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ON AUTOMATIC REASONING FOR SCHEMA INTEGRATION*

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ABSTRACT

Success in database schema integration depends on the ability to capture real world semantics of the schema objects, and to reason about the semantics. Earlier schema integration approaches mainly rely on heuristics and human reasoning. In this paper, we discuss an approach to automate a significant part of the schema integration process.

Our approach consists of three phases. An attribute hierarchy is generated in the first phase. This involves identifying relationships (equality, disjointness and inclusion) among attributes. We discuss a strategy based on user-specified semantic clustering. In the second phase, a *classification* algorithm based on the semantics of class *subsumption* is applied to the class definitions and the attribute hierarchy to automatically generate a class taxonomy. This class taxonomy represents a partially integrated schema. In the third phase, the user may employ a set of well-defined comparison operators in conjunction with a set of restructuring operators, to further modify the schema. These operators as well as the automatic reasoning during the second phase are based on subsumption.

The formal semantics and automatic reasoning utilized in the second phase is based on a terminological logic as adapted in the CANDIDE data model. Classes are completely defined in terms of attributes and constraints. Our observation is that the inability to completely define attributes and thus completely capture their real world semantics imposes a fundamental limitation on the possibility of automatically reasoning about attribute definitions. This necessitates human reasoning during the first phase of the integration approach.

Keywords: Schema integration, attribute relationship, class taxonomy, formal semantics, human and automatic reasoning, classification, subsumption, CANDIDE, terminological logic.

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1. Introduction

Many organizations need to develop and maintain databases (either centrali or distributed) that provide shared and consistent access to the data by multi applications and users. The process of schema or view integration is extrem valuable for such organizations because it can support: (1) the development a large data intensive application, (2) the development of multiple applicati that share data, or (3) the integration of several existing (possibly distribut heterogeneous, and autonomous) databases.[a]

There is a body of work in schema integration [5,9,43] which views sche integration as a well-defined task of synthesizing dependencies (e.g. functional, clusion, and exclusion) from underlying domains. We believe that the integrati process requires information that goes well beyond such dependencies. Some of t reasons that aggravate the problem are [38]: (1) semantic (or other) data mc els are unable to sufficiently capture the semantics of real world objects in ter of their meaning and use, (2) it is necessary to capture more meta-data (dictic ary/directory) information about the modeled objects than is typically captured a schema, as well as information about intended use of the integrated schemas, a (3) there can be multiple views and interpretations of a given application doma which may change with time. Thus schema integration involves a subjective activ which relies heavily on the knowledge and intuition of the user[b] about the applic tion domain (domain of discourse), intended use of the integrated schema, and t systems that manage data modeled by the schemas. Thus, the results of a sche integration activity are not unique and *cannot* be generated totally automaticall

An important goal of our work is to automate the schema integration proce *as much as possible*. In this paper, we discuss our views with respect to the tas of the schema integration process that can be automated and the tasks that ha to rely primarily upon human guidance. It is to be noted that substantial hum work is needed before automatic tasks can be performed. The automatic tasks a facilitated by a formal semantics and the human tasks are tied to heuristic reasoni driven by the user. We also discuss appropriate vehicles for performing the bas tasks. Specifically, the main contributions of this paper are:

(1) identification of the portion of the schema integration process which can l meaningfully automated,

(2) use of the formal model CANDIDE [4] which provides subsumption and class fication as a vehicle for automated class integration, and

(3) the development of the overall framework based on a three-step approach th involves human interaction (that is, heuristic reasoning) where necessary ar the use of automatic reasoning where possible.

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[a] The first two activities are often called view integration and the third one is often called databa integration. Both are jointly referred to as schema integration in [2].

[b] By user, we shall mean the person who is integrating the database schemas.

This paper is organized as follows. Section 2 provides the background — it discusses relevant previous work on schema integration, the role and choice of a canonical data model for schema representation, and introduces the problem of schema analysis. In our approach, the schema integration process consists of three phases, namely, schema analysis, class integration, and schema restructuring. In Section 3, we discuss schema analysis[c] which results in the specification of attribute relationships (`equivalent`, `contains/contained-in`, and `disjoint`). An attribute hierarchy can then be automatically created using attribute relationships. We comment on the inadequacy of the attribute equivalence theory proposed in [20] and introduce the notion of semantic clustering of attributes. The semantic clustering is a heuristic process that is largely driven by the user. Yu *et al.* [42] and Sciore *et al.* [27] investigated the generation of a concept hierarchy that can aid in determining attribute relationships.

Using the attribute hierarchy thus generated, an automated reasoning process (called `classification`), *automatically* performs class integration. This constitutes the second phase, called class integration, and is discussed in Sec. 4. The third phase called schema restructuring phase is discussed in Sec. 5. in which we define operators to modify the integrated schema to make up for the limitations of the earlier phases. We thus derive a final, integrated schema. Section 6 gives an example and we give our conclusions in Sec. 7.

2. Background

In this section, we briefly review related work, comment on the common model in which automatic class integration is performed, and introduce our approach.

2.1. Previous Approaches to Schema Integration

The survey paper by Batini *et al.* [2] discusses and compares 12 methodologies for schema integration work. These methodologies are oriented towards integration that involve only human reasoning (i.e. all relationships among schema objects are identified by the user). The portion of the integration process that can be automatically (and meaningfully) performed in most methodologies purely on the basis of schema definition is severely limited. Two distinct types of operations are performed during integration:

(i) specifying relationships between classes based on the user's understanding of the domain, and

(ii) specifying mappings between the integrated schema and the *component schemas* (i.e. the schemas that are integrated).

[c] We assume that all schemas to be integrated are represented in the same data model, which in our case happens to be CANDIDE. This approach has been extended to integrate E-R schemas by developing mappings between Extended E-R models and CANDIDE models [33].

The second type of operations are not strictly necessary to generate an integrated schema, but are very useful if the integrated schema is to be used for multi-database access. Such mappings are not discussed in this paper.

Batini *et al.* [2] divide schema integration activity into five steps: preintegration, comparison, conforming, merging, and restructuring. The preintegration step involves translation of schemas into a common data model so that they can be compared. Additionally, it may also include specification of global constraints and defining a catalog of naming correspondences (e.g. specifying a thesaurus that may be used for identifying naming conflicts, homonyms, synonyms, etc.).

The comparison activity involves analyzing and comparing various aspects of the component schemas, including identification of naming conflicts (e.g. homonym and synonym detection), domain (i.e. value type) conflicts, differences in structure and constraints. Conforming activities are closely tied to the comparing activities since the comparing activities lead to an identification of what needs to be conformed. Comparison is not meaningful unless the same information or concept is represented in a similar way in different schemas. Naming conflicts are usually resolved by renaming. Structural differences are dealt with by the conforming activities in which some structures are transformed into others so that the same structure is equivalently represented (i.e. having the same semantics). For example, [1] and [32] show how to translate one E-R structure into another. Spaccapietra *et al.* [41] also allow specification of assertions between the objects that are structurally different.

One significant result of schema analysis is attribute equivalence specification. In the previous methodologies [22,13,20] as well as tools [11,16,37], attribute equivalence has been used as a heuristic in the process of specifying how classes are related in the component schemas. User specification of class relationships then leads to the merging activity, which can be automated (e.g. lattice generation in [37]).

We recognize attribute relationship specification and class relationship specification (called assertion specification in [13]) to be the most critical tasks in the integration of schemas. Attribute relationships include attribute equivalences as well as attribute inclusions (also called containment). Most earlier work was limited to using only attribute equivalences.[d] Attribute equivalence is an attempt to identify different attributes that represent the same property across "related" classes. All previous efforts that use attribute equivalence, to our knowledge, require the user to identify the equivalent attributes, or propose heuristics (e.g. [11,16]).

Elmasri *et al.* [13] discuss using attribute equivalence as a heuristic to order pairs of classes that may be related. The user then specifies all relationships between each pair of related classes. These relationships are used as an input to a lattice generation or merging activity to derive a single integrated schema. Some of the efforts, particularly those that do not use class relationships for automatic merging, provide a set of operators for the user to correlate or integrate the classes in the component schemas to generate an integrated schema [6,21].

[d] Larson *et al.* [20] and Mannino and Effelsberg [22] consider the equal and containment relationships among domains of the attributes.

2.2. Choice of a Canonical Data Model

The data model into which all schemas are translated is called a common (or unified or canonical) data model (CDM). If a schema is not in the CDM, it should be translated from its native data model into the CDM. This process is called schema translation. For example, to integrate a CODASYL database schema and a relational database schema, the corresponding CODASYL and relational schemas should be translated into the *equivalent* CDM representation to facilitate their analysis and merging [18]. Typically, schema translation is treated as an entirely separate process from that of schema integration. Due to the lack of formal semantics of the data models usually involved, equivalence can only be informally justified in terms of the knowledge of a person doing the translation, and cannot be formally proved.[6]

The choice of the CDM is critical in the process of schema integration. The CDM should be semantically rich, in that it should be able to provide constructs, abstractions and constraints relevant to schema integration. Semantic (or conceptual) data models are much preferred over a traditional data model such as relational, network, or hierarchical. However, choosing the semantic data model as the CDM from among many known models (e.g. those surveyed in [15,31]) is difficult. We believe that a model that has too many non-orthogonal constructs or abstractions may have benefits when defining or designing schemas (by providing constructs to the schema designer that s/he is familiar with), but is not well suited for schema integration because it makes schema analysis and modification very difficult. Automating any part of the schema integration process would be facilitated by a model that is formal, provides orthogonality of constructs leading to a basis for automatic reasoning.

2.3. Proposed Approach

Here we give an overview of three phases in our schema integration approach: schema analysis, class integration, and schema restructuring. While these phases can be found in many previous approaches, our framework significantly differs in details. All schemas are assumed to be represented in a canonical data model (to be defined in Sec. 4). Each component schema contains a class taxonomy and an attribute hierarchy (see Sec. 3). The integration process involves generating an attribute hierarchy common to all component schemas and subsequently a class taxonomy involving all classes of the component schema. This approach has been implemented in a tool developed at Bellcore [33,39].

2.3.1. Schema analysis

The main result of the schema analysis phase is the generation of a *global* attribute hierarchy. This *global* attribute hierarchy is generated by integrating in-

[6] Equivalence has been formally defined in the case of schema restructuring within a well defined model [32].

dividual attribute hierarchies corresponding to each component schema. Sectic 3.2 discusses a methodology based on a clustering technique to generate the a tribute hierarchy. In [13,22,37], schema analysis results in the specification of a s of pairwise attribute equivalences. In our approach, instead, an attribute hiera chy is produced which, in addition to equivalence, also represents disjointness an inclusion relationships between attributes.

The conforming phase takes care of the *relativism* [8] which is said to occ when the same concept is represented using different model constructs (e.g. a entity and an attribute represent the same *thing*). This is a critical issue an when necessary, we resort to the proposals for transformations among differen constructs (e.g. [1,17]). As mentioned earlier, the task of conforming is very strongl related to that of comparing because comparing is difficult when the representation (constructs) do not conform. Hence, we regard both of them as belonging to th schema analysis phase.

2.3.2. Class integration

In previous efforts, all relationships among classes were supplied by the user, although algorithms for simple graph manipulation to combine class hierarchies have been given (e.g. lattice generation in [13,37]). On the other hand, in our approach, identification of class relationships and the subsequent class integration process is *completely* automated. This is done by classifying every class from each component schema into a single class taxonomy. The global attribute hierarchy generated in the schema analysis phase is used to perform the classification. The resulting class taxonomy represents a partially integrated schema. The approach in [13] relies on a classification of attributes into equivalence classes followed by a specification of pairwise relationships between related objects. These relationships are: `equal`, `contained-in`, `contains`, `overlap` and `disjoint-but-integrate`. In our approach, the first three relationship types are deduced (and the schema duly restructured) by the automatic reasoner while the last two are deferred to the latter phase of schema restructuring (even though the system can deduce `overlap` and `disjoint` — see Sec. 5). It is important to note that while use of attribute equivalence in [13,37] is only as a heuristic to facilitate the object class assertion specification, in our approach, the information contained in the attribute hierarchy is fully exploited for merging various schemas (see Sec. 4.3).

2.3.3. Schema restructuring

In some of the previous efforts, merging and restructuring have not been treated separately (see Sec. 2.8 in [2]). However, use of an automatic reasoner necessarily makes these tasks distinct. The case of `disjoint-but-integrate` mentioned above can be safely specified only by the user in the schema restructuring phase. Alternatively, this relationship may be considered during the schema analysis phase while creating the attribute hierarchy. Since we believe that semantics cannot be

completely represented and automatically reasoned about [35,36], we provide a set of well-defined operators to allow the user to make any changes to the partially integrated schema. The class integration phase merges the component schemas into a single schema. The schema restructuring phase involves user driven modification of the integrated schema with a well defined set of operators defined in Sec. 5.

3. On Attribute Relationships

Here we show that the attribute descriptors as defined in the schema integration literature are *only a partial list* of characteristics and therefore inadequate to establish equivalence. We next describe our methodology to generate an attribute hierarchy.

3.1. Comments on Attribute Equivalence in Previous Works

Use of attribute equivalence for schema integration has been discussed in [22,20]. In [20], an attribute is defined in terms of the following descriptors (i.e. meta-data information): Uniqueness, Lower Bound, Upper Bound, Domain, Static Semantic Integrity Constraints, Dynamic Semantic Integrity Constraints, Security Constraints, Allowable Operations, and Scale. Furthermore, they tie the attribute to a class (entity type or relationship type) definition. The attribute equivalence theory proposed by them essentially states that if there exists a certain mapping function between the domains (i.e. the value set) of two attributes, then the two attributes are said to be equivalent. They further define different types of equivalences based on whether the mapping is an isomorph and whether the mappings hold at the current time or for all values of time. However, these details are inconsequential to our discussion. We now observe that this attribute equivalence definition is *incomplete* and *inadequate*. First, the particular set of descriptors used to define an attribute are arbitrary. That is, we can always add some more descriptors or choose a different set of descriptors. These descriptors are mostly relevant to the information that is traditionally stored in a schema. Second, the descriptors fail to capture the semantics of an attribute. For example, consider two attributes `person.name` (i.e. attribute `name` belonging to an entity type `person`) and `department.name`. We may be able to define a mapping (possibly isomorphic) between the domains of these two attributes, and thereby, according to [20], declare them equivalent. Unfortunately, this is contrary to the intended semantics of the two attributes. Furthermore, according to [20], the user has to define the mappings. We do not dispute the utility of defining the domain mappings (they must be defined in order to allow multi-database access from an integrated schema), *but the existence of a mapping does not imply attribute equivalence* in the semantic sense. Furthermore, we do not know of a particular set of descriptors with which to compute attribute relationships. At best, given a set of descriptors, one can define heuristics that may help in discovering attribute equivalence. However, such heuristics may either make incorrect equivalences or fail to detect all meaningful equivalences. The issue of schematic and semantic relationships has been discussed in more detail in [36].

3.2. Attribute Hierarchy Generation

The purpose of data modeling is to create an isomorphic mapping between the intended real world semantics of a given universe and its symbolic representation on a machine. It is this isomorphic mapping which allows us to manipulate real world concepts (or objects) on a machine in a *meaningful* manner. As mentioned earlier, within the framework of schema integration, we are interested in identifying relationships among attributes and among classes that lead to the creation of an integrated schema consisting of a taxonomy of classes. In our approach, we first establish attribute relationships, which then help us in automatically computing class relationships. Note that this step is optional, that is, the class integration algorithm (to be described in Sec. 4) does not require an attribute hierarchy as mandatory input. The attribute relationships of interest are equivalences and inclusions. That is, for two attributes, `a` and `b`, one of the following hold:

(1) `a` and `b` are **`equivalent`**, or $a \equiv b$,

(2) `a contains (is-contained-in) b`, or $a \supset (\subset) b$,

(3) If neither of the above, then `a` and `b` are **`disjoint`**.

Our attribute hierarchy is a strict partial ordering of inclusion relationships.[f] Given the relationship between every pair of attributes, an attribute hierarchy can easily be generated [22]. We now propose heuristics for reasoning about attributes as follows.

We limit our universe to

(1) assertions about attribute definitions, and their relationships, and

(2) assertions about object definitions, and their relationships.

Let `RWS(U)` denote the intended real world semantics for some universe of discourse `U`. Further, let `RWAS(a)` denote the real world semantics of an attribute `a`, and `RWCS(c)` that of a class `c` in `U`. We can now define a semantic space[g] for the `U` in which schemas are being integrated as follows:

$$\texttt{RWS(U)} = \{\texttt{RWCS}(c_i)\} \cup \{\texttt{RWAS}(a_j)\},\ 1 \leq i \leq m,\ 1 \leq j \leq n$$

where `m`, `n` are the total number of classes and attributes in `U`, respectively. We assume that class definitions are denoted by single-place predicates `P(x)` and attributes are denoted by two-place predicates `Q(x, y)`.[h] Here, we define a framework

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[f] This is a restriction imposed by our canonical data model. It further implies that it is not possible to model overlapping attributes.

[g] The semantic space is seen as an abstraction of the semantics in the user's mind.

[h] This is a reasonable assumption since one can always translate object definitions in most structured representation schemes (such as semantic data models, semantic networks and frame description languages) into equivalent logic statements which consist of only single- and two-place predicates. For example, $ParentOfMen(x) \rightarrow Parent(x)$ is the same as $\{ParentOfMen\} \subset \{Parent\}$, and means that for all values of x in the universe satisfying the predicate *ParentOfMen*, those same values must also satisfy the predicate *Parent*. A similar argument is made for attributes, an example of which is $Son(x, y) \rightarrow Child(x, y)$.

within which we can formulate a theory for attribute relationships. A given universe is dichotomized into two subspaces in this manner so that we can first reason about attributes and then about classes. As argued in Sec. 3.1, a complete specification of the real world semantics for attributes is not possible. This imposes a fundamental limitation, and therefore, we describe some heuristics below to define an attribute hierarchy. On the other hand, it is possible to define a limited model for classes (or entity types) in which we automatically determine class relationships (see Sec. 4).

The problem of attribute equivalence can be broken into two subproblems:

(1) moving from the space of attribute labels and their characterization to its corresponding semantic space RWAS (i.e. establishing a correspondence), and

(2) generating an attribute hierarchy in the semantic space.

By looking at Fig. 1, we can see that the links between the attribute definitions space S $\{Q(x, y)\}$ and the semantic space RWAS $\{Q\ (x, y)\}$ denote the mappings:

$f : Q(x, y) \rightarrow RWAS(Q(x, y))$, and

$g : RWAS(Q(x, y)) \rightarrow \{Q(x, y)\}$

It can be easily seen that the mapping f is 1-1 whereas the inverse link g is $1 - n$. Consider a point $Q_i(x, y)$ in the semantic space. Corresponding to this point we can have many points, $Q_{i_j}(x, y)$, in the attribute definition space. For example, we see that the attribute labels *emp_name*, *worker_name* and *name* map onto the same point in the semantic space. This necessarily means that the three attributes in question are equivalent in U. Additionally, there are other attributes *person_name* and *student_name* which map onto two other distinct points in the semantic space. Similarly, *emp_num* and *ss_num* map onto two distinct semantic points, while *dept_name* maps onto yet another semantic point.

We now make the following observations:

- Since *emp_name*, *worker_name* and *name* map onto the same semantic point Q_1, they are semantically equivalent.
- It is also the case in our universe that *person_name* and *student_name* which map onto Q_2 and Q_3 respectively, are related to Q_1 and are therefore located close to each other and to Q_1 in the semantic space.
- *emp_num* and *ss_num* map onto Q_4 and Q_5 respectively, and their distance from Q_1 is greater than that between Q_2 and Q_3.
- On the other hand, *dept_name* maps onto the semantic point Q_6 which is **disjoint** from Q_1.

The above suggests a certain classification pattern based upon equivalence and inclusion relationships between attributes as well as their relative meaning. Thus, we can define the following clusters in our semantic space, called *semantic clusters*:

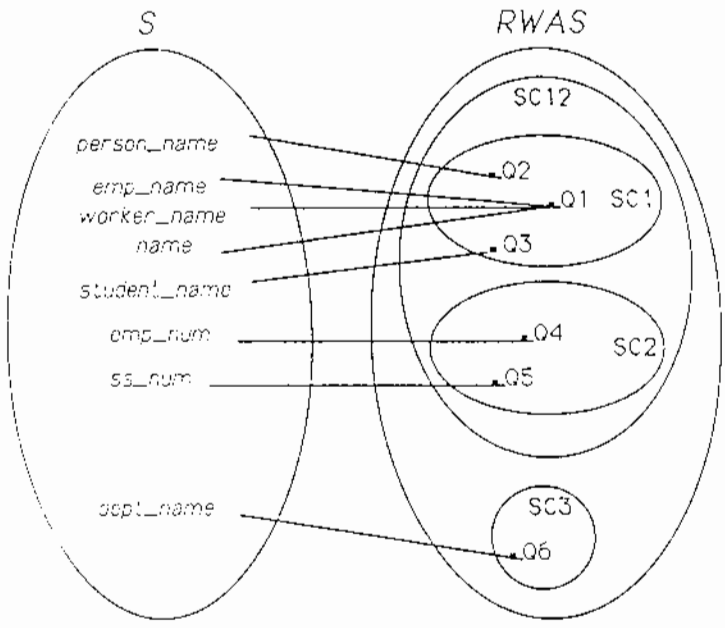


Fig. 1. Mapping attributes into semantic space.

(1) $SC_1 = \{Q_1, Q_2, Q_3\}$

The semantic cluster denoted by SC_1, labeled as *people_names* for convenience, includes *emp_name*, *person_name* and *student_name* (the set is non-exhaustive and mutually exclusive). However, it may also be the case that $Q_1 \subset Q_2$ and $Q_3 \subset Q_2$. This is equivalent to saying that `RWAS(emp_name)` $\subset$ `RWAS(person_name)` and `RWAS(student_name)` $\subset$ `RWAS(person_name)`. Thus, there may be a strict ordering within a given semantic cluster. However, any two semantic clusters are necessarily disjoint. This hierarchy is shown in Fig. 2.

(2) $SC_2 = \{Q_4, Q_5\}$

The cluster SC_2 labeled *people_numbers* contains, among other semantic points, *emp_num* and *ss_num*.

(3) $SC_3 = \{Q_6\}$

(4) $SC_{12} = SC_1 \cup SC_2$

This is a semantic cluster labeled say, *people_identifiers*, which includes, among other things, the clusters *people_names* and *people_numbers*. Again, this cluster is a non-exhaustive and mutually exclusive union of two semantic subspaces.

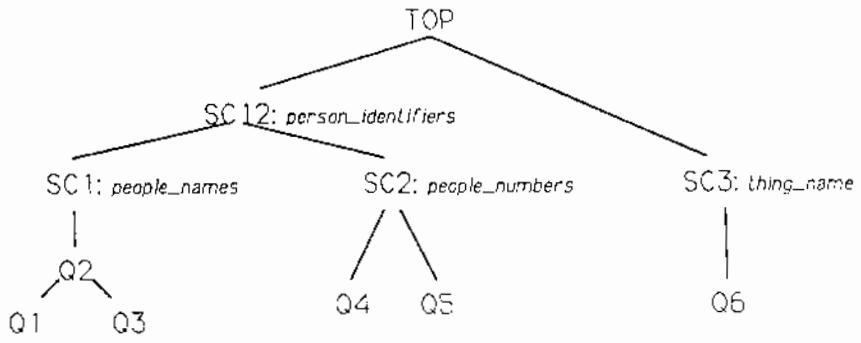


Fig. 2. An example attribute hierarchy.

We now propose the following methodology to deal with attribute **equivalence** and **inclusion**:

(1) Make a list of all attribute names appearing in all the schemas to be integrated.
(2) The user (a domain expert or DBA) must now identify various appropriate semantic clusters (this can be done in advance or dynamically when considering a new attribute not belonging to a previously defined semantic cluster).
(3) All sets of equivalent attributes should be determined and each set must be denoted by a unique **RWAS**.
(4) All remaining attributes are then associated with their respectively unique **RWAS**s.
(5) Each **RWAS** is placed in exactly one semantic cluster based on the judgement and intuition of the user.
(6) Now that each semantic cluster contains a set of unique **RWAS**s, the user can specify piece-meal information about inclusion between two **RWAS**s within the same semantic cluster (recall that any two semantic clusters are necessarily disjoint), which is then assimilated into a strictly ordered hierarchy.

The **global** attribute hierarchy thus generated can be used to merge n different schemas.

3.3. An Underlying Assumption

We identify two different kinds of attribute relationships, namely, those that hold true throughout the universe of discourse, and those that hold true only within a given class. For example, consider the class of **person** with attributes **son** and the class **parents-whose-sons-are-business-partners** with attributes **son** and **business-partners**. We observe two facts about this universe:

- It makes sense to say that any value in our universe that satisfies the attribute **son** (regardless of what class it is attached to) also satisfies the attribute **child** (regardless of the class to which it is attached), i.e. **son** $\subset$ **child**.

- A similar relationship cannot hold between **son** and **business-partners** because their relationship is merely a *constraint* imposed on them in order to define the class in question. The relationship **son** $\subset$ **business-partners** does not hold outside the class **parents-whose-sons-are-business-partners**.

Such a distinction is not made in previous works on attribute equivalence. Thus, *the attribute relationships (in terms of equivalence or inclusion) should be determined such that they are valid throughout the domain of discourse*. This is necessary since the classes of the component schemas are merged against a single global attribute hierarchy. Therefore, attribute relationships within this hierarchy must hold true throughout the universe of discourse. While an attribute's association in the class as it appears in the component schema may provide part of the (and in some cases significant) semantics required to determine a relationship with another attribute, it is neither the only nor the overriding factor. For example, when considering attribute **age** in class **Employee** and attribute **age** in class **Engineer**, we may wish to refer to the semantics of age in persons, humans, or living organisms (regardless of whether corresponding classes appear in the original schemas) and limit the semantics of the attributes to the classes that they help define in the component schemas. Attribute relationships that hold only within a single class definition (e.g. **car.model** and **car.model.option**) have no place in the global attribute hierarchy (and should be dealt with in the class integration phase).[1]

4. Class Integration

This is the second phase of our approach to schema integration, in which various class relationships are automatically deduced. We first describe CANDIDE, our canonical data model, in Sec. 4.1. Then we give an example of class definitions, and show the role played by the attribute hierarchy in computing subsumption in Sec. 4.2. In Sec. 4.3, we discuss why CANDIDE was chosen as the canonical data model.

4.1. Overview of the CANDIDE Data Model

CANDIDE belongs to the KL-ONE [7] family of systems, also known as terminological logics or term subsumption languages. It is essentially an extension of the KANDOR knowledge representation system [30]. This extension involved using a notation that conforms to the more common data modeling terms, and adding constructs to simplify representation of standard data domains. For example, we have added the domain constructors **range**, **set**, and **composite** domain, and allowed for additional built-in domains such as **real**. These do not really increase the power of the model or affect computational complexity; but they improve the applicability of the model. CANDIDE is a correct and complete model of computation and

[1] Such constraints can be represented in a system as expressive as KL-ONE [7] (in which computing subsumption is undecidable), but not in the CANDIDE system (in which computing subsumption is decidable and is at least co-NP-hard).

the problem of computing subsumption in CANDIDE is at least co-NP-hard [25]. CANDIDE can be viewed as an orthogonal, minimal, and relativistic model [15]. A complete description of CANDIDE can be found in [3, 4]. It was employed in the Federated Information Base project as the canonical model [24]. Here we provide a description of some of the concepts, particularly those that are relevant to class integration.

4.1.1. Structural aspects of the data model

The CANDIDE model explicitly supports the abstractions of aggregation and generalization. A relationship or association between two or more classes is modeled as a class which is the aggregation of attributes referencing each member class (of the relationship), in addition to other possible attributes which the relationship may have.

The database schema consists of two partial orders, one for the attribute hierarchy, and the other for the class taxonomy. In the attribute hierarchy, which has a root called "Top", each attribute can have at most one parent attribute along with an associated domain. This domain is either an instance, or a set of instances typified by a class defined in the class taxonomy. The domain of an attribute must be an improper subclass of the domain of its parent attribute. The root of the class taxonomy is a universal class called "Thing".

An attribute appearing in a class description can be qualified by additional value constraints on its domain specified within the class description. Further, these attribute constraints in a class must logically imply the constraints on each corresponding attribute of each of its superclasses. Such constraints also specify satisfiability requirements for instances to be members of the class. A class can have many superclasses, subclasses, and instances. A disjoint class means that the named subclasses of a given class cannot have any common instance.

4.1.2. Constraint specification

A class description comprises its superclasses, subclasses, instances, and attributes. One can specify additional constraints on these attributes. There are four kinds of constraints: **max**, **some**, **exactly**, and **all**. The **max** n constraint means that an attribute can have at most n values. The **some** m constraint means that there exist at least m values, each value belonging to a certain domain qualified by value constraints. The **exactly** constraint means that exactly a specified number of attributes must satisfy a value constraint; it is the combination of **some** n and **max** n. The **all** constraint specifies that all values of an attribute must belong to a given domain qualified by value constraints. Note the similarity of the **all** and **some** constraints to the universal and existential quantifiers of first order predicate calculus [19].

Value constraints on attributes specify domains. Domains may be specified by naming the class as in **class** ⟨classname⟩, **string**, **integer** or **real**, or by using the

domain constructors **range**, **set**, **setdif**, and **composite**. **Range** specifies a range of values between some upper and lower bounds which may be inclusive, exclusive, or **nil** ($\pm$ infinity), and is typed over reals and integers. The **set** construct allows a set of domains to be specified such that the attribute values must belong to the union of these domains. A set may recursively include other value constraints. **setdif** allows a special form of negation (set difference) to be handled in a safe way. For example, "**setdif** f g", where f is a class and g is its subclass, denotes a set consisting of only those instances belonging to f and not to g. The **composite** domain is the aggregation of other (possibly complex) domains, in which each component domain is labeled by an attribute name along with its constraints. For example, a **composite** domain for an attribute called *Date* would have component attributes of *Month*, *Day*, and *Year*.

4.1.3. Classification and subsumption

A class f **subsumes** a class g if and only if every instance of g is also an instance of f, i.e. f is a superclass of g. This subsumption relationship is computed on the basis of whether the attribute constraints for class g logically imply the corresponding attribute constraints for class f. Computing subsumption can be automated because a class definition provides necessary and sufficient conditions for deciding class membership. The classification operation can compute missing class-subclass relationships (that is, those left unspecified by the user when building the class taxonomy) by a controlled application of the subsumption function, and can completely specify the class taxonomy.

Classification can be viewed as the process of correctly locating a new class in an existing taxonomy. The correct location is immediately below the most specific class(es) which subsume the new class and immediately above the most general class(es) subsumed by this new class. One simple way of generating a class taxonomy is to take the transitive reduction over a boolean matrix generated by applying subsumption between all possible pairs of classes in the schema. Since there are n^2 such pairs, classification is an $O(n^2)$ algorithm where the fundamental unit of computation is the subsumption operation.

4.2. Role of the Attribute Hierarchy in Computing Subsumption

To see how subsumption can be computed in CANDIDE, consider an example of two classes, where c_1 is defined to have an attribute *child* with the domain *man*, and c_2 is defined to have an attribute *son* with the domain *person*. Suppose that we are also given that *man* is beneath *person* in the class taxonomy and *son* is beneath *child* in the attribute hierarchy. These classes are defined in CANDIDE as follows:

class c_1 **defined**
superclass thing
attributes
    child: **all class** *man*

class c_2 **defined**
superclass thing
attributes
son: **all class** *person*

Therefore, c_2 is above c_1 in the class taxonomy when **subsume** (c_2, c_1) = **true**. This happens if and only if the logical constraints on c_1 — logical constraints on c_2, i.e.

child: **all class** *man* → *son*: **all class** *person*

This can be derived as follows from a set of inference rules that define the computation of subsumption. From these rules, we know that

if attribute r is above s then r: **all** $f \rightarrow s$: **all** f.

Since *child* is above *son* in the attribute hierarchy, applying this rule in our example tells us that

child: **all class** *man* → *son*: **all class** *man*

There is another inference rule which says that

if subsume(g, f) = **true** then s: **all** $f \rightarrow s$: **all** g.

Since *person* is above *man* in the class taxonomy, applying this rule in our example tells us that

son: **all class** *man* → *son*: **all class** *person*

Therefore, from these two deductions, we have by transitivity of implication,

child: **all class** *man* → *son*: **all class** *person*

Thus without explicitly having stated anything about the precise definition of son, but just based on information about the *child-son* and *person-man* inclusion dependencies, we were able to determine that c_2 subsumes c_1. The formal semantics of CANDIDE are derived from KANDOR which appear in [30], along with a decision procedure for computing subsumption. It is important to note that this inference could not have been made if we did not have information about the inclusion of *son* within *child* in the attribute hierarchy. Thus, the class taxonomy contains information about the inclusion relationship between single place predicates whereas the attribute hierarchy deals with two-place predicates. The decision procedure for computing subsumption allows us to automatically generate the class taxonomy based on object definitions given an attribute hierarchy. If the attribute hierarchy is a flat structure (i.e. a tree of depth 1), then this lack of depth *will be reflected* in the class taxonomy. For example, given a flat attribute hierarchy, we cannot say things like every son is necessarily a child. In such a situation, the system could never have deduced that c_1 is a subclass of c_2. Further, note that a flat attribute hierarchy structure is the same as having no attribute hierarchy at all, or rather, just a list of attribute names. This means that the previous step of building an

attribute hierarchy is entirely optional with a caveat that attributes with the same name will be assumed to have the same meaning.

4.3. Choice of CANDIDE as the Canonical Data Model

There are many reasons for choosing CANDIDE as the canonical data model.

(1) It has a well defined semantics which allows us to automatically compute the class-subclass (subsumption) relationship. That is, the system can reason about class definitions in a correct and complete manner.

(2) The same subsumption function can be used to decide whether
   (a) a given class is incoherent,
   (b) two given classes are disjoint,
   (c) two given classes overlap, and
   (d) two given classes are equivalent.

(3) CANDIDE incorporates an attribute hierarchy as an integral part of the database schema definition, i.e. it is assumed that an attribute hierarchy is given to the system. This allows us to *dichotomize* between heuristic reasoning (to determine the attribute hierarchy) and automatic reasoning (to determine class relationships). This means that the question of whether an attribute a is above b in a given hierarchy is treated like an oracle. Thus, the system does not care how the attribute hierarchy is generated, but given one, it will correctly reason about class definitions within the schema. In other words, information about attribute inclusion is exploited in the inference rules for computing subsumption in a sound fashion.

(4) It is a minimal model as it allows only the generalization and aggregation abstractions [40]. The schema graph (or class taxonomy) can be generated by using only the two abstractions provided. A class (or node in the schema graph) can be defined by specifying cardinality and domain constraints for each attribute of the class. These two kinds of constraints are orthogonal to each other. Domains can be atomic, simple or complex (generated by using the domain constructors).

(5) It is a relativistic model since the system semantics allow us to automatically determine that two different forms representing the same concept are equivalent. This is done by reducing such class equivalence to computing bidirectional implication of the constraints on each corresponding attribute defining the classes in question (see Sec. 5.1).

(6) The CANDIDE classifier computes the minimal superclasses and maximal subclasses of a given class by employing the subsumption function as described above. Thus merging n schemas essentially reduces to classifying each class in each schema to generate a new or global schema. This schema is generated by modifying the class-subclass links for each class as dictated by the classification function and is independent of the order in which schemas or classes are chosen for merging. Note that the aggregation links are left unchanged. Also, no new classes are created that did not already exist in at least one of the n schemas. We shall see more about this in Sec. 5.

The first two items imply that there is no need for the user to specify the class assertions of the type equal and inclusion (contains/contained-in) as in [13.27] since the classifier automatically deduces such assertions. Furthermore, subsumption can be used to deduce "overlap" and "disjoint" relationships between two classes. However, the classifier cannot generate a new class and cannot decide whether two classes that overlap or are disjoint should be merged (we elaborate this in Sec. 5). These two cases are handled in the third phase by the use of appropriate operators by the user.

5. Schema Reorganization

After the n component schemas have been merged, the user can employ a set of well-defined operators to reorganize the schema. We first define a set of comparison operators which help in determining class relationships, and then a set of restructuring operators. We then discuss some guidelines for applying these operators to restructure schemas.

5.1. Operators to Determine Class Relationships

As mentioned above, it is important to automatically compute various class relationships such as `equivalent`, `includes`, `is-included-in`, `overlaps`, and `disjoint`. The `subsume` function computes `includes` and `is-included-in` in an obvious manner. We now give a few definitions which show how these relationships can be computed with the help of the `subsume` function. Let f, g be two classes and $E[f]$, $E[g]$ represent their respective extensions, i.e. set of instances.

(1) Subsume

$$\texttt{subsume}\ (f, g) = \textbf{true iff}\ E[f] \supseteq E[g]$$

However, as explained in Sec. 4.1.3, subsumption is computed on the basis of class definitions and not the actual extensions. This means that the `subsume` function returns **true** if and only if the constraints on *each* attribute of g logically imply the constraints on the corresponding attribute of f. Therefore, `subsume` $(f, g) = f$ `includes` $g \equiv g$ `is-included-in` f.

(2) Equivalence

$$\texttt{equivalent}\ (f, g) = \textbf{true iff}\ E[f] \equiv E[g]$$

This function can be computed using subsumption as follows:

$$\texttt{equivalent}\ (f, g) = \texttt{subsume}\ (f, g) \wedge \texttt{subsume}\ (g, f)$$

(3) Overlap

`Overlap` is defined as follows:

$$\texttt{overlap}\ (f, g) = \textbf{true iff}\ E[f] \cap E[g] \neq \emptyset$$

`Overlap` can be computed as follows:

$$\texttt{overlap}\ (f, g) = \textbf{true iff}\ \texttt{subsume}\ (f, g) \wedge \neg\ \texttt{subsume}\ (g, f) \wedge \neg\ \texttt{disjoint}\ (f, g)$$

That is, two classes overlap if they do not subsume each other, and are not disjoint. As an example, consider the two classes *Instructor* and *Student*. They can overlap because an instance of *Instructor* may also be an instance of *Student*, such as a *Teaching Assistant*.

(4) Disjoint

Two classes are defined as disjoint if the intersection of all possible extensions of the two classes is empty.

$$\texttt{disjoint}\ (f, g) = \textbf{true iff}\ E[f] \cap E[g] = \emptyset$$

`Disjoint` can be computed as follows:

$$\texttt{disjoint}\ (f, g) = \textbf{true iff}\ \texttt{incoherent}\ (\texttt{conjunction}(f, g))$$

Here `conjunction` is a function which returns a new class from two given classes such that the extension of the new class is the intersection of the extensions of the given classes:

$$E[\texttt{conjunction}(f, g)] = E[f] \cap E[g]$$

`Incoherent` is a boolean function which tests for logical inconsistency in constraints on the attributes of a given class. For example, the maximum cardinality cannot be less than the minimum cardinality on any attribute (for more details see [30]). This means that there cannot be any instances of an incoherent class: $E\ [\texttt{incoherent}(f)] = \emptyset$ We compute incoherency of a class by checking if the class is subsumed by a known incoherent class: $\texttt{incoherent}(f) = \texttt{subsume}(i, f)$ where i is a known incoherent class.

For example, the class *Part-time-student* from schema *sc*1 with the constraint that a part-time student can register for a maximum of nine credit hours, and the class *Full-time-student* from schema *sc*2 with the constraint that a full time student must register for at least 12 credit hours, clearly show that there cannot be a student who is both part-time and full-time. As another example, if a class *Student-evening-club* has the constraint that it must have at least two part-time students among its members and the class *Honor-society* has the constraint that only a full-time student can be its member, then these two classes do not have a common instance. A conjunction of these two classes will lead to an incoherency. Therefore, the classes are identified as disjoint.

The functions defined above are based on the ability to compute subsumption, i.e. they are based on the semantics of class definitions. However, it is possible to define boolean functions which return true or false based on more syntactic criteria such as attribute relationships. Therefore, we define two additional operators. These are merely alternate definitions of the notions of overlap and disjoint. They are defined here because the user may wish to use these definitions rather than the ones defined above.

(5) `attr_overlap`(f, g)

This function returns true if and only if there exists at least one pair of attributes $a1$ and $a2$ such that $a1 \equiv a2$ or $a1 \subset a2$ or $a2 \subset a1$ where $a1$ is any attribute of f and $a2$ is any attribute of g.

(6) `attr_disjoint`(f, g)

This function returns true if and only if there does not exist any pair of attributes $a1$ and $a2$ such that $a1 \equiv a2$ or $a1 \subset a2$ or $a2 \subset a1$ where $a1$ is any attribute of f and $a2$ is any attribute of g.

All these functions can be computed automatically. The user can now restructure the global schema based on his or her perspective of the universe of discourse with the help of these functions.

5.2. Schema Restructuring Operators

This second set of operators can be used to create new classes from existing ones and/or delete existing classes. The schema integrator uses these operators to restructure the schema.

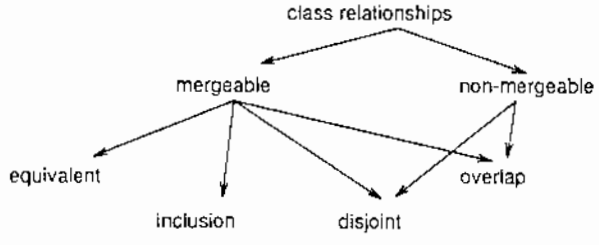
- `delete`(f): This function will delete the class f from the integrated schema and check for consistency. If the resulting schema is found inconsistent then the user is alerted with an appropriate message. For example, it might be the case that there is a class "student" which has an attribute "belongs to", the domain of which is the class "department" which was just deleted. Such deletion will be disallowed.
- c = `generalize1`(f, g): The two classes f and g are generalized to create a new class c (the label for class c is provided by the user, e.g. *teacher* = `generalize1`(*faculty*, *instructor*). Only the common attributes are chosen for c, and a union (or logical disjunction) of the constraints on these attributes is defined. The resulting class is checked for incoherency, and is well-defined if the following relationships are satisfied: $E[f] \supseteq E[c]$ and $E[g] \supseteq E[c]$.
- c = `generalize2`(f, g): The same as `generalize1` except that f and g are now deleted from the schema. This is useful when there is no need for definitions of the classes in the component schemas from which a class in the integrated schema is derived. An example is when a new database is created based on the integration and potential users have their own view of what the schema should look like (e.g. once the two classes *schema1.employee* and *schema2.employee* are generalized to create *final.employee*, there may be no need to keep the original two versions of employee in the integrated schema).
- c = `specialize1`(f, g): The two classes f and g are specialized to create a new class c (the label for class c is provided by the user). For the common attributes of f and g chosen for c, the logical conjunction of the constraints on these attributes is defined. The remaining attributes are merely concatenated to the definition of c. The resulting class is then checked for incoherency, and is well-defined if the following relationships are satisfied: $E[c] \supseteq E[f]$ and $E[c] \supseteq E[g]$.

- c = **specialize2**(f, g): The same as **specialize1** except that f and g are then deleted from the schema. This function is needed for similar reasons as **generalize2**.

5.3. Applying Functions to Integrate Schemas

To integrate two schemas, $sc1$ and $sc2$, we apply the above class comparison functions between each pair of classes f and g such that $f \in sc1$ and $g \in sc2$. (It is assumed that each individual schema is already "well-defined". By well-defined, we mean that there are no inconsistencies in the individual schemas.) Whenever two classes are identified as **equivalent**, they are merged into a single class. Similarly, when one class **subsumes** another class, the integrated schema is appropriately restructured. The user then applies the schema restructuring operators to get a final, integrated schema based on his knowledge of the universe of discourse. Disjoint or overlapping classes may or may not be merged depending on the situation. For example, *birds* and *aircraft* may be disjoint classes, but can be merged under a common superclass called *flying objects* by executing the following operator: *flying_objects* = **generalize1**(*birds*, *aircraft*). Similarly, *instructors* and *students* may overlap, and can be possibly merged to form a common subclass called *teaching assistants*. On the other hand, even though *courses* and *instructors* are related in the sense that instructors teach courses, and regardless of whether they overlap or are disjoint, they need not be merged into a common class. Such decisions are and can be made solely by the user.

Shown below are two types of class relationships: mergeable, and non-mergeable. If two classes satisfy the semantics for equivalence or inclusion relationship based on subsumption, then they are obviously mergeable. However, as explained above, if two classes overlap or are disjoint, then user intervention is required to decide whether they are mergeable or not.



The following rules provide guidelines to decide mergeability which the user can exploit to restructure the schema:

(1) **if** `class-rel = equivalent or includes` **then** merge in obvious manner.

(2) **if** `class-rel = disjoint or overlap` **and** the two classes have a common ancestor other than root **then** the two classes can be generalized.

(3) **if** `class-rel = overlap` **and** the two classes have a common subclass **then** the two classes can be specialized.

(4) **if** `class-rel = disjoint or overlap` **and** the two classes do not have a common ancestor other than root **then** the user makes a decision.

(5) **if** `class-rel = overlap` **and** the two classes do not have a common subclass **then** the user makes a decision.

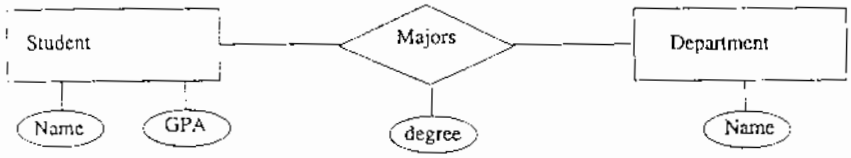
The first rule is already taken care of in the schema merging phase described earlier since it is the result of the classification function. The second and third rules can also be incorporated as part of the automatic reasoner. However, user intervention becomes a must when one of the last two rules is triggered.

6. An Example of Schema Integration

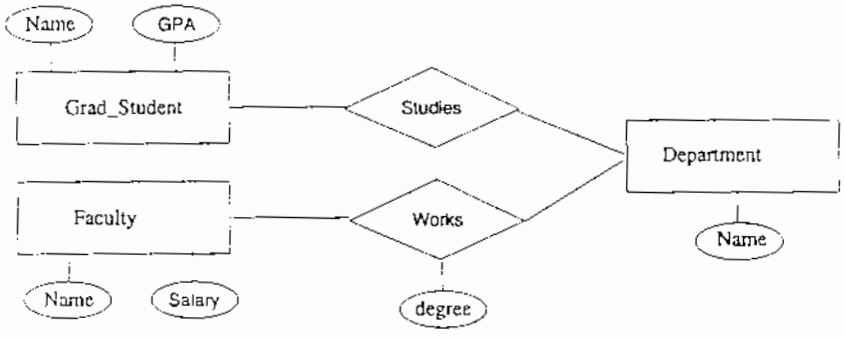
We now show how our approach will apply to a simple example used in [13]. Figure 3 shows two E-R schemas, $s1$ and $s2$, to be integrated. Figure 4 shows the equivalent CANDIDE schemas consisting of the respective attribute hierarchies and class taxonomies. Figure 5 shows the attribute hierarchy against which these two schemas are to be integrated.

The attribute hierarchy essentially represents the various semantic clusters and the attribute relationships within a given cluster. For example, *Name* of *Department* in schema $s1$ is equivalent to *Name* of *Department* in schema $s2$, and $Student.Name \subset Grad\_Student.Name$. The distinction between points in the semantic space and the attribute definition space can be dropped once the attribute relationships have been decided by the user. Any set of equivalent attributes must be replaced by a single label since they all map onto the same semantic point (and also given the fact that the attribute hierarchy actually represents the relationships between semantic points). Further, ambiguity may be resolved by appending the attribute by a schema identifier as in $s1.Department$. Entities and attributes can have the same labels — this causes no ambiguity in the CANDIDE classifier.

All attribute relationships need not be known in advance. The integration process can be iterative in the sense that if the user is not satisfied with the results obtained by classifying each class in all schemas being integrated, s/he can modify the attribute hierarchy and start again. Thus the user can start with a flat structure (the same as having no attribute hierarchy) and iteratively modify and refine this structure until a satisfactory schema is achieved. The classification process essentially reorganizes the entities in each schema by discovering the class/subclass relationship among entities regardless of which schemas they occur in. This phase is called class integration and is followed by the schema restructuring phase. Figure 6 shows the result of class integration in our example. Figure 7 shows the finally integrated schema including the effects of schema restructuring operators. Note that the mere application of the classification function will not result in the generation of new classes (entities) such as *E_Stud_Faculty*. Furthermore, the names of newly generated classes are given by the user.

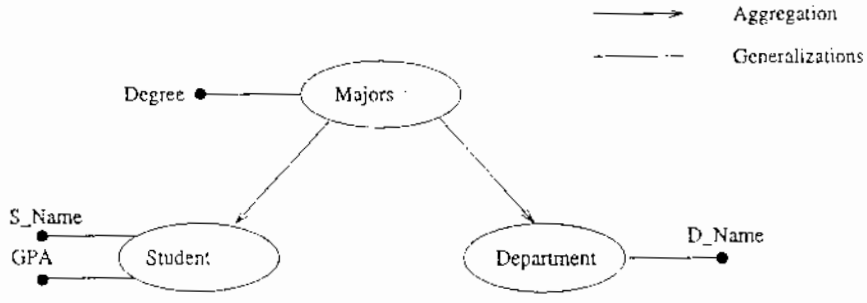


(a)

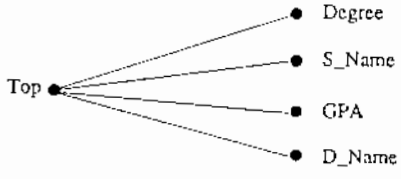


(b)

Fig. 3. Input schemas $s1$ and $s2$.

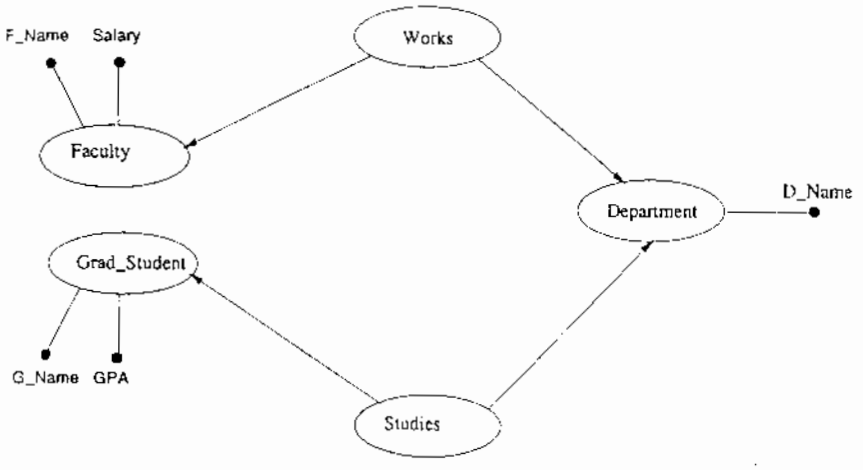


(i)

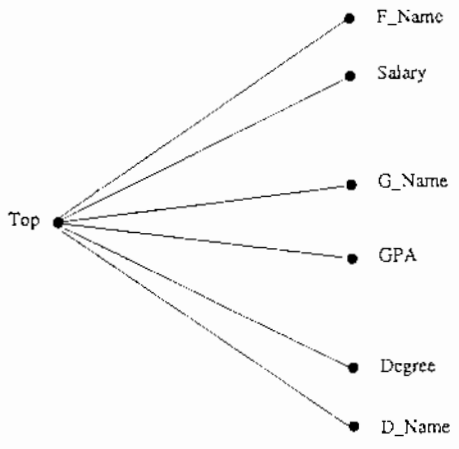


(ii)

Fig. 4(a). (i) CANDIDE class hierarchy for $s1$. (ii) CANDIDE attribute hierarchy for $s2$.



(i)



(ii)

Fig. 4(b). (i) CANDIDE class hierarchy for $s2$. (ii) CANDIDE attribute hierarchy for $s2$.

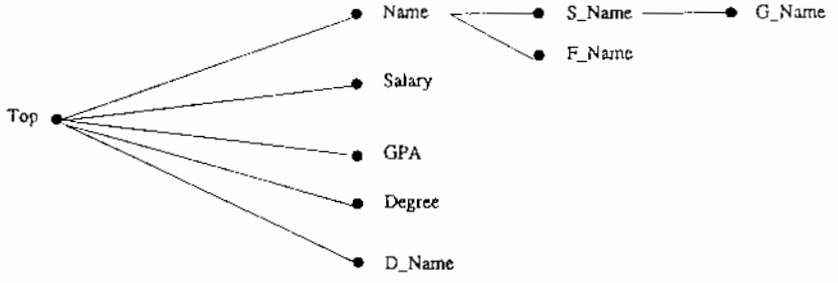


Fig. 5. Result of Phase I: Global attribute hierarchy.

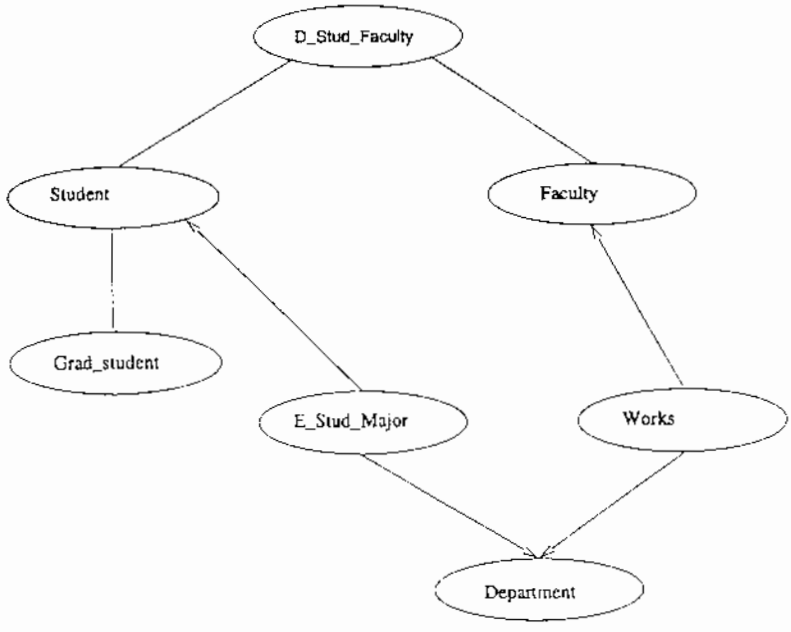


Fig. 6. Result of Phase II + III: Integrated CANDIDE schema.
D_Stud_Faculty = **generalize1** (*Student*, *Faculty*)
E_Stud_Major = **generalize2** (*Studies*, *Major*)

The integration phase is independent of the order in which schemas are integrated, and can be described by the following steps:

(1) Translate each E-R schema into an equivalent CANDIDE schema (see [33] for more details).

(2) Optionally, define an attribute hierarchy using the guidelines presented in Sec. 3. This hierarchy will be used for integrating all schemas in a given domain of discourse.

(3) Start building the integrated schema by beginning with some arbitrary schema and classify each entity in that schema with respect to the integrated schema.

(4) For all remaining schemas, classify each entity in each schema.

(5) Apply schema restructuring operators to make further modifications to the integrated schema.

(6) If the integrated schema is dissatisfactory, refine the attribute hierarchy and reclassify all classes in the integrated schema. Repeat Step 6 until the integrated schema can be made satisfactory by applying the schema restructuring operators.

Steps 5 is driven by the user, and was discussed in Sec. 5. As an example, the *faculty* and *instructor* entities can be generalized into the *teacher* entity, and *teacher* and *student* can be further generalized into *person*. The number of iterations (that is, Step 6) is also decided by the user.

7. Conclusions

We have discussed certain limitations of previous approaches to schema integration, especially with respect to automatically discovering attribute relationships. We then proposed a methodology with which the user can identify attribute relationships. This information is used to generate a global attribute hierarchy. The second phase of our approach involves *automatically* integrating classes from component schemas based on a classification algorithm. The fundamental unit of computation in this algorithm is subsumption.

Based on the semantics of the CANDIDE data model, we have been able to dichotomize the schema integration activity into first reasoning about attributes and then classes. Reasoning about attributes involves heuristic reasoning (performed by a human) while reasoning about classes utilizes automatic and formal reasoning. Reasoning about the relationships between attributes is by no means an easy task and we have discussed that this task cannot be automated. It can however be made somewhat manageable and structured using the methodology discussed in the paper. We also discussed why the attribute reasoning should not be limited by their associations with the classes they belong to in the component schemas.

Once the attribute hierarchy is generated, most relationships between the classes can be automatically determined and an integrated schema can be generated automatically by merging or associating related classes using the process of classification. The inference rules to compute subsumption exploit the attribute relationship information contained in the attribute hierarchy in a sound manner. They also adhere to the constraints that are captured in the class definitions. The order in which a given class is classified is immaterial. The subsumption operator is further used to define a set of comparison operators. The user can exploit these comparison operators in the final phase of schema reorganization, for which a well-defined set of schema restructuring operators are given.

The main contributions of this paper are:

(1) identifying portions of the schema integration process that can be meaningfully automated and those portions that are necessarily user-driven,
(2) exploiting the notions of classification and subsumption to provide a vehicle for automatic class integration,
(3) defining a set of schema comparison and restructuring operators, and
(4) developing an overall schema integration methodology with three phases.

A schema integration toolkit called BERDI based on the approach discussed in this paper has been implemented and tested at Bellcore [33,39]. The user interface of BERDI is based on an extended E-R model. It supports generation of attribute

hierarchy as described in this paper, which can then be used for automatic class integration as discussed here, or alternatively used as constraints when the user asserts class relationships. For the automatic class integration option, after generating an attribute hierarchy, the component E-R schemas are semi-automatically translated into equivalent CANDIDE schemas, integrated as described in this paper, and translated back into an extended E-R schema.

An area for further research is to investigate possible learning algorithms which can help in discerning attribute relationships. It may also be desirable to decide, perhaps through an extensive empirical study involving real schemas, how complete and how good the integrated schema is at the end of the second phase, and how much work is needed in the third phase. We hope that the use of automatic reasoning, in our case, one based on terminological logics, and our study on where automatic reasoning is possible and where it is not possible (although limited to the context of schema integration), will be a step towards developing future intelligent and cooperative information systems.

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References

[1] C. Batini and M. Lenzerini, A methodology for data schema integration in the entity relationship model, *IEEE Trans. Softw. Eng.* 10, 6 (1984).

[2] C. Batini, M. Lenzerini and S. Navathe, A comparative analysis of methodologies for database schema integration, *ACM Comput. Surv.* 18, 4 (1986) 323–364.

[3] H. Beck, A Terminological Knowledge Representation System Based on Theories of Categorization, Ph.D. Thesis, University of Florida, May 1990.

[4] H. W. Beck, S. Gala and S. B. Navathe, Classification as a query processing technique in the CANDIDE semantic data model, in *Proc. 5th Int. Conf. on Data Engineering*, Los Angeles, Feb. 1989.

[5] J. Biskup and B. Convent, A formal view integration method, in *Proc. ACM SIGMOD Int. Conf. on Management of Data*, Washington D.C., May 1986.

[6] M. Bouzeghoub and I. Comyn-Wattiau, View integration by semantic unification and transformation of data structures, in *Proc. 9th Int. E-R Conf.*, Lausanne, ER Institute, 1990.

[7] R. Brachman and G. Schmolze, An overview of the KL-ONE knowledge representation system, *Cogn. Sci.* 9, 2 (1985) 171–216.

[8] M. Brodie, On the development of data models, in *On Conceptual Modeling*, Eds. M. Brodie, J. Mylopoulos and Schmidt (Springer Verlag, 1984).

[9] B. Convent, Unsolvable problems related to the view integration approach, in *Proc. Int. Conf. on Database Theory*, Rome, Sept. 1986.

[10] B. Czejdo, M. Rusinkiewicz, and D. Embley, An approach to schema integration and query formulation in federated database systems, in *Proc. 3rd Int. Conf. on Data Engineering*, Los Angeles, Feb. 1987.

[11] J. De Souza, SIS: A Schema Integration System, in *Proc. BNCOD5 Conf.*, ACM, 1986.

[12] S. Deen, R. Amin, G. Ofori-Dwumfuo, and M. Taylor, Data integration in distributed databases, *IEEE Trans. Softw. Eng.* **13**, 7 (1987).

[13] R. Elmasri, J. Larson and S. B. Navathe, Schema integration algorithms for federated databases and logical database design, Technical Report CSC-86-9, Honeywell CSDD, Minneapolis, MN, Jan. 1986.

[14] W. Effelsberg and M. Mannino, Attribute equivalence in global schema design for heterogeneous distributed databases, *Inf. Syst.* **9**, 3 & 4 (1984).

[15] R. Hull and R. King, Semantic database modeling: Survey, applications and research issues, *ACM Comput. Surv.* **19**, 3 (1987) 201–260.

[16] S. Hayes and S. Ram, Multi-user view integration system (MUVIS): An expert system for view integration, in *Proc. 6th Int. Conf. on Data Engineering*, Los Angeles, Feb. 1990.

[17] W. Kim, W. Kelley, S. Gala, and I. Choi, On resolving schematic heterogeneity in multidatabase systems, *Distributed and Parallel Databases: An International Journal* 1, 3 (1993).

[18] J. Larson, Bridging the gap between network and relational database management systems, *IEEE Computer* **16** (1983) 82–92.

[19] H. Levesque and R. Brachman, A fundamental tradeoff in knowledge representation and reasoning (revised version), in *Readings in Knowledge Representation*, Eds. R. J. Brachman and H. J. Levesque (Morgan Kaufmann, Los Altos, CA, 1985).

[20] J. Larson, S. Navathe and R. Elmasri, A theory of attribute equivalence in databases with applications to schema integration, *IEEE Trans. Softw. Eng.* **15**, 4 (1989) 449–463.

[21] A. Motro and P. Buneman, Constructing superviews, in *Proc. ACM SIGMOD Conf.*, May 1981.

[22] M. Mannino and W. Effelsberg, Matching techniques in global schema design, in *Proc. 1st Int. Conf. on Data Engineering*, Los Angeles, April 1984.

[23] S. Navathe, R. Elmasri and J. Larson, Integrating user views in database design, *IEEE Computer*, **19**, 1 (1986) 15–62.

[24] S. Navathe, S. Gala and S. Geum, Application of the CANDIDE semantic data model for federation of information bases (invited paper), in *Proc. Conf. on Management of Data (COMAD'91)*, Bombay, India, Dec. 1991.

[25] B. Nebel, Computational complexity of terminological reasoning in BACK, *Artif. Intell.* **34**, 3 (1988).

[26] E. Neuhold and M. Schrefl, Global Schema Integration by Iterative Classification, Tech. Rep., Dept. of Applied Comp. Sc., Tech. Univ. of Vienna, Sept. 1985.

[27] E. Sciore, M. Siegal and A. Rosenthal, Context interchange using meta attributes, in *Proc. 1st Int. Conf. on Information and Knowledge Management*, Baltimore, Nov. 1992.

[28] S. Spaccapietra, C. Parent and Y. Dupont, Automating heterogeneous schema integration, Technical Report, Ecole Polytechnique Federale, Lausanne, Switzerland, Apr. 1991.

[29] P. Patel-Schneider, R. Brachman and H. Levesque, ARGON: Knowledge Representation Meets Information Retrieval, Fairchild Technical Report 654, FLAIR, 1984.

[30] P. F. Patel-Schneider, Small can be Beautiful in Knowledge Representation, Technical Report 37, FLAIR, Oct. 1984.

[31] J. Peckham and J. Maryanski, Semantic data models, *ACM Comput. Surv.* **20**, 3 (1988) 153–190.

[32] A. Rosenthal and D. Reiner, Theoretically sound transformations for practical database design, in *Proc. Int. Conf. on the Entity-Relationship Approach*, New York, Nov. 1987.

[33] A. Savasere, An Approach to Schema Integration Using Classification, M.S. Thesis, Department of Computer and Information Sciences, University of Florida, Gainesville, 1990.

[34] A. Savasere, A. Sheth, S. Gala, S. Navathe and H. Marcus, On applying classification to schema integration, in *Proc. Int. Workshop on Interoperability in Multidatabase Systems*, Kyoto, Japan, April 1991.

[35] A. Sheth and S. Gala, Attribute relationships: An impediment in automating schema integration, in *Proc. Workshop on Heterogeneous Database Systems*, Chicago, Dec. 1989.

[36] A. Sheth and V. Kashyap, So far (schematically) yet so near (semantically), in *Proc. DS-5 Conference on Semantics of Interoperable Database Systems*, Lorne, Australia, Nov. 1992.

[37] A. Sheth, J. Larson, A. Cornelio and S. Navathe, A tool for integrating conceptual schemas and user views, in *Proc. 4th Int. Conf. on Data Engineering*, Los Angeles, Feb. 1988.

[38] A. Sheth and J. Larson, Federated database systems for managing distributed, heterogeneous, and autonomous databases, *ACM Comput. Surv.* **22**, 3 (1990) 183–236.

[39] A. Sheth and H. Marcus, Schema Analysis and Integration: Methodology, Techniques, and Prototype Toolkit, Technical Memorandum TM-STS-019981/1, Mar. 1992.

[40] J. Smith and D. Smith, Database abstractions: Aggregation and generalization, *ACM Trans. Database Systems*, June (1977) 105–133.

[41] S. Spaccapietra, C. Parent and Y. Dupont, Model independent assertions for integration of heterogeneous schemas, *The VLDB Journal* **1**, 1 (1992) 81–126.

[42] C. Yu, W. Sun, S. Dao and D. Keirsey, Determining relationships among attributes for interoperability of multi-database systems, in *Proc. Int. Workshop on Interoperability in Multidatabase Systems*, Kyoto, Japan, Apr. 1991.

[43] M. Casanova and M. Vidal, Toward a sound integration methodology, in *Proc. 2nd ACM SIGMOD/SIGACT Conf. on Principles of Database Systems*, Atlanta, GA, Mar. 1993.