

Databases

Lecture 14

Query Optimization in Relational Databases. Evaluating Relational Algebra Operators
Data Streams

SQL Statements Execution

- client application - SQL statement execution request
 - for any query - minimum response time
- statement execution - stages:
 - client: generate SQL statement (non-procedural language), send it to server
 - server:
 - analyze SQL statement (syntactically)
 - translate statement into an internal form (relational algebra expression)
 - transform internal form into an optimal form
 - generate a procedural execution plan
 - evaluate procedural plan, send result to client

- the following operators are necessary in the querying process:
 - selection: $\sigma_C(R)$
 - projection: $\pi_\alpha(R)$
 - cross-product: $R_1 \times R_2$
 - union: $R_1 \cup R_2$
 - set-difference: $R_1 - R_2$
 - intersection: $R_1 \cap R_2$
 - theta join: $R_1 \otimes_\Theta R_2$
 - natural join: $R_1 * R_2$
 - left outer join: $R_1 \bowtie_C R_2$
 - right outer join: $R_1 \bowtie_C R_2$
 - full outer join: $R_1 \bowtie_C R_2$
 - left semi join: $R_1 \triangleright R_2$
 - right semi join: $R_1 \triangleleft R_2$
 - division: $R_1 \div R_2$
 - duplicate elimination: $\delta(R)$
 - sorting: $S_{\{list\}}(R)$
 - grouping: $\gamma_{\{list1\} \text{ group by } \{list2\}}(R)$

- an SQL query can be written in multiple ways
- example for a relational database
- primary keys are underlined, foreign keys are written in blue
programs[id, pname, pdescription]
groups[id, **program**, yearofstudy, gdescription]
students[cnp, lastname, firstname, **sgroup**, gpa, addr, email]
- query: find students (lastname, firstname, year of study, program name, gpa) in a given program (e.g., with id = 2, can be a parameter), with a gpa >= 9 (can be a parameter):

a)

```
SELECT lastname, firstname, yearofstudy, pname, gpa
FROM students st, groups gr, programs pr
WHERE st.sgroup = gr.id AND gr.program = pr.id
      AND program = 2 and gpa >= 9
```

b)

```
SELECT lastname, firstname, yearofstudy, pname, gpa
FROM (students st INNER JOIN groups gr ON
      st.sgroup = gr.id)
      INNER JOIN programs pr ON gr.program = pr.id
WHERE program = 2 AND gpa >= 9
```

c)

```
SELECT lastname, firstname, yearofstudy, pname, gpa  
FROM
```

```
(
```

```
  (SELECT lastname, firstname, sgroup, gpa  
    FROM students
```

```
    WHERE gpa >= 9) st
```

```
INNER JOIN
```

```
  (SELECT * FROM groups WHERE program = 2) gr  
    ON st.sgroup = gr.id
```

```
)
```

```
INNER JOIN
```

```
  (SELECT id, pname FROM programs WHERE id = 2) pr
```

```
ON gr.program = pr.id
```

- the previous query versions are equivalent (they provide the same answer)
- equivalent relational algebra expressions:

a.

$$\pi_{\beta}(\sigma_C(students \times groups \times programs))$$

b.

$$\pi_{\beta}(\sigma_{C_1}((students \otimes_{C_2} groups) \otimes_{C_3} programs))$$

c.

$$\pi_{\beta}(((\pi_{\beta_1}(\sigma_{C_2}(students))) \otimes_{C_3} (\sigma_{C_4}(groups))) \otimes_{C_5} (\pi_{\beta_2}(\sigma_{C_6}(programs))))$$

- an evaluation tree can be constructed for a relational algebra expression
- problems:
 - which version is better?
 - when generating the execution plan:
 - which parameters are optimized?
 - what information is required?
 - what can the optimizer (DBMS component) do?

Relational Algebra Operators - Evaluation

- operands for relational operators:
 - database tables (can have attached indexes)
 - temporary tables (obtained by evaluating some relational operators)
- several evaluation algorithms can be used for a relational algebra operator
- when generating the execution plan:
 - choose the algorithm with the lowest complexity (for the current database context); take into account data from the system catalog, statistical information

- a join can be defined as a cross-product followed by a selection
- joins arise more often in practice than cross-products
- in general, the result of a cross-product is much larger than the result of a join
- it's important to implement the join without materializing the underlying cross-product, by applying selections and projections as soon as possible, and materializing only the subset of the cross-product that will appear in the result of the join

Cross Join

- this algorithm is used to evaluate a cross-product:
 - R CROSS JOIN S
 - R INNER JOIN S ON C (C evaluates to TRUE)
 - SELECT ... FROM R, S ..., no join condition between R and S
- b_R, b_S
 - the number of blocks storing R and S, respectively
- m, n
 - the number of blocks from R and S that can simultaneously appear in the main memory (there are m+n buffers for the 2 tables)

Cross Join

- the following algorithm can be used to generate the cross-product $\{(r, s) \mid r \in R, s \in S\}$:
- for every group of max. m blocks in R :
 - read the group of blocks from R into main memory; let M_1 be the set of records in these blocks
 - for every group of max. n blocks in S :
 - read the group of blocks from S into main memory; let M_2 be the set of records in these blocks
 - for every $r \in M_1$:
 - for every $s \in M_2$: add (r, s) to the result

Cross Join

- algorithm complexity: total number of read blocks (from the 2 tables):

$$b_R + \left\lceil \frac{b_R}{m} \right\rceil * b_S \quad (1)$$

(number of blocks in R; for every group of max. m blocks in R, read S)

- to minimize this value, m should be maximized (the other operands are constants); one buffer can be used for S (so n = 1), while the remaining space can be used for R (m max.)
- switch the 2 relations (in the algorithm and when computing the complexity)
=> complexity:

$$b_S + \left\lceil \frac{b_S}{n} \right\rceil * b_R \quad (2)$$

- choose better version
- obs.: if $b_R \leq m$ or $b_S \leq n \Rightarrow$ complexity $b_R + b_S$

Nested Loops Join

- the Cross Join algorithm can be used to evaluate a join between 2 tables
- for every element (r, s) in the cross-product, evaluate the condition in the join operator
- elements (r, s) that don't meet the join condition are eliminated

Indexed Nested Loops Join

- this algorithm is used to evaluate $R \bowtie_C S$, where $C \equiv (R.A=S.B)$, and there is an index on A (in R) or on B (in S)
- in the algorithm description below, we assume there is an index on column B in table S
- for every block in R:
 - read the block into main memory; let M be the set of records in the block
 - for every $r \in M$:
 - determine $v = \pi_A(r)$
 - use the index on B in S to determine records $s \in S$ with value v for B; for every such record s, the pair (r,s) is added to the result
- obs.: depending on the type of index - at most 1 / multiple matching records in S

Merge Join

- this algorithm is used to evaluate $R \bowtie_C S$, where $C \equiv (R.A=S.B)$, and there are no indexes on A (in R) and B (in S)
- sort R and S on the columns used in the join: R on A, S on B
- scan obtained tables; let r in R and s in S be 2 current records
 - if $r.A = s.B$: add (r', s') to the result; r' is in the set of all consecutive records in R with $A = r.A$, similarly for s' in S; $\text{next}(r)$; $\text{next}(s)$ (get a record with the next value for A and B)
 - if $r.A < s.B$: $\text{next}(r)$ (determine record in sorted R with the next value for A)
 - if $r.A > s.B$: $\text{next}(s)$ (determine record in sorted S with the next value for B)

Relational Algebra Equivalences

- SQL statement - transformed into a relational algebra expression (based on a set of transformation rules for the clauses that appear in the statement)
- transform relational expression (such that the evaluation algorithm has a lower complexity)
- certain transformation rules are used (mathematical properties of the relational operators)

$$* \sigma_C(\pi_\alpha(R)) = \pi_\alpha(\sigma_C(R))$$

- selection reduces the number of records for projection; in the second expression, the projection operator analyzes fewer records
- optimization - algorithm that evaluates both operators in a single pass of R

* perform one pass instead of 2:

$$\sigma_{C_1}(\sigma_{C_2}(R)) = \sigma_{C_1 \text{ AND } C_2}(R)$$

* replace cross-product and selection by condition join (a number of condition join algorithms don't evaluate the cross-product):

$$\sigma_C(R \times S) = R \bowtie_C S$$

, where C - join condition between R and S

* R and S - compatible schemas:

$$\sigma_C(R \cup S) = \sigma_C(R) \cup \sigma_C(S)$$

$$\sigma_C(R \cap S) = \sigma_C(R) \cap \sigma_C(S)$$

$$\sigma_C(R - S) = \sigma_C(R) - \sigma_C(S)$$

* $\sigma_C(R \times S)$

particular cases:

- C contains only attributes from R:

$$\sigma_C(R \times S) = \sigma_C(R) \times S$$

- $C = C1 \text{ AND } C2$, $C1$ contains only attributes from R, $C2$ - only attributes from S:

$$\sigma_{C1 \text{ AND } C2}(R \times S) = \sigma_{C1}(R) \times \sigma_{C2}(S)$$

- $C = C1 \text{ AND } C2$, $C2$ - join condition between R and S:

$$\sigma_{C1 \text{ AND } C2}(R \times S) = \sigma_{C1}(R \bowtie_{C2} S)$$

* $\pi_{\alpha}(R \cup S) = \pi_{\alpha}(R) \cup \pi_{\alpha}(S)$

* $\pi_{\alpha}(R \otimes_C S) = \pi_{\alpha}(\pi_{\alpha_1}(R) \otimes_C \pi_{\alpha_2}(S))$

- α_1 : attributes in R that appear in α or C
- α_2 : attributes in S that appear in α or C

* associativity and commutativity for some relational operators

- associativity and commutativity for \cup and \cap
- associativity for the cross-product and the natural join
- "equivalent" results (same records, but different column order) when commuting operands in \times and certain join operators
 - $R \times S = S \times R$ – when using the Cross Join algorithm, the order of the data sources is important

* transitivity of some relational operators for the join operators - additional filters could be applied before the join:

- $(A > B \text{ AND } B > 3) \equiv (A > B \text{ AND } B > 3 \text{ AND } A > 3)$

- example: A is in R, B is in S:

$$R \otimes_{A > B \text{ AND } B > 3} S = (\sigma_{A > 3}(R)) \otimes_{A > B} (\sigma_{B > 3}(S))$$

- $(A = B \text{ AND } B = 3) \equiv (A = B \text{ AND } B = 3 \text{ AND } A = 3)$

- example: A is in R, B is in S:

$$R \otimes_{A = B \text{ AND } B = 3} S = (\sigma_{A = 3}(R)) \otimes_{A = B} (\sigma_{B = 3}(S))$$

* evaluating $\sigma_C(R)$, where $C \equiv (R.A \in \delta(\pi_{\{B\}}(S)))$; avoid evaluating C for every record of R; the initial evaluation is equivalent to:

$$R \otimes_{R.A = S.B} (\delta(\pi_{\{B\}}(S)))$$

- consider again the query described on the database:
programs[id, pname, pdescription]
groups[id, program, yearofstudy, gdescription]
students[cnp, lastname, firstname, sgroup, gpa, addr, email]
- query: find students (lastname, firstname, year of study, program name, gpa) in a given program (e.g., with id = 2), with a gpa ≥ 9 :

```
SELECT lastname, firstname, yearofstudy, pname, gpa
FROM students, groups, programs
WHERE students.sgroup = groups.id AND
      groups.program = programs.id AND
      program = 2 and gpa  $\geq$  9
```

- denote by:

$C \equiv (\text{students.sgroup} = \text{groups.id} \text{ AND } \text{groups.program} = \text{programs.id} \text{ AND } \text{program} = 2 \text{ and } \text{gpa} \geq 9)$

$\beta = \{\text{lastname}, \text{firstname}, \text{yearofstudy}, \text{pname}, \text{gpa}\}$ – attributes in the SELECT clause

- the corresponding relational expression:

$$\pi_{\beta}(\sigma_C(\text{students} \times \text{groups} \times \text{programs}))$$

* carry out the following transformations, using previously discussed rules:

- associativity for \times :

$students \times groups \times programs = (students \times groups) \times programs$ or

$students \times groups \times programs = students \times (groups \times programs)$

- commute σ with \times (a particular case); use the transitivity of the equality operator:

$(groups.program = programs.id \text{ AND } program = 2)$

$\equiv (groups.program = programs.id \text{ AND } program = 2 \text{ AND } programs.id = 2)$

students.sgroup = groups.id AND groups.program = programs.id AND program = 2 AND gpa >= 9 AND programs.id = 2				
C1	C2	C3	C4	C5

$\sigma_C(students \times groups \times programs) =$

$\sigma_{C1 \text{ AND } C2}((\sigma_{C4}(students) \times \sigma_{C3}(groups)) \times \sigma_{C5}(programs))$ or

$\sigma_{C1 \text{ AND } C2}(\sigma_{C4}(students) \times (\sigma_{C3}(groups) \times \sigma_{C5}(programs)))$

- replace selection and cross-product with condition join:

$$= ((\sigma_{c_4}(students)) \otimes_{c_1} (\sigma_{c_3}(groups))) \otimes_{c_2} (\sigma_{c_5}(programs))$$

or

$$= (\sigma_{c_4}(students)) \otimes_{c_1} ((\sigma_{c_3}(groups)) \otimes_{c_2} (\sigma_{c_5}(programs)))$$

- choose a version based on statistical information from the database; we consider the first version:

$$\Rightarrow e = \pi_{\beta}(((\sigma_{c_4}(students)) \otimes_{c_1} (\sigma_{c_3}(groups))) \otimes_{c_2} (\sigma_{c_5}(programs)))$$

- commute π with join:

$\beta 1 = \{\text{lastname, firstname, gpa, sgroup}\}$ - useful for β and join

$\beta 2 = \{\text{id, program, yearofstudy}\}$ - useful for β and join

$\beta 3 = \{\text{id, pname}\}$ - useful for β and join

$$e = \pi_{\beta}(((\pi_{\beta 1}(\sigma_{c_4}(students))) \otimes_{c_1} (\pi_{\beta 2}(\sigma_{c_3}(groups)))) \otimes_{c_2} (\pi_{\beta 3}(\sigma_{c_5}(programs))))$$

- the last expression corresponds to the statement:

```
SELECT lastname, firstname, yearofstudy, pname, gpa
```

```
FROM
```

```
(
```

```
(SELECT lastname, firstname, gpa, sgroup FROM students WHERE gpa >= 9) st
```

```
INNER JOIN
```

```
(SELECT id, program, yearofstudy FROM groups WHERE program = 2) gr
```

```
ON st.sgroup = gr.id
```

```
)
```

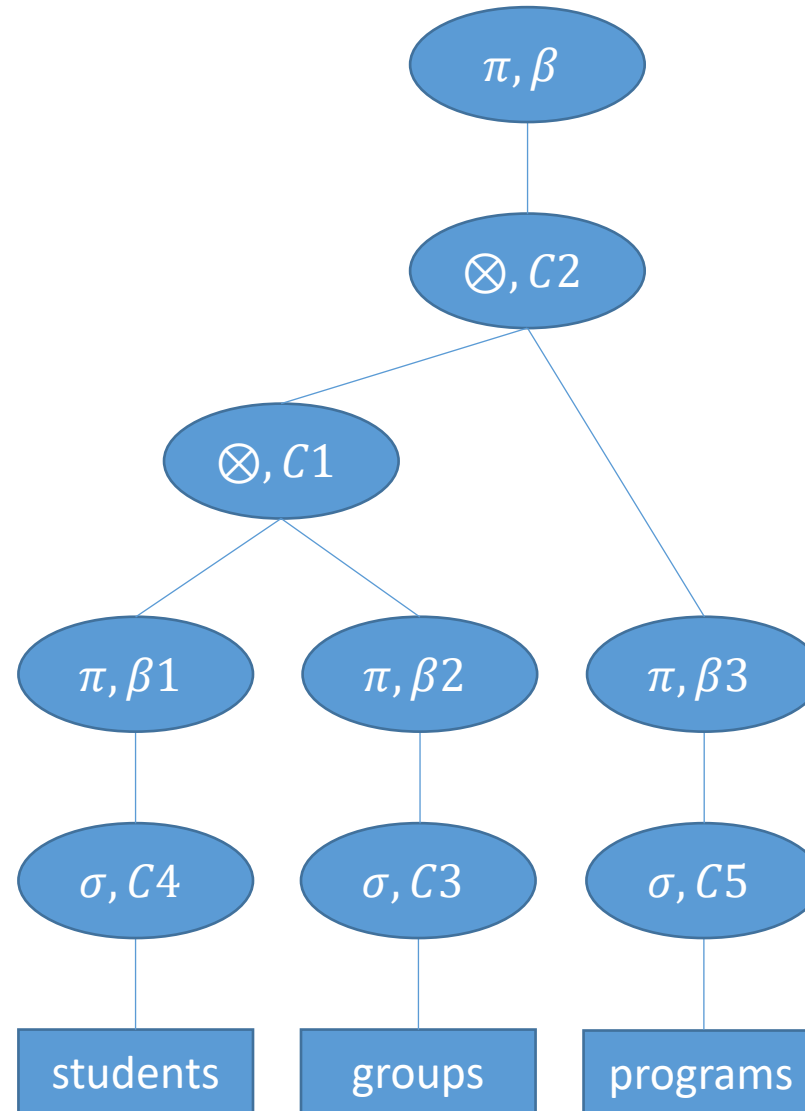
```
INNER JOIN
```

```
(SELECT id, pname FROM programs WHERE programs.id = 2) pr
```

```
ON gr.program = pr.id
```

- an evaluation tree can be constructed for the last version of the relational algebra expression

- using information from the system catalog and possibly statistical information, an execution plan can be generated from the last version of the expression; every relational operator is replaced by an evaluation algorithm



* Let P, Q, R be 3 relations with schemas P[PID, P1, P2, P3], Q[QID, Q1, Q2, Q3, Q4, Q5], R[RID, R1, R2, R3], and E an expression in the relational algebra:

$$E = \pi_{\{P2, Q2, Q4, R3\}} (\sigma_{PID = Q1 \text{ AND } QID = R2 \text{ AND } P3 = 'Bilbo' \text{ AND } Q5 = 100 \text{ AND } R1 = 7} (P \times Q \times R))$$

Optimize E and draw the evaluation tree for the optimized version of the expression.

Data Streams

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

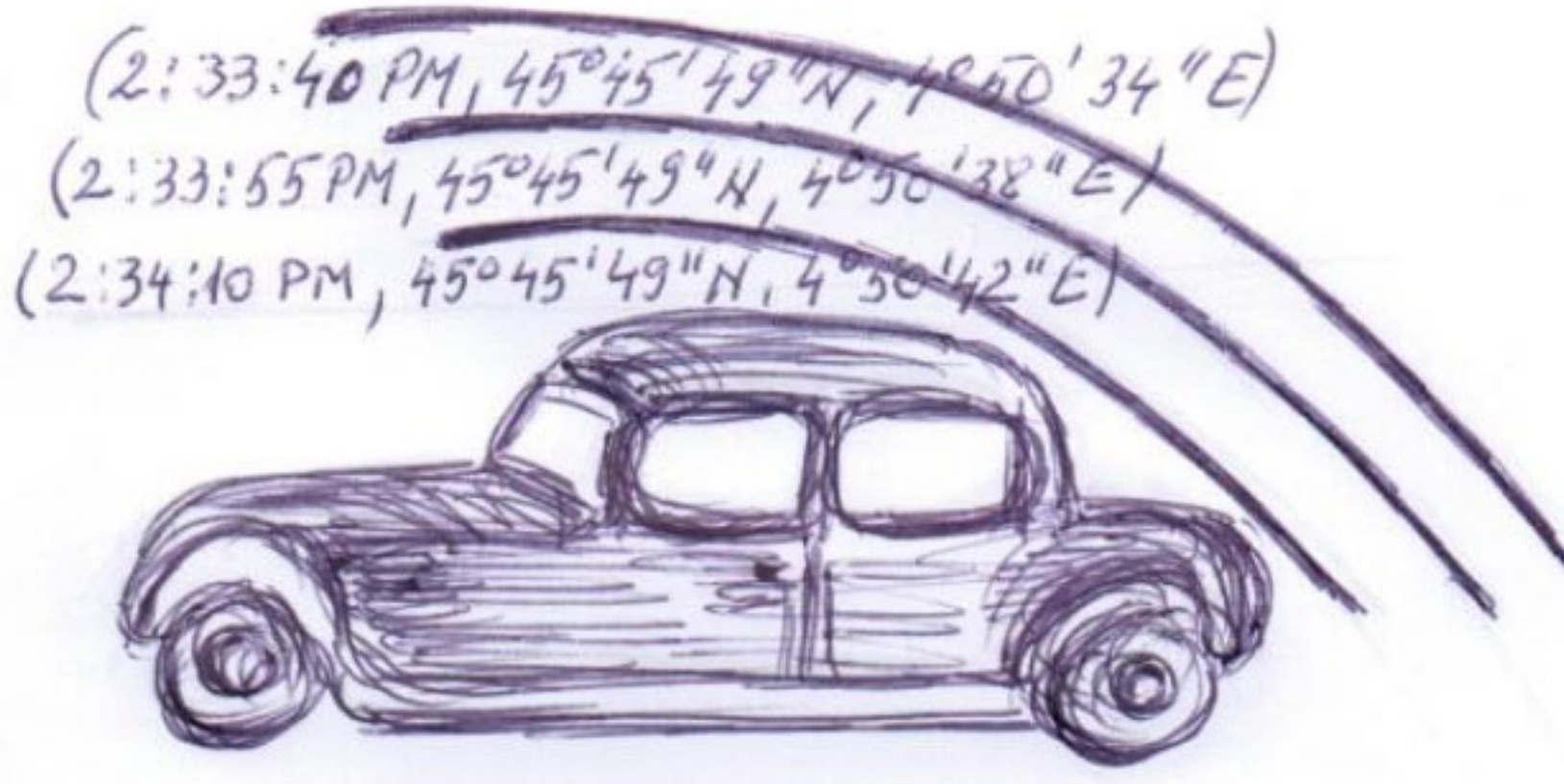
Data Streams

- 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*
- 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

Data Streams

- 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 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.

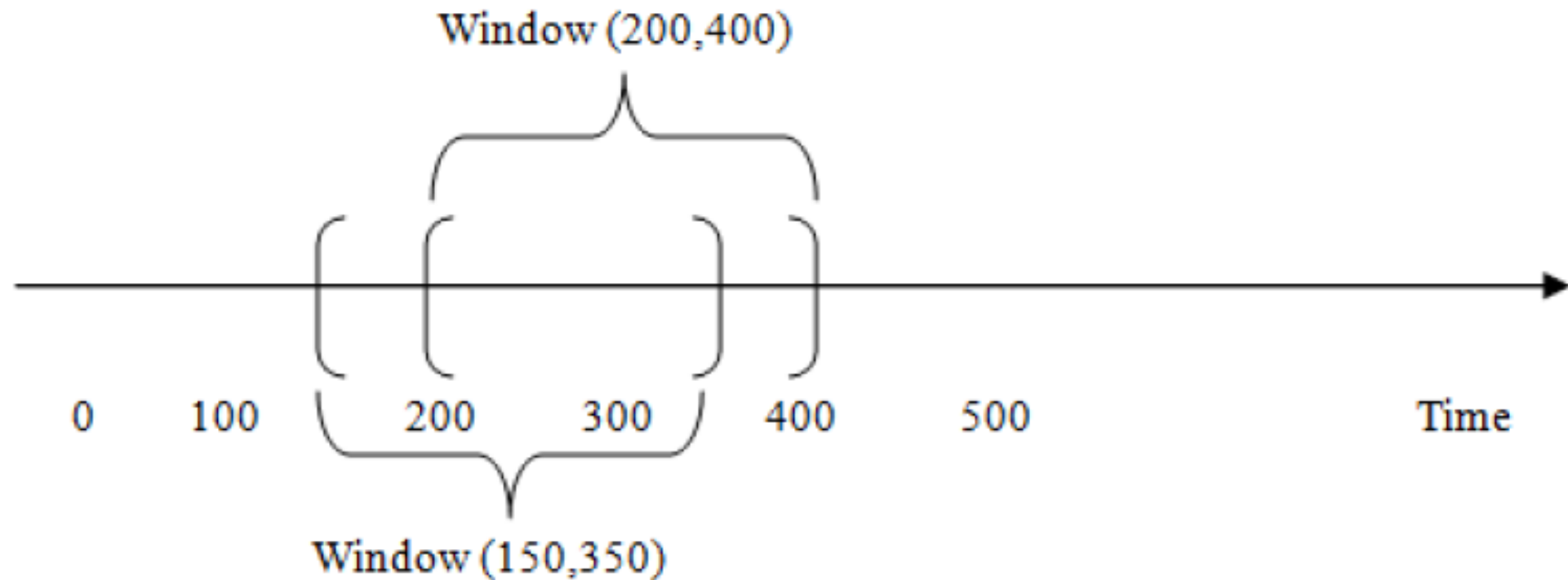
Window-Based Processing Model

- 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 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

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 - STandard stREam datA Manager

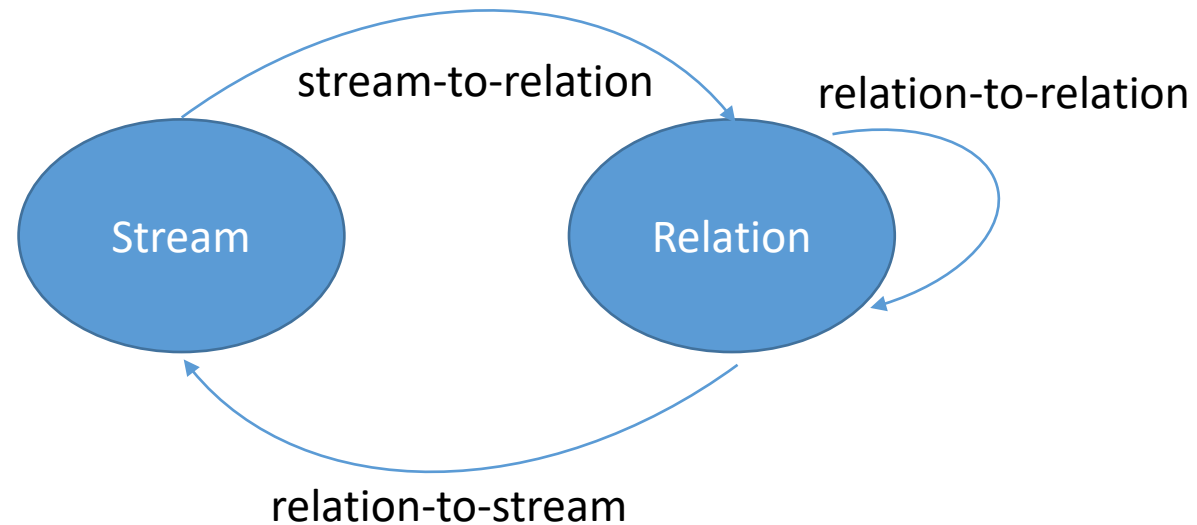
- DSMS prototype developed at Stanford
- objective
 - study data management and query processing in monitoring apps
- continuous queries on streams / stored data sets
- formal abstract semantics for continuous queries
- concrete declarative language, i.e., the Continuous Query Language (similar to SQL)

STREAM - abstract semantics

- 2 data types
 - streams and relations
- discrete, ordered time domain T
 - a timestamp t - a temporal moment from T
 - $\{0, 1, \dots\}$
- data stream S
 - unbounded multiset of tuple-timestamp pairs $\langle s, t \rangle$
 - 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.
- 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
 - $S[\text{Rows } N]$ produces a relation R
 - at time t , $R(t)$ contains the N tuples that arrived on S and have the largest timestamps $\leq t$
 - special case
 - $N = \infty$
 - $S[\text{Rows Unbounded}]$ - append-only window

STREAM - Continuous Query Language

- time-based sliding window
 - S - stream, t_i - temporal interval
 - $S[\text{Range } t_i]$ produces a relation R
 - at time t , $R(t)$ contains the tuples that arrived on S and have the timestamps between $t - t_i$ and t
- special cases
 - $t_i = 0$
 - i.e., the tuples on S with timestamp = t
 - $S[\text{Now}]$
 - $t_i = \infty$
 - $S[\text{Range Unbounded}]$

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

- relation-to-stream operators
- Istream (insert stream)
 - applied to a relation R , it contains $\langle s, t \rangle$ 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 $\langle s, t \rangle$ 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 $\langle s, t \rangle$ 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 $S1$ with the tuples that arrived on $S2$ in the past 5 minutes; only tuples with $Attr < 500$ are part of the result

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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