Stream Analytics with SQL on Apache Flink®



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Strata Data Conference, London *May, 24th 2017*

About me



- Apache Flink PMC member
 - Contributing since day 1 at TU Berlin
 - Focusing on Flink's relational APIs since 1.5 years



- Co-founder of data Artisans
- Co-author of "Stream Processing with Apache Flink"
 - Work in progress...
- PhD in Computer Science

dataArtisans



Original creators of **Apache Flink**®



Providers of the **dA Platform**, a supported Flink distribution

Apache Flink



- Platform for scalable stream processing
- Fast
 - Low latency and high throughput
- Accurate
 - Stateful streaming processing in event time
 - Exactly-once state guarantees
- Reliable
 - Highly available cluster setup
 - Snapshot and restart applications



Powered by Flink



























Flink's DataStream API



- The DataStream API is very expressive
 - Application logic implemented as user-defined functions
 - Windows, triggers, evictors, state, timers, async calls, ...
- Many applications follow similar patterns
 - Do not require the expressiveness of the DataStream API
 - Can be specified more concisely and easily with a DSL
- Q: What's the most popular DSL for data processing?

SQL!



- Many good reasons to use SQL
 - Declarative specification
 - Effective optimization
 - Efficient execution
 - "Everybody" knows SQL
- But does SQL work for streams as well?

SQL was not designed for streams



- Relations are bounded (multi-)sets.
- ⇔ Streams are infinite sequences.

 DBMS can access all data. Streaming data arrives over time.

- SQL queries return a result and complete.
- Streaming queries
 continuously emit results
 and never complete.

Some RDBMS do it anyway ©



- Materialized views (MV) are similar to regular views, but persisted to disk or memory
 - Used to speed-up analytical queries
 - MVs must be updated when the base tables change
- MV maintenance is very similar to SQL on streams
 - Base table updates are a changelog stream
 - MV definition is SQL query to evaluate
 - MV is query result

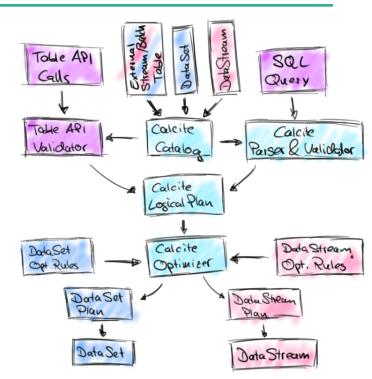
Apache Flink's Relational APIs



- Standard SQL & LINQ-style Table API
- Unified APIs for batch & streaming data

A query specifies exactly the same result regardless whether its input is static batch data or streaming data.

- Common translation layers
 - Optimization based on Apache Calcite
 - Type system & code-generation
 - Table sources & sinks



Show me Code!



```
sensors can be a
val tableApiResult: Table = tEnv
                                                    - CSV file,
  .scan("sensors")
                                                    - MySQL table,
  .window(Tumble over 1.hour on 'mtime as 'w)
                                                    - Kafka topic, ...
  .groupBy('w, 'room)
  .select('room, 'w.end, 'temp.avg as 'avgTemp)
val sqlResult: Table = tEnv.sql("""
  SELECT room,
          TUMBLE_END(mtime, INTERVAL '1' HOUR),
          AVG(temp) AS avgTemp
  | FROM sensors
  GROUP BY TUMBLE(mtime, INTERVAL '1' HOUR), room
  """.stripMargin)
```

Continuous Queries



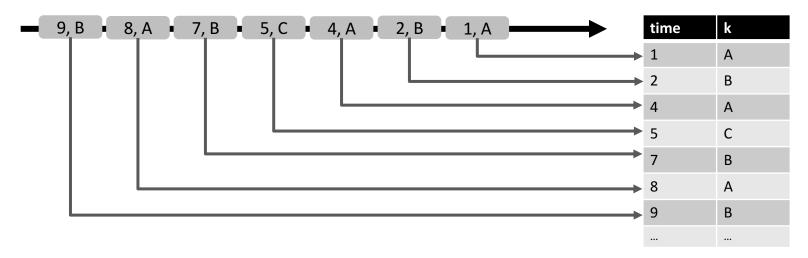
- Core concept is a "Dynamic Table"
 - Dynamic tables are changing over time
 - Insert, update, and delete changes
- Dynamic tables can be queries like static batch tables
 - Queries produce new dynamic tables
 - Queries do not terminate
- Stream → Dynamic table conversions



Stream → Dynamic Table



- Stream records are appended to dynamic table
 - Table grows as more data arrives



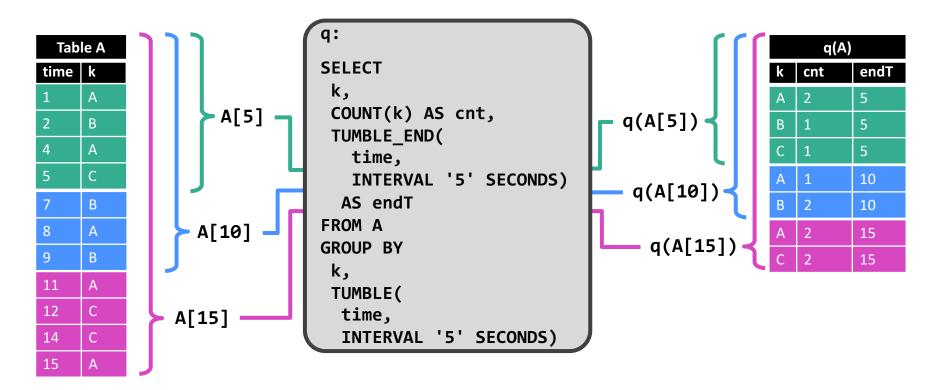
Querying a Dynamic Table



- Dynamic tables change over time
 - A[t]: Table A at time t
- Dynamic tables are queried with regular SQL
 - q(A[t]): Evaluate query q on table A at time t
- As time progresses, the result is continuously updated
 - Similar to maintaining a materialized view

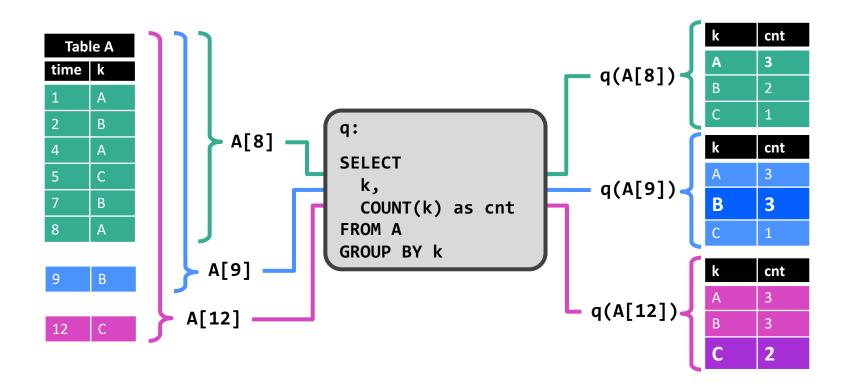
Querying a Dynamic Table





Querying a Dynamic Table





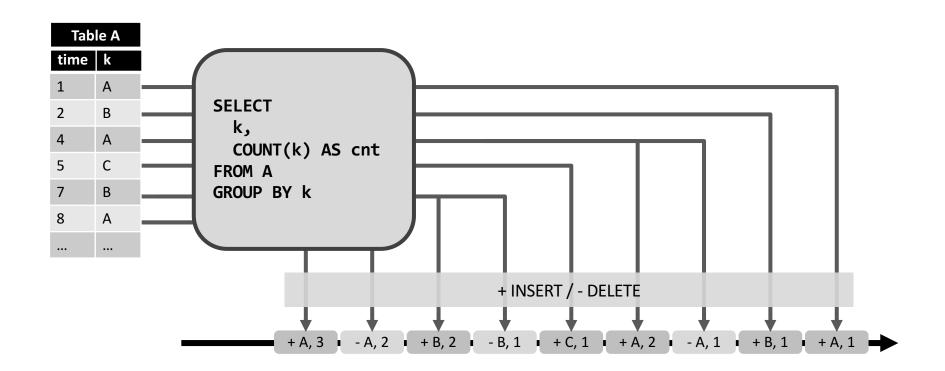
Dynamic Table → Stream



- Converting a dynamic table into a stream
 - Dynamic tables can be updated
 - Updates must be encoded in outgoing stream
- Conversion of tables to streams inspired by DBMS logs
 - DBMS use logs to restore databases (and tables)
 - Logs are streams of records that encode updates

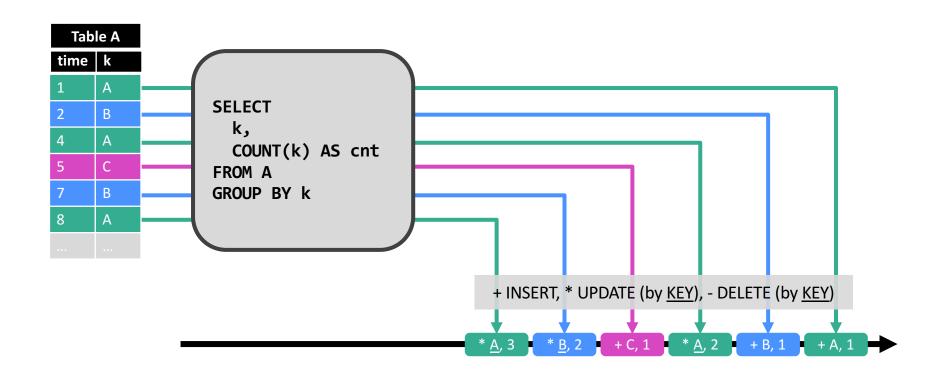
Dynamic Table → Stream: REDO/UNDO





Dynamic Table → Stream: REDO





Can We Run Any Query on Dynamic Tables?



- No, there are space and computation constraints ⊗
- State size may not grow infinitely as more data arrives
 SELECT sessionId, count(*) FROM clicks GROUP BY sessionId;
- A change of an input table may only trigger a partial re-computation of the result table

SELECT userId, RANK() OVER (ORDER BY highScore) FROM users;

Bounding the Size of Query State



Adapt the semantics of the query

```
SELECT sessionId, COUNT(*) AS clickCnt
FROM clicks
WHERE last(ctime, INTERVAL '1' DAY)
GROUP BY sessionId
```

- Aggregate data of last 24 hours. Discard older data.
- Trade the accuracy of the result for size of state
 - Remove state for keys that became inactive.

Current State of SQL & Table API



- Flink's relational APIs are rapidly evolving
 - Lots of interest by community and many contributors
 - Used in production at large scale

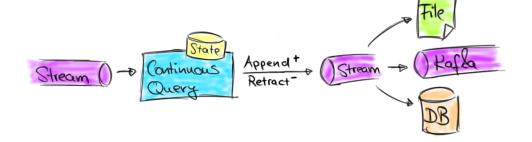
Features of the upcoming Flink 1.3.0 release

- GroupBy & Over windowed aggregates
- Non-windowed aggregates (with update changes)
- User-defined aggregation functions

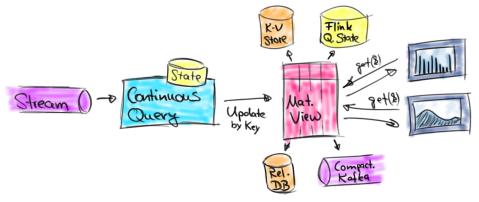
What can we build with this?



Continuous ETL & Data Import



Dashboards & Stateful Microservices

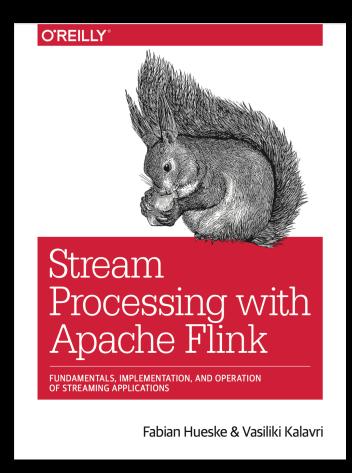


Conclusion



- Table API & SQL support many streaming use cases
 - High-level / declarative specification
 - Automatic optimization and translation
 - Efficient execution
- Updating results enables many exciting applications
 - Materialize a table that is updated by a stream in a KV store
- Check it out!





Thank you!

- @fhueske
- @ApacheFlink
- @dataArtisans

Available on O'Reilly Early Release!

dataArtisans

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