# Principles of Distributed Database Systems

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# Outline

- Introduction
- Distributed and Parallel Database Design
- Distributed Data Control
- Distributed Query Processing
- Distributed Transaction Processing
- Data Replication
- Database Integration – Multidatabase Systems
- Parallel Database Systems
- Peer-to-Peer Data Management
- Big Data Processing
- NoSQL, NewSQL and Polystores
- Web Data Management

# Outline

- Database Integration – Multidatabase Systems
  - Schema Matching
  - Schema Integration
  - Schema Mapping
  - Query Rewriting
  - Optimization Issues

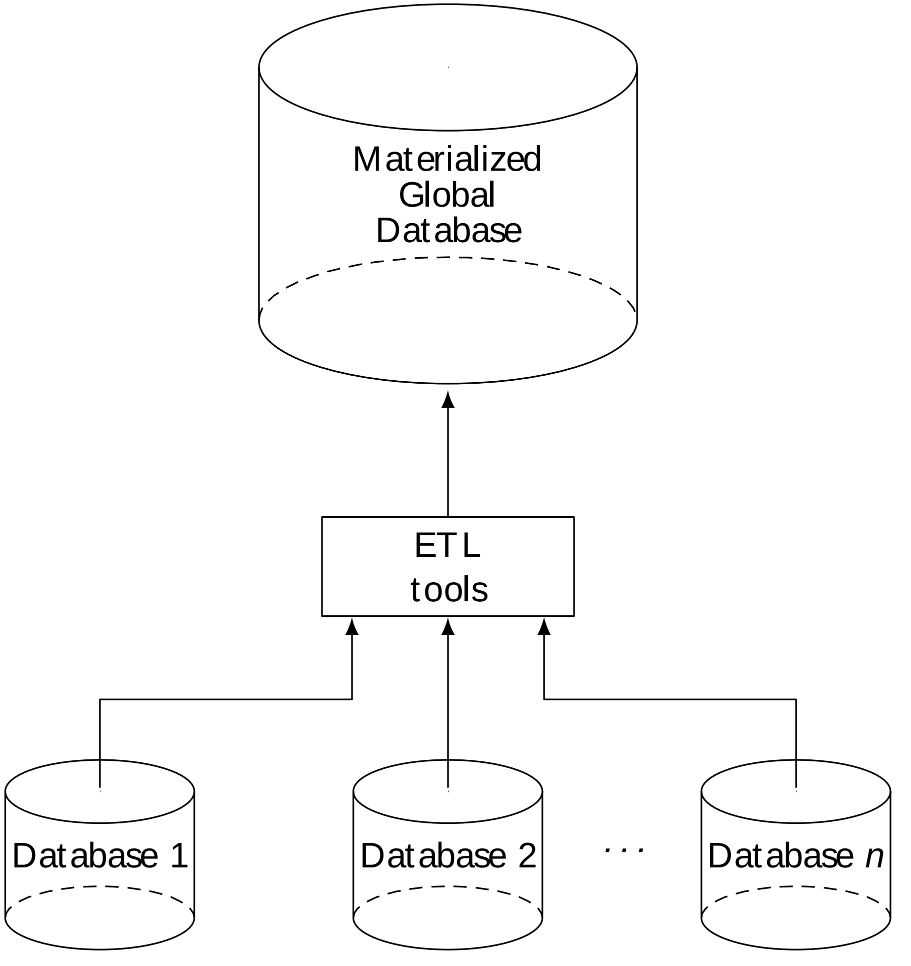
# Problem Definition

- Given existing databases with their Local Conceptual Schemas (LCSs), how to integrate the LCSs into a Global Conceptual Schema (GCS)
  - GCS is also called *mediated schema*
- Bottom-up design process

# Integration Alternatives

- Physical integration
  - Source databases integrated and the integrated database is materialized
  - Data warehouses
- Logical integration
  - Global conceptual schema is virtual and not materialized
  - Enterprise Information Integration (EII)

# Data Warehouse Approach

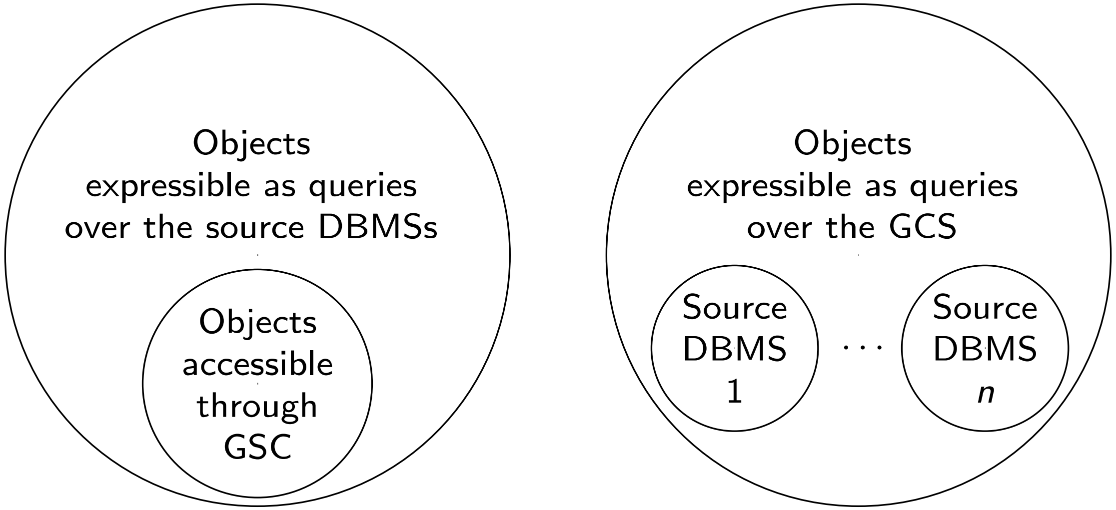


# Bottom-up Design

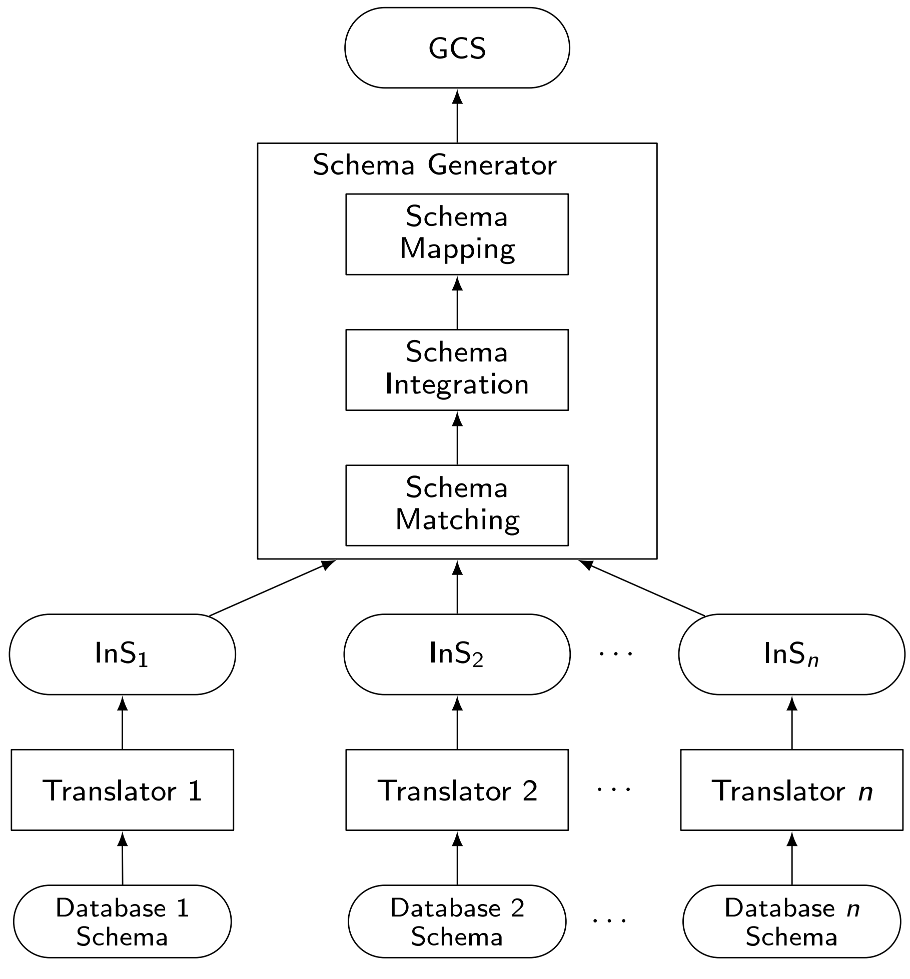
- GCS (also called mediated schema) is defined first
  - Map LCSs to this schema
  - As in data warehouses
- GCS is defined as an integration of parts of LCSs
  - Generate GCS and map LCSs to this GCS

# GCS/LCS Relationship

- Local-as-view
  - The GCS definition is assumed to exist, and each LCS is treated as a view definition over it
- Global-as-view
  - The GCS is defined as a set of views over the LCSs



# Database Integration Process



# Database Integration Issues – Schema Translation

- Component database schemas translated to a common intermediate canonical representation
- What is the canonical data model?
  - Relational
  - Entity-relationship
    - DIKE
  - Object-oriented
    - ARTEMIS
  - Graph-oriented
    - DIPE, TranScm, COMA, Cupid
- Translation algorithms
  - These are well-known

# Database Integration Issues – Schema Generation

- Intermediate schemas are used to create a global conceptual schema
- Schema matching
  - Finding the correspondences between multiple schemas
- Schema integration
  - Creation of the GCS (or mediated schema) using the correspondences
- Schema mapping
  - How to map data from local databases to the GCS
- Important: sometimes the GCS is defined first, and schema matching and schema mapping is done against this target GCS

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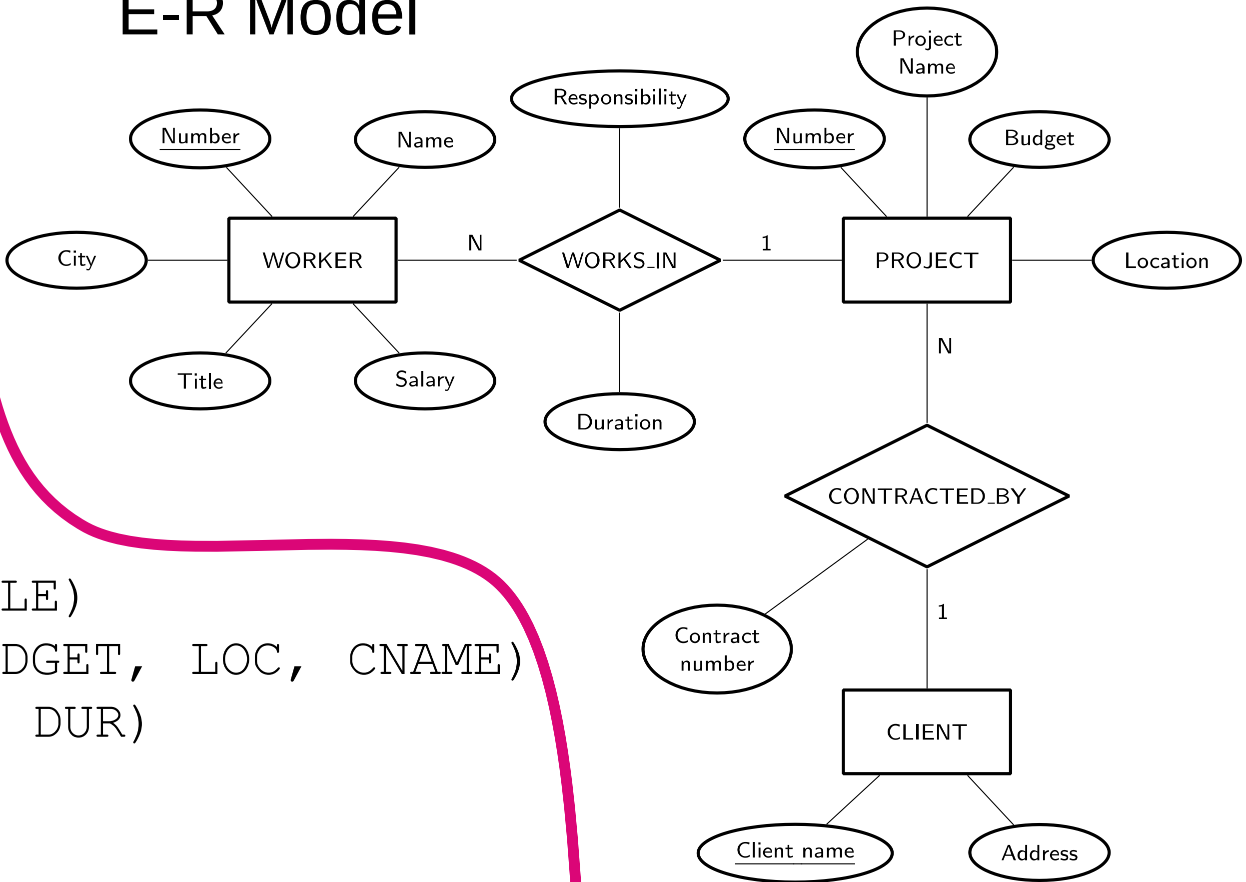
# Running Example

Relational

E-R Model




EMP(<u>ENO</u>, ENAME, TITLE)

PROJ(<u>PNO</u>, PNAME, BUDGET, LOC, CNAME)

ASG(<u>ENO, PNO</u>, RESP, DUR)

PAY(<u>TITLE</u>, SAL)

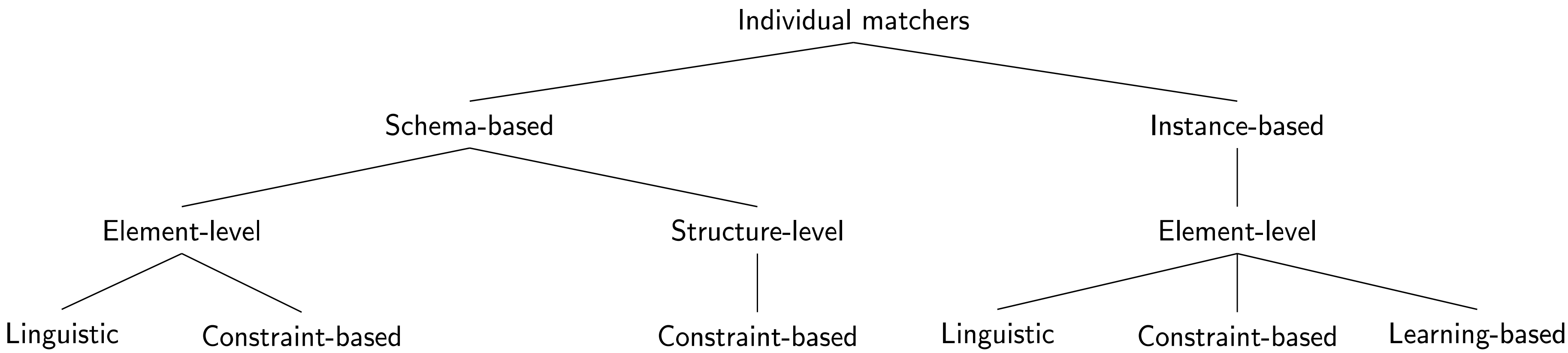
# Schema Matching

- Schema heterogeneity
  - Structural heterogeneity
    - Type conflicts
    - Dependency conflicts
    - Key conflicts
    - Behavioral conflicts
  - Semantic heterogeneity
    - More important and harder to deal with
    - Synonyms, homonyms, hypernyms
    - Different ontology
    - Imprecise wording

# Schema Matching (cont'd)

- Other complications
  - Insufficient schema and instance information
  - Unavailability of schema documentation
  - Subjectivity of matching
- Issues that affect schema matching
  - Schema versus instance matching
  - Element versus structure level matching
  - Matching cardinality

# Schema Matching Approaches



# Linguistic Schema Matching

- Use element names and other textual information (textual descriptions, annotations)
- May use external sources (e.g., Thesauri)
- 〈SC1.element-1 ≈ SC2.element-2, *p*,*s*〉
  - Element-1 in schema SC1 is similar to element-2 in schema SC2 if predicate *p* holds with a similarity value of *s*
- Schema level
  - Deal with names of schema elements
  - Handle cases such as synonyms, homonyms, hypernyms, data type similarities
- Instance level
  - Focus on information retrieval techniques (e.g., word frequencies, key terms)
  - "Deduce" similarities from these

# Linguistic Matchers

- Use a set of linguistic (terminological) rules
- Basic rules can be hand-crafted or may be discovered from outside sources (e.g., WordNet)
- Predicate *p* and similarity value *s*
  - hand-crafted ⇒ specified,
  - discovered ⇒ may be computed or specified by an expert after discovery
- Examples
  - 〈uppercase names ≈ lower case names, *true*, 1.0〉
  - 〈uppercase names ≈ capitalized names, *true*, 1.0〉
  - 〈capitalized names ≈ lower case names, *true*, 1.0〉
  - 〈DB1.ASG ≈ DB2.WORKS_IN, *true*, 0.8〉

# Automatic Discovery of Name Similarities

- Affixes
  - Common prefixes and suffixes between two element name strings
- N-grams
  - Comparing how many substrings of length *n* are common between the two name strings
- Edit distance
  - Number of character modifications (additions, deletions, insertions) that needs to be performed to convert one string into the other
- Soundex code
  - Phonetic similarity between names based on their soundex codes
- Also look at data types
  - Data type similarity may suggest stronger relationship than the computed similarity using these methods or to differentiate between multiple strings with same value

# N-gram Example

- 3-grams of string “Responsibility” are the following:
  - Res
  - ibi
  - bip
  - ili
  - lit
  - ity
  - sib
  - esp
  - spo
  - pon
  - ons
  - nsi
- 3-grams of string “Resp” are
  - Res
  - esp
- 3-gram similarity: 2/12 = 0.17

# Edit Distance Example

- Again consider “Responsibility” and “Resp”
- To convert “Responsibility” to “Resp”
  - Delete characters “o”, “n”, “s”, “i”, “b”, “i”, “l”, “i”, “t”, “y”
- To convert “Resp” to “Responsibility”
  - Add characters “o”, “n”, “s”, “i”, “b”, “i”, “l”, “i”, “t”, “y”
- The number of edit operations required is 10
- Similarity is $1 - (10/14) = 0.29$

# Constraint-based Matchers

- Data always have constraints – use them
  - Data type information
  - Value ranges
  - …
- Examples
  - RESP and RESPONSIBILITY: n-gram similarity = 0.17, edit distance similarity = 0.19 (low)
  - If they come from the same domain, this may increase their similarity value
  - ENO in relational, WORKER.NUMBER and PROJECT.NUMBER in E-R
  - ENO and WORKER.NUMBER may have type INTEGER while PROJECT.NUMBER may have STRING

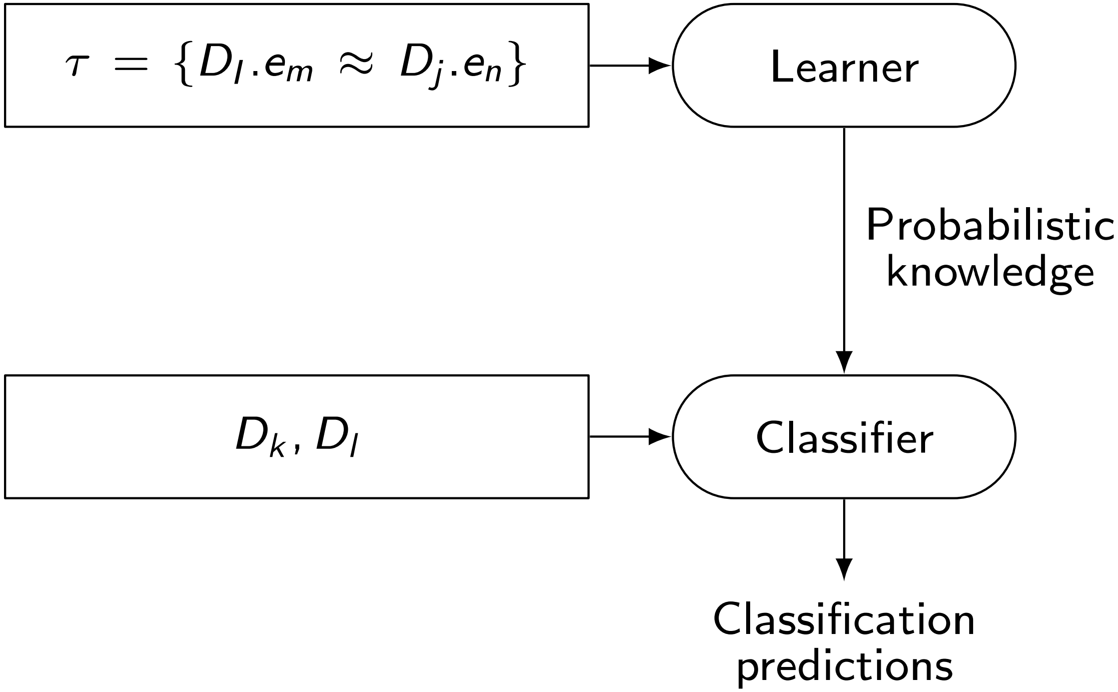
# Constraint-based Structural Matching

- If two schema elements are structurally similar, then there is a higher likelihood that they represent the same concept
- Structural similarity:
  - Same properties (attributes)
  - “Neighborhood” similarity
    - Using graph representation
    - The set of nodes that can be reached within a particular path length from a node are the neighbors of that node
    - If two concepts (nodes) have similar set of neighbors, they are likely to represent the same concept

# Learning-based Schema Matching

- Use machine learning techniques to determine schema matches
- Classification problem: classify concepts from various schemas into classes according to their similarity. Those that fall into the same class represent similar concepts
- Similarity is defined according to features of *data instances*
- Classification is "learned" from a training set

# Learning-based Schema Matching



# Combined Schema Matching Approaches

- Use multiple matchers
  - Each matcher focuses on one area (name, etc)
- Meta-matcher integrates these into one prediction
- Integration may be simple (take average of similarity values) or more complex (see Fagin's work)

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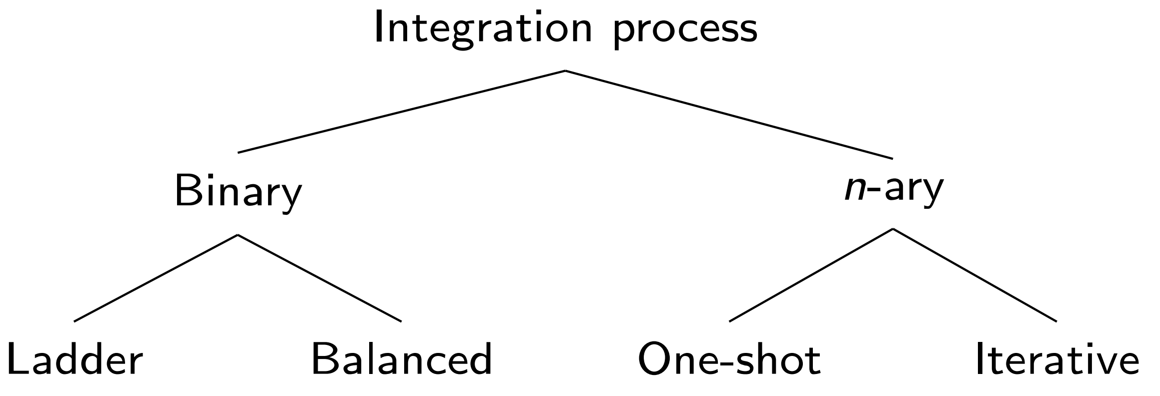
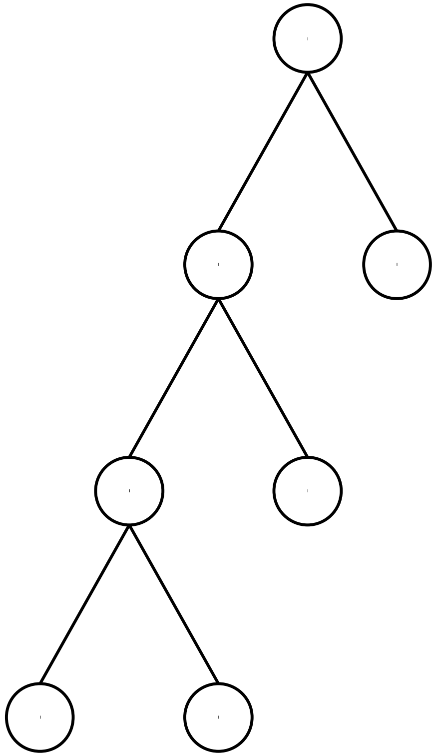
# Schema Integration

- Use the correspondences to create a GCS
- Mainly a manual process, although rules can help

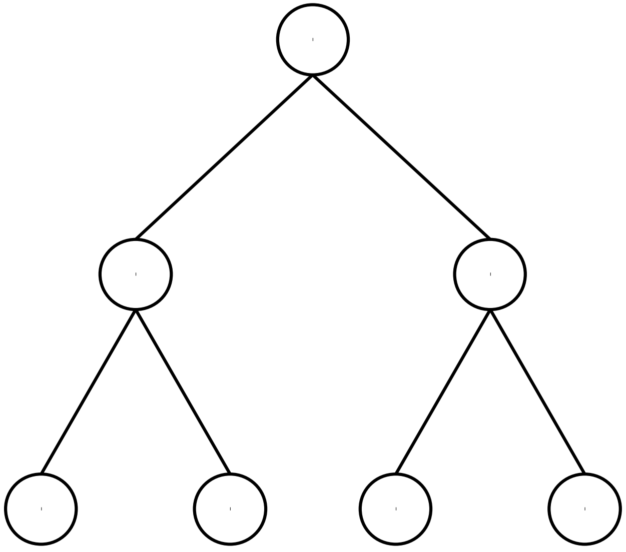


# Binary Integration Methods

Stepwise

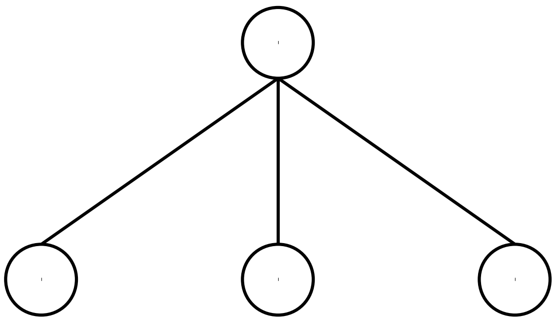


Pure binary

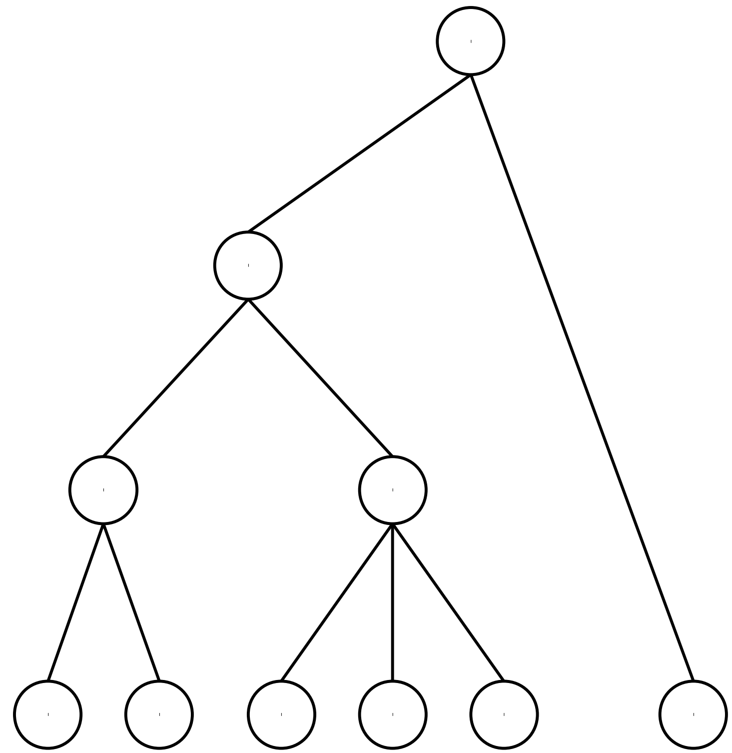


# N-ary Integration Methods

One-pass



Iterative



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# Schema Mapping

- Mapping data from each local database (source) to GCS (target) while preserving semantic consistency as defined in both source and target.
- Data warehouses ⇒ actual translation
- Data integration systems ⇒ discover mappings that can be used in the query processing phase
- Mapping creation
- Mapping maintenance

# Mapping Creation

Given

- A source LCS: $\mathcal{S} = \{S_i\}$
- A target GCS: $\mathcal{T} = \{T_i\}$
- A set of value correspondences discovered during schema matching phase: $\mathcal{V} = \{V_i\}$

Produce a set of queries that, when executed, will create GCS data instances from the source data.

We are looking, for each $T_k$, a query $Q_k$ that is defined on a (possibly proper) subset of the relations in $S$ such that, when executed, will generate data for $T_i$ from the source relations

# Mapping Creation Algorithm

General idea:

- Consider each $T_k$ in turn.
  - Divide $V_k$ into subsets $\{V_k^1, \ldots, V_k^n\}$ such that each $V_k^j$ specifies one possible way that values of $T_k$ can be computed
- Each $V_k^j$ can be mapped to a query $q_k^j$ that, when executed, would generate *some* of $T_k$'s data.
- Union of these queries gives $Q_k (= \bigcup_j q_k^j)$

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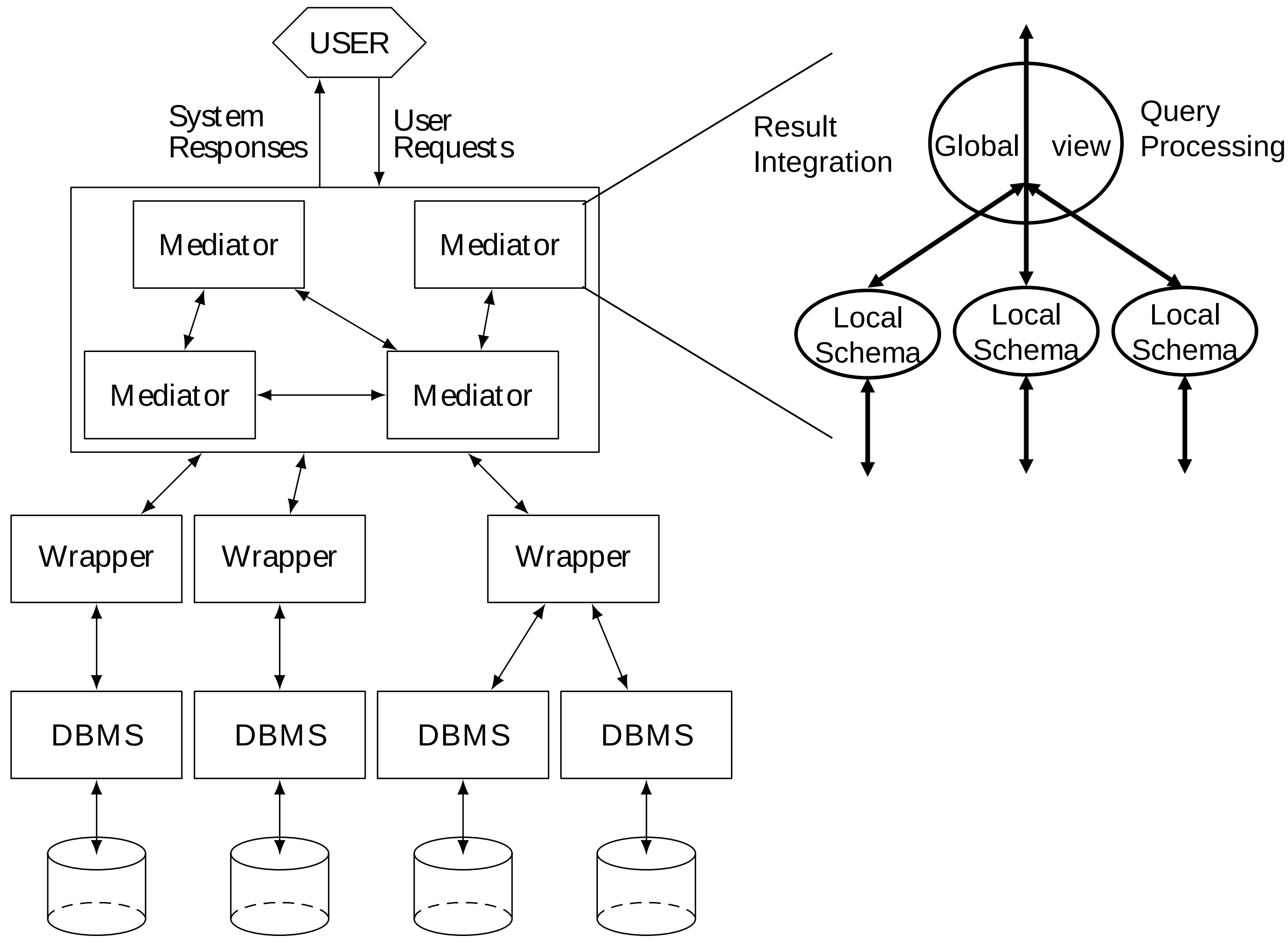
# Multidatabase Query Processing

- Mediator/wrapper architecture
- MDB query processing architecture
- Query rewriting using views
- Query optimization and execution
- Query translation and execution

# Recall Mediator/Wrapper Architecture



# Issues in MDB Query Processing

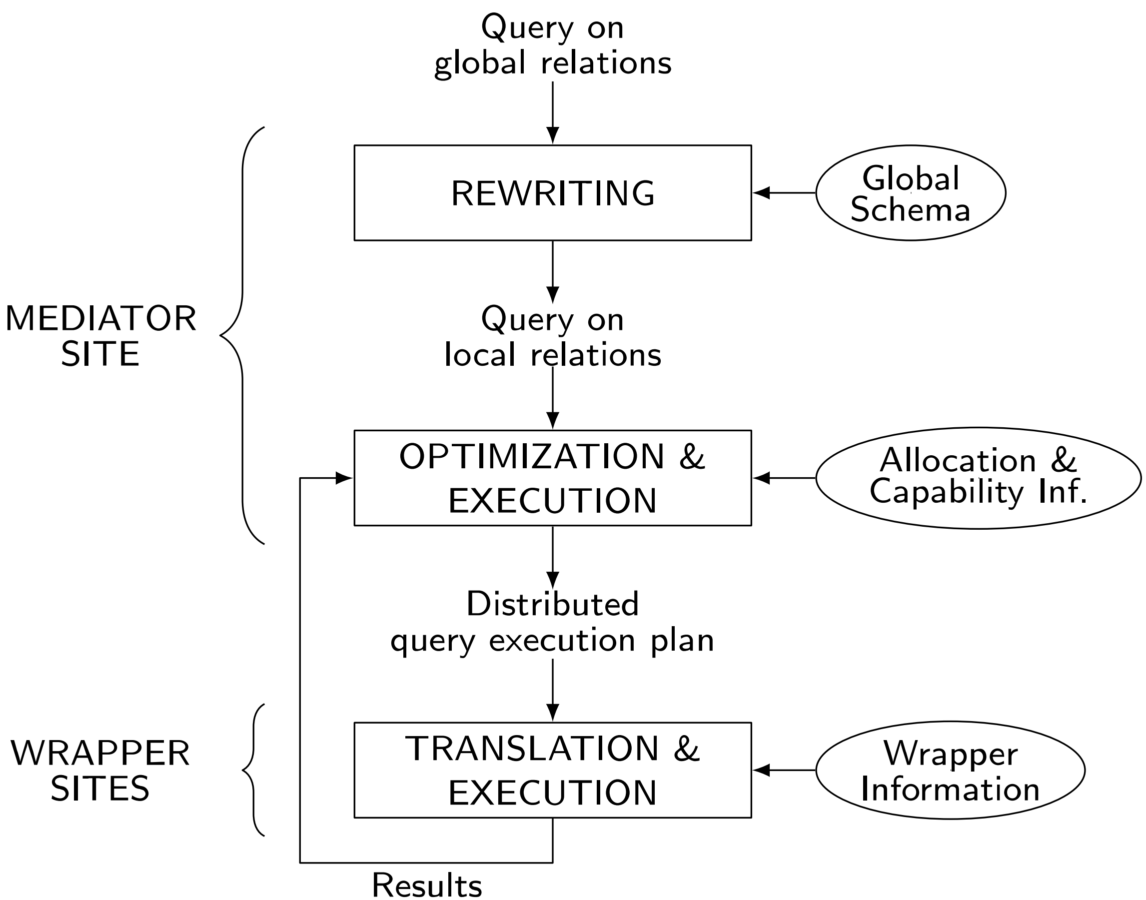
- Component DBMSs are autonomous and may range from full-fledge relational DBMS to flat file systems
  - Different computing capabilities
    - Prevents uniform treatment of queries across DBMSs
  - Different processing cost and optimization capabilities
    - Makes cost modeling difficult
  - Different data models and query languages
    - Makes query translation and result integration difficult
  - Different runtime performance and unpredictable behavior
    - Makes query execution difficult

# Component DBMS Autonomy

- Communication autonomy
  - The ability to terminate services at any time
  - How to answer queries completely?
- Design autonomy
  - The ability to restrict the availability and accuracy of information needed for query optimization
  - How to obtain cost information?
- Execution autonomy
  - The ability to execute queries in unpredictable ways
  - How to adapt to this?

# MDB Query Processing Architecture




Global/local correspondences

Allocation and capabilities

Local/DBMS mappings

# Query Rewriting Using Views

- Views used to describe the correspondences between global and local relations
  - Global As View: the global schema is integrated from the local databases and each global relation is a view over the local relations
  - Local As View: the global schema is defined independently of the local databases and each local relation is a view over the global relations
- Query rewriting best done with Datalog, a logic-based language
  - More expressive power than relational calculus
  - Inline version of relational domain calculus

# Datalog Terminology

- Conjunctive (SPJ) query: a rule of the form
  - $Q(T)$ :- $R_1(T_1), \ldots R_n(T_n)$
  - $Q(T)$ : head of the query denoting the result relation
  - $R_1(T_1), \ldots R_n(T_n)$: subgoals in the body of the query
  - $R_1, \ldots R_n$: predicate names corresponding to relation names
  - $T_1, \ldots T_n$: refer to tuples with variables and constants
  - Variables correspond to attributes (as in domain calculus)
  - “-” means unnamed variable
- Disjunctive query = *n* conjunctive queries with same head predicate

# Datalog Example

```
EMP(E#,ENAME,TITLE,CITY)
WORKS(E#,P#,RESP,DUR)
```

```
    SELECT    E#, TITLE, P#
    FROM      EMP NATURAL JOIN WORKS
    WHERE     TITLE = "Programmer" OR DUR=24
```

```
Q(E#,TITLE,P#) :- EMP(E#,ENAME,"Programmer",CITY),
                  WORKS(E#,P#,RESP,DUR).
Q(E#,TITLE,P#) :- EMP(E#,ENAME,TITLE,CITY),
                  WORKS(E#,P#,RESP,24).
```

# Rewriting in GAV

- Global schema similar to that of homogeneous distributed DBMS
  - Local relations can be fragments
  - But no completeness: a tuple in the global relation may not exist in local relations
    - Yields incomplete answers
  - And no disjointness: the same tuple may exist in different local databases
    - Yields duplicate answers
- Rewriting (*unfolding*)
  - Similar to query modification
    - Apply view definition rules to the query and produce a union of conjunctive queries, one per rule application
    - Eliminate redundant queries

# GAV Example Schema

Global relations

```
EMP(E#,ENAME,CITY)
WORKS(E#,P#,TITLE,DUR)
```

Local relations

```
EMP1(E#,ENAME,TITLE,CITY)
EMP2(E#,ENAME,TITLE,CITY)
WORKS(E#,P#,DUR)
```

EMP(E#,ENAME,CITY):- EMP1(E#,ENAME,TITLE,CITY). $(d_1)$

EMP(E#,ENAME,CITY):- EMP2(E#,ENAME,TITLE,CITY). $(d_2)$

WORKS(E#,P#,TITLE,DUR):- EMP1(E#,ENAME,TITLE,CITY),
WORKS(E#,P#,DUR). $(d_3)$

WORKS(E#,P#,TITLE,DUR):- EMP2(E#,ENAME,TITLE,CITY),
WORKS(E#,P#,DUR). $(d_4)$

# GAV Example Query

Let Q: project for employees in Paris

```
Q(e,p) :- EMP(e,ENAME,"Paris"),WORKS(e,p,TITLE,DUR).
```

Unfolding produces *Q′*

```
Q'(e,p) :- EMP1(e,ENAME,"Paris"),
           WORKS(e,p,TITLE,DUR).              (q1)
Q'(e,p):- EMP2(e,ENAME,"Paris"),
           WORKS(e,p,TITLE,DUR).              (q2)
```

where

$q_1$ is obtained by applying $d_3$ only or both $d_1$ and $d_3$

In the latter case, there are redundant queries

same for $q_2$ with $d_2$ only or both $d_2$ and $d_4$

# Rewriting in LAV

- More difficult than in GAV
  - No direct correspondence between the terms in GS (EMP, ENAME) and those in the views (EMP1, EMP2, ENAME)
  - There may be many more views than global relations
  - Views may contain complex predicates to reflect the content of the local relations
    - e.g. a view EMP3 for only programmers
- Often not possible to find an equivalent rewriting
  - Best is to find a *maximally-contained query* which produces a maximum subset of the answer
    - e.g. EMP3 can only return a subset of the employees

# Rewriting Algorithms

- The problem to find an equivalent query is NP-complete in the number of views and number of subgoals of the query
- Thus, algorithms try to reduce the numbers of rewritings to be considered
- Three main algorithms
  - Bucket
  - Inverse rule
  - MiniCon

# LAV Example Schema

Local relations

```
EMP1(E#,ENAME,TITLE,CITY)
EMP2(E#,ENAME,TITLE,CITY)
WORKS1(E#,P#,DUR)
```

Global relations

```
EMP(E#,ENAME,CITY)
WORKS(E#,P#,TITLE,DUR)
```

```
EMP1(E#,ENAME,TITLE,CITY):- EMP(E#,ENAME,CITY)          (d5)
                          WORKS(E#,P#,TITLE,DUR).
EMP1(E#,ENAME,TITLE,CITY):- EMP(E#,ENAME,CITY)          (d6)
                          WORKS(E#,P#,TITLE,DUR).
WORKS(E#,P#,DUR):- WORKS(E#,P#,TITLE,DUR).              (d7)
```

# Bucket Algorithm

- Considers each predicate of the query *Q* independently to select only the relevant views

Step 1

- Build a bucket *b* for each subgoal *q* of *Q* that is not a comparison predicate
- Insert in *b* the heads of the views which are relevant to answer *q*

Step 2

- For each view *V* of the Cartesian product of the buckets, produce a conjunctive query
  - If it is contained in *Q*, keep it
- The rewritten query is a union of conjunctive queries

# LAV Example Query

$Q(e,p)$ :- EMP($e$,ENAME,"Paris"), WORKS($e$,$p$,TITLE,DUR).

Step1: we obtain 2 buckets (one for each subgoal of $Q$)

$b_1$ = {EMP1(E#,ENAME,TITLE',CITY),
EMP2(E#,ENAME,TITLE',CITY)}

$b_2$ = {WORKS1(E#,P#,DUR')}

(the prime variables (TITLE' and DUR') are not useful)

Step2: produces

$Q'(e,p)$ :- EMP1(e,ENAME,TITLE,"Paris"),
WORKS1($e$,$p$,DUR). ($q_1$)

$Q'(e,p)$ :- EMP2(e,ENAME,TITLE,"Paris"),
WORKS1($e$,$p$,DUR). ($q_2$)

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# Query Optimization and Execution

- Takes a query expressed on local relations and produces a distributed QEP to be executed by the wrappers and mediator
- Three main problems
  - Heterogeneous cost modeling
    - To produce a global cost model from component DBMS
  - Heterogeneous query optimization
    - To deal with different query computing capabilities
  - Adaptive query processing
    - To deal with strong variations in the execution environment

# Heterogeneous Cost Modeling

- Goal: determine the cost of executing the subqueries at component DBMS
- Three approaches
  - Black-box: treats each component DBMS as a black-box and determines costs by running test queries
  - Customized: customizes an initial cost model
  - Dynamic: monitors the run-time behavior of the component DBMS and dynamically collect cost information

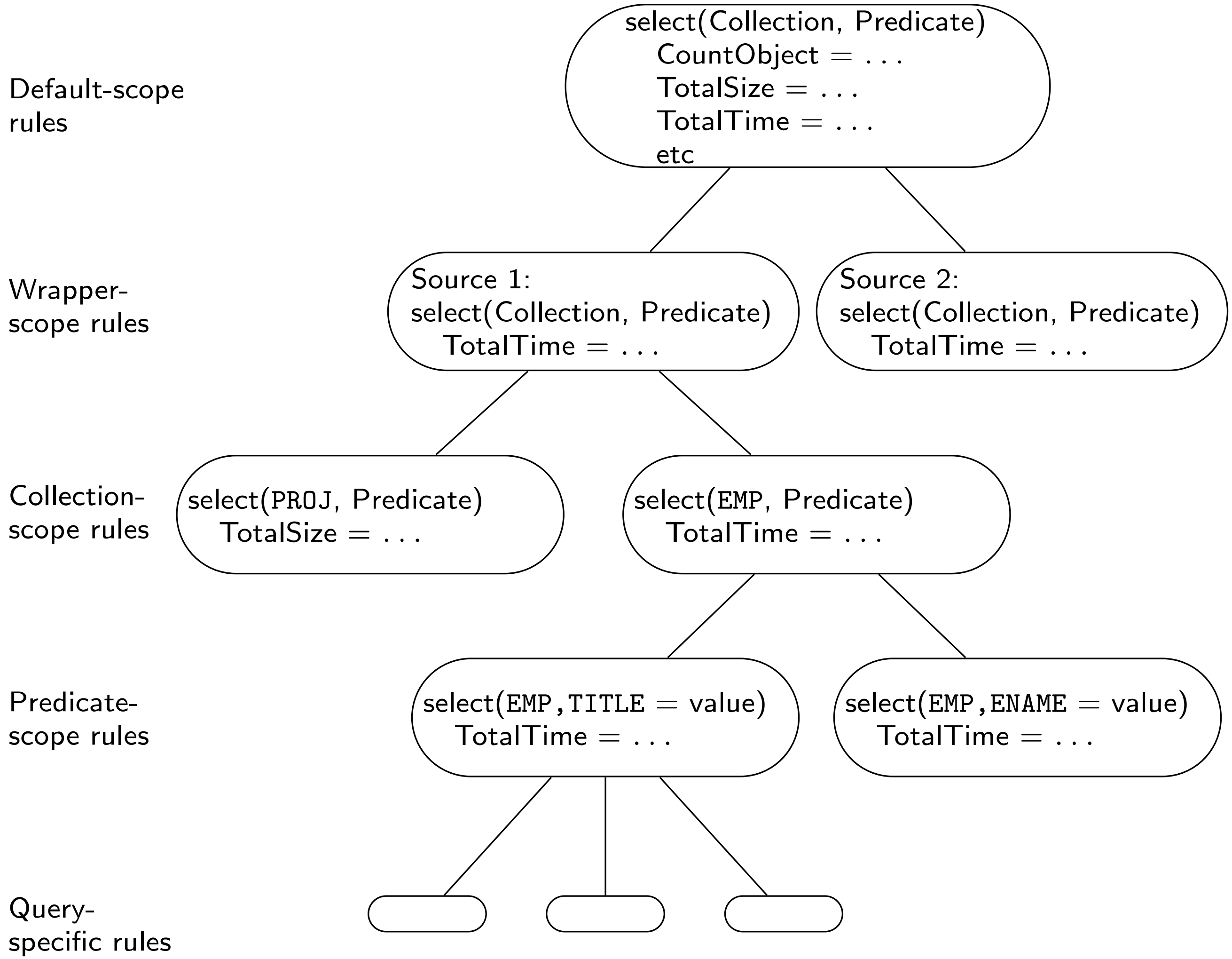
# Black-box Approach

- Define a logical cost expression
  - *Cost = init cost + cost to find qualifying tuples*
    *+ cost to process selected tuples*
    - The terms will differ much with different DBMS
- Run probing queries on component DBMS to compute cost coefficients
  - Count the numbers of tuples, measure cost, etc.
  - Special case: sample queries for each class of important queries
    - Use of classification to identify the classes
- Problems
  - The instantiated cost model (by probing or sampling) may change over time
  - The logical cost function may not capture important details of component DBMS

# Customized Approach

- Relies on the wrapper (i.e. developer) to provide cost information to the mediator
- Two solutions
  - Wrapper provides the logic to compute cost estimates
    - Access_cost = reset + (card-1)*advance
      - reset = time to initiate the query and receive a first tuple
      - advance = time to get the next tuple (advance)
      - card = result cardinality
  - Hierarchical cost model
    - Each node associates a query pattern with a cost function
    - The wrapper developer can give cost information at various levels of details, depending on knowledge of the component DBMS

# Hierarchical Cost Model



# Dynamic Approach

- Deals with execution environment factors which may change
  - Frequently: load, throughput, network contention, etc.
  - Slowly: physical data organization, DB schemas, etc.
- Two main solutions
  - Extend the sampling method to consider some new queries as samples and correct the cost model on a regular basis
  - Use adaptive query processing which computes cost during query execution to make optimization decisions

# Heterogeneous Query Optimization

- Deals with heterogeneous capabilities of component DBMS
  - One DBMS may support complex SQL queries while another only simple select on one fixed attribute
- Two approaches, depending on the M/W interface level
  - Query-based
    - All wrappers support the same query-based interface (e.g. ODBC or SQL/MED) so they appear homogeneous to the mediator
    - Capabilities not provided by the DBMS must be supported by the wrappers
  - Operator-based
    - Wrappers export capabilities as compositions of operators
    - Specific capabilities are available to mediator
    - More flexibility in defining the level of M/W interface

# Query-based Approach

- We can use 2-step query optimization with a heterogeneous cost model
  - But centralized query optimizers produce left-linear join trees whereas in MDB, we want to push as much processing in the wrappers, i.e. exploit bushy trees
- Solution: convert a left-linear join tree into a bushy tree such that
  - The initial total cost of the QEP is maintained
  - The response time is improved
- Algorithm
  - Iterative improvement of the initial left-linear tree by moving down subtrees while response time is improved

# Operator-based Approach

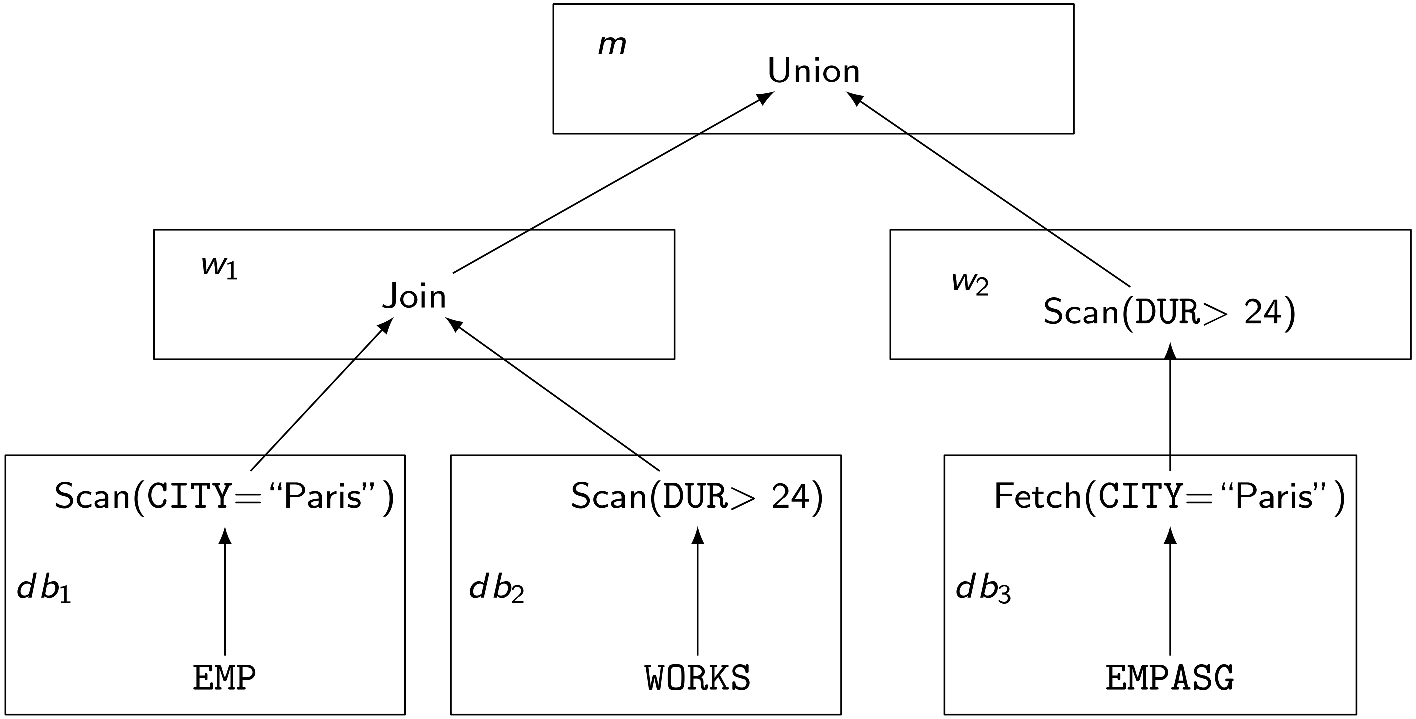
- M/W communication in terms of subplans
- Use of planning functions (Garlic)
  - Extension of cost-based centralized optimizer with new operators
    - Create temporary relations
    - Retrieve locally stored data
    - Push down operators in wrappers
    - accessPlan and joinPlan rules
  - Operator nodes annotated with
    - Location of operands, materialization, etc.

# Planning Functions Example

- Consider 3 component databases with 2 wrappers:
  - $w_1.db_1$: `EMP(ENO,ENAME,CITY)`
  - $w_1.db_2$: `ASG(ENO,PNAME,DUR)`
  - $w_2.db_3$: `EMPASG(ENAME,CITY,PNAME,DUR)`
- Planning functions of $w_1$
  - `accessPlan`(R: rel, A: attlist, *P*: pred) = `scan`(R, A, *P*, db(R))
  - `joinPlan`($R_1$, $R_2$: rel, A: attlist, *P*: joinpred) = `join`($R_1$, $R_2$, A, *P*)
    - condition: db($R_1$) ≠ db($R_2$)
    - implemented by $w_1$
- Planning functions of $w_2$
  - `accessPlan`(R: rel, A: attlist, *P*: pred) = `fetch`(city=*c*)
    - condition: (city=*c*) included in *P*
  - `accessPlan`(R: rel, A: attlist, *P*: pred) = `scan`(R, A, *P*, db(R))
    - implemented by $w_2$

# Heterogenous QEP

```
SELECT   ENAME,PNAME,DUR
FROM     EMPASG
WHERE    CITY = "Paris" AND DUR>24
```

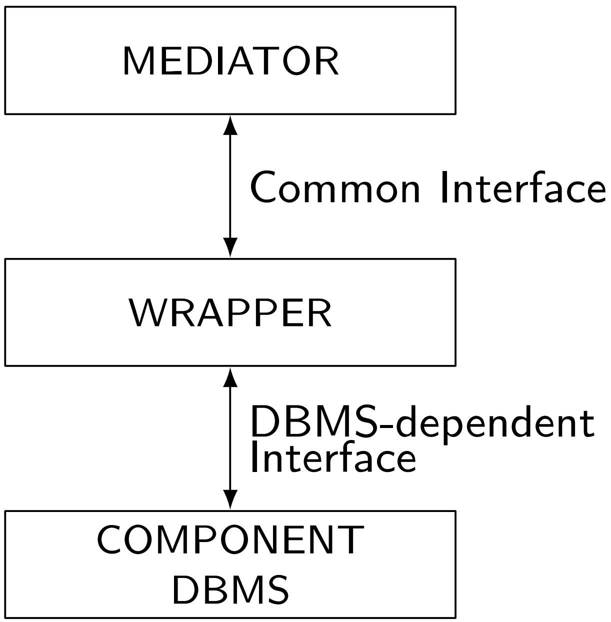


# Query Translation and Execution

- Performed by wrappers using the component DBMS
  - Conversion between common interface of mediator and DBMS-dependent interface
    - Query translation from wrapper to DBMS
    - Result format translation from DBMS to wrapper
  - Wrapper has the local schema exported to the mediator (in common interface) and the mapping to the DBMS schema
  - Common interface can be query-based (e.g. ODBC or SQL/MED) or operator-based
- In addition, wrappers can implement operators not supported by the component DBMS, e.g. join

# Wrapper Placement

- Depends on the level of autonomy of component DB
- Cooperative DB
  - May place wrapper at component DBMS site
  - Efficient wrapper-DBMS com.
- Uncooperative DB
  - May place wrapper at mediator
  - Efficient mediator-wrapper com.
- Impact on cost functions



# SQL Wrapper for Text Files

- Consider EMP (ENO, ENAME, CITY) stored in a Unix text file in componentDB
  - Each EMP tuple is a line in the file, with attributes separated by ":"
- SQL/MED definition of EMP

```
CREATE FOREIGN TABLE EMP
   ENO INTEGER, ENAME VARCHAR(30), CITY CHAR(30)
SERVER componentDB
OPTIONS(Filename '/usr/EngDB/emp.txt', Delimiter ':')
```

- The query

```
SELECT ENAME FROM EMP
```

Can be translated by the wrapper using a Unix shell command

```
cut -d: -f2/ usr/EngDB/emp
```

# Wrapper Management Issues

- Wrappers mostly used for read-only queries
  - Makes query translation and wrapper construction easy
  - DBMS vendors provide standard wrappers
    - ODBC, JDBC, ADO, etc.
- Updating makes wrapper construction harder
  - Problem: heterogeneity of integrity constraints
    - Implicit in some legacy DB
  - Solution: reverse engineering of legacy DB to identify implicit constraints and translate in validation code in the wrapper
- Wrapper maintenance
  - schema mappings can become invalid as a result of changes in component DB schemas
    - Use detection and correction, using mapping maintenance techniques