Data Management
13 Stream Processing

Matthias Boehm

Graz University of Technology, Austria
Computer Science and Biomedical Engineering
Institute of Interactive Systems and Data Science
BMVIT endowed chair for Data Management

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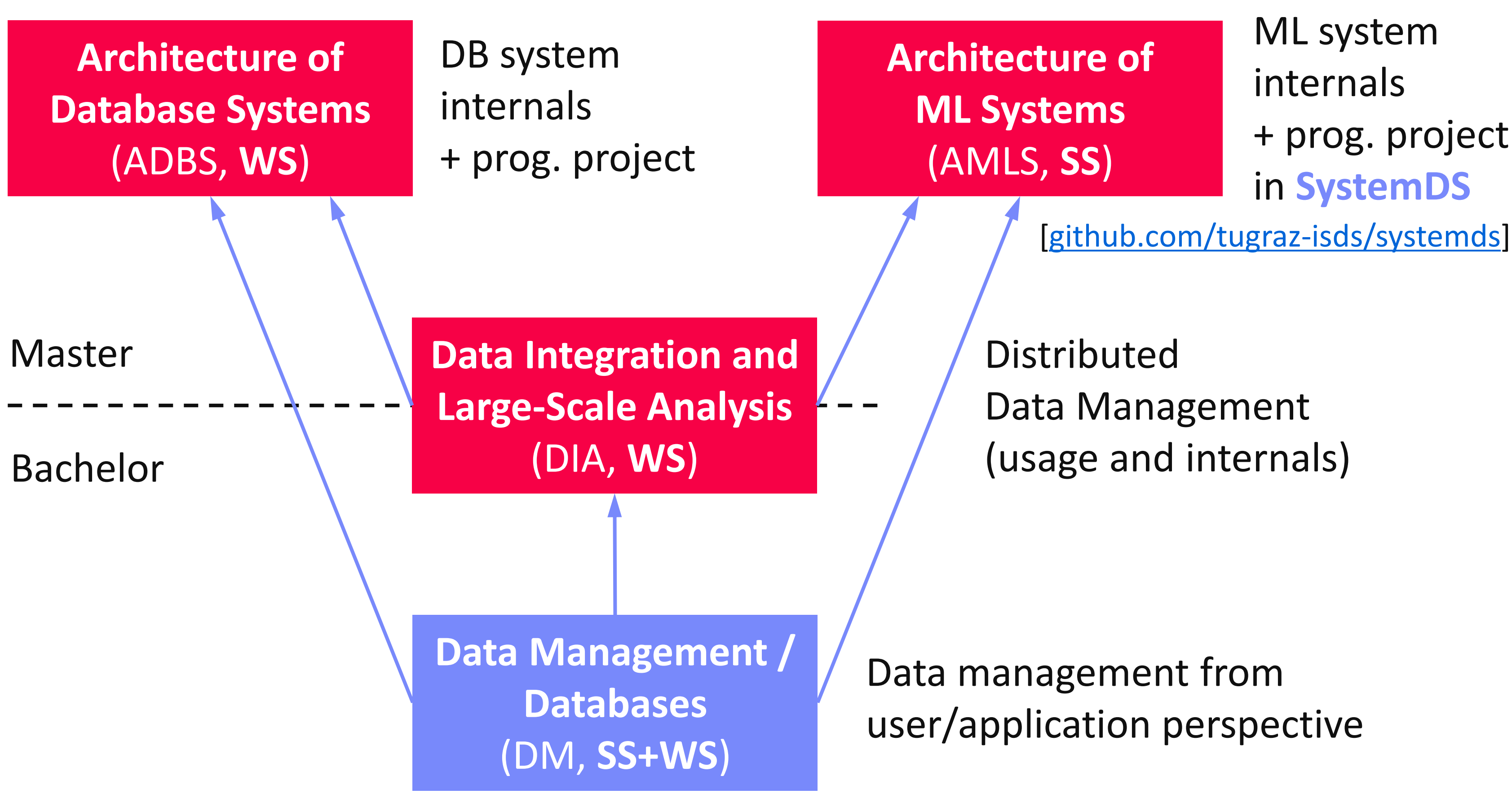
SCIENCE
PASSION
TECHNOLOGY

Announcements/Org

- **#1 Video Recording**
  - Link in TeachCenter & TUbe (lectures will be public)
- **#2 Exercises**
  - Exercise 1/2 graded, feedback in TC, office hours
  - **Exercise 3 in progress of being graded**
  - **Exercise 4 due Jan 21, 11.59pm**
- **#3 Course Evaluation**
  - Evaluation period: **Jan 14 – Feb 14**
  - Please, participate w/ honest feedback (pos/neg)
- **#4 Exam**
  - Dates: **Jan 30, 5.30pm**; **Jan 31, 5.30pm**; **Feb 6, 4pm**
  - Registration closes one day before exam
  - **Q&A and Exam Preparation** in today's lecture

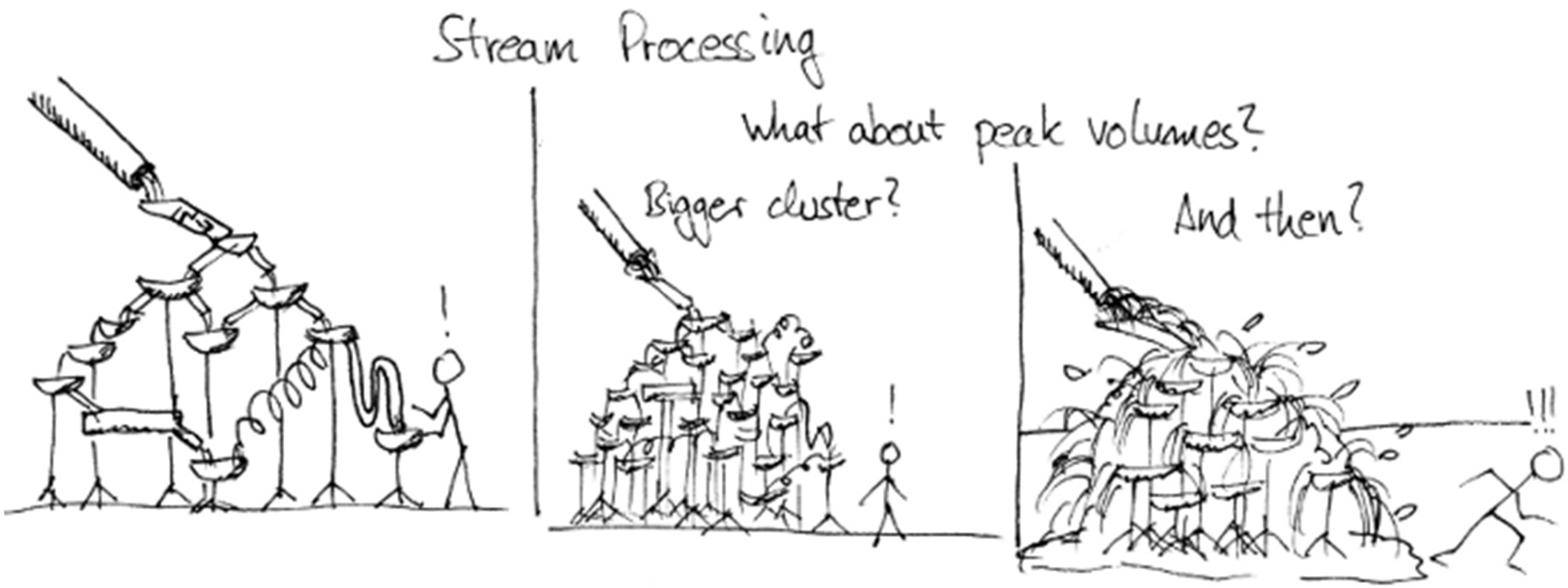
#5 Data Management Courses



Agenda

- **Data Stream Processing**
- ~~**Distributed Stream Processing**~~
- **Q&A and Exam Preparation**

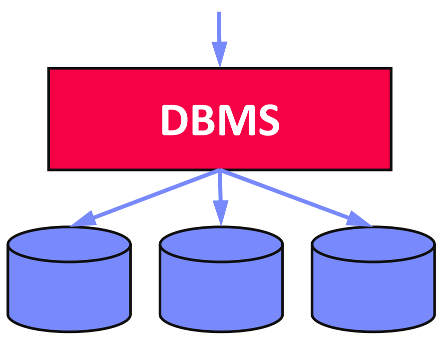
Data Integration and Large-Scale Analysis (DIA)
(bachelor/master)

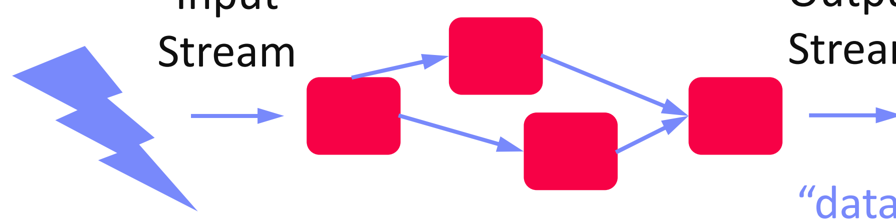


Data Stream Processing

Stream Processing Terminology

- **Ubiquitous Data Streams**
  - Event and message streams (e.g., click stream, twitter, etc)
  - Sensor networks, IoT, and monitoring (traffic, env, networks)
- **Stream Processing Architecture**
  - **Infinite input streams**, often with window semantics
  - Continuous (aka standing) queries





Stream Processing Terminology, cont.

- **Use Cases**
  - **Monitoring and alerting** (notifications on events / patterns)
  - **Real-time reporting** (aggregate statistics for dashboards)
  - **Real-time ETL** and event-driven data updates
  - Real-time decision making (fraud detection)
  - Data stream mining (summary statistics w/ limited memory)

Continuously active

- **Data Stream**
  - Unbounded stream of data tuples $S = (s_1, s_2, \ldots)$ with $s_i = (t_i, d_i)$
  - See **08 NoSQL Systems** (time series)
- **Real-time Latency Requirements**
  - **Real-time:** guaranteed task **completion by a given deadline** (30 fps)
  - **Near Real-time:** few milliseconds to seconds
  - In practice, used with much weaker meaning

History of Stream Processing Systems

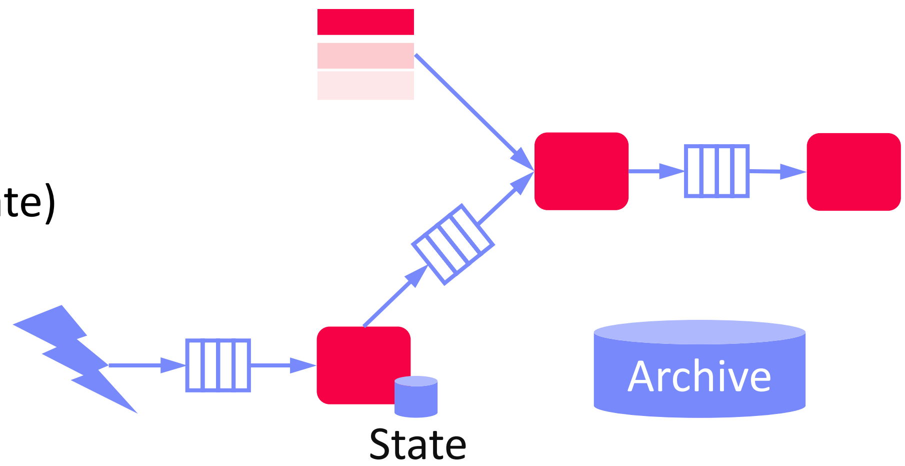
- **2000s**
  - **Data stream management systems** (DSMS, mostly academic prototypes): **STREAM** (Stanford'01), **Aurora** (Brown/MIT/Brandeis'02) → **Borealis** ('05), **NiagaraCQ** (Wisconsin), **TelegraphCQ** (Berkeley'03), and many others

    → but mostly unsuccessful in industry/practice
  - **Message-oriented middleware** and **Enterprise Application Integration** (EAI): IBM **Message Broker**, SAP **eXchange Infra.**, MS **Biztalk Server**, **TransConnect**

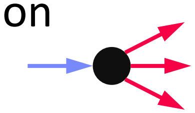
- **2010s**
  - **Distributed stream processing engines**, and "unified" batch/stream processing
  - **Proprietary systems:** Google Cloud Dataflow, MS StreamInsight / Azure Stream Analytics, IBM InfoSphere Streams / Streaming Analytics, AWS Kinesis
  - **Open-source systems:** **Apache Spark Streaming** (Databricks), **Apache Flink** (Data Artisans), **Apache Kafka** (Confluent), **Apache Storm**

System Architecture – Native Streaming

- **Basic System Architecture**
  - Data flow graphs (potentially w/ multiple consumers)
  - **Nodes:** asynchronous ops (w/ state) (e.g., separate threads)
  - **Edges:** data dependencies (tuple/message streams)
  - **Push model:** data production controlled by source



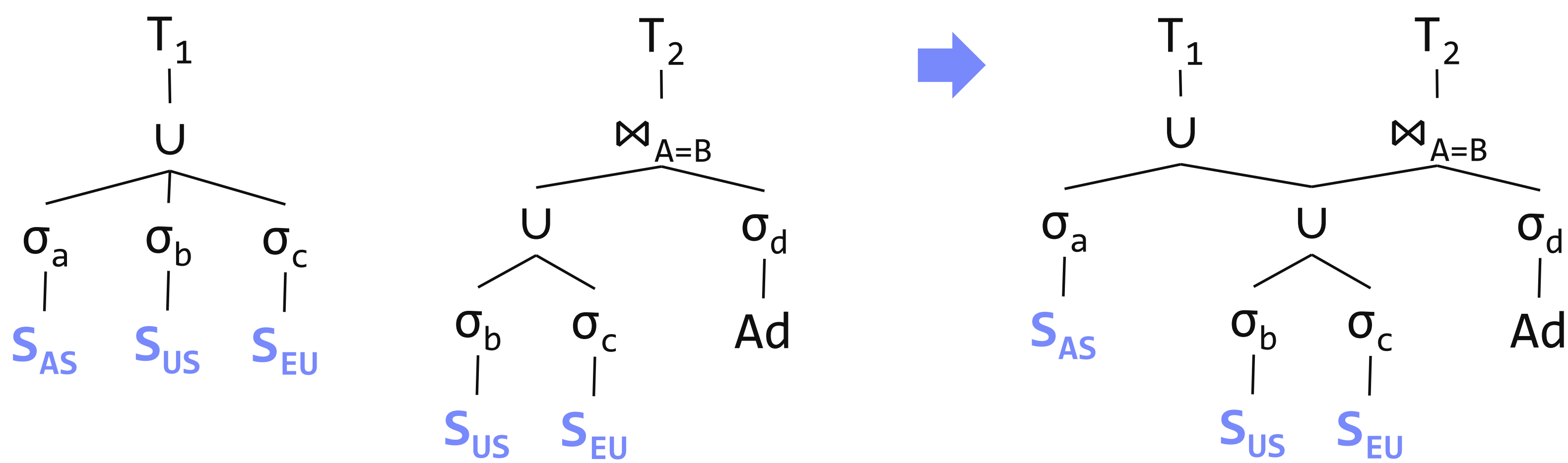
- **Operator Model**
  - Read from input queue
  - Write to potentially many output queues
  - Example Selection $\sigma_{A=7}$



```
while( !stopped ) {
   r = in.dequeue(); // blocking
   if( pred(r.A) )   // A==7
      for( Queue o : out )
         o.enqueue(r); // blocking
}
```

System Architecture – Sharing

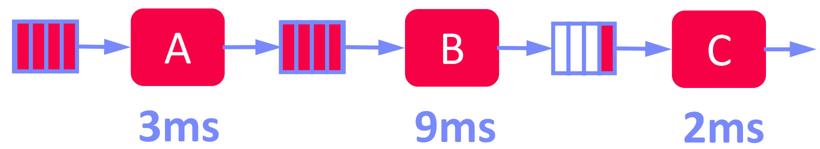
- **Multi-Query Optimization**
  - Given **set of continuous queries** (deployed), compile minimal DAG w/o redundancy (see **08 Physical Design MV**) → **subexpression elimination**



- **Operator and Queue Sharing**
  - **Operator sharing:** complex ops w/ multiple predicates for adaptive reordering
  - **Queue sharing:** avoid duplicates in output queues via masks

System Architecture – Handling Overload

- **#1 Back Pressure**
  - Graceful handling of overload w/o data loss
  - **Slow down sources**
  - E.g., blocking queues



Self-adjusting operator scheduling
Pipeline runs at rate of slowest op

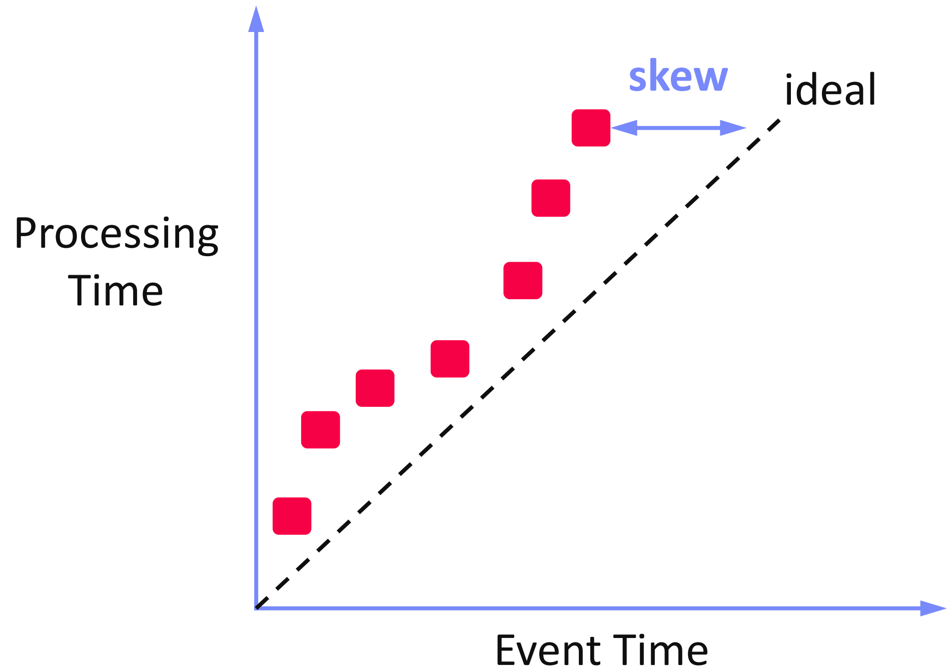
- **#2 Load Shedding**
  - #1 **Random-sampling**-based load shedding
  - #2 **Relevance-based** load shedding
  - #3 **Summary-based** load shedding (synopses)
  - Given SLA, select queries and shedding placement that minimize error and satisfy constraints

[Nesime Tatbul et al: Load Shedding in a Data Stream Manager. **VLDB 2003**]

- **#3 Distributed Stream Processing** (see course DIA)
  - Data flow partitioning (distribute the query)
  - Key range partitioning (distribute the data stream)

Time (Event, System, Processing)

- **Event Time**
  - Real time when the event/ data item was created
- **Ingestion Time**
  - System time when the data item was received
- **Processing Time**
  - System time when the data item is processed



- **In Practice**
  - Delayed and unordered data items
  - Use of heuristics (e.g., **water marks = delay threshold**)
  - Use of more complex triggers (**speculative and late results**)

Durability and Consistency Guarantees

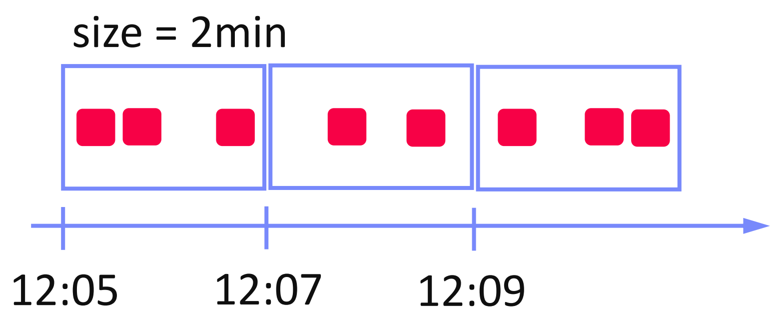
- **#1 At Most Once**
  - **“Send and forget”**, ensure data is never counted twice
  - Might cause data loss on failures

- **#2 At Least Once**
  - **“Store and forward”** or acknowledgements from receiver, replay stream from a checkpoint on failures
  - Might create incorrect state (processed multiple times)

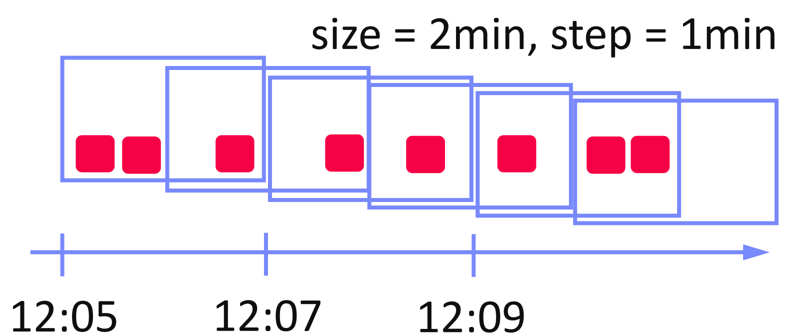
- **#3 Exactly Once**
  - **“Store and forward” w/ guarantees** regarding state updates and sent msgs
  - Often via dedicated transaction mechanisms

Window Semantics

- **Windowing Approach**
  - Many operations like joins/aggregation **undefined over unbounded streams**
  - Compute operations over **windows of time or elements**
- **#1 Tumbling Window**
  - Every data item is only part of a single window
  - Aka Jumping window



- **#2 Sliding Window**
  - Time- or tuple-based sliding windows
  - Insert new and expire old data items

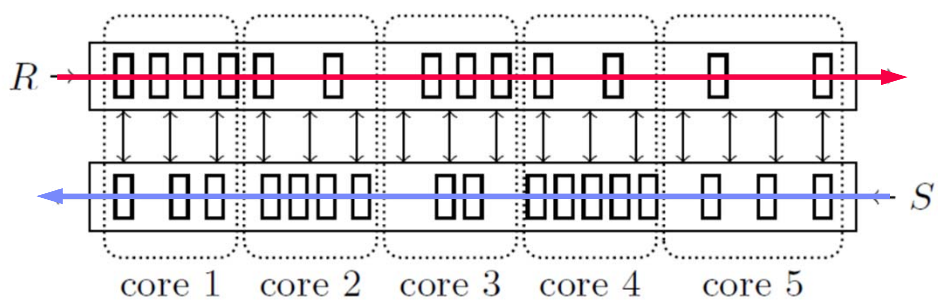


Stream Joins

- **Basic Stream Join**
  - **Tumbling window:** use classic join methods
  - **Sliding window** (symmetric for both R and S)
    - Applies to arbitrary join pred
    - See 08 Query Processing (NLJ)

```
For each new r in R:
   1. Scan window of stream S
      to find match tuples
   2. Insert new r into window
      of stream R
   3. Invalidate expired tuples
      in window of stream R
```

- **Excursus: How Soccer Players Would do Stream Joins**
  - Handshake-join w/ 2-phase forwarding

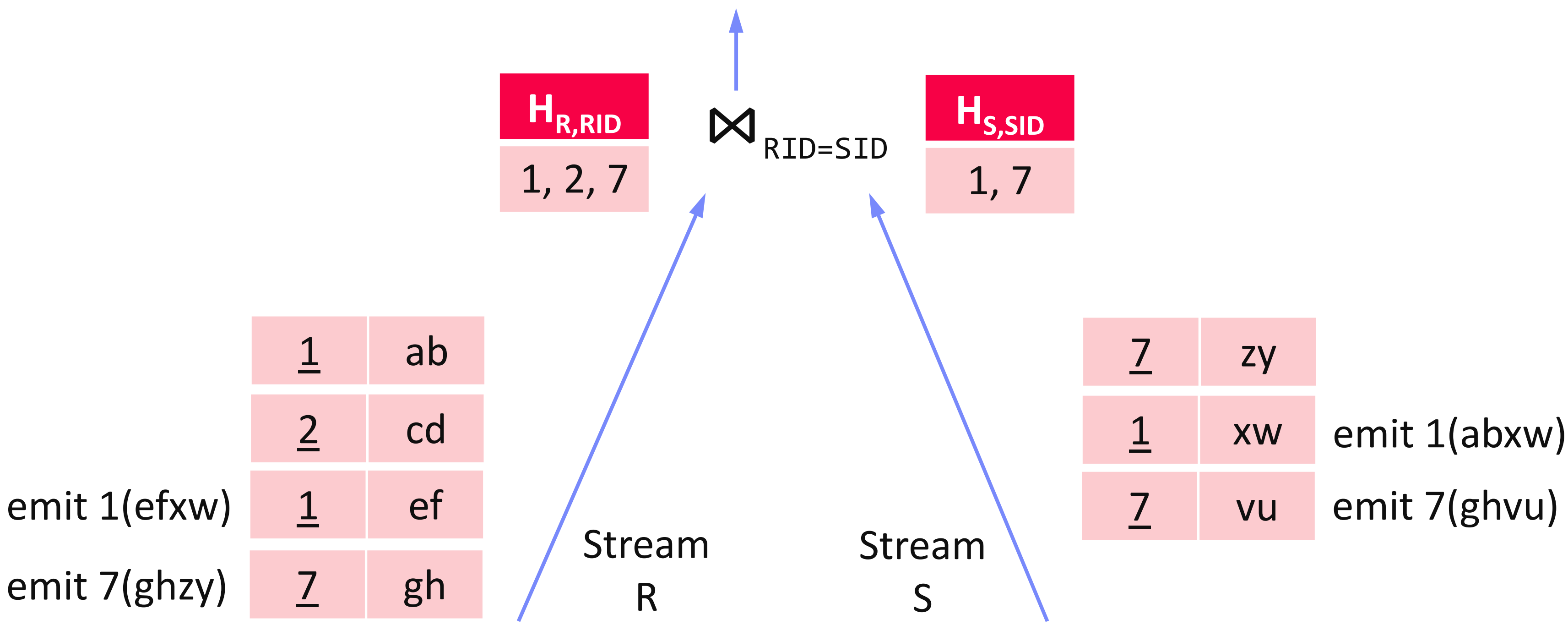


[Jens Teubner, René Müller: How soccer players would do stream joins. **SIGMOD 2011**]

Stream Joins, cont.

[Zachary G. Ives, Daniela Florescu, Marc Friedman, Alon Y. Levy, Daniel S. Weld: An Adaptive Query Execution System for Data Integration. **SIGMOD 1999**]

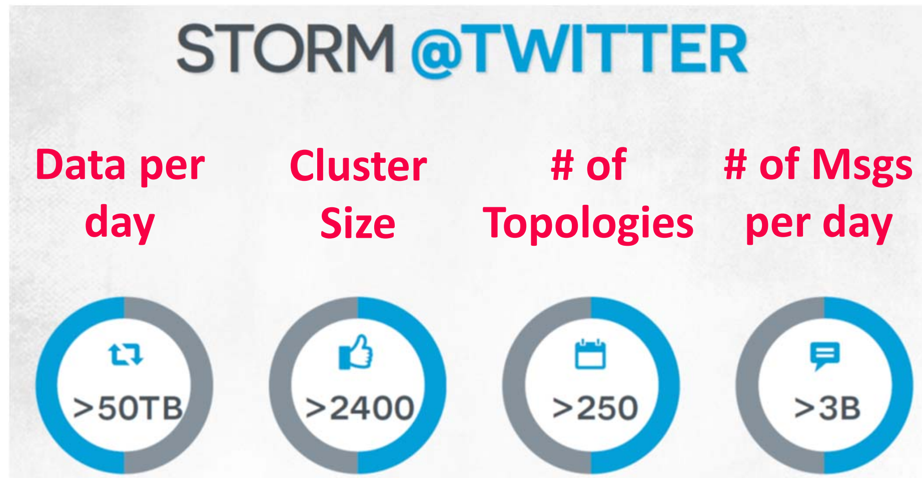
- **Double-Pipelined Hash Join**
  - Join of bounded streams (or unbounded w/ invalidation)
  - **Equi join predicate**, **symmetric and non-blocking**
  - For every incoming tuple (e.g. left): probe (right)+emit, and build (left)



Excursus: Example Twitter Heron

[**Credit:** Karthik Ramasamy]

- **Motivation**
  - **Heavy use of Apache Storm** at Twitter
  - Issues: **debugging**, **performance**, shared **cluster resources**, back pressure mechanism



- **Twitter Heron**
  - API-compatible distributed streaming engine
  - **De-facto streaming engine at Twitter** since 2014

[Sanjeev Kulkarni et al: Twitter Heron: Stream Processing at Scale. **SIGMOD 2015**]

- **Dhalion (Heron Extension)**
  - Automatically reconfigure Heron topologies to meet throughput SLO

[Avrilia Floratou et al: Dhalion: Self-Regulating Stream Processing in Heron. **PVLDB 2017**]

- **Now back pressure implemented in Apache Storm 2.0 (May 2019)**