Stream Analytics with SQL on Apache Flink®



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Berlin Buzzwords June, 13th 2017

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? A: SQL!

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 some code!

val tableApiResult: Table = tEnv
.scan("clicks")

- .filter('url.like("https://www.xyz.com%")
- .groupBy('user)
- .select('user, 'link.count as 'cnt)

"clicks" can be a

- file
- database table,
- stream, ...

What if "clicks" is a file?



Q: What if we get more click data? A: We run the query again.

What if "clicks" is a stream?



 We want the same results as for batch input!

 Does SQL work on 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.

DBMSs run queries on streams

- Materialized views (MV) are similar to regular views, but persisted to disk or memory
 - Used to speed-up analytical queries
 - MVs need to be updated when the base tables change
- MV maintenance is very similar to SQL on streams
 - Base table updates are a stream of DML statements
 - MV definition query is evaluated on that stream
 - MV is query result and continuously updated

Continuous Queries in Flink

- Core concept is a "Dynamic Table"
 - Dynamic tables are changing over time
- Queries on dynamic tables
 - produce new dynamic tables (which are updated based on input)
 - do not terminate
- Stream ↔ Dynamic table conversions



$\textbf{Stream} \rightarrow \textbf{Dynamic Table}$



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

	user	cTime	url	link
u1, 12:00:00, https://, l1	u1	12:00:00	https://	1
u2, 12:00:00, https://, l2	u2	12:00:00	https://	12
u1, 12:00:05, https://, l3	u1	12:00:05	https://	13
u3, 12:01:00, https://, l2	u3	12:01:00	https://	12
u2, 12:01:30, https://, l4	u2	12:01:30	https://	4
u1, 12:01:45, https://, l2	u1	12:01:45	https://	12

$\textbf{Stream} \rightarrow \textbf{Dynamic Table}$



- Upsert mode
 - Stream records have (composite) key attributes
 - Records are inserted or update existing records with same key



Querying a Dynamic Table



Rows of result table are updated.

What about windows?



```
val tableApiResult: Table = tEnv
  .scan("clicks")
  .window(Tumble over 1.hour on 'cTime as 'w)
  .groupBy('w, 'user)
  .select('user, 'w.end AS endT, 'link.count as 'cnt)
val sqlResult: Table = tEnv.sql("""
  SELECT user,
          TUMBLE_END(cTime, INTERVAL '1' HOURS) AS endT,
          COUNT(link) AS cnt
  FROM clicks
  GROUP BY TUMBLE(cTime, INTERVAL '1' HOURS), user
  """.stripMargin)
```

Computing Window Aggregates



Rows are appended to result table.

$\textbf{Dynamic Table} \rightarrow \textbf{Stream}$



- Converting a dynamic table into a stream
 - Dynamic tables might update or delete existing rows
 - Updates must be encoded in outgoing stream
- Conversion of tables to streams inspired by DBMS logs
 - DBMS use logs to restore databases (and tables)
 - REDO logs store new records to redo changes
 - UNDO logs store old records to undo changes

Dynamic Table \rightarrow Stream: REDO/UNDO



$\textbf{Dynamic Table} \rightarrow \textbf{Stream: REDO}$



- No, there are space and computation constraints ©
- State size may not grow infinitely as more data arrives

SELECT user, COUNT(link) FROM clicks GROUP BY user;

 A change of an input table may only trigger a partial re-computation of the result table

SELECT user, RANK() OVER (ORDER BY lastLogin) FROM users;

Bounding the Size of Query State

Adapt the semantics of the query

SELECT user, COUNT(link) AS cnt
FROM clicks
WHERE last(cTime, INTERVAL '1' DAY)
GROUP BY user

- 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 by Alibaba and others
- Features released in Flink 1.3.0
 - GroupBy & Over windowed aggregates
 - Non-windowed aggregates (with update changes)
 - User-defined aggregation functions



What can be built with this?





- Continuous ETL
 - Continuously ingest data
 - Process with transformations & window aggregates
 - Write to files (Parquet, ORC), Kafka, PostgreSQL, HBase, ...

What can be built with this?





- Dashboards, reporting & event-driven architectures
 - Flink updates query results with low latency
 - Result is written to KV store, DBMS, compacted Kafka topic
- Later, results can be maintained as queryable state

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Conclusion

- Table API & SQL support many streaming use cases
 - High-level / declarative specification
 - Automatic optimization and translation
 - Efficient execution
 - Scalar, table, aggregation UDFs for flexibility
- Updating results enable many exciting applications
- Check it out!

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Stream Processing with Apache Flink

FUNDAMENTALS, IMPLEMENTATION, AND OPERATION OF STREAMING APPLICATIONS

Fabian Hueske & Vasiliki Kalavri

Thank you!

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Tables are materialized streams

- A table is the materialization of a stream of modifications
 - SQL DML statements: INSERT, UPDATE, and DELETE
 - DBMSs process statements by modifying tables

INSERT (u1, Mary,	"2017-03-01")			
INSERT (u2, Peter	,"2017-05-01")			
UPDATE (lastLogin = "2017-06-01") WHERE (user = u1)				
DELETE WHERE (user = u2)				

user	name	lastLogin
u1	Mary	2017-06-01
u2	Peter	2017-05-01

About me

- Apache Flink PMC member
 - Contributing since day 1 at TU Berlin
 - Focusing on Flink's relational APIs since 1.5 years
- Co-author of "Stream Processing with Apache Flink"
 - Work in progress...
- Co-founder of data Artisans





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PLATFORM

Original creators of Apache Flink® Providers of the **dA Platform**, a supported Flink distribution