Combining Declarative and Procedural Knowledge to Automate and Represent Ontology Mapping

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Abstract. Ontologies on the Semantic Web are by nature decentralized. From the body of ontology mapping approaches, we can draw a conclusion that an effective approach to automate ontology mapping requires both data and metadata in application domains. Most existing approaches usually represent data and metadata by ad-hoc data structures, which is lack of formalisms to capture the underlying semantics. Moreover, to approach semantic interoperability, there is a need to represent mappings between ontologies with well-defined semantics that guarantee accurate exchange of information. To address these problems, we propose that domain ontologies attached with extraction procedures are capable of representing knowledge required to find direct and indirect matches between ontologies. Also mapping ontologies attached with query procedures not only support equivalent inferences and computations on equivalent concepts and relations but also improve query performance by applying query procedures to derive target-specific views. We conclude that a combination of declarative and procedural representation with ontologies favors the analysis and implementation for ontology mapping that promises accurate and efficient semantic interoperability.

1 Introduction

Ontologies on the Semantic Web, by nature, are decentralized and built independently by distinct groups. The research on *ontology mapping* is to compare ontological descriptions for finding and representing semantic affinities between two ontologies. By analyzing the body of ontology mapping approaches [2] [5] [6] [7] [12] [14] [17], a key conclusion is that an effective ontology mapping approach requires a principled combination of several base techniques such as linguistic matching of names of ontology elements, detecting overlap in the choice of data types and representation of data values, considering patterns of relationships between elements, and using domain knowledge[12].

To support knowledge sharing between base ontology-mapping techniques, a knowledge base that describes domain models is of great value. The knowledge bases in most existing approaches, however, are represented informally by ad-hoc data structures, which are difficult to capture well defined semantics effectively. To further facilitate interoperability between ontologies, there is a need to represent mappings between ontologies such that the mapping representation guarantees to successfully exchange

information. The research work that addressed this ontology-mapping representation problem is usually done separately from the research that focuses on finding semantic affinities [3] [9] [10] [13], which is lack of support for an efficient approach to achieve interoperability on the Semantic Web. To approach these problems within one knowledge-representation framework, we argue that a combination of declarative and procedural representation based on ontologies favors the analysis and implementation for ontology mapping and promises accurate and efficient semantic interoperability.

Our declarative representation for ontology mapping includes (1) domain ontologies that provide semantic bridges to establish communications between base techniques in order to find semantic affinities between ontologies; and (2) mapping ontologies that provide means to correctly exchange information. Declaratively, ontologies are usually expressed in a logic-based language so that detailed, accurate, consistent, sound, and meaningful distinctions can be made among concepts and relations. Their logic base therefore promises proper reasoning and inference on ontologies.

However, the expression power of ontologies is limited with ontology mapping. Ontologies have difficulties to effectively express semantic heterogeneity between ontologies. For example, within a domain, different vocabulary terms can describe a same concept and populated concept instances can have various lexical appearance. Unfortunately, the capability of handling semantic heterogeneity is extremely important for ontology mapping since its goal is to find and represent semantic affinities between semantically heterogeneous ontologies. Moreover, to support interoperability across ontologies, based on a debate on the mailing list of the IEEE Standard Upper Ontology working group,[3] semantic operability is to use logic in order to guarantee that, after data are transmitted from a sender system to a receiver, all implications made by one system had to hold and be provable by the other, and that there should be a logical equivalence between those implications. To express equivalent concepts and relations between two ontologies, we must issue queries to compute views over ontologies since ontologies rarely match directly [17]. The associated set of inference rules with ontologies, however, neither support expressing complex queries nor reasoning queries efficiently.

Procedural attachment is a common technique to enforce the expression power in case where an expression power is limited [16]. A *procedural attachment* is a method that is implemented by an external procedure. We employ two types of procedural attachments in our approach. A domain ontology shared by base ontology-mapping techniques is attached with *extraction procedures*. An extraction procedure is an encoded method with extraction patterns that express the lexical instantiations of ontology concepts. A mapping ontology, on the other hand, is attached with *query procedures* to establish a communication across ontologies. Each mapping instance maps a *source* ontology to a *target* ontology, which is formally specified such that source data is ready to load into the target. Because it is not always promising that we have direct mappings [7] [17], a *query procedure* computes a target-specific view over the source so that the view data satisfies all implications made by the target when we can not map a source ontology to a target ontology directly.

In this paper, we offer the following contributions: (1) attaching extraction procedures with domain ontologies to represent knowledge shared by base techniques to find

[3] Message thread on the SUO mailing list initiated at http://suo.ieee.org/email/msg07542html.

semantic affinities between ontologies; and (2) attaching query procedures with mapping ontologies to efficiently interoperate heterogeneous ontologies based on mapping results produced by base techniques. We present the details of our contribution as follows. Section 2 describes elements in input and domain ontologies and how to apply domain ontologies to support finding semantic affinities between ontologies. Section 3 describes source-to-target mappings as mapping ontologies and how the representation supports accurate and efficient semantic interoperability. Section 4 gives an experimental result to demonstrate the contribution of applying domain ontologies to ontology mapping. Finally, we summarize and draw conclusions in Section 5.

2 Domain Model Representations

2.1 Input Ontology

An ontology include classes, slots, slot restrictions, and instances [4]. Classes and instances form an ontology. A class is a collection of entities. Each entity of the class is said to be an instance of that class. With *IS-A* and *PART-OF* relationships, classes constitute a hierarchy. Slots attached to a class describe properties of objects in the class. Each slot has a set of restrictions on its values, such as cardinalities and ranges. By adapting an algebra approach to represent ontologies as logical theories [10], We provide the following definition.

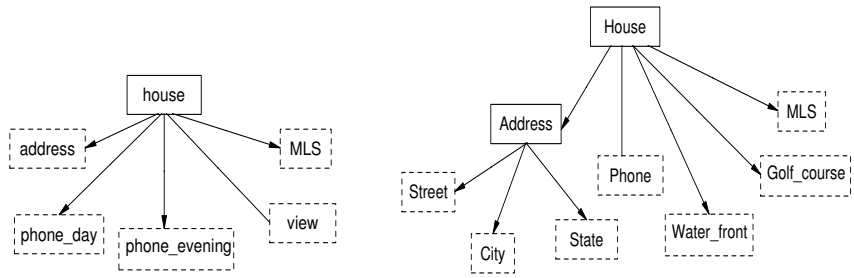
Definition 1. An *input ontology* $O = (S, A, F)$, where S is the *signature* that describes the vocabulary for classes and slots, A is a set of *axioms* that specify the intended interpretation of the vocabulary in some domain of discourse, and F is a set of ground facts that classifying instances with class and slot symbols in the signature S.

For discussion convenience, in this paper we use rooted hypergraphs graphs to illustrate structure properties between classes and slots in ontological signatures. A hypergraph includes a set of nodes modeling classes and slots and a set of edges modeling relations between them. The root node is representing a designated class of primary interest. Figure 1, for example, shows two ontology hypergraphs (whose roots are $house$ and $House$). In hypergraphs, we present a class or slot using either a solid box or a dashed one where a dashed box indicates that there is data populated for the concept, a functional relation using a line with an arrow from its domain to its range, and a nonfunctional relation using a line without arrowhead.

2.2 Domain Ontology

To represent domain knowledge to find semantic affinities between two ontologies, we use domain ontologies attached with extraction procedures to capture semantics for ontology mapping. Ground facts are not part of a domain ontology since the domain ontology is not populated with instances. We define a domain ontology as follows.

Definition 2. A *domain ontology* $O = (S, A, P)$, where S is the ontological signature, A is a set of ontological axioms, and P is a set of *procedures* that extract metadata



(a) Ontology Signature 1 (partial) (b) Ontology Signature 2 (partial)

Fig. 1. Signatures of Input Ontologies

and data from vocabulary terms and populated instances of input ontologies based on extraction rules.

Extraction procedures attached with domain ontologies apply data extraction techniques [8] to retrieve data and metadata when matching two ontologies. Each extraction procedure is designed for either a class or slot in a domain ontology. When an extraction procedure is invoked, a recognizer does the extraction by applying a set of extraction rules specified using regular expressions. Figure 2 shows the regular expressions using the Perl syntax for slot $View$ and $Phone$ in a real-estate domain.

Each list of regular expressions include declarations for data values that can potentially populate a class or slot and keywords that can be used as vocabulary terms to name classes and slots. We describe the data values using *extract* clauses and the keywords using *keyword* clauses. When applied to an input ontology, both the *extract* and *keyword* clauses causes a string matching a regular expression to be extracted, where the string can be a vocabulary term in the ontological signature or a data values classified by the ontological ground facts.

2.3 Application of Domain Ontology

Figure 3 shows three components in a real-estate domain ontology, which we used to automate the mapping between two ontologies in Figure 1 and also for mapping real-world ontologies in the real-estate domain in general. Each dashed box in Figure 3 associates with an extraction procedure that is capable of extracting both populated values and vocabulary terms for the concept. Filled-in (black) triangles denote aggregation ("PART-OF" relationships). And open (white) triangles denote generalization/specialization ("IS-A" superclasses and subclasses).

Provided with the domain ontology described in Figure 3, we can discover many semantic affinities between Ontology 1 in Figure 1(a) and Ontology 2 in Figure 1(b) as follows.

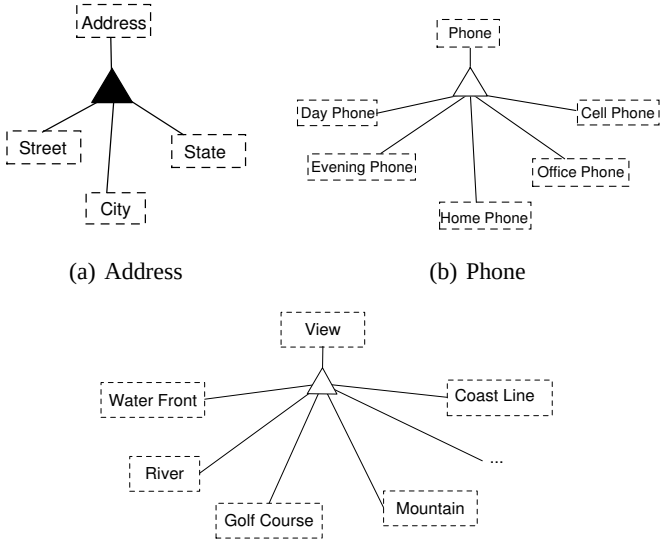
1. Terminological Relationships. The extraction patterns applied by extraction procedures specify common vocabulary terms used to name classes and slots. Based on the $Phone$ component in Figure 3(b), the vocabulary term $phone\_day$ in Ontology

```
View matches [15] case insensitive
    constant
        { extract “\bmountain\sview\b”; },
        { extract “\bwater\sfront\b”; },
        { extract “\briver\sview\b”; },
        { extract “\bpool\sview\b”; },
        { extract “\bgolf\s*course\b”; },
        { extract “\bcoastline\sview\b”; },
            ...
        { extract “\bgreenbelt\sview\b”; };
    keyword
        “\bview(s)?\b”;
End;
Phone matches [15] case insensitive
    constant
        { extract “\b\d{3}-\d{4}\b”; }, – nnn-nnnn
        { extract “\b\(\d{3}\)\s*\d{3}-\d{4}\b”; }, – (nnn) nnn-nnnn
        { extract “\b\d{3}-\d{3}-\d{4}\b”; }, – nnn-nnn-nnnn
        { extract “\b\d{3}\\\d{3}-\d{4}\b”; }, –nnn\nnn-nnnn
        { extract “\b1-\d{3}-\d{3}-\d{4}\b”; }; – 1-nnn-nnn-nnnn
    Keyword
        “\bcall\b”,“\bphone\b”;
End;
```

Fig. 2. Example of regular expressions in a real-estate domain

1 matches with keywords specified for concept $Day\ Phone$ and the term $Phone$ in Ontology 2 matches with keywords for concept $Phone$. Based on the “IS-A” relationship between $Day\ Phone$ and $Phone$, we can find the semantic affinity between $phone\_day$ in Ontology 1 and $Phone$ in Ontology 2.

2. *Merged/Split Values*. Based on the $Address$ declared in the ontology in Figure 3(a), the attached extraction procedure detects that (1) the values of $address$ in Ontology 1 match with extraction patterns for concept $Address$, and (2) the values of $Street$, $City$, and $State$ in Ontology 2 match with extraction patterns for concepts $Street$, $City$, and $State$ respectively. Based on “PART-OF” relationships in Figure 3(a), we can find the “PART-OF” relationships between $Street$, $City$, and $State$ in Ontology 2 and $address$ in Ontology 1.
3. *Superset/Subset*. By calling extraction procedures attached with in Figure 3(b), $phone\_day$ in Ontology 1 matches with both keywords and data value patterns for $Day\ Phone$ and $phone$ in Ontology 2 matches with $Phone$. In Figure 3(b) the ontology explicitly declares $Phone$ is a superset of $Day\ Phone$ based on the “IS-A” relationship between $Day\ Phone$ and $Phone$. Thus we can find the semantic affinity between $phone\_day$ in Ontology 1 and $Phone$ in Ontology 2.
4. *Vocabulary Terms/Data Instances*. Extraction procedures apply extraction patterns to recognize keywords and value patterns over both ontology terms and populated instances since it is difficult to distinguish boundaries between metadata and populated data instances in complex knowledge representation systems. In Ontology 1, $Watherfront$ is data classified for $view$ in its ontological ground facts. In On-



(a) Address (b) Phone

(c) View

Fig. 3. Real-estate domain ontology (partial)

tology 2, $Water\_front$ is a vocabulary term in its ontological signature. Boolean values "Yes" and "No" associated with $Water\_front$ in Ontology 2 are not its values but to show whether the values $Water\_front$ should be included as description values for $view$ of $House$ in Ontology 1 if we do mapping. The extraction procedure for concept $View$ in Figure 3(c) recognizes terms such as $Water\_front$ in Ontology 2 as values while the procedure for concept $Water\ Front$ can recognize keyword "*water front*" associated with $view$ in Ontology 1. Since $Water\ Front$ "IS-A" $View$ in Figure 3(c), by derivation, we can detect that $view$ in Ontology 1 has a semantic affinity with $Water\_front$ in Ontology 2.

3 Mapping Result Representation

3.1 Source-to-target Mapping

We adopt an ontology mapping definition as follows [10].

Definition 3. A *source-to-target mapping* M_{ST} from $O_S = (S_S, A_S, F_S)$ to $O_T = (S_T, A_T, F_T)$ is a morphism $f(S'_S) = S'_T$ such that $A'_T| = f(A'_S)$, i.e. all interpretations that satisfy O'_T axioms also satisfy O'_S translated axioms if there exists two sub-ontologies $O'_S = (S'_S, A'_S, F'_S)$ ($S'_S \subseteq S_S, A'_S \subseteq A_S, F'_S \subseteq F_S$) and $O'_T = (S'_T, A'_T, F'_T)$ ($S'_T \subseteq S_T, A'_T \subseteq A_T, F'_T \subseteq F_T$).

Our representation solution for source-to-target mapping allows a variety of source derived data based on the discovered semantic affinities between two input ontologies. These source derive data include missing generalizations and specializations, merged

and split values, and etc. Therefore, our solution "extends" elements in an ontological signature S_S of a source ontology O_S by including views computed via queries, each of which we call a *view* element. We let V_S denote the extension of S_S with derived, source view elements.

Every source-to-target mapping M_{ST} is composed of a set of triples. Each triple $t = (e_t, e_s, q_e)$ is a *mapping element*, where $e_t \in S_T$, $e_s \in V_S$, q_e is either empty or a *mapping expression*. We call a triple $t = (e_t, e_s, q_e)$ a *direct match* which binds $e_s \in S_S$ to $e\_t \in S_T$, or an *indirect match* which binds a view element $e_s \in V_S - S_S$ to $e\_t \in S_T$. When a mapping element t is an indirect match, q_e is a *mapping expression* to illustrate how to compute the view element e_s over the source ontology O_S.

To represent source-to-target mapping as logic theories, we specify source-to-target mappings as populated instances of a mapping ontology, which is defined as follows.

Definition 4. A mapping ontology $O = (S, A, F, P)$, where S is the ontological signature, A is the set of ontological axioms, F is a set of ground facts presenting source-to-target mappings, and P is a set of query procedures that describe designed query behaviors to compute views over ontologies.

If a mapping element $t = (e_t, e_s, q_e)$ in a source-to-target mapping M_{ST} is an indirect match, i.e. e_s is a source view element, a query procedure is attached with t to compute e_s by applying the mapping expression q_e.

3.2 Mapping Expressions

We can view each class and class slot (including view elements corresponding to either classes or class slots) in ontologies as single-attribute or multiple-attribute relations. Relational algebra is ready to be applied to describe procedural behaviors for query procedures attached with mapping ontologies. Therefore, we present mapping expressions by an extended relational algebra since traditional operators in relational algebra do not cover the ones required to address problems such as *Merged/Split values* and *Vocabulary Terms/Data Instances*.

For example, to address *Merged/Split Values*, we designed two operations *Composition* and *Decomposition* in the extended relational algebra. We describe the two operations as follows. In the notation, a relation r has a set of attributes; $attr(r)$ denotes the set of attributes in r; and $|r|$ denotes the number of tuples in r.

- *Composition* λ. The λ operator has the form $\lambda_{(A_1,\ldots,A_n),A} r$ where each A_i, $1 \leq i \leq n$, is either an attribute of r or a string, and A is a new attribute. Applying this operation forms a new relation r', where $attr(r') = attr(r) \cup \{A\}$ and $|r'| = |r|$. The value of A for tuple t on row l in r' is the concatenation, in the order specified, of the strings among the A_i's and the string values for attributes among the A_i's for tuple t' on row l in r.
- *Decomposition* γ. The γ operator has the form $\gamma^R_{A,A'} r$ where A is an attribute of r, and A' is a new attribute whose values are obtained from A values by applying a routine R. Applying this operation forms a new relation r', where $attr(r') = attr(r) \cup \{A'\}$ and $|r'| = |r|$. The value of A' for tuple t on row l in r' is obtained by applying the routine R on the value of A for tuple t' on row l in r.

Assuming that Ontology 1 in Figure 1(a) is the target and Ontology 2 in Figure 1(b) is the source, the follow lists the derivation of a view element $House - address'$ in Ontology 2 that matches with $house - address$ in Ontology 1.

$$Address - Address' \Leftarrow \pi_{Address, Address'} \lambda_{(Street, \text{“, ”}, City, \text{“, ”}, State), Address'} (Address - Street \bowtie Address - City \bowtie Address - State)$$
$$House - address' \Leftarrow \rho_{Address' \leftarrow address'} \pi_{House, Address'} (House - Address \bowtie Address - Address')$$

The λ operator denotes the *Composition* operation in the relational algebra. The Composition operation merges values in $Street$, $City$ and $State$ for a new concept $Address'$.

3.3 Semantic Interoperability

Definition 5. A *semantic interoperable system* $I = (O_T, \{O_{S_i}\}, \{M_{S_iT}\})$, where O_T is a target ontology, $\{O_{S_i}\}$ is a set of n source ontologies, and $\{M_{S_iT}\}$ is a set of n source-to-target mappings, such that for each source ontology O_{S_i} there is a mapping M_{S_iT} from O_{S_i} to O_T, $1 \leq i \leq n$.

The following theorem provides that accurate information exchange between ontologies is guaranteed by derived source-to-target mappings.

Theorem 1. *Given a semantic interoperable system I = (O_T, $\{O_{S_i}\}$, $\{M_{S_iT}\}$) where $1 \leq i \leq n$, data facts $F_{O_{S_i} \rightarrow O_T}$ flowing from O_{S_i} to O_T based M_{S_iT} hold and are provable by O_T.*

Note that data facts $F_{O_{S_i}}$ flowing from O_{S_i} to O_T based on M_{S_iT} have classifications to either signature or view elements in O_{S_i}. Since a source-to-target mapping defines a morphism $f(S'_{O_{S_i}}) = S'_{O_T}$, the data facts $F_{O_{S_i}}$ hence hold the classifications to the signature elements in O_T that correspond source elements in O_S.

Assume that user queries issued over I are Select-Project-Join queries and we also assume that they do not contain comparison predicates such as $\leq$ and $\neq$. We use the following standard notation for conjunctive queries.

$$Q(\overline{X}) : -P_1(\overline{X_1}), ..., P_n(\overline{X_n})$$

$\overline{X}$, $\overline{X_1}$,..., $\overline{X_n}$ are tuples of variables, and $\overline{X} \subseteq \overline{X_1} \bigcup ... \bigcup \overline{X_n}$. The predicates P_i ($1 \leq i \leq n$) is a target signature element. When evaluating query answers for a user query Q, the semantic interoperable system I transparently reformulates Q as Q^{ext}, a query over the target and source ontologies in I. Since each target signature element P_i possibly corresponds to a set of source elements $\{s | s \rightarrow P_1\}$, to obtain Q^{ext}, we substitute P_i in Q by adjoining P_i to $\{s | s \rightarrow P_i\}$. Note that a source element s in the substitution set for P_i in Q may be a source view element, derived by invoking a query procedure.

With query reformulation in place, we can now prove that query answers are *sound*—every answer to a user query Q is an entailed fact according to the source(s) and the target—and that query answers contain all the entailed facts for Q that the sources and the target have to offer—*maximal* for the query reformulation.

Theorem 2. *Let Q_I^{ext} be the query answers obtained by evaluating Q^{Ext} over I. Given a user query Q over I, a tuple $< a_1, a_2, \ldots, a_M >$ in Q_I^{Ext} is a sound answer in Q_I^{ext} for Q.*

Theorem 3. *If Q^{Ext} is a reformulated query in I for a query Q over I, Q^{Ext} is a maximally contained reformulation for q with respect to I.*

4 Experimental Result

We used a real-world application, *Real Estate*, to evaluate applications of a domain ontology shared by a set of matching technique [17]. The *Real Estate* application has five ontologies. We decided to let any one of the ontologies be the target and let any other ontology be the source. In summary, we tested 20 pairs of ontologies for the *Real Estate* application. In the test, *Merged/Split Values* appear four times, *Superset/Subset* appear 48 times, and *Vocabulary Terms/Data Instances* appear 10 times. With all other indirect and direct matches, there are a total of 876 matches. We evaluate the performance of our approach based on three measures: precision, recall and the F-measure, a standard measure for recall and precision together [1]. By exploiting knowledge specified in the domain ontologies attached with extraction procedures, the performance reached 94% recall, 90% precision, and an F-measure of 92%[4].

One obvious limitation to our approach is the need to manually construct an application-specific domain ontology with extraction procedures. To facilitate the knowledge acquiring process to build domain ontologies, we can reuse existing ontologies. Machine learning techniques can also be applied to facilitate the construction of extraction patterns for extraction procedures. Since we predefine a domain ontology for a particular application, we can compare any two ontologies for the application using the same domain ontology. Therefore, the work of creating a domain ontology is amortized over repeated usage.

5 Conclusions

We have proposed an approach to automate and represent ontology mappings by combining both declarative and procedural representations. We have tested that a set of base techniques are able to establish communications via domain ontologies attached with extraction procedures. By sharing the domain ontologies, the base techniques detected indirect matches related to problems such as *Superset/Subset*, *Merged/Split values*, as well as *Vocabulary Terms/Data Instances*. To approach semantic interoperability across ontologies, we present source-to-target mappings as mapping ontologies attached with query procedures, which not only support equivalent inferences and computations on equivalent concepts and relations but also improve query performance by applying query procedures. The source-to-target mapping instances lead automatically to a rewriting of every target element as a union of the target element and corresponding virtual source-view elements. Query reformulation thus reduces to rule unfolding

[4] See a detailed explanation about the experiment in [17]

by applying the view definition expressions for the target elements in the same way database systems apply view definitions.

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