

Stream Analytics with SQL on Apache Flink®



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Original creators of Apache
Flink®



PLATFORM

Providers of
dA Platform 2, including
open source Apache Flink +
dA Application Manager

The DataStream API



- Flink's 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!

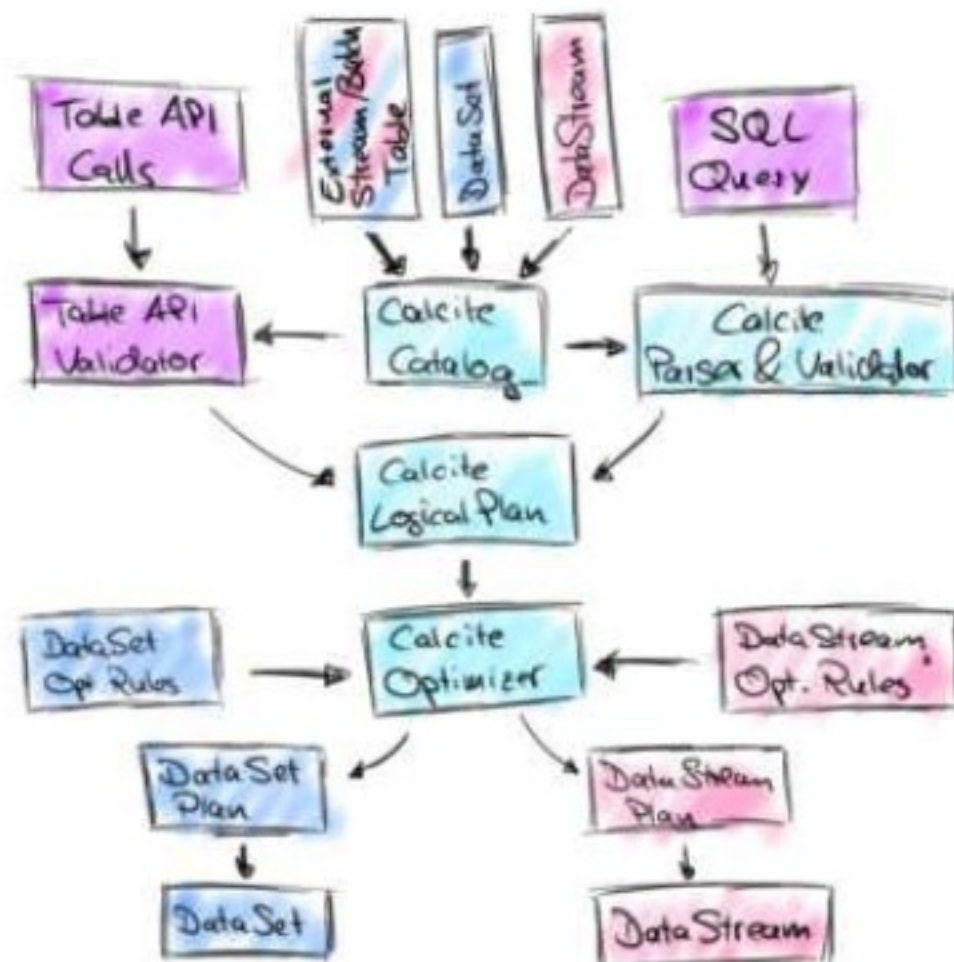
Apache Flink's relational APIs



- *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!



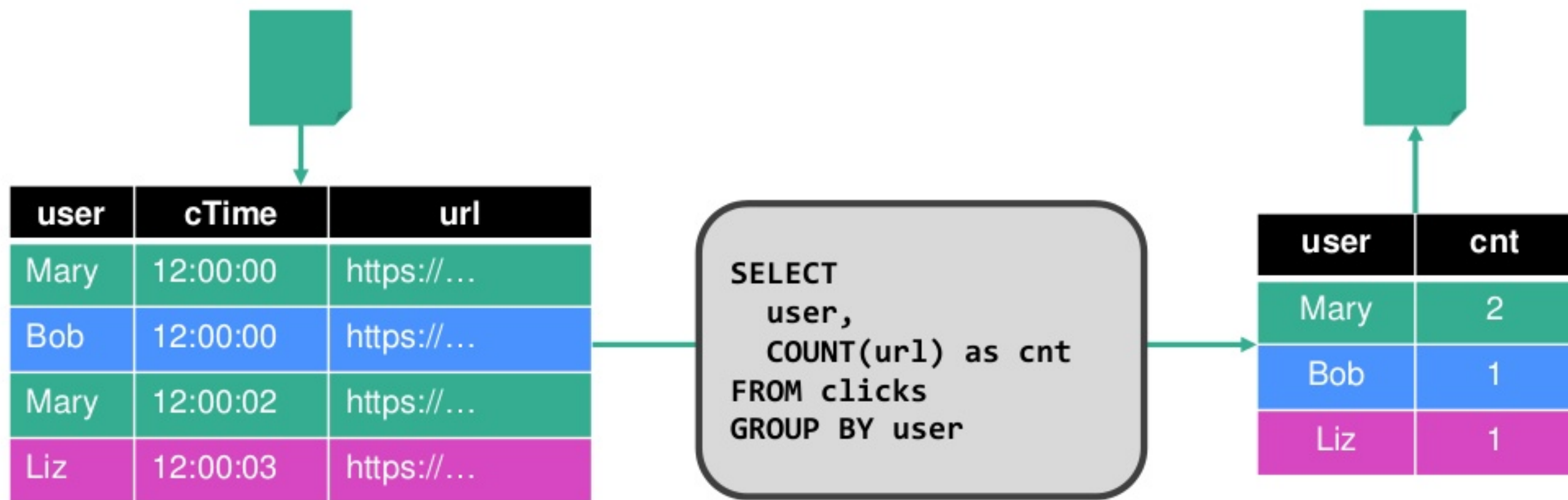
```
tableEnvironment  
  .scan("clicks")  
  .filter('url.like("https://www.xyz.com%")  
  .groupBy('user')  
  .select('user', 'url.count as 'cnt')
```

"clicks" can be a

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

```
SELECT user, COUNT(url) AS cnt  
FROM clicks  
WHERE url LIKE 'https://www.xyz.com%'  
GROUP BY user
```

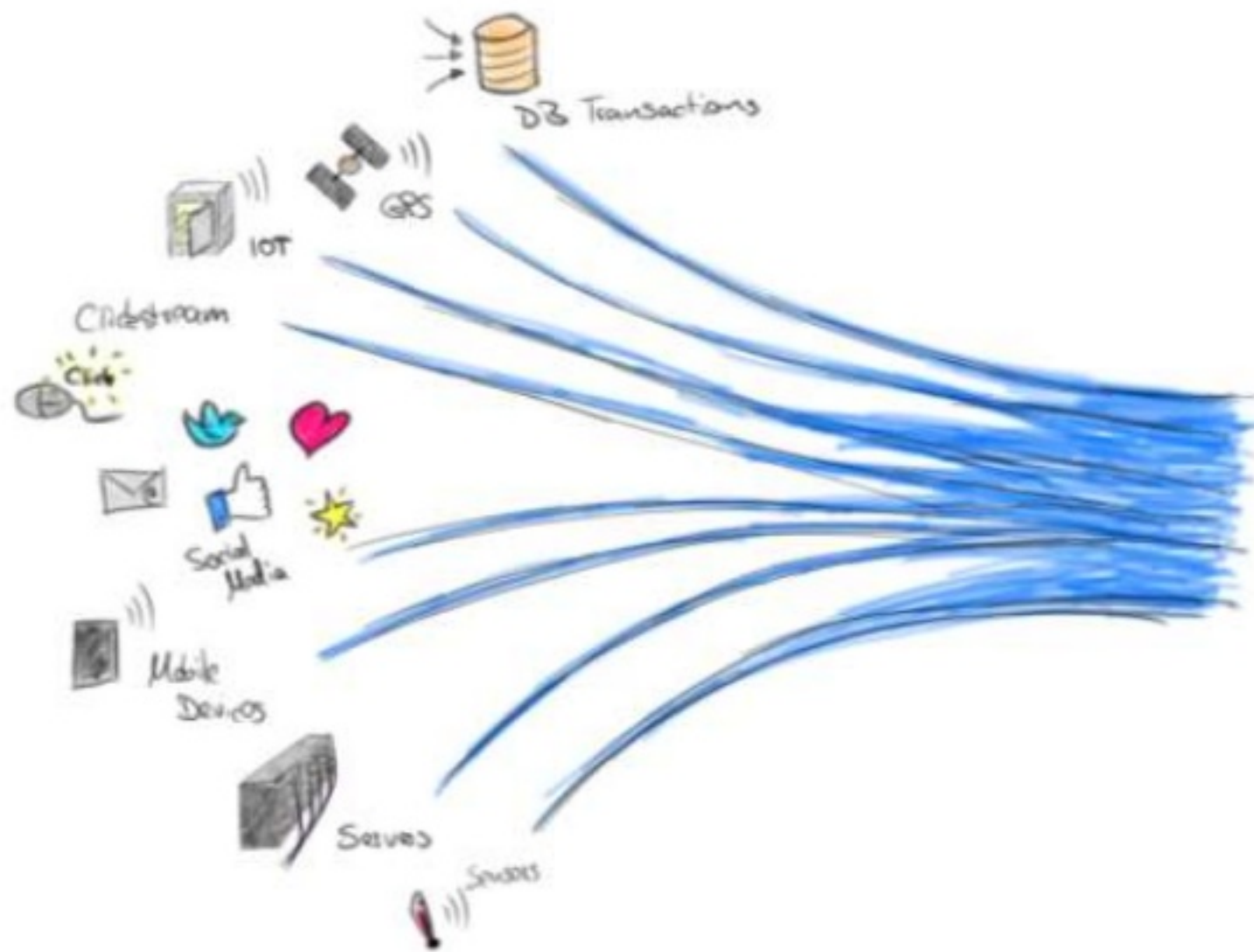
What if “clicks” is a file?



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!
- Can we query a stream with SQL 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



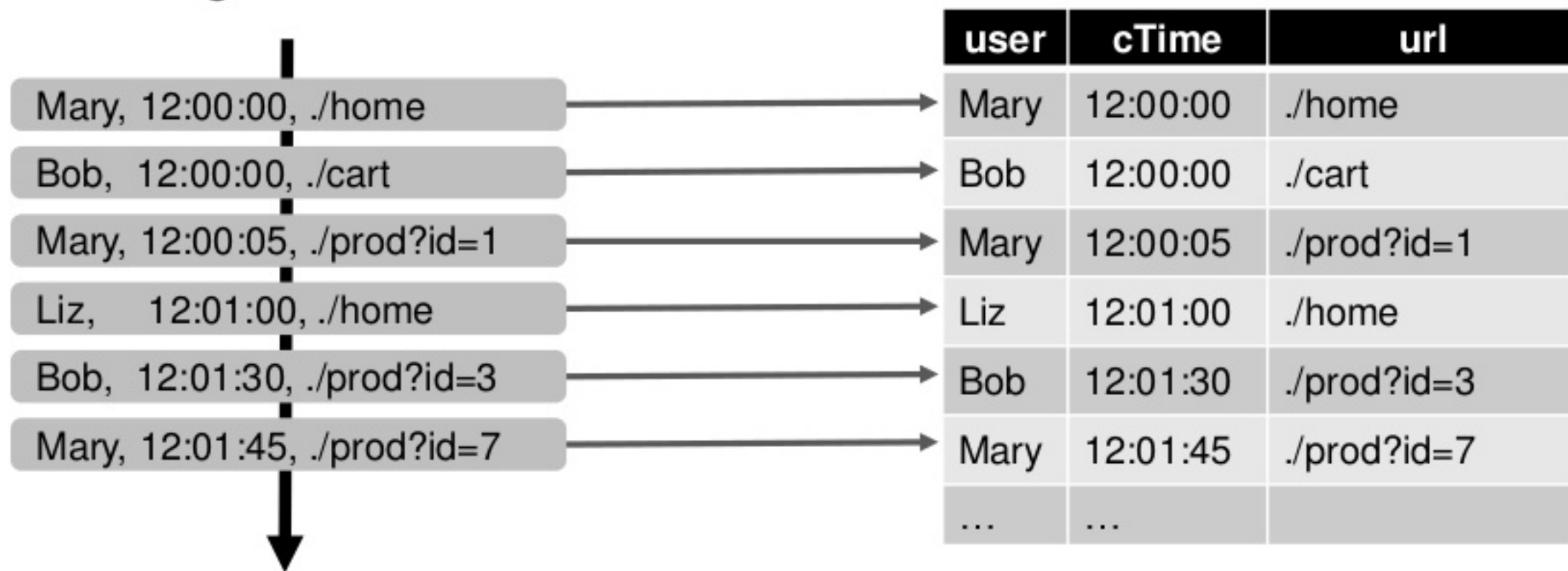
- Core concept is a “*Dynamic Table*”
 - Dynamic tables are changing over time
- Queries on dynamic tables
 - produce new dynamic tables (which are updated based on input)
 - do not terminate
- Stream ↔ Dynamic table conversions



Stream → Dynamic Table



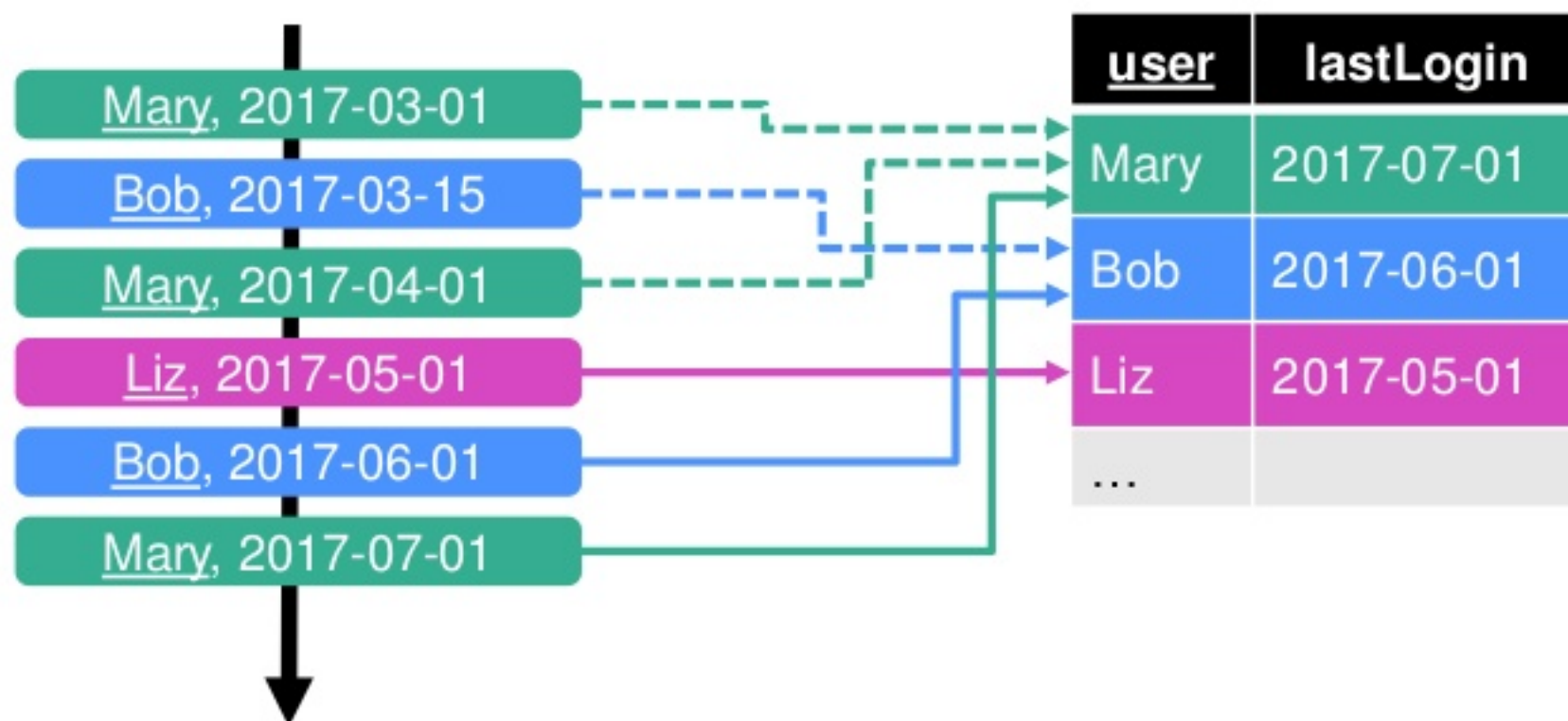
- Append mode
 - Stream records are appended to table
 - Table grows as more data arrives



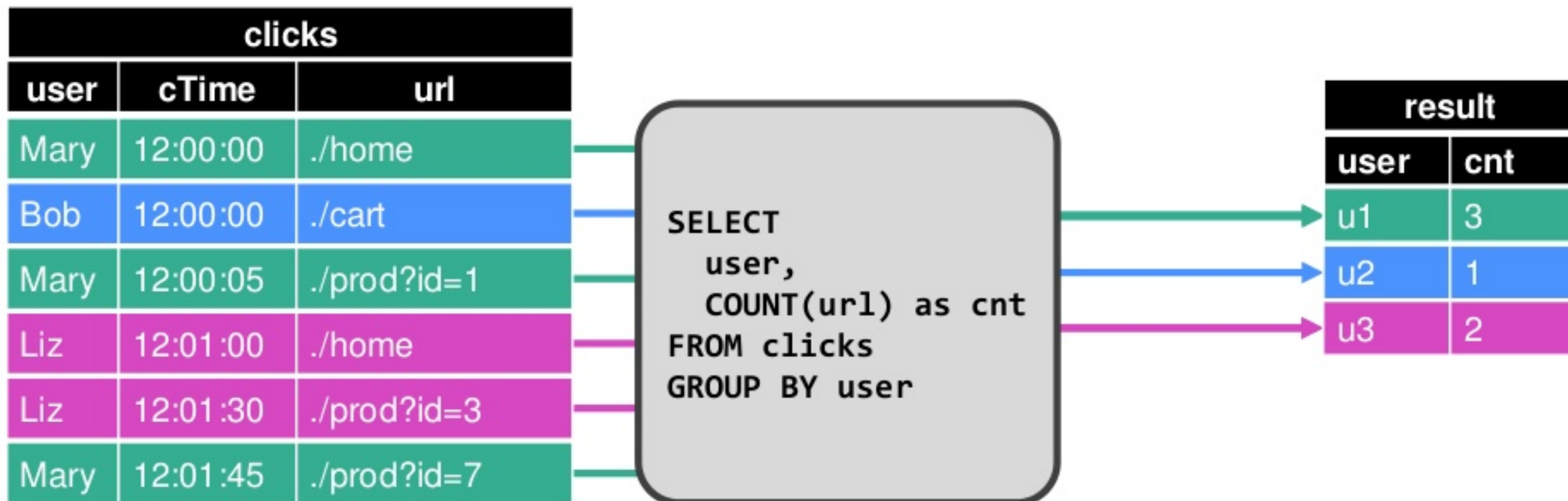
Stream → Dynamic Table



- 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.

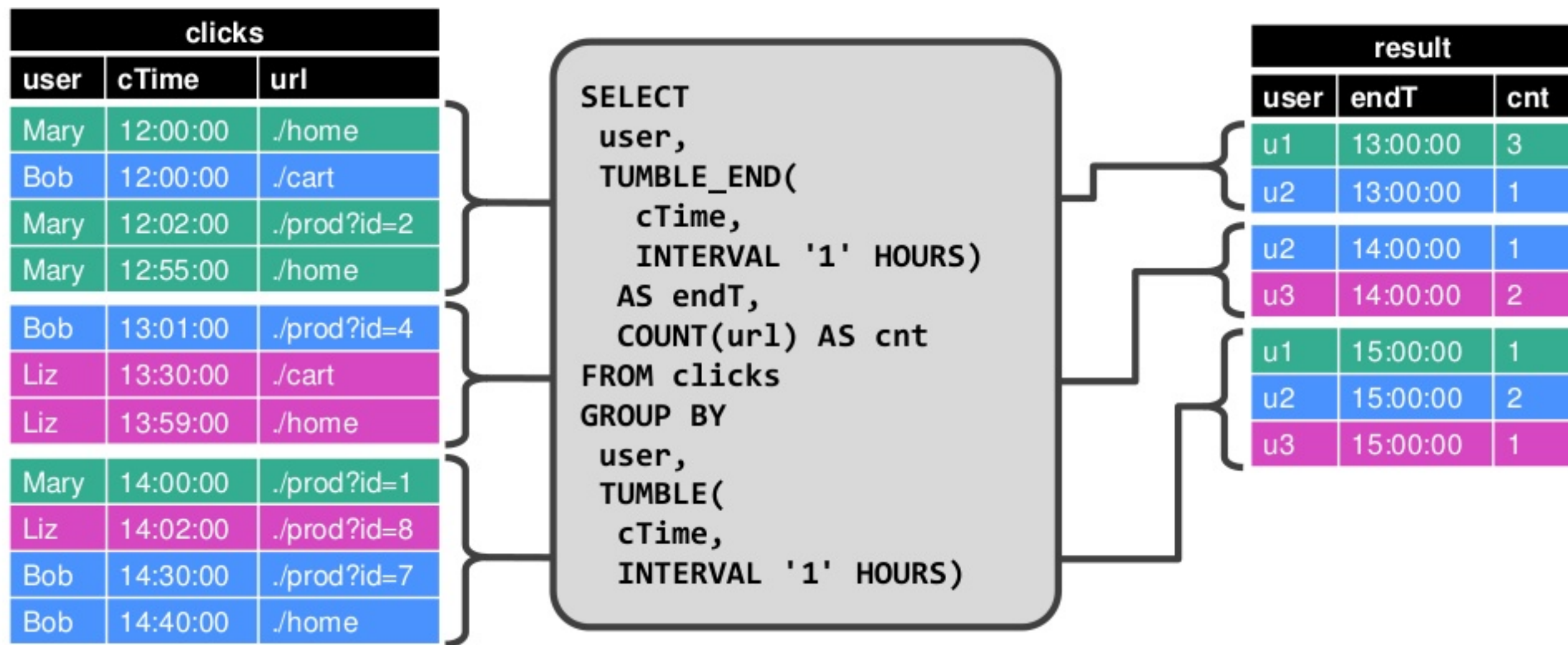
What about windows?



```
tableEnvironment  
  .scan("clicks")  
  .window(Tumble over 1.hour on 'cTime as 'w)  
  .groupBy('w, 'user)  
  .select('user, 'w.end AS endT, 'url.count as 'cnt)
```

```
SELECT user,  
       TUMBLE_END(cTime, INTERVAL '1' HOURS) AS endT,  
       COUNT(url) AS cnt  
FROM clicks  
GROUP BY TUMBLE(cTime, INTERVAL '1' HOURS),  
         user
```

Computing window aggregates



Rows are appended to result table.

Why are results always appended?



```
SELECT user,  
       TUMBLE_END(cTime, INTERVAL '1' HOURS) AS endT,  
       COUNT(url) AS cnt  
FROM clicks  
GROUP BY TUMBLE(cTime, INTERVAL '1' HOURS),  
         user
```

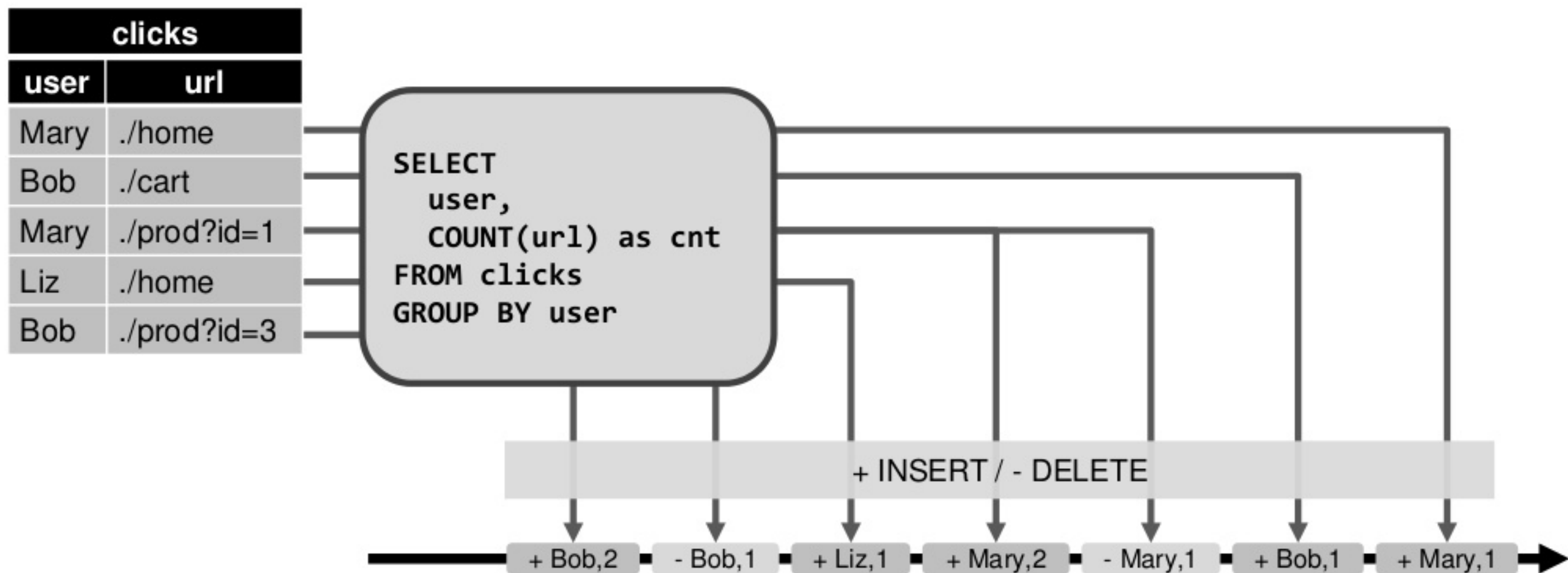
- cTime attribute is event-time attribute
 - Guarded by watermarks
 - Internally represented as special type
 - User-facing as TIMESTAMP
- Special plans for queries that operate on event-time attributes

Dynamic Table \rightarrow Stream

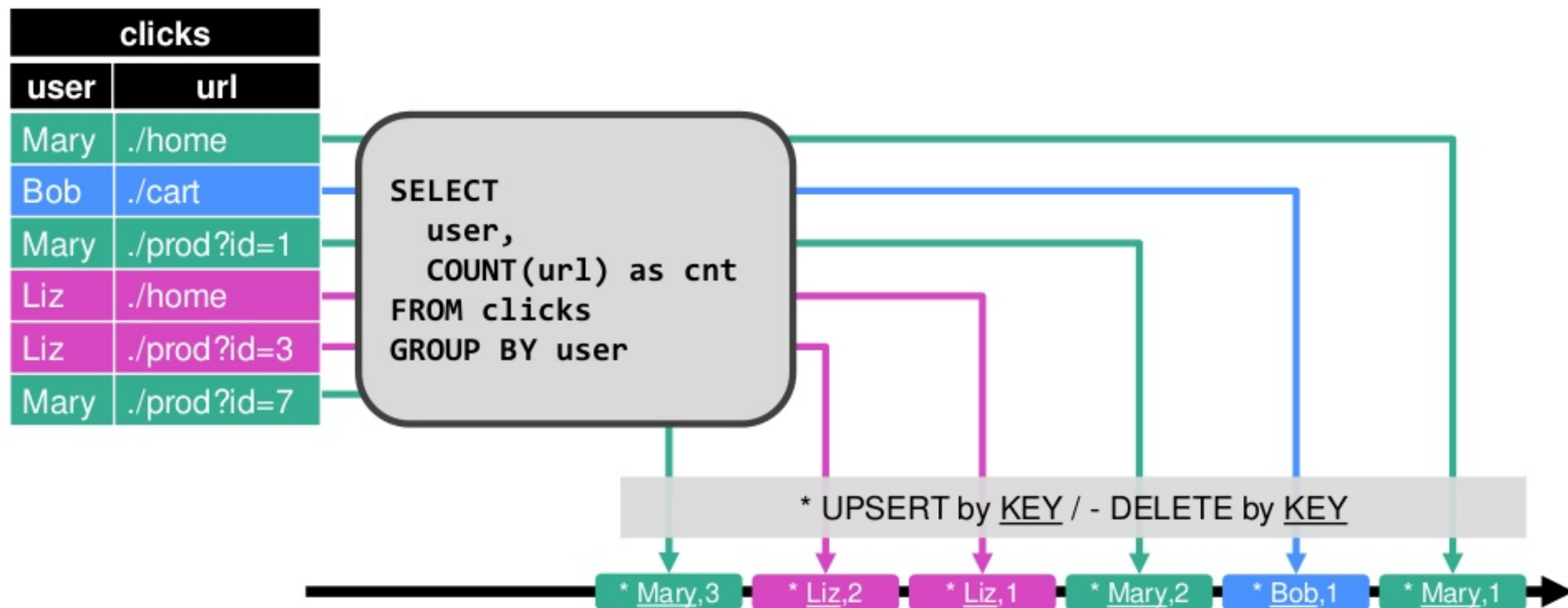


- Converting a dynamic table into a stream
 - Dynamic tables might update or delete existing rows
 - Updates must be encoded in outgoing stream
- Conversion of tables to streams inspired by DBMS logs
 - DBMS use logs to restore databases (and tables)
 - REDO logs store new records to redo changes
 -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

Dynamic Table → Stream: REDO/UNDO



Dynamic Table → Stream: REDO



Can we run any query on a dynamic table?



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

```
SELECT sessionId, COUNT(url) FROM clicks GROUP BY sessionId;
```

- 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 sessionId, COUNT(url) AS cnt
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.

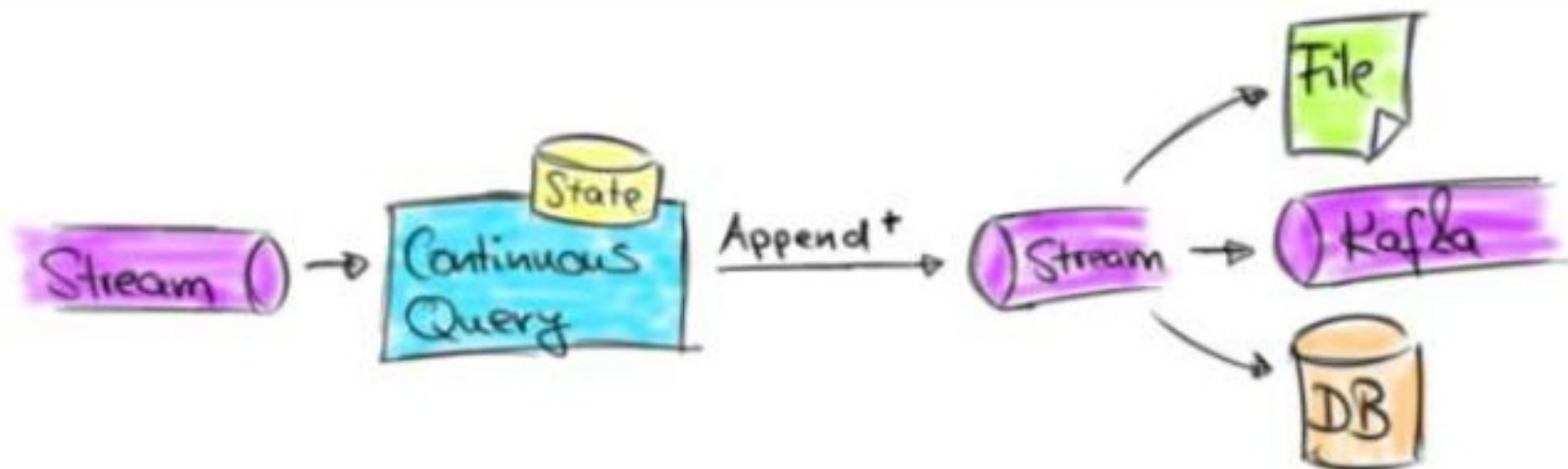
Current state of SQL & Table API



- Flink's relational APIs are rapidly evolving
 - Lots of interest by community and many contributors
 - Used in production at large scale by Alibaba and others
- Features released in Flink 1.3
 - GroupBy & Over windowed aggregates
 - Non-windowed aggregates (with update changes)
 - User-defined aggregation functions
- Features coming with Flink 1.4
 - Windowed Joins
 - Reworked connectors APIs



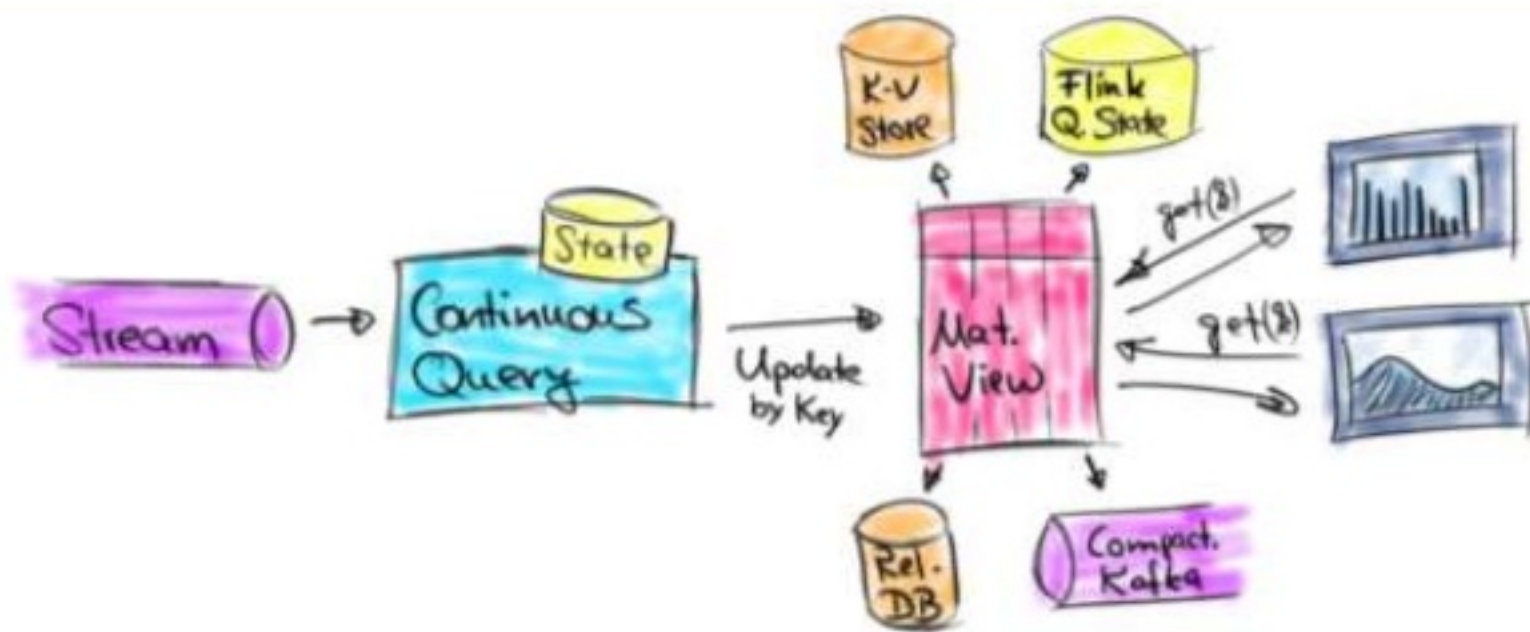
What can be built with this?



■ Continuous ETL

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

What can be built with this?

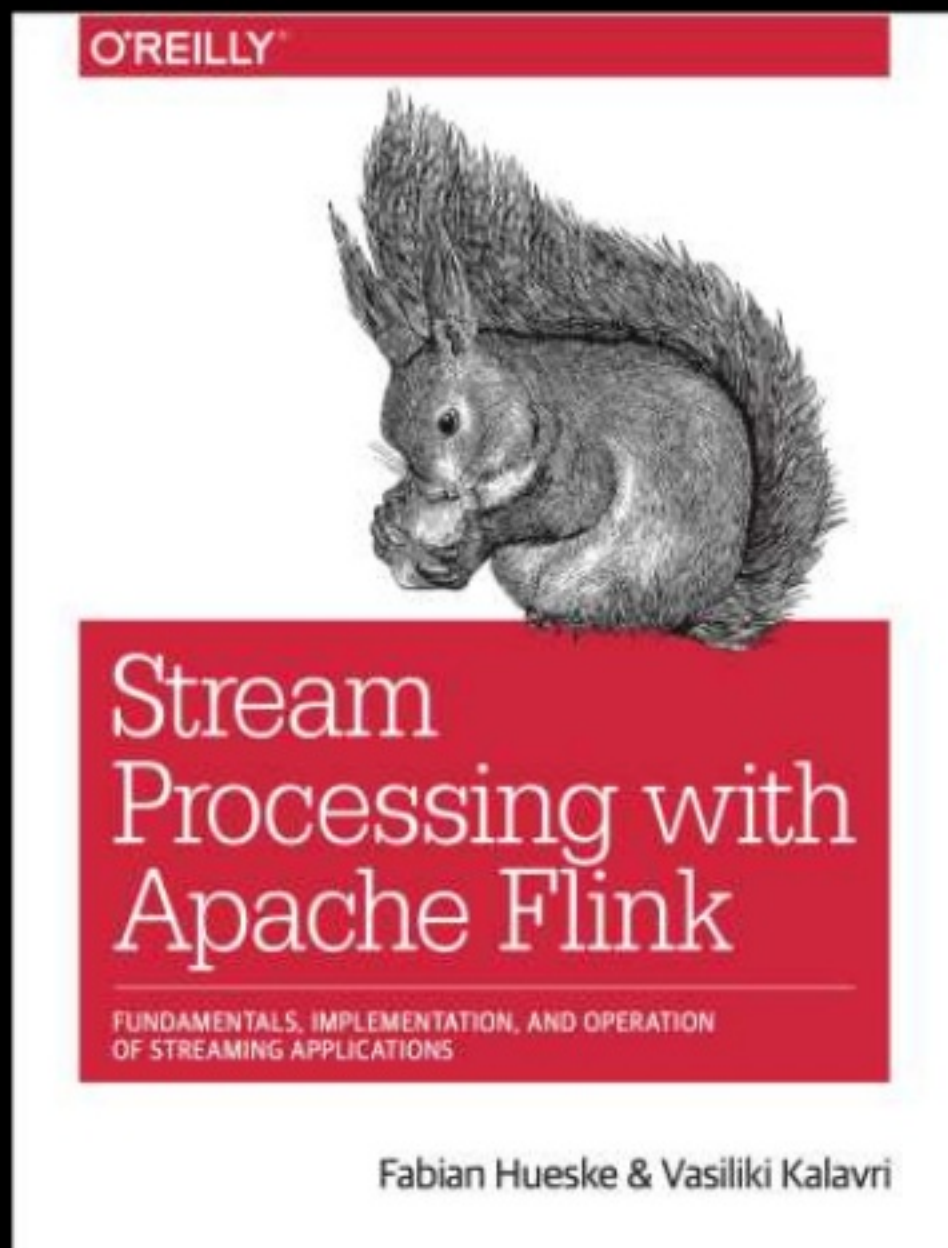


- Dashboards, reporting & event-driven architectures
 - Flink updates query results with low latency
 - Result can be written to KV store, DBMS, compacted Kafka topic
 - Maintain result table as queryable state

Wrap-up!



- 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!



Thank you!

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@ApacheFlink

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Available on O'Reilly Early Release!

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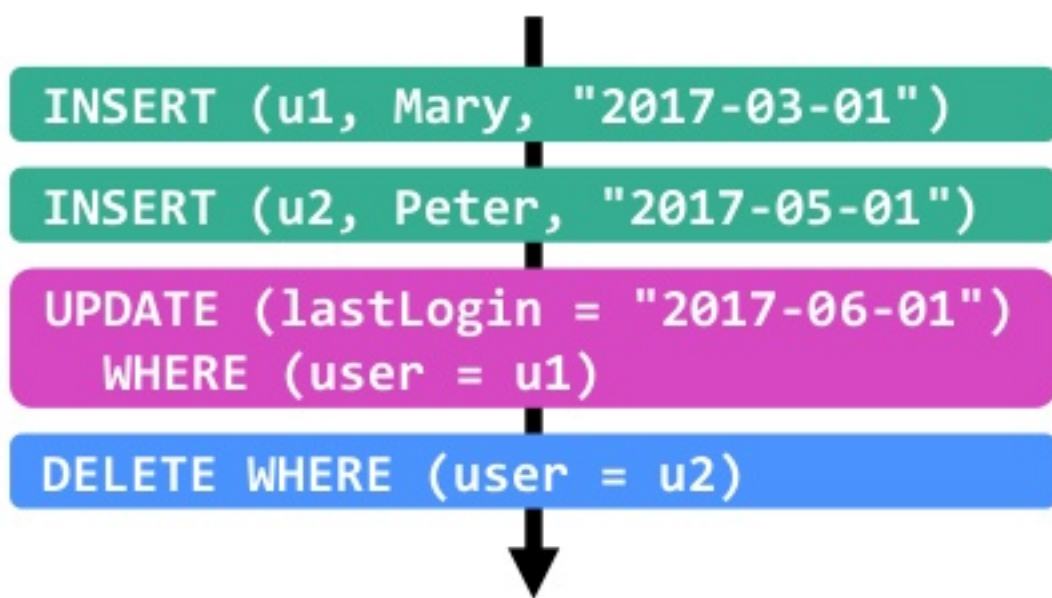
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Tables are materialized streams



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



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