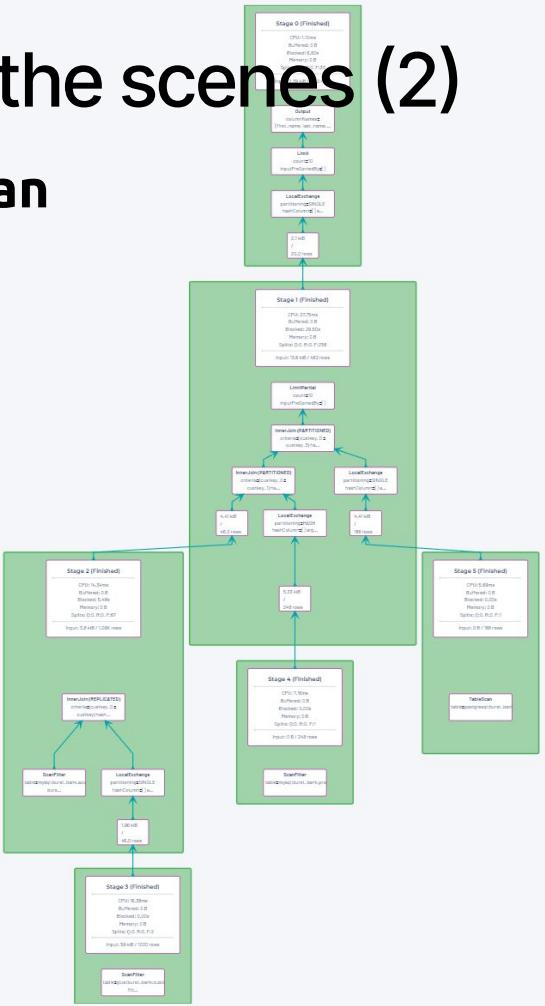
Query te

```
    )
)
INNER JOIN (
    SELECT
        "custkey" ~ "r_mkez_custkey"
        , "products" ~ "products"
        , "cc_number" ~ "cc_number"
        , "mortgage_id" ~ "mortgage_id"
    FROM
    (
        SELECT
            "custkey"
            , "products"
            , "cc_number"
            , "mortgage_id"
        FROM
        (
            SELECT *
            FROM
                mysql.burst_bank.account
        )
    )
)
) ON ("r_mkez_custkey" = "1_jnri_custkey"))
)
)
INNER JOIN (
    SELECT
        "custkey" ~ "custkey"
        , "cc_type" ~ "cc_type"
    FROM
    (
        SELECT
            "custkey"
            , "cc_type"
        FROM
        (
            SELECT *
            FROM
                mysql.burst_bank.product_profile
        )
    )
)
) ON ("custkey" = "1_jnri_custkey"))
)
)
INNER JOIN (
    SELECT
        "custkey" ~ "r_wza9_custkey"
        , "customer_segment" ~ "customer_segment"
    FROM
    (
        SELECT
            "custkey"
            , "customer_segment"
        FROM
        (
            SELECT *
            FROM
                postgresql.burst_bank.customer_profile
        )
    )
)
) ON ("r_wza9_custkey" = "1_jnri_custkey"))
)
)
WHERE ("customer_segment" = 'diamond')
)
)
WHERE ("estimated_income" > CAST(200000 AS BIGINT))
)
)
WHERE ("cc_type" = 'basic')
)
)
OFFSET 0 ROWS
LIMIT 10
```

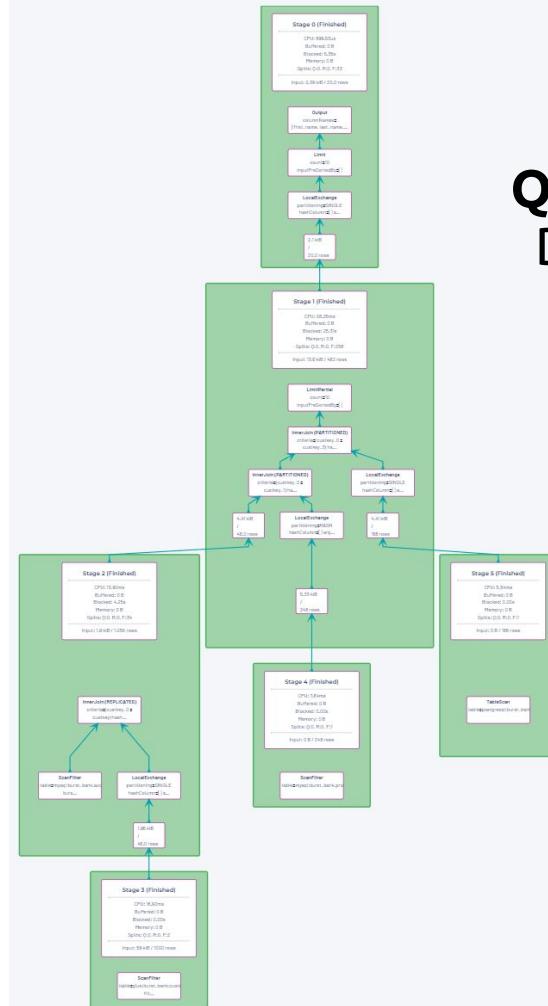


Behind the scenes (2)

Query Plan Human



Query Plan Dataframe



Dataframe API options with Trino

PyStarburst



PyStarburst

Ibis



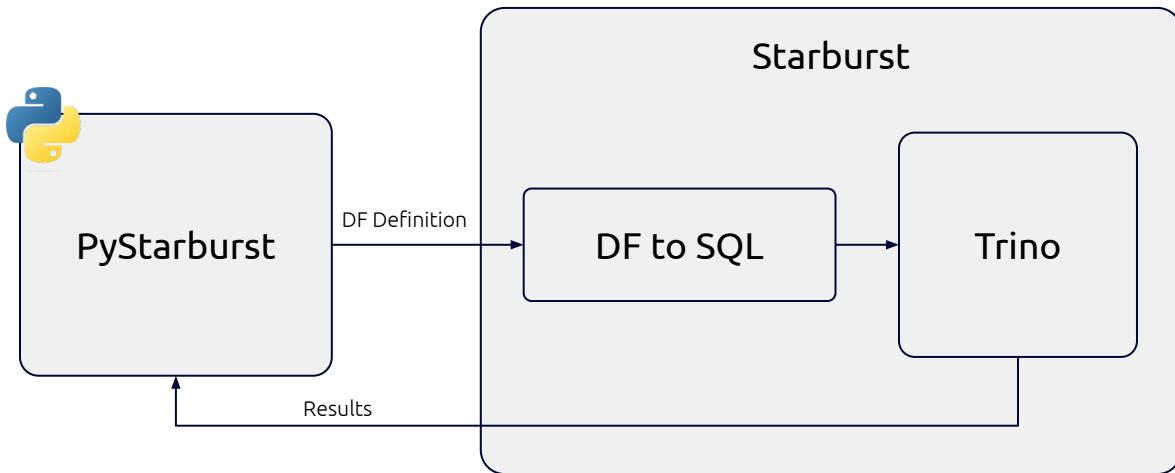
PyStarburst overview

```
df_missions = df_missions.with_column("date", f.sql_expr("COALESCE(TRY(date_parse(\"date\"), '%a %b %d, %Y %H:%i UTC')), NULL)"))

print(df_missions.schema)

df_missions = df_missions\
    .filter(col("date") > datetime(2000, 1, 1))\
    .sort(col("date"), ascending=True)

df_missions.show()
```



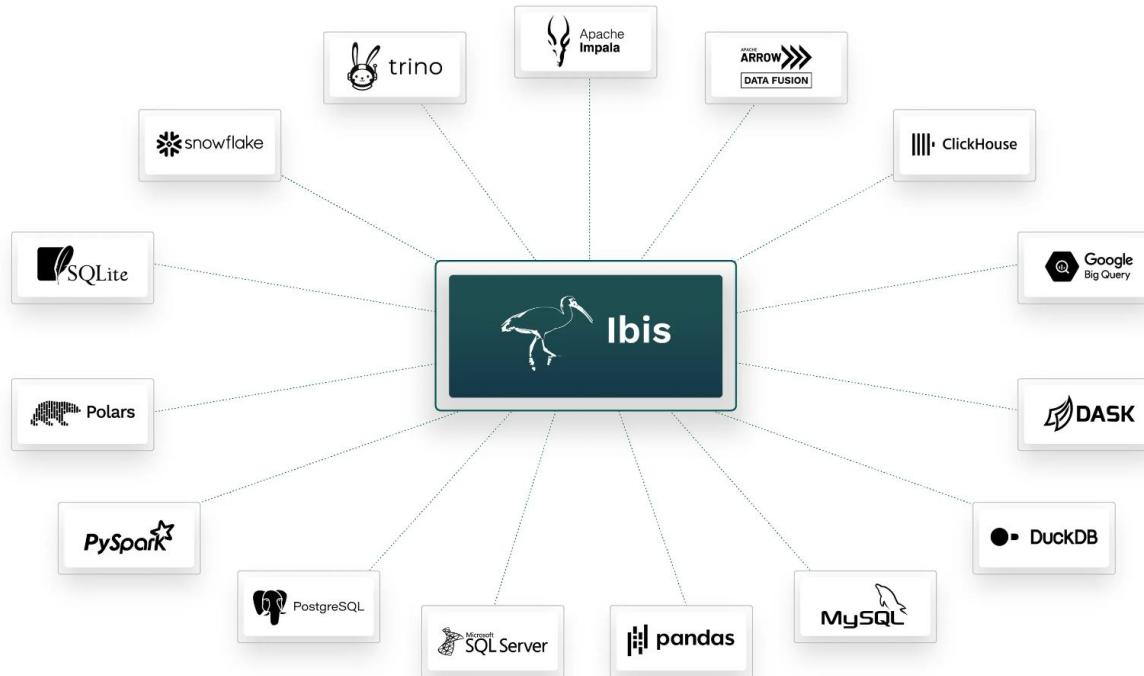
- PySpark-like Syntax
- Lazy execution
- Python gets converted to SQL
- Heavy lifting done by Trino

Links: [API Docs](#) & [Example Code](#)

Only supported on Starburst Galaxy and Starburst Enterprise

Ibis overview

A common Dataframe API for data manipulation in Python, and compiling that API into a variety of backend native languages



Similar APIs

PyStarburst

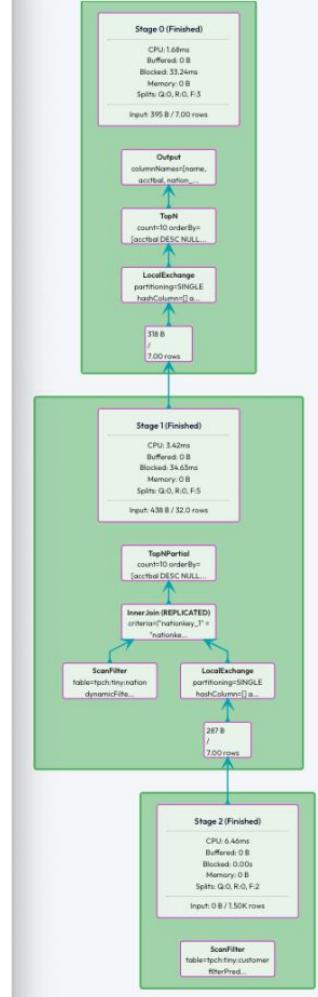
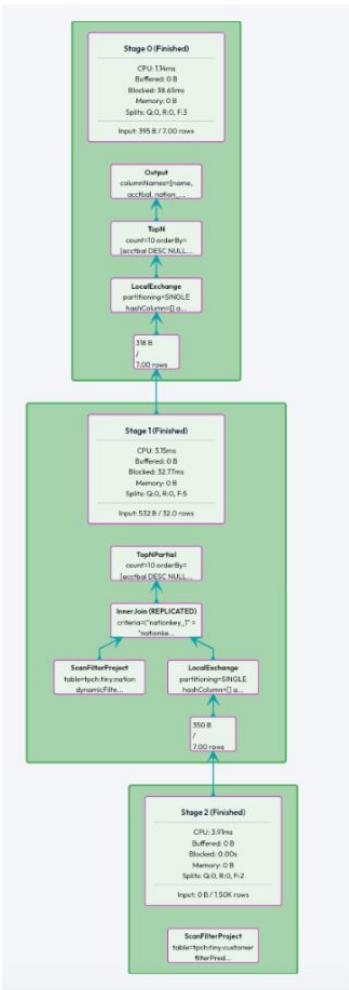
```
nationDF = session.table("tpch.tiny.nation") \  
    .drop("regionkey", "comment") \  
    .rename("name", "nation_name") \  
    .rename("nationkey", "n_nationkey")  
  
custDF = session.table("tpch.tiny.customer") \  
    .select("name", "acctbal", "nationkey") \  
    .filter(col("acctbal") > 9900.0)  
  
apiSQL = custDF.join(nationDF,  
    col("nationkey") == nationDF.n_nationkey) \  
    .drop("nationkey").drop("n_nationkey") \  
    .sort(col("acctbal"), ascending=False)  
  
apiSQL.show()
```

Ibis

```
nationDF = con.table("nation") \  
    .drop("regionkey", "comment") \  
    .rename(  
        dict(  
            nation_name="name",  
            n_nationkey="nationkey"  
        )  
    )  
  
custDF = con.table("customer") \  
    .select("name", "acctbal", "nationkey") \  
    .filter(projectedDF["acctbal"] > 9900.0)  
  
apiSQL = custDF.join(nationDF,  
    custDF.nationkey == nationDF.n_nationkey) \  
    .drop("nationkey", "n_nationkey") \  
    .order_by([ibis.desc("acctbal")])  
  
print(apiSQL.head(10))
```

Similar results

Query Plan PyStarburst



Query Plan Ibis

Trino for your data pipelines

Trino is, and has been, an appropriate clustering technology for running your transformation processing jobs

- Fault-tolerant execution mode makes it even more robust
- Data engineers can leverage SQL and/or Python



trino

Dataframe API recommendations

If you use Starburst products → Choose PyStarburst

- More similar to PySpark Dataframe API
- More likely to be optimized better for Trino than Ibis

If you are using OSS Trino → Choose Ibis

- PyStarburst is not supported here
- Gain optionality for backend execution engine

Thank You



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