Streaming SQL

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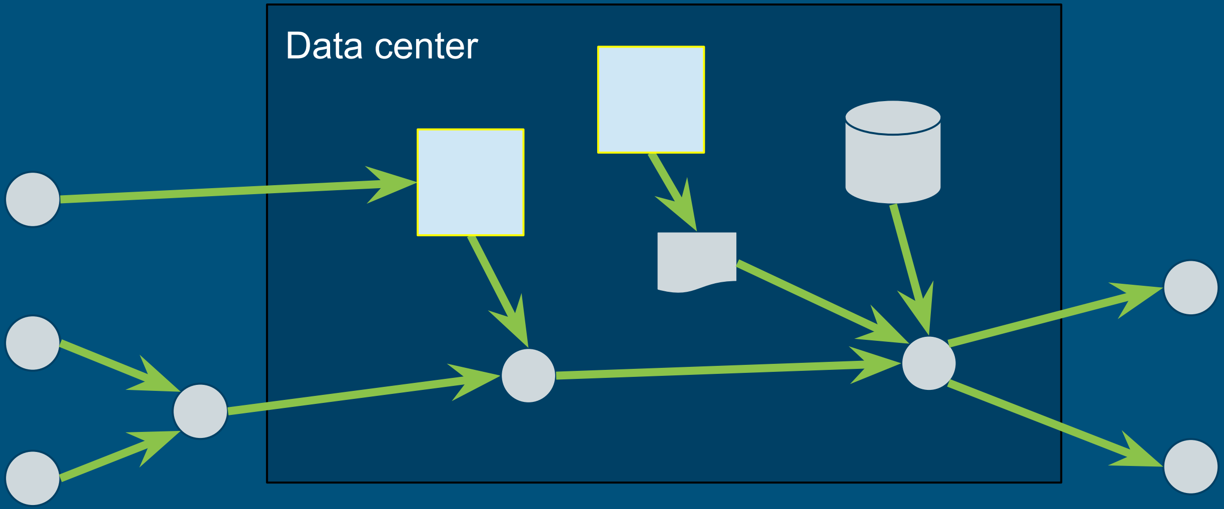
Apache member
Original author of Apache Calcite
PMC Apache Arrow, Drill, Eagle, Kylin

Why SQL?

Data in motion, data at rest - it’s all just data

Stream / database duality

SQL is the best language ever created for data (because it’s declarative)



Building a streaming SQL standard via consensus

Please! No more “SQL-like” languages!

Key technologies are open source (many are Apache projects)

Calcite is providing leadership: developing example queries, TCK

Complements Apache Beam’s work on a common streaming API/algebra

(Optional) Use Calcite’s framework to build a streaming SQL parser/planner for your engine

Several projects are working with us: Apex, Flink, Samza, Storm. (Also non-streaming SQL in Cassandra, Drill, Druid, Elasticsearch, Hive, Kylin, Phoenix.)

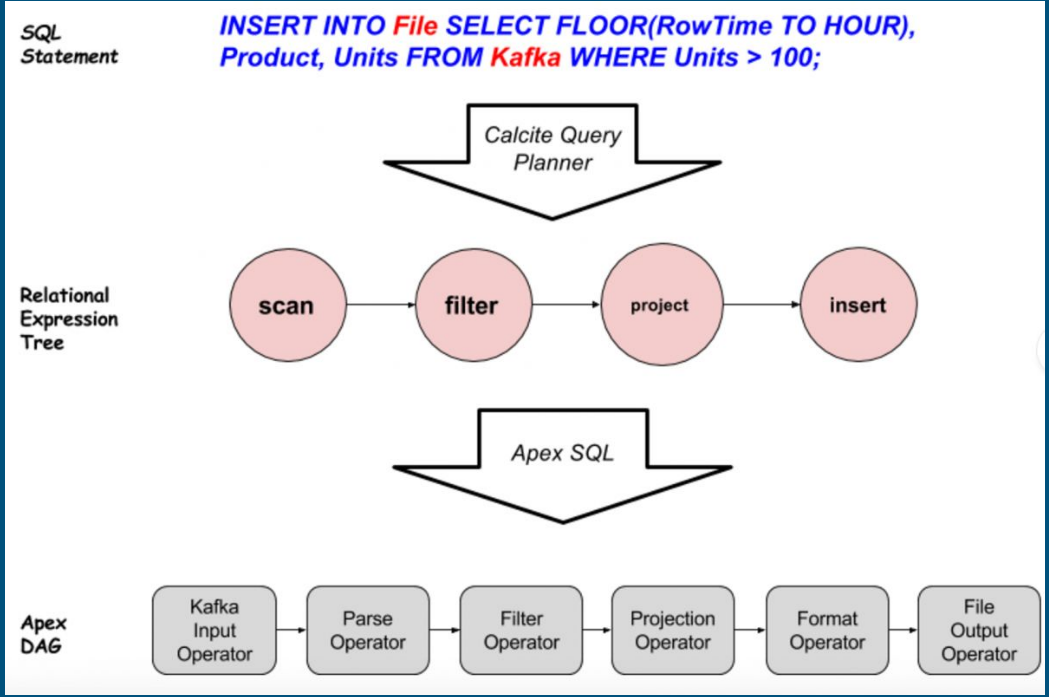
SQL in Apex

SQL support is part of Malhar (malhar-sql) [1]

Disclaimer: Not everything I describe today is in Apex

Operators: Scan, Filter, Project

Coming soon: Window operators



```
INSERT INTO File SELECT FLOOR(RowTime TO HOUR),
Product, Units FROM Kafka WHERE Units > 100;
```

[1] https://www.datatorrent.com/blog/sql-apache-apex/

Simple queries

```
select *
from Products
where unitPrice < 20
```

- Traditional (non-streaming)
- `Products` is a table
- Retrieves records from -∞ to now

```
select stream *
from Orders
where units > 1000
```

- Streaming
- `Orders` is a stream
- Retrieves records from now to +∞
- Query never terminates

Stream-table duality

```
select *
from Orders
where units > 1000
```

```
select stream *
from Orders
where units > 1000
```

- Yes, you can use a stream as a table
- And you can use a table as a stream
- Actually, `Orders` is both
- Use the **stream** keyword
- Where to actually find the data? That’s up to the system

Combining past and future

```
select stream *
from Orders as o
where units > (
  select avg(units)
  from Orders as h
  where h.productId = o.productId
  and h.rowtime > o.rowtime - interval ‘1’ year)
```

- ➢ Orders is used as both stream and table
- ➢ System determines where to find the records
- ➢ Query is invalid if records are not available

Semantics of streaming queries

The replay principle:

> *A streaming query produces the same result as the corresponding non-streaming query would if given the same data in a table.*

Output must not rely on implicit information (arrival order, arrival time, processing time, or watermarks/punctuations)

(Some triggering schemes allow records to be emitted early and re-stated if incorrect.)

Controlling when data is emitted

Early emission is the defining characteristic of a streaming query.

The emit clause is a SQL extension inspired by Apache Beam's "trigger" notion. (Still experimental… and evolving.)

A relational (non-streaming) query is just a query with the most conservative possible emission strategy.

```
select stream productId,
  count(*) as c
from Orders
group by productId,
  floor(rowtime to hour)
emit at watermark,
  early interval '2' minute,
  late limit 1;
```

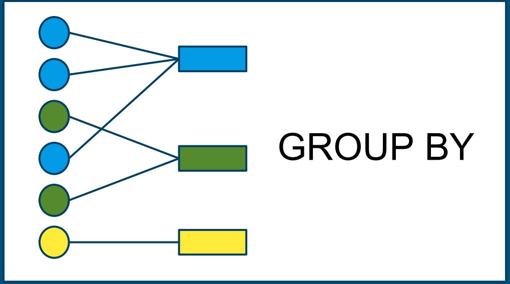
```
select *
from Orders
emit when complete;
```

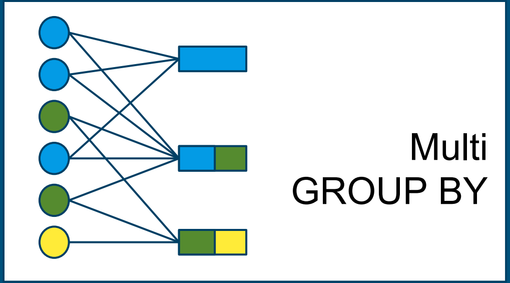
Aggregation and windows on streams

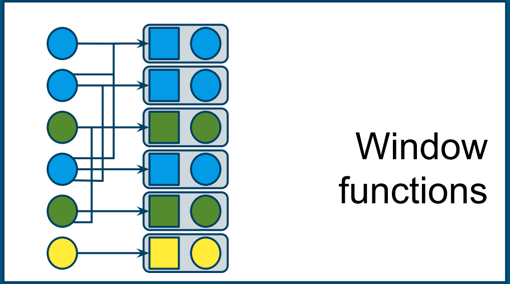
GROUP BY aggregates multiple rows into sub-totals

- ➢ In regular GROUP BY each row contributes to exactly one sub-total
- ➢ In multi-GROUP BY (e.g. HOP, GROUPING SETS) a row can contribute to more than one sub-total

Window functions (OVER) leave the number of rows unchanged, but compute extra expressions for each row (based on neighboring rows)

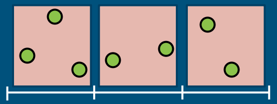






Tumbling, hopping & session windows in SQL

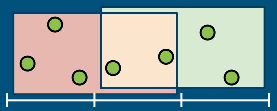
Tumbling window



```
select stream … from Orders
group by floor(rowtime to hour)
```

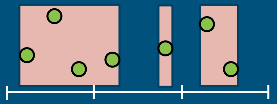
```
select stream … from Orders
group by tumble(rowtime, interval ‘1’ hour)
```

Hopping window



```
select stream … from Orders
group by hop(rowtime, interval ‘1’ hour,
    interval ‘2’ hour)
```

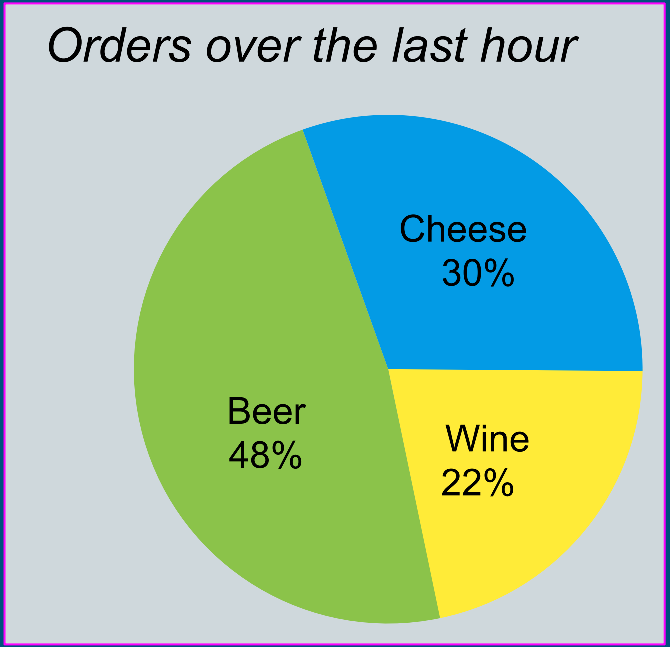
Session window



```
select stream … from Orders
group by session(rowtime, interval ‘1’ hour)
```

The “pie chart” problem

- Task: Write a web page summarizing orders over the last hour
- Problem: The `Orders` stream only contains the current few records
- Solution: Materialize short-term history



Orders over the last hour

```
select productId, count(*)
from Orders
where rowtime > current_timestamp - interval ‘1’ hour
group by productId
```

Join stream to a table

Inputs are the Orders stream and the Products table, output is a stream.

Acts as a “lookup”.

Execute by caching the table in a hash-map (if table is not too large) and stream order will be preserved.

What if Products table is being modified while query executes?

```
select stream *
from Orders as o
join Products as p
  on o.productId = p.productId
```

Join stream to a stream

We can join streams if the join condition forces them into “lock step”, within a window (in this case, 1 hour).

Which stream to put input a hash table? It depends on relative rates, outer joins, and how we’d like the output sorted.

```
select stream *
from Orders as o
join Shipments as s
on o.productId = p.productId
and s.rowtime
  between o.rowtime
  and o.rowtime + interval ‘1’ hour
```

Other operations

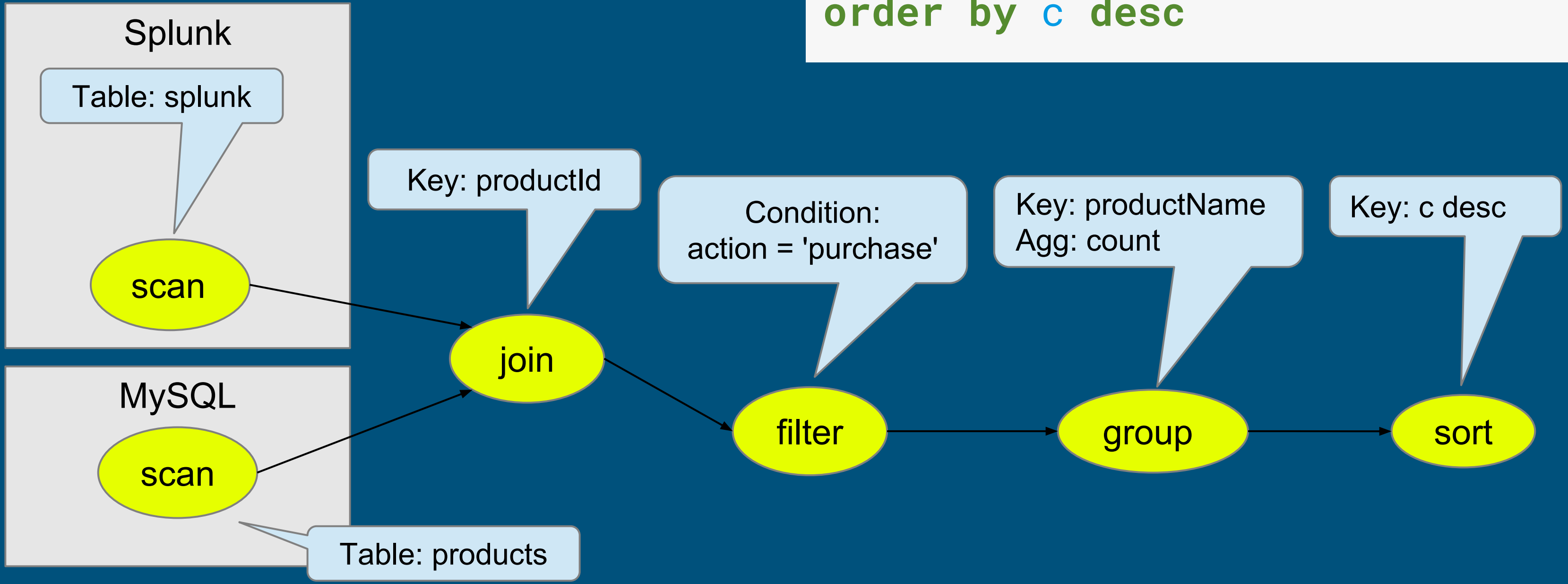
Other relational operations make sense on streams (usually only if there is an implicit time bound).

Examples:

- `order by` - E.g. Each hour emit the top 10 selling products
- `union` - E.g. Merge streams of orders and shipments
- `insert`, `update`, `delete` - E.g. Continuously insert into an external table
- `exists`, `in` sub-queries - E.g. Show me shipments of products for which there has been no order in the last hour
- `view` - Expanded when query is parsed; zero runtime cost
- `match_recognize` - Complex event processing (CEP)

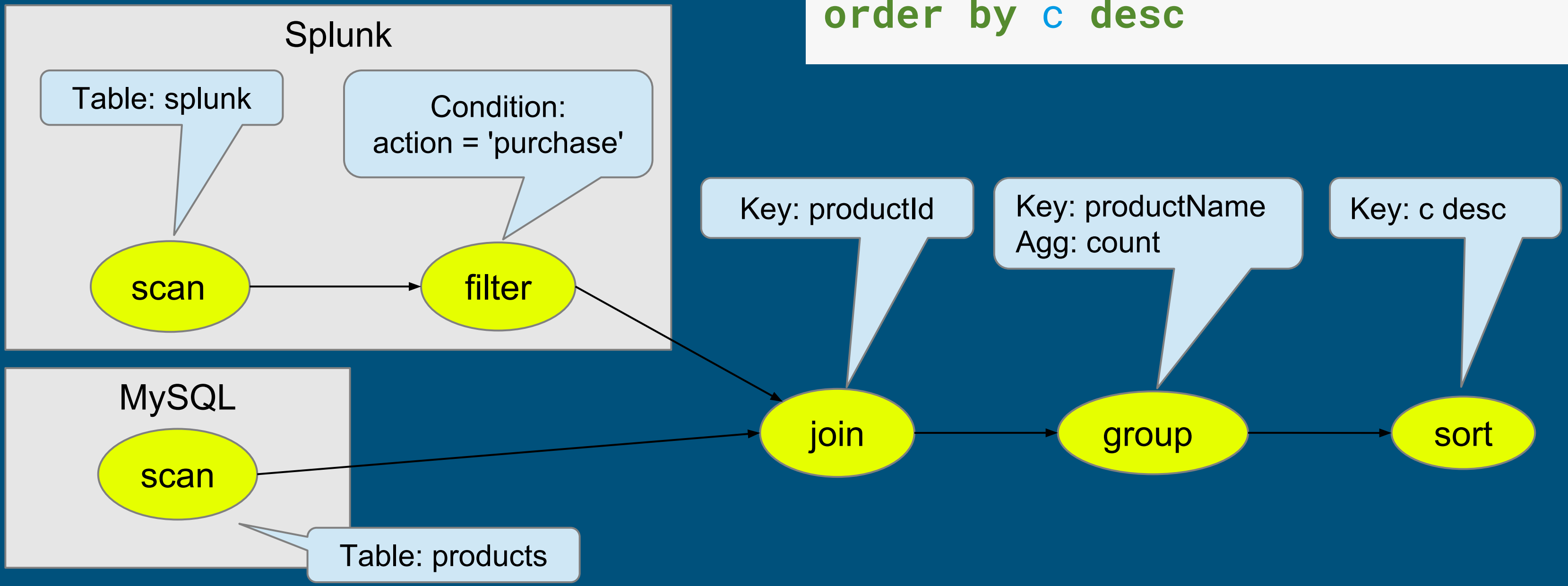
Planning queries

```
select p.productName, count(*) as c
from splunk.splunk as s
    join mysql.products as p
    on s.productId = p.productId
where s.action = 'purchase'
group by p.productName
order by c desc
```



Optimized query

```
select p.productName, count(*) as c
from splunk.splunk as s
    join mysql.products as p
    on s.productId = p.productId
where s.action = 'purchase'
group by p.productName
order by c desc
```



Apache Calcite

Apache top-level project since October, 2015

Query planning framework

- ➢ Relational algebra, rewrite rules
- ➢ Cost model & statistics
- ➢ Federation via adapters
- ➢ Extensible

Packaging

- ➢ Library
- ➢ Optional SQL parser, JDBC server
- ➢ Community-authored rules, adapters

Embedded	Adapters	Streaming
Apache Drill Apache Hive Apache Kylin Apache Phoenix* Cascading Lingual	Apache Cassandra Apache Spark CSV Druid Elasticsearch In-memory JDBC JSON MongoDB Splunk Web tables	Apache Apex Apache Flink Apache Samza Apache Storm

** Under development*

Join the community!

Calcite and Apex are projects of the Apache Software Foundation

The Apache Way: meritocracy, openness, consensus, community

We welcome new contributors!

Apache Apex™

Apache Calcite

THE APACHE™ SOFTWARE FOUNDATION

Thank you!

@julianhyde

@ApacheCalcite

http://calcite.apache.org

http://calcite.apache.org/docs/stream.html

References

- Hyde, Julian. "Data in flight." Communications of the ACM 53.1 (2010): 48-52. [pdf]
- Akidau, Tyler, et al. "The dataflow model: a practical approach to balancing correctness, latency, and cost in massive-scale, unbounded, out-of-order data processing." Proceedings of the VLDB Endowment 8.12 (2015): 1792-1803. [pdf]
- Arasu, Arvind, Shivnath Babu, and Jennifer Widom. "The CQL continuous query language: semantic foundations and query execution." The VLDB Journal—The International Journal on Very Large Data Bases 15.2 (2006): 121-142. [pdf]

Extra slides

Summary

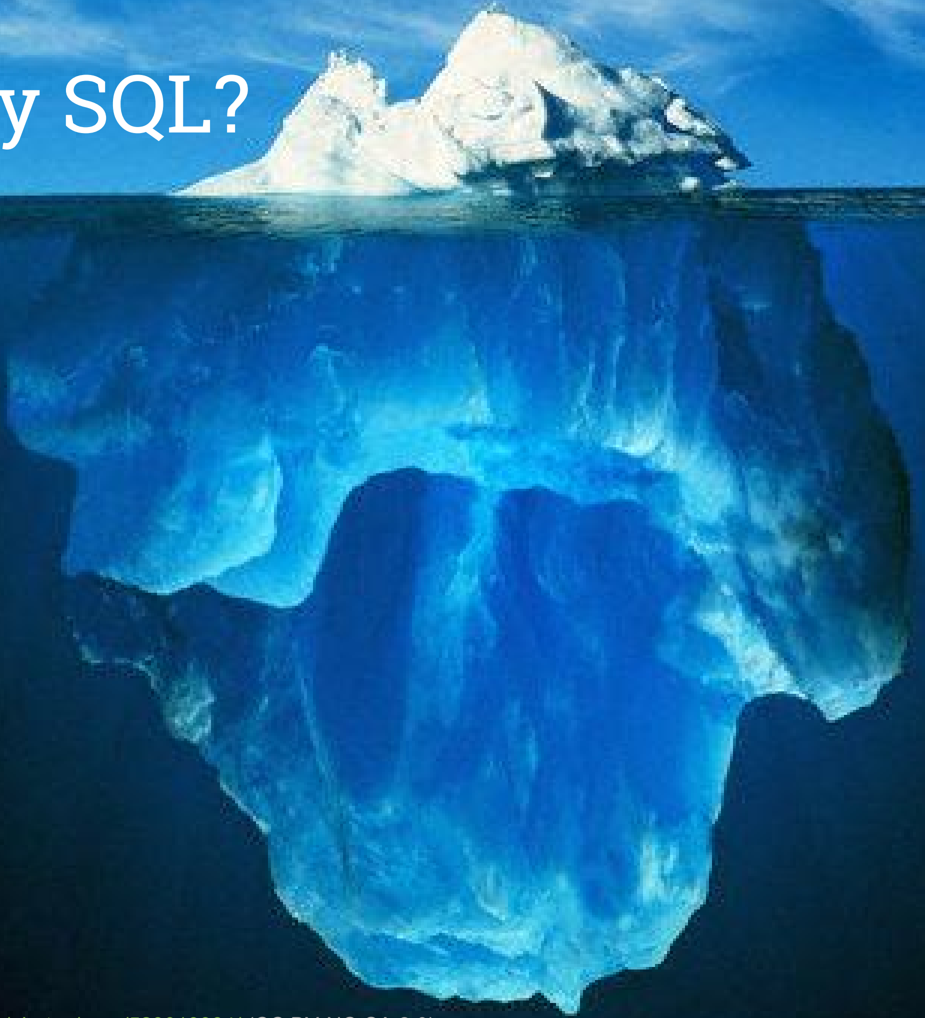
Features of streaming SQL:

- Standard SQL over streams and relations
- Relational queries on streams, and vice versa
- Materialized views and standing queries

Benefits:

- Brings streaming data to DB tools and traditional users
- Brings historic data to message-oriented applications
- Lets the system optimize quality of service (QoS) and data location

Why SQL?



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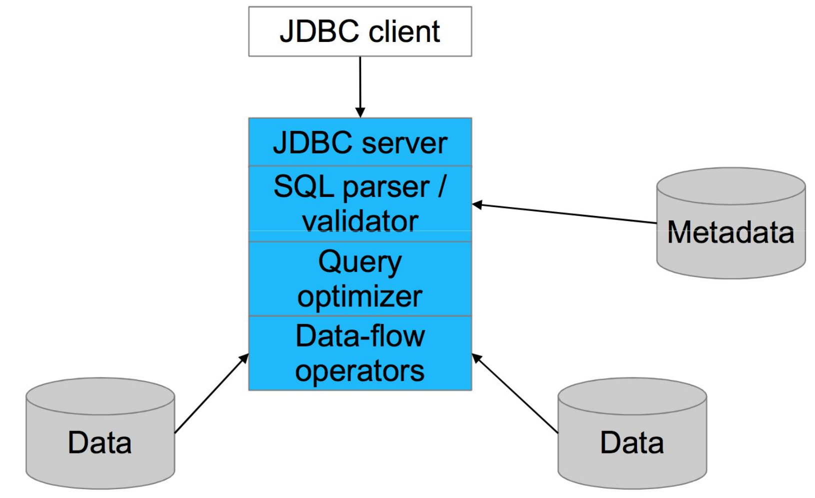
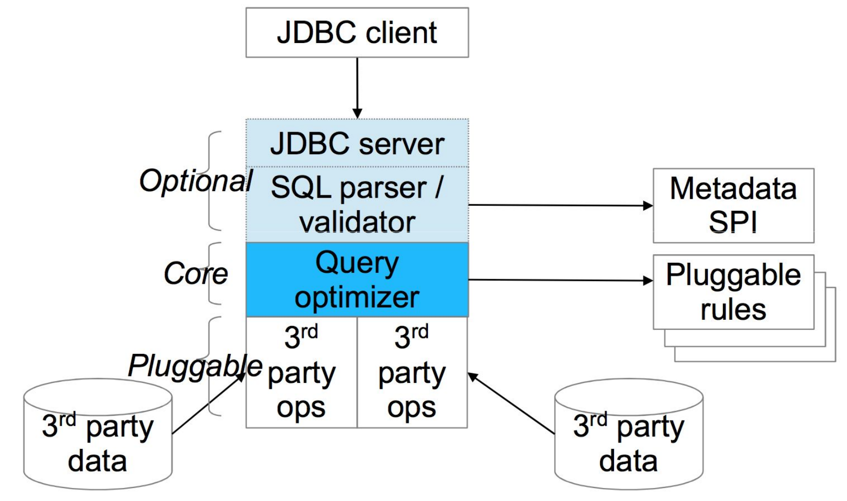
- API to your database
- Ask for ***what you want***, system decides ***how to get it***
- Query planner (optimizer) converts logical queries to physical plans
- Mathematically sound language (relational algebra)
- For all data, not just “flat” data in a database
- Opportunity for novel data organizations & algorithms
- Standard

Architecture

Conventional database



Calcite



Relational algebra (plus streaming)

Core operators:

- ➢ Scan
- ➢ Filter
- ➢ Project
- ➢ Join
- ➢ Sort
- ➢ Aggregate
- ➢ Union
- ➢ Values

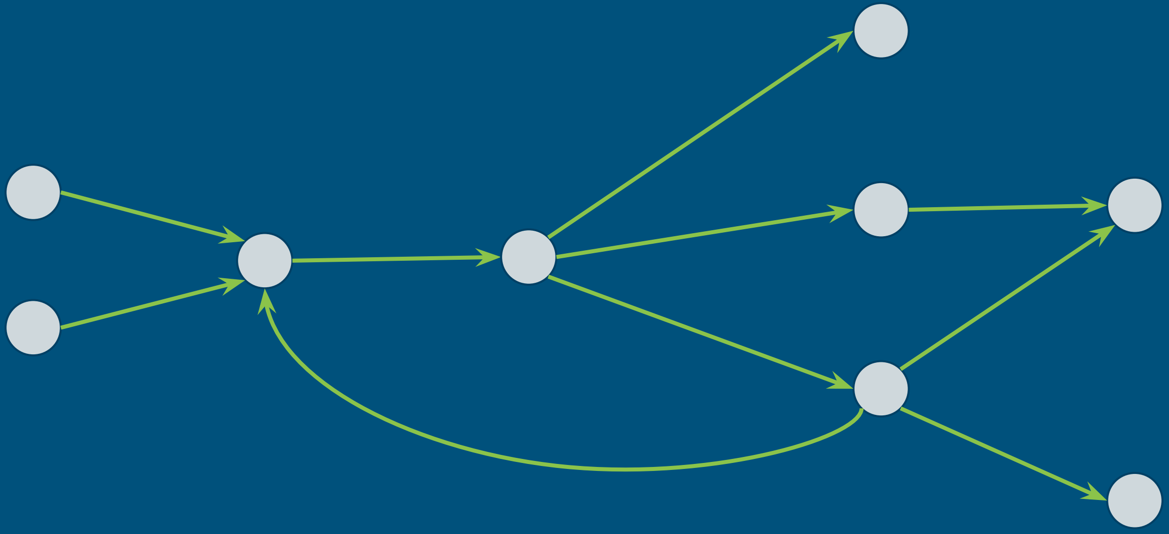
Streaming operators:

- ➢ Delta (converts relation to stream)
- ➢ Chi (converts stream to relation)

In SQL, the STREAM keyword signifies Delta

Streaming algebra

- Filter
- Route
- Partition
- Round-robin
- Queue
- Aggregate
- Merge
- Store
- Replay
- Sort
- Lookup



Optimizing streaming queries

The usual relational transformations still apply: push filters and projects towards sources, eliminate empty inputs, etc.

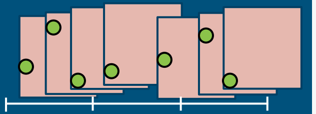
The transformations for delta are mostly simple:

- Delta(Filter(r, predicate)) → Filter(Delta(r), predicate)
- Delta(Project(r, e0, ...)) → Project(Delta(r), e0, …)
- Delta(Union(r0, r1), ALL) → Union(Delta(r0), Delta(r1))

But not always:

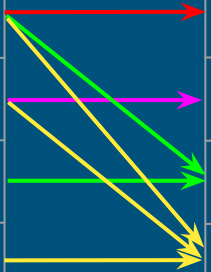
- Delta(Join(r0, r1, predicate)) → Union(Join(r0, Delta(r1)), Join(Delta(r0), r1)
- Delta(Scan(aTable)) → Empty

Sliding windows in SQL



```
select stream
  sum(units) over w (partition by productId) as units1hp,
  sum(units) over w as units1h,
  rowtime, productId, units
from Orders
window w as (order by rowtime range interval ‘1’ hour preceding)
```

rowtime	productId	units
09:12	100	5
09:25	130	10
09:59	100	3
10:17	100	10



units1hp	units1h	rowtime	productId	units
5	5	09:12	100	5
10	15	09:25	130	10
8	18	09:59	100	3
23	13	10:17	100	10

Join stream to a *changing* table

Execution is more difficult if the `Products` table is being changed while the query executes.

To do things properly (e.g. to get the same results when we re-play the data), we'd need temporal database semantics.

(Sometimes doing things properly is too expensive.)

```
select stream *
from Orders as o
join Products as p
  on o.productId = p.productId
  and o.rowtime
    between p.startEffectiveDate
    and p.endEffectiveDate
```