Outline

- Introduction & architectural issues
- Data distribution
- Distributed query processing
- Distributed query optimization
- Distributed transactions & concurrency control
- Distributed reliability
- Data replication
- Parallel database systems
- Database integration & querying
  - Schema matching
  - Schema mapping
- Peer-to-Peer data management
- Stream data management
- MapReduce-based distributed data management

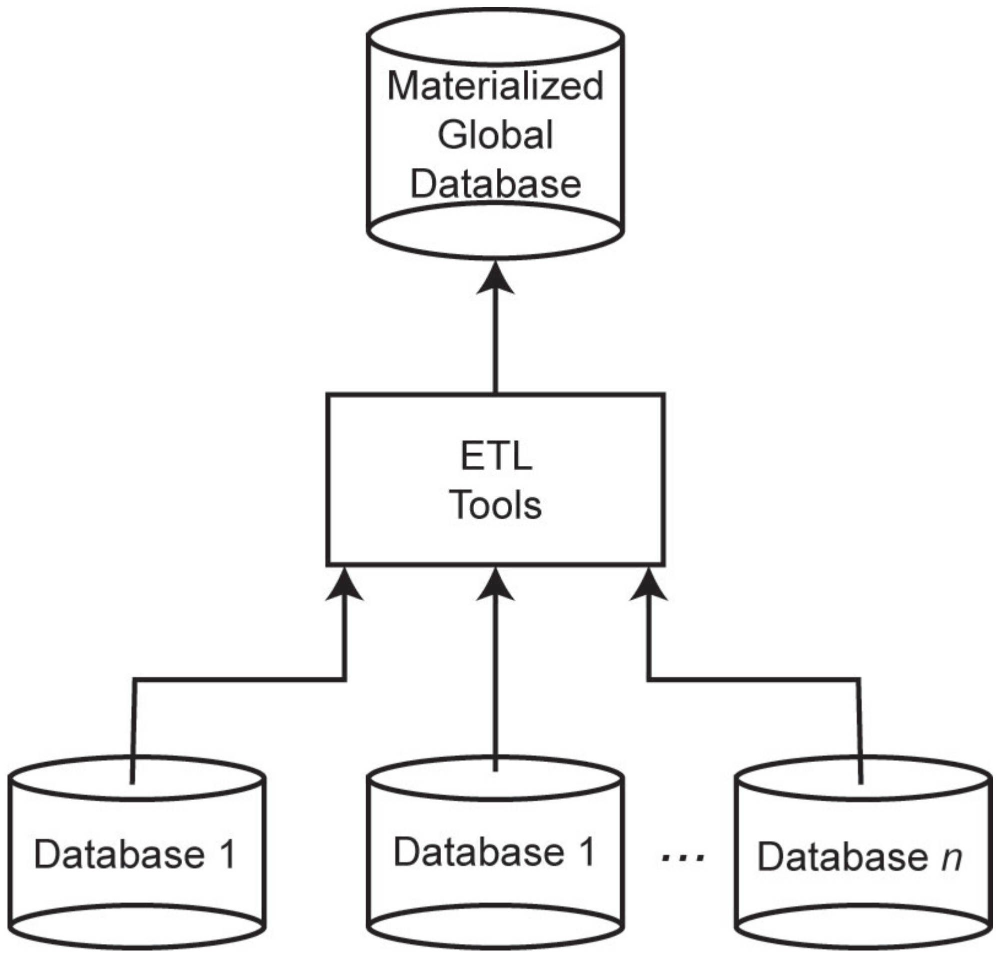
Problem Definition

- 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

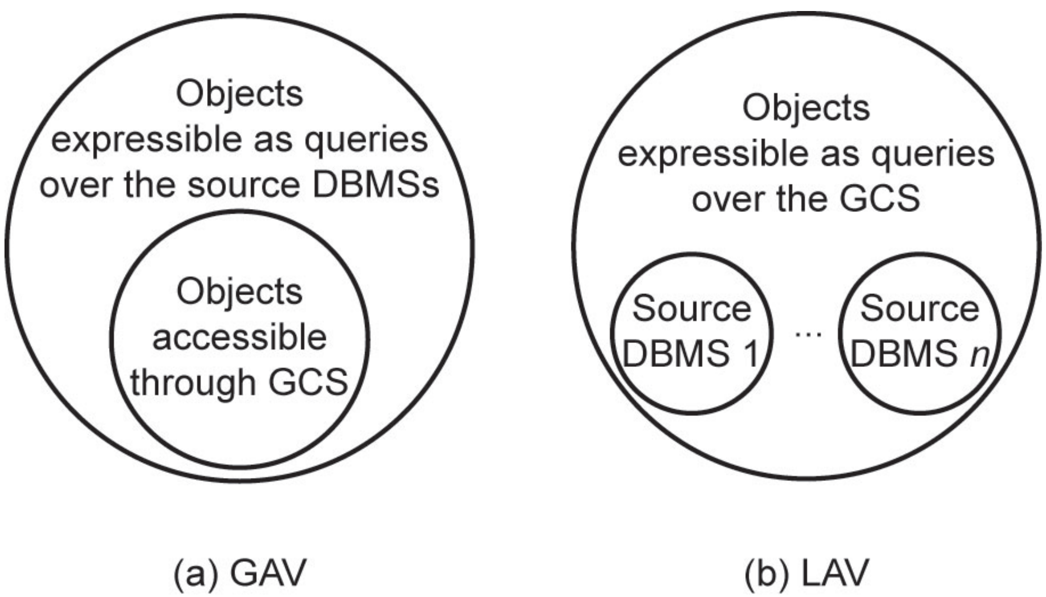


Bottom-up Design

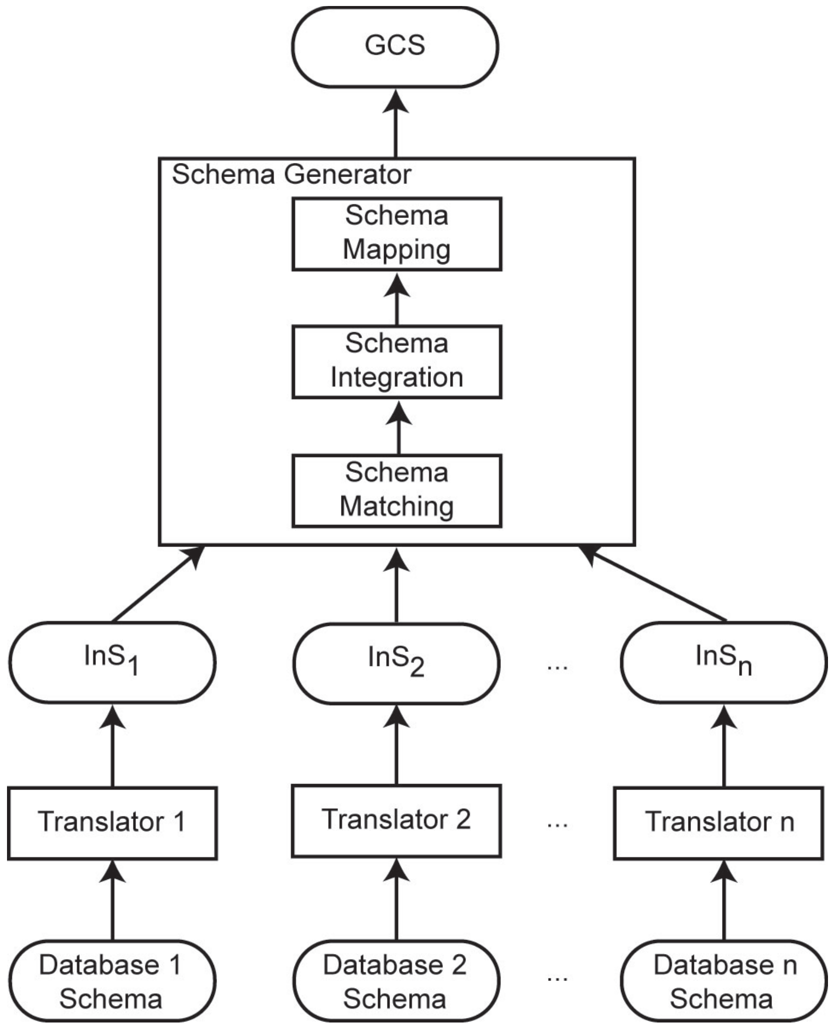
- GCS (also called mediated schema) is defined first
  - Map LCSs to this schema
  - As in data warehouses
- GCS is defined as an integration of parts of LCSs
  - Generate GCS and map LCSs to this GCS

GCS/LCS Relationship

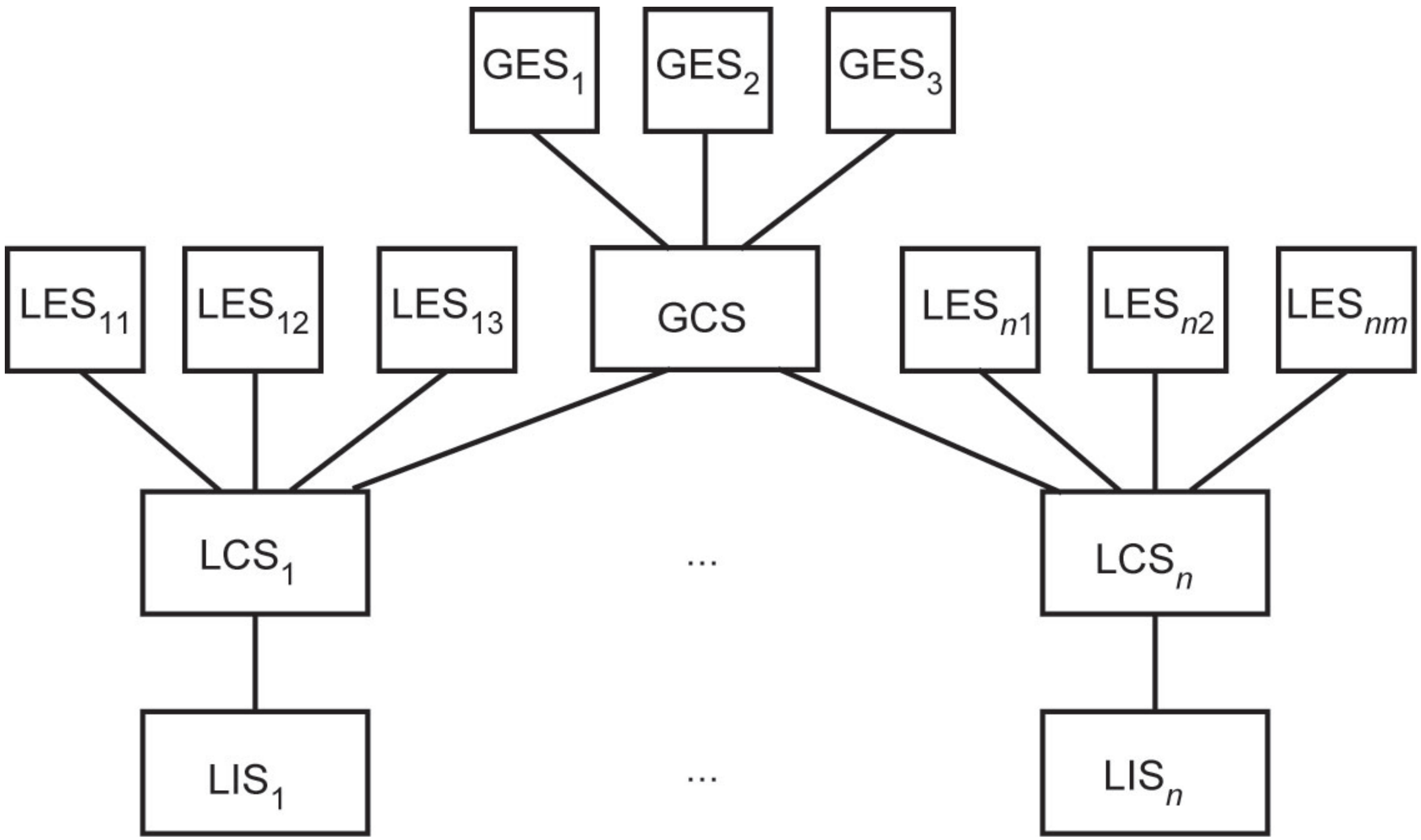
- Local-as-view
  - The GCS definition is assumed to exist, and each LCS is treated as a view definition over it
- Global-as-view
  - The GCS is defined as a set of views over the LCSs



Database Integration Process



Recall Access Architecture



Database Integration Issues

- Schema translation
  - Component database schemas translated to a common intermediate canonical representation
- Schema generation
  - Intermediate schemas are used to create a global conceptual schema

Schema Translation

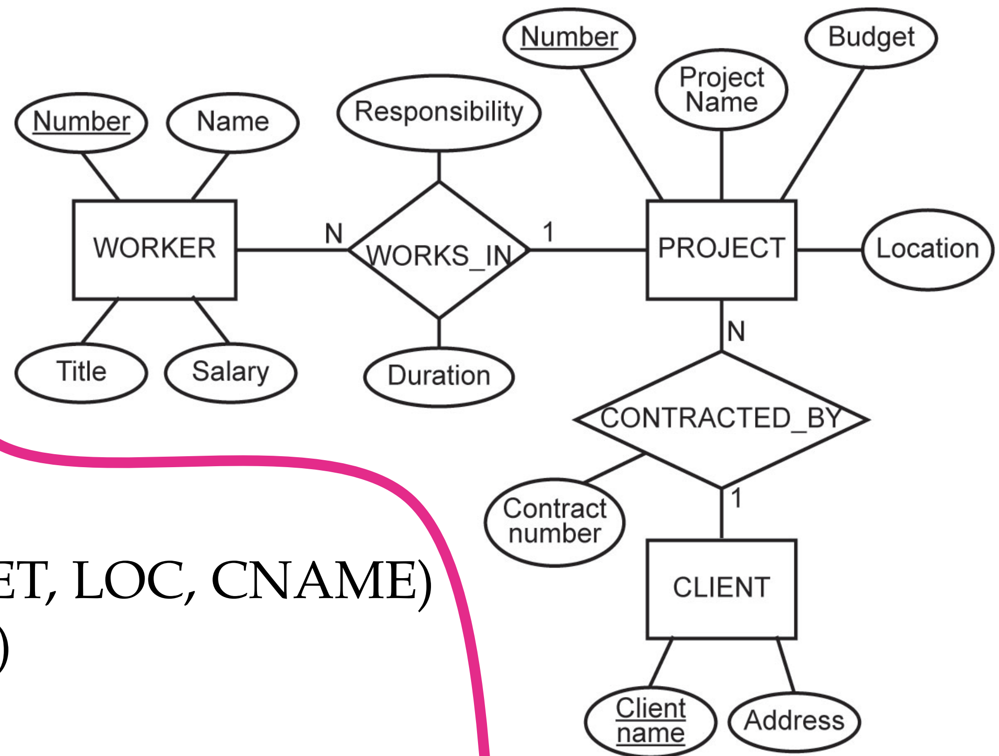
- What is the canonical data model?
  - Relational
  - Entity-relationship
    - DIKE
  - Object-oriented
    - ARTEMIS
  - Graph-oriented
    - DIPE, TranScm, COMA, Cupid
    - Preferable with emergence of XML
    - No common graph formalism
- Mapping algorithms
  - These are well-known

Schema Generation

- 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

Running Example

E-R Model



Relational

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)

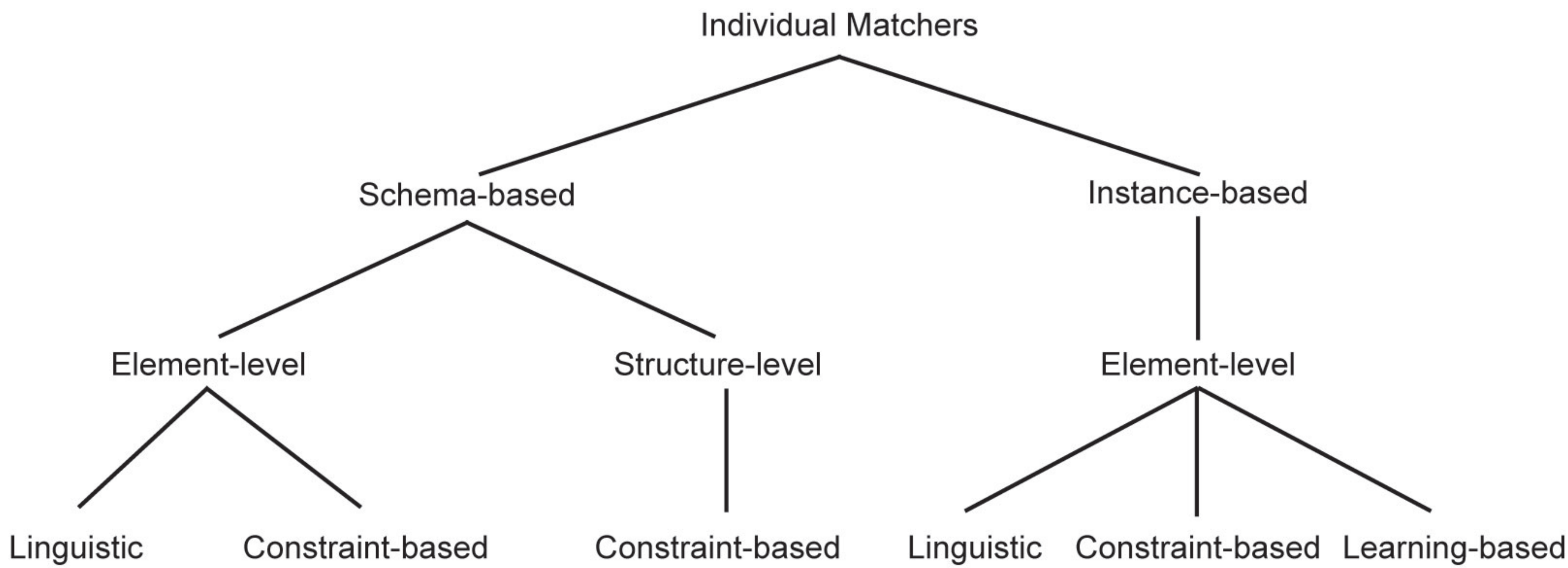
Schema Matching

- 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)
- $\langle$SC1.element-1 $\approx$ SC2.element-2, *p*,*s*$\rangle$
  - 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 relationship

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

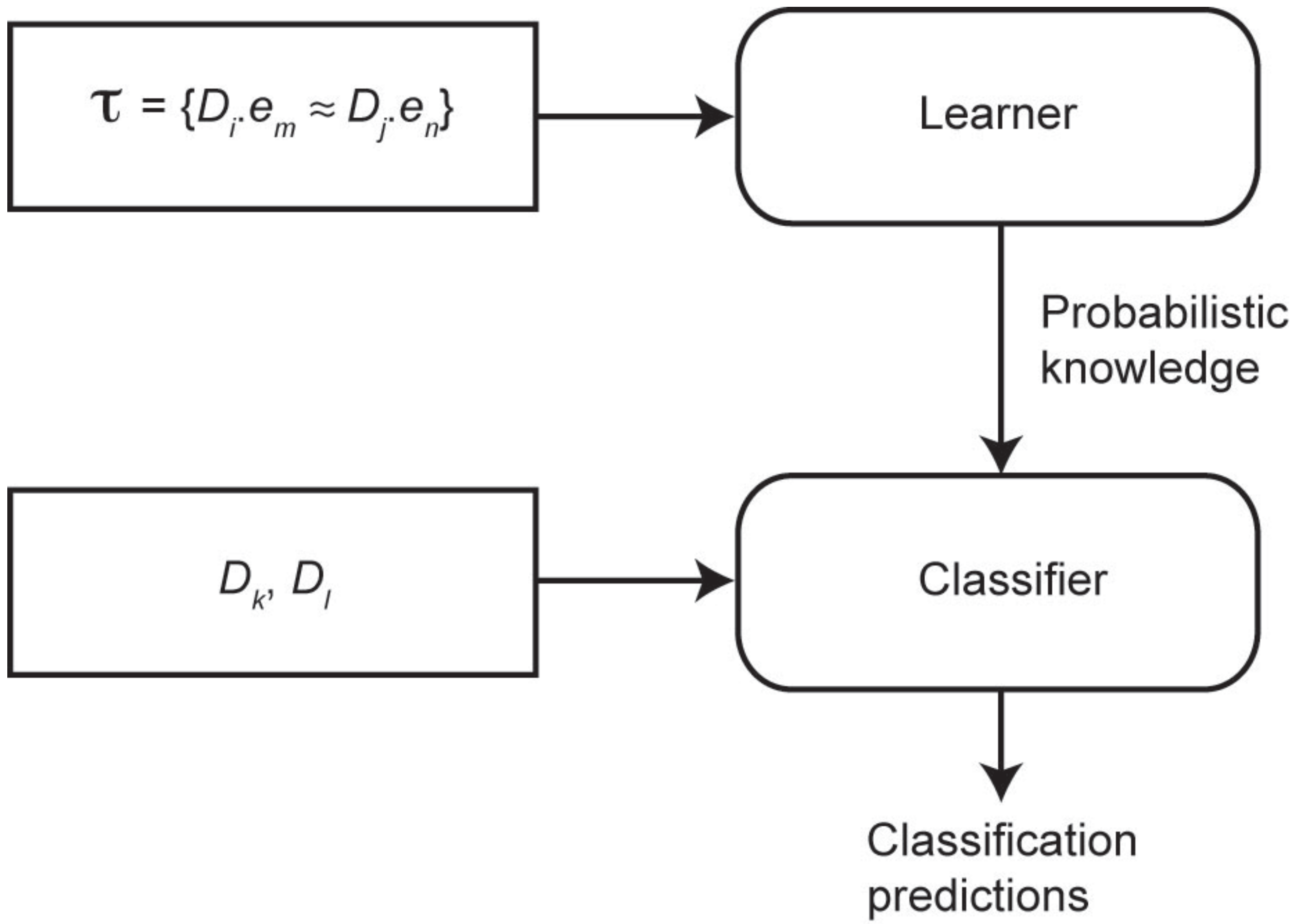
Constraint-based Structural Matching

- 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

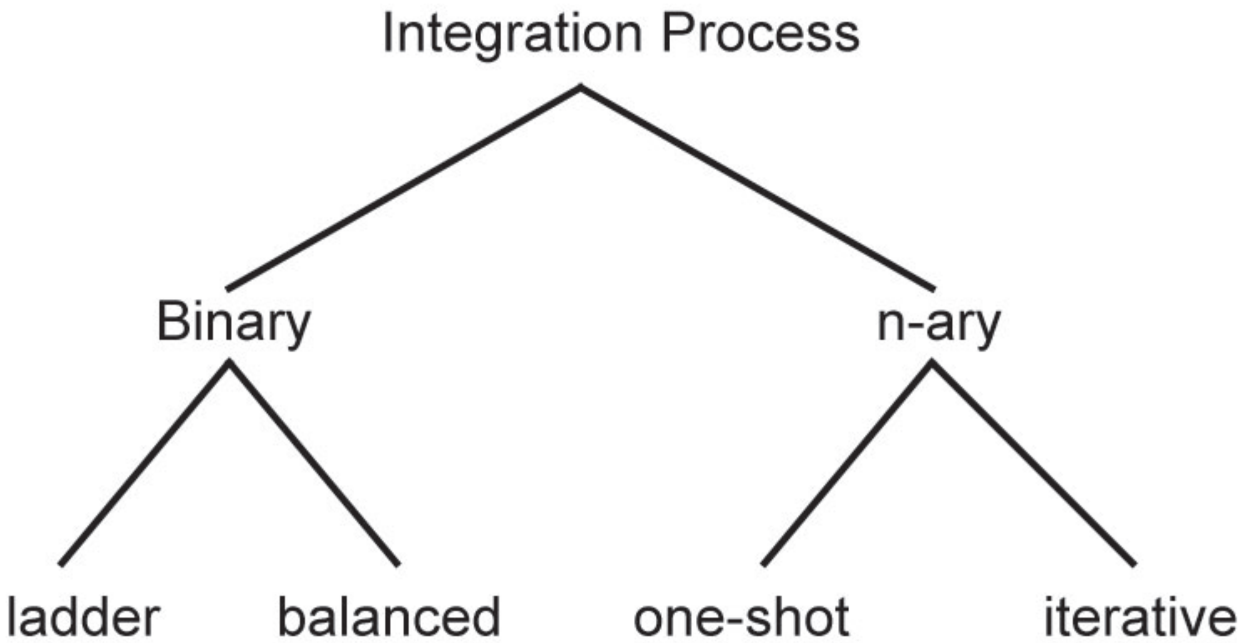


Combined Schema Matching Approaches

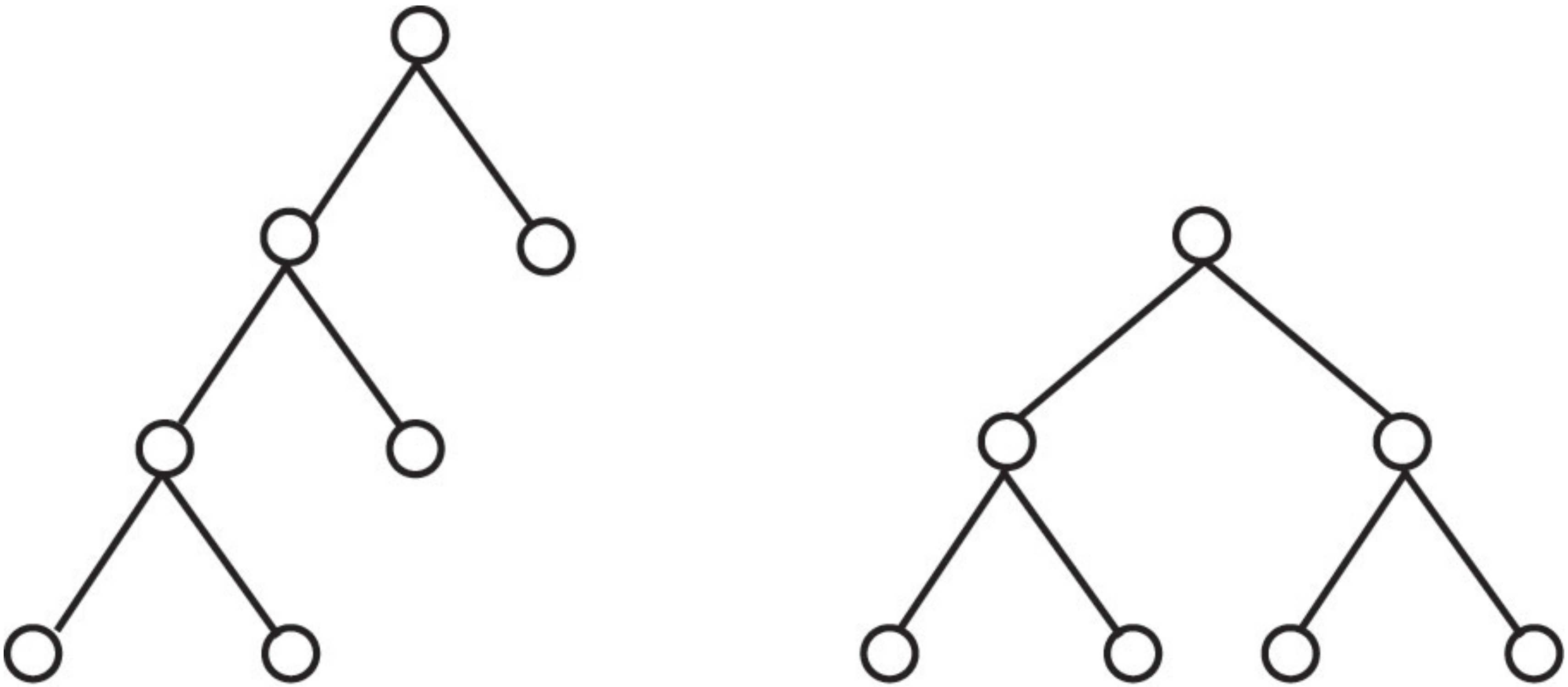
- Use multiple matchers
  - Each matcher focuses on one area (name, etc)
- Meta-matcher integrates these into one prediction
- Integration may be simple (take average of similarity values) or more complex (see Fagin's work)

Schema Integration

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

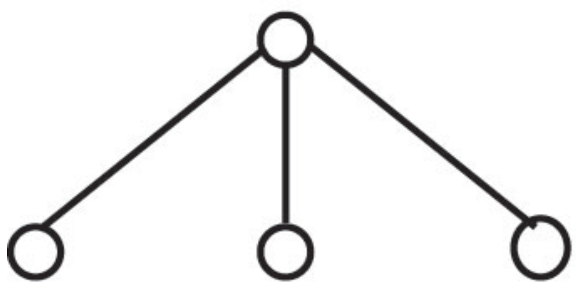


Binary Integration Methods

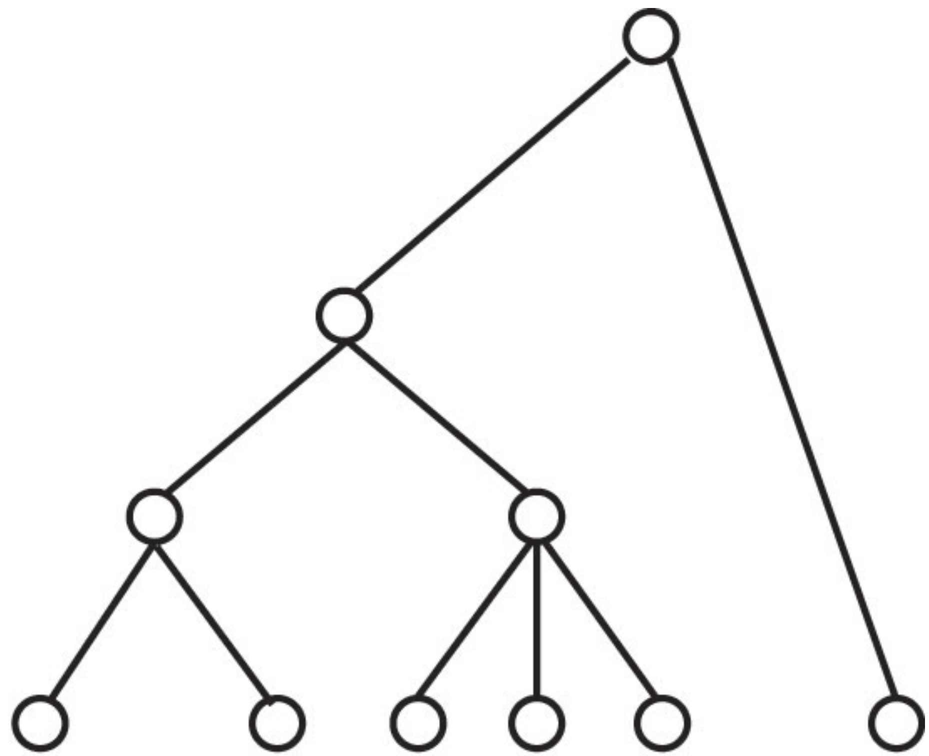


(a) Stepwise (b) Pure binary

N-ary Integration Methods



(a) One-pass



(b) Iterative

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 $\mathcal{S}$ 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

$$Q_k (= \cup_j q_k^j)$$