Databases

Lecture 14

Data Streams

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Data Processing in Traditional DBMSs

- classical DBMSs answer the needs of traditional business applications
- finite data sets
- users execute queries on the database when necessary
- *one-shot* (*one-time*) query
    - executed on the current instance of the data (entirely stored)
    - finite time interval
    - specific to traditional DBMSs
- *human-active, DBMS-passive (HADP) model*
    - database - passive repository
    - users execute queries on the database when necessary

Data Processing in Traditional DBMSs

- triggers
  - *second-class citizens*
- only the current state of the data is important
  - current data values are easy to obtain, whereas previous values can be painstakingly extracted from the log
- queries provide exact answers
- applications don’t have real-time requirements

Data Streams

- in a range of applications, data cannot be efficiently managed with a classical DBMS, as information takes the form of the so-called *data streams*
- e.g., astronomy, meteorology, seismology, financial services, e-commerce, etc
- *data stream*
  - temporal sequence of values produced by a data source
  - potentially infinite
  - data arriving on the stream is associated with temporal values, i.e., *timestamps*

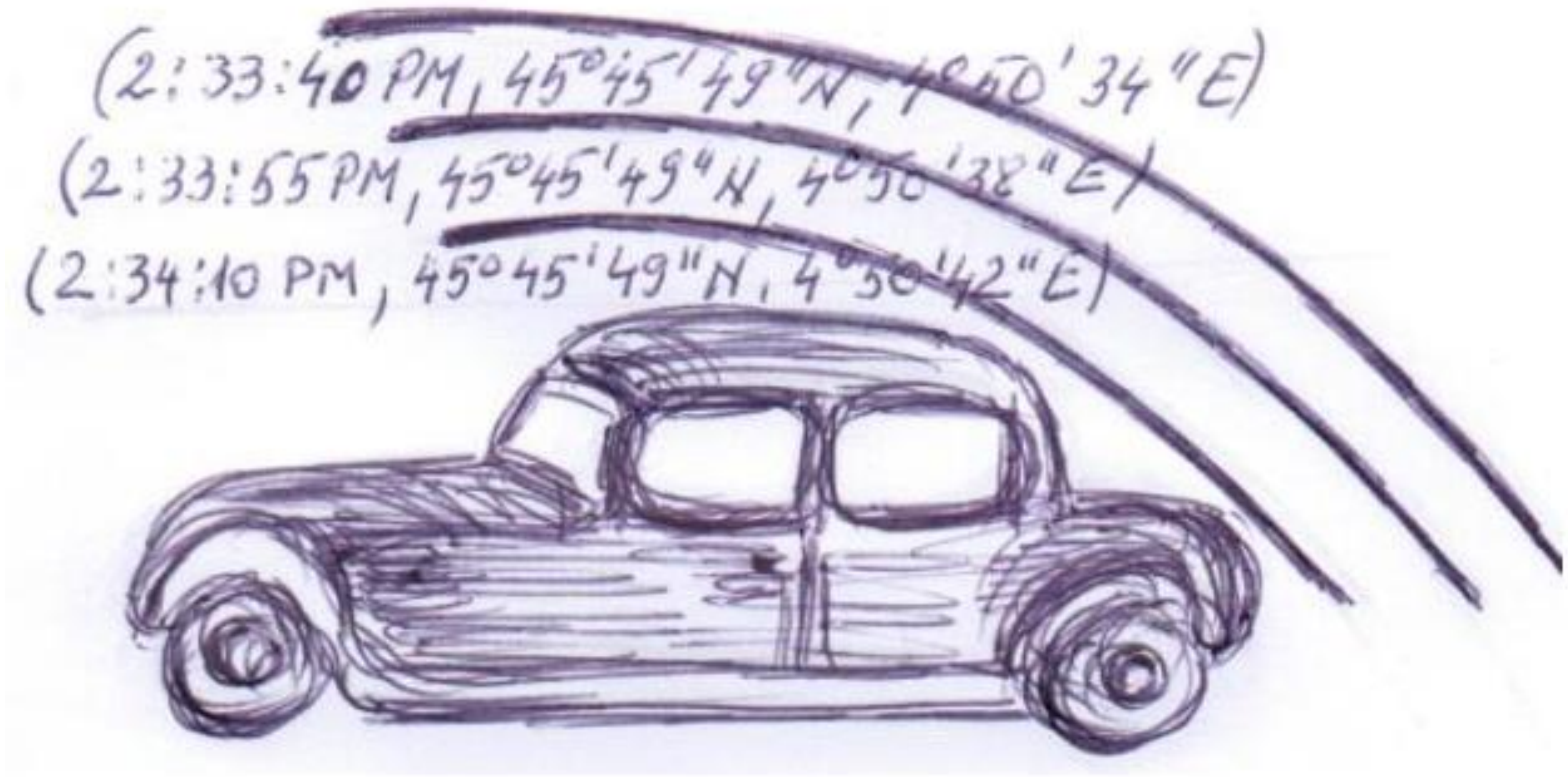
Data Streams

- examples
  - a sequence of values provided by a temperature sensor
  - a sequence of GPS coordinates emitted by a car as it runs on a highway
  - a sequence of values representing a patient's heart rate and blood pressure
- time - common element in the examples above
- *event*
  - elementary unit of information that arrives on a data stream (similar to a record in relational databases); synonyms in this lecture, unless otherwise noted - *tuple*, *element*
- systems discussed in this lecture – structured data streams

Data Streams

- *data source*
  - a device that provides a stream of values over time, in a digital format (a temperature sensor, a GPS device, a device that monitors a patient's heart, etc)

Data Streams



- 3 tuples on a stream of coordinates produced by the GPS device of a car
- the GPS emits the current location of the car (latitude and longitude) every 15 seconds

Data Stream Monitoring Applications

- *monitoring applications*
  - applications that scan data streams, process incoming values, and compute the desired result
- e.g., military applications, financial analysis applications, variable tolling applications, etc

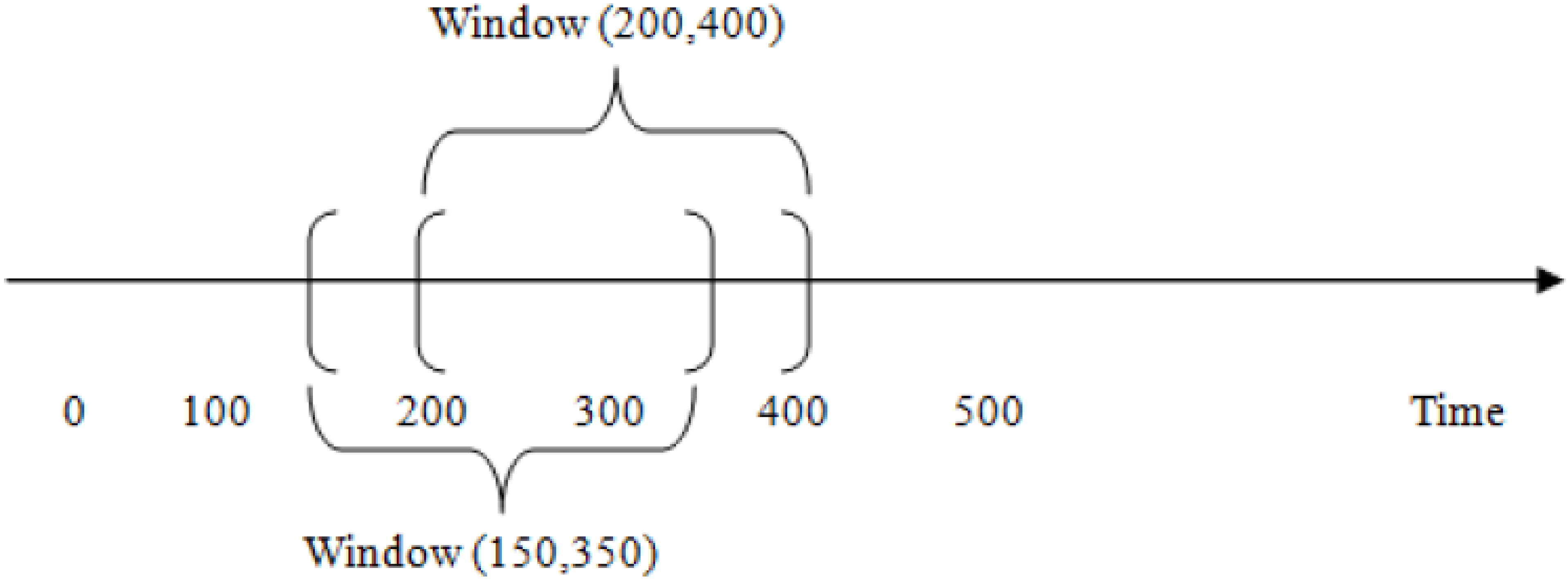
Window-Based Processing Model

- data streams
  - potentially infinite
  - high data rates
- traditional DBMSs
  - vast storage space, secondary memory
- systems that process streams
  - usually rely on the main memory
- storing all the data - impossible
- data arriving on a stream
  - instantaneously processed, then eliminated
- evaluating queries on data streams
  - window-based model

Window-Based Processing Model

- consider a temperature sensor in a refrigeration container; the user wants to be alerted whenever the temperature in the container exceeds a threshold 3 times in the last 10 minutes; it's enough to analyze the window of data that arrived on the stream in the previous 10 minutes; as time goes by and new tuples arrive on the stream, the window slides over the data in the stream
- *sliding window*
  - a contiguous portion of data from a stream
  - parameters
    - size - number of events / temporal instants
    - step size - number of events / temporal instants

Window-Based Processing Model



- sliding window
  - size = 200 timestamps
  - step size = 50 timestamps

Continuous Queries

- perpetually running queries, continuously producing results, while being fed with data from one or several streams
- provide real-time results, as required by many monitoring applications
  - e.g., variable tolling app that computes highway tolls based on dynamic factors such as accident proximity or traffic congestion
    - a driver must be alerted in real time whenever a new toll is issued for his or her car
    - providing this answer later in the future would be of no use
  - e.g., nuclear plant management

Continuous Queries

- share similarities with views / triggers
  - materialized views change as the underlying tables change
  - condition statements from triggers
  - one could add a large number of triggers to a DBMS and perform continuous processing in a traditional, although enhanced context
  - the literature shows that a classical DBMS doesn't scale well past a certain number of triggers, whereas a monitoring application could easily track hundreds of streams with a large number of running continuous queries

Continuous Queries

- continuous processing paradigm
  - *DBMS-active, human-passive (DAHP)*
  - database – active role
  - user – passive role

Data Stream Management Systems

- the number of data sources providing monitored streams can grow significantly
- stream rates can be uniform, but data can also arrive in bursts (e.g., a stream of clicks from the website of a company when a new product is launched)
- the number of continuous queries / monitored data streams can also fluctuate considerably
- the complexity of the running queries can vary over time
- as system resources are limited, the system can become overloaded and unable to provide real-time results
- traditional DBMSs cannot tackle these challenges, being unable to efficiently manage data streams; dedicated systems, that use various strategies to handle such problems, are being used instead

Data Stream Management Systems

- dedicated systems can execute continuous queries, while meeting the requirements of monitoring applications
- *Data Stream Management System*
  - system that processes streams of data in a perpetual manner, by running continuous queries
  - built around a query processing engine, which performs data manipulation operations
- academic prototypes
  - STREAM, Aurora, Borealis, etc
- commercial systems
  - Azure Stream Analytics

Data Stream Management Systems

- experimental results
  - a stream processing engine surpasses a traditional data processing engine in terms of performance when processing continuous and one-shot queries on streams and traditional data sets for a monitoring application

Classical Databases Versus Data Streams

- classical DBMSs
  - permanent elements
    - data
  - temporary elements
    - queries
- DSMSs
  - permanent elements
    - continuous queries
  - transient elements
    - data arriving on streams

STREAM - STandord stREam datA Manager

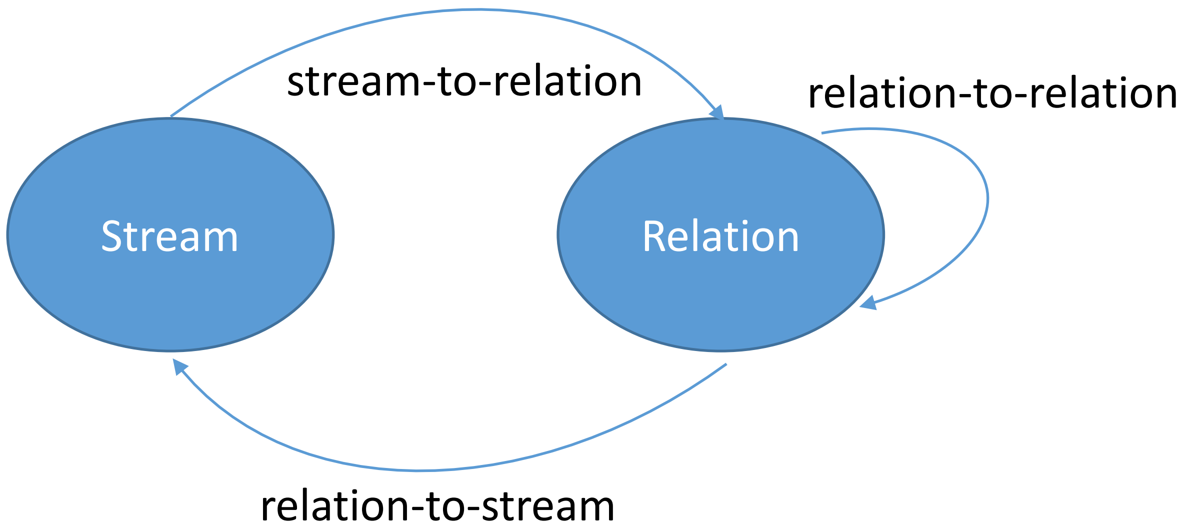
- DSMS prototype developed at Stanford
- objective
  - study data management and query processing in monitoring apps
- continuous queries on streams / stored data sets
- formal abstract semantics for continuous queries
- concrete declarative language, i.e., the Continuous Query Language (similar to SQL)

STREAM - abstract semantics

- 2 data types
  - streams and relations
- discrete, ordered time domain T
  - a timestamp t - a temporal moment from T
  - {0, 1, ...}
- data stream S
  - unbounded multiset of tuple-timestamp pairs <s, t>
  - fixed schema, named attributes
- relation R
  - time-varying multiset of tuples
  - R(t) - instantaneous relation (i.e., the multiset of tuples at time t)
  - fixed schema, named attributes

STREAM - abstract semantics

- 3 classes of operators
  - relation-to-relation
  - stream-to-relation
  - relation-to-stream



STREAM - abstract semantics

- *relation-to-relation* operator
  - takes one or several input relations and produces an output relation
- *stream-to-relation* operator
  - takes an input stream and produces an output relation
- *relation-to-stream* operator
  - takes an input relation and produces an output stream
- stream-to-stream operators can be defined using the 3 classes of operators from the semantics
- operator classes
  - black box components
  - the semantics depends on the generic properties of each class, not on the operators' implementations

STREAM - Continuous Query Language (CQL)

- minor extension of SQL
- defined by instantiating operators in the abstract semantics
- relation-to-relation operators
  - SQL constructs that transform several relations into a single relation
  - select, project, union, except, intersect, aggregate, etc
  - O_r - traditional relational operator over instantaneous input relations R_1, ..., R_n

  => corresponding relation-to-relation operator in CQL O_c produces the time-varying relation R; at timestamp t: $R(t) = O_r(R_1(t), ..., R_n(t))$

STREAM - Continuous Query Language

- stream-to-relation operators
  - extract a sliding window from a stream
  - window-specification language derived from SQL-99
- sliding window - 3 types
  - tuple-based sliding window
  - time-based sliding window
  - partitioned sliding window

STREAM - Continuous Query Language

- tuple-based sliding window
  - contains the last N tuples from the stream
  - S - stream, N - positive integer
  - S[Rows N] produces a relation R
  - at time t, R(t) contains the N tuples that arrived on S and have the largest timestamps <= t
  - special case
    - N = ∞
      - S[Rows Unbounded] - append-only window

STREAM - Continuous Query Language

- time-based sliding window
  - S - stream, ti - temporal interval
  - S[Range ti] produces a relation R
  - at time t, R(t) contains the tuples that arrived on S and have the timestamps between t-ti and t
  - special cases
    - ti = 0
      - i.e., the tuples on S with timestamp = t
      - S[Now]
    - ti = ∞
      - tuples obtained from the elements of S up to t
      - S[Range Unbounded]

STREAM - Continuous Query Language

- time-based sliding window
  - e.g., CarStream(CarID, Speed, Position, Direction, Road)
    - CarStream[Range 60 seconds]
    - CarStream[Now]
    - CarStream[Range Unbounded]

STREAM - Continuous Query Language

- partitioned sliding window
  - stream S, N - positive integer, $\{A_1, ..., A_k\}$ - attributes in S
  - S[Partition By $A_1, ..., A_k$ Rows N]
  - logically partition S into substreams based on specified attributes
  - compute a tuple-based sliding window of size N on each substream
  - compute the union of resulting windows to produce the output relation

  - e.g., CarStream(CarID, Speed, Position, Direction, Road)
    - CarStream[Partition By CarID Rows 1]

STREAM - Continuous Query Language

- relation-to-stream operators
- Istream (insert stream)
  - applied to a relation R, it contains <s, t> whenever s is in R(t) - R(t-1) (s is added to R at time t)
- Dstream (delete stream)
  - applied to a relation R, it contains <s, t> whenever s is in R(t-1) - R(t) (s is removed from R at time t)
- Rstream (relation stream)
  - applied to a relation R, it contains <s, t> whenever s is in R(t) (every current tuple in R is streamed at every time instant)

STREAM - Continuous Query Language

- example CQL queries
- CarStream(CarID, Speed, Position, Direction, Road)

- at any given time, display the set of active cars (i.e., having transmitted a position report in the past 60 seconds)

```
SELECT DISTINCT CarID
FROM CarStream[Range 60 Seconds]
```

- the result is a relation

STREAM - Continuous Query Language

- example CQL queries
- windowed join of 2 streams

```
SELECT *
FROM S1 [ROWS 200], S2 [RANGE 5 Minutes]
WHERE S1.Attr = S2.Attr AND S1.Attr < 500
```

- result = relation
- at every temporal instant t, the result contains the join (on *Attr*) of the last 200 tuples of *S*1 with the tuples that have arrived on S2 in the past 5 minutes; only tuples with *Attr* < 500 are part of the result

STREAM - Continuous Query Language

- example CQL queries
- stream containing new *Attr* values, as they appear in the join

```
SELECT Istream(S1.Attr)
FROM S1 [ROWS 200], S2 [RANGE 5 Minutes]
WHERE S1.Attr = S2.Attr AND S1.Attr < 500
```

- result = stream

STREAM - Continuous Query Language

- example CQL queries
- SegmentSpeedStream(segment, road, dir, speed, ...)

- display, at any given time, the set of congested road segments, i.e., segments for which the avg. speed of cars in the past 10 min is below 70 kph

```
SELECT segment, road, dir
FROM SegmentSpeedStream[Range 10 Minutes]
GROUP BY segment, road, dir
HAVING AVG(speed) < 70
```

STREAM - Continuous Query Language

- example CQL queries
- SegmentSpeedStream(CarID, Segment, Road, Dir, Speed)

- display the current road segments for all active vehicles

```
SELECT DISTINCT U.CarID, U.Segment, U.Road, U.Dir
FROM SegmentSpeedStream[Range 60 Seconds] A,
 SegmentSpeedStream[Partition By CarID Rows 1] U
WHERE A.CarID = U.CarID
```

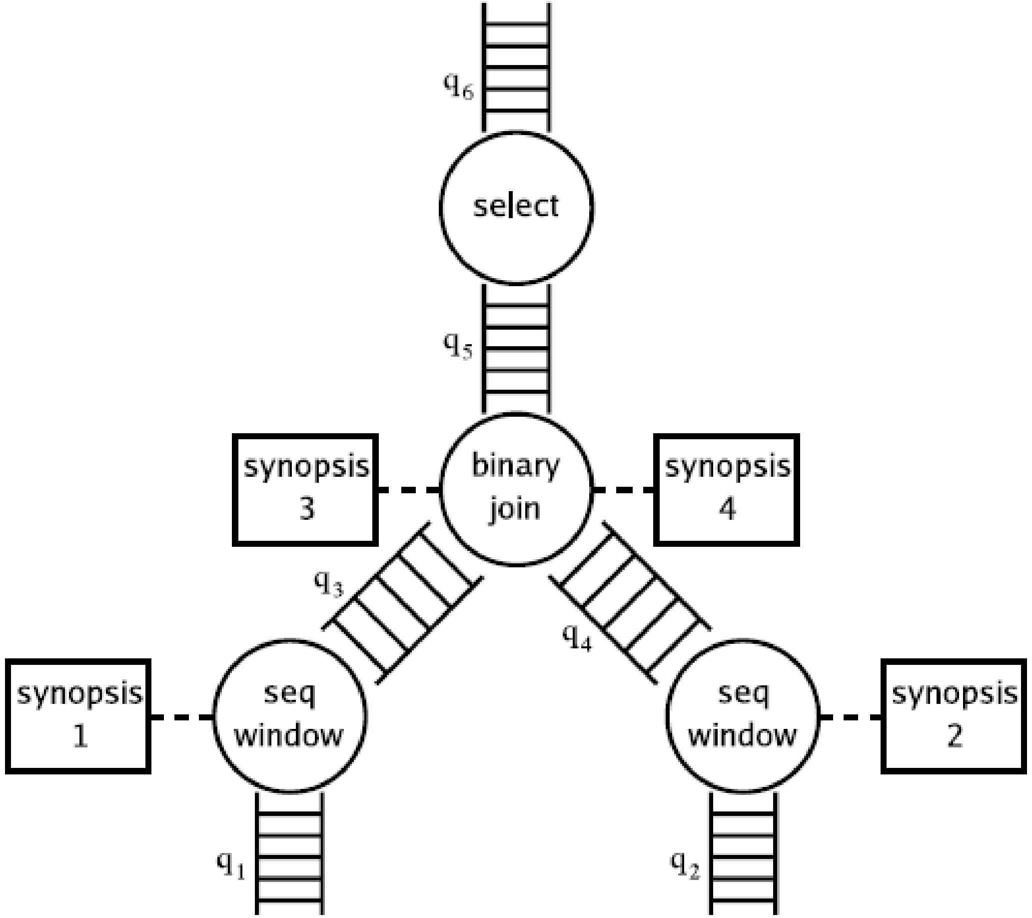
- result = relation

STREAM – execution plans

- when registered with the system, a CQL query is compiled into a physical query plan
- plan
  - tree structure
  - operators
    - perform the processing
  - inter-operator queues
    - hold elements as they move between operators
  - synopses attached to operators
    - store state when necessary, e.g., a join of 2 windows
    - operators that don't require a synopsis
      - selection, duplicate-preserving union, etc
  - leaves - inputs; root operator - computes the result of the query

STREAM – execution plans

```
SELECT *
FROM S1 [ROWS 200], S2 [RANGE 5 Minutes]
WHERE S1.Attr = S2.Attr AND S1.Attr < 500
```



STREAM - maybe in 2 years from now (Master's Programmes) :)

- sharing data & computation within and across execution plans
- exploiting stream constraints - ordering, clustering, etc
- load-shedding
- etc.

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