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Abstract

Agent communication languages such as ACL and KQML provide a standard for agent communication. These languages enable an agent to specify the intention and the content of a message as well as the protocol, the language, and the ontology that are used. For the protocol and the language some standards are available and should be known by the communicating agents.

The ontology used in a communication depends on the subject of the communication. Since the number of subjects is almost infinite and since the concepts used for a subject can be described by different ontologies, the development of generally accepted standards will take a long time. This lack of standardization, which hampers communication and collaboration between agents, is known as the interoperability problem. To overcome the interoperability problem, agents must be able to establish a mapping between their ontologies.

This paper investigates a new approach to the interoperability problem. The proposed approach requires neither a correspondence between concepts used in the ontologies nor a correspondence between the structure of the ontologies. It only requires that some instances of the subject about which the agents try to communicate are known by both agents.

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1 Introduction

The rapid growth of networks such as the Internet offers new possibilities for accessing information. At the same time increasingly more information is generated. To keep up with this growing supply of information, intelligent tools are required. Agent technology is one of the most promising ways of distributing and gathering information. The reason for this is that communication and collaboration are central issues of Multi Agent Systems (MAS).

Agent communication languages such as ACL and KQML provide a standard for agent communication in an open MAS. These languages enable an agent to specify the intention and the content of a message as well as the protocol, the language and the ontology that are used. For the protocol and the language, some standards are available and should be known by the communicating agents (e.g., FIPA protocols, KIF, SP).

The ontology [2] used in a communication depends on the subject of the communication. Since the number of possible subjects is almost infinite and since the concepts used for a subject can be described by different ontologies, the development of generally accepted standards will take a long time. This lack of standardization, which hampers communication and collaboration between agents, is known as the *interoperability* problem [7, 11, 12].

The interoperability problem also occurs in the area of heterogeneous databases [1, 3, 5, 6]. The Internet makes it possible to access (legacy) databases that have been developed in isolation, either because they belong to different legal entities or because they are located at different sites between which no communication was possible before the era of the Internet. Asking queries that require access to several of these databases, is impossible unless we know how to relate the information of the databases. One way to relate the information of different database is to use an ontology to describe the underlying semantic structure of a database.

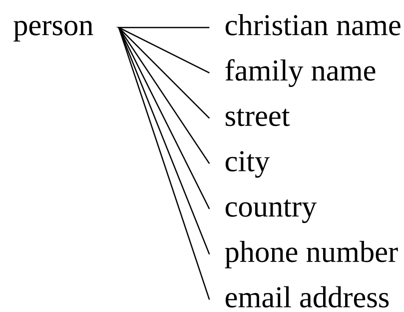
The remainder of the paper is organized as follows. Section 2 discusses the interoperability problem in more detail and Section 3 points out some problems in current approaches. Section 4 outlines our approach and Section 5 reports on the experiments with our approach. Section 6 concludes the paper.

2 Interoperability

In order to reach interoperability, two problems must be dealt with, namely: *structural heterogeneity* and *semantic heterogeneity* [4]. Structural heterogeneity concerns the different representations of information. Information described by the same ontology can be represented in different ways. This is a problem for heterogeneous databases but usually not for agents. In a multi agent system an ontology is the basis for communication. The actual way information is stored by an agent is shielded from the environment by the agent. Nevertheless there can still be structural heterogeneity. Suppose for instance that agents exchange the family name of a person. One agent might use ‘van den Herik’ to describe a person’s family name while another agent uses ‘Herik, van den’. These different representations, which we will denote as *representation conflicts*, require some transformation of the represented data during communication.

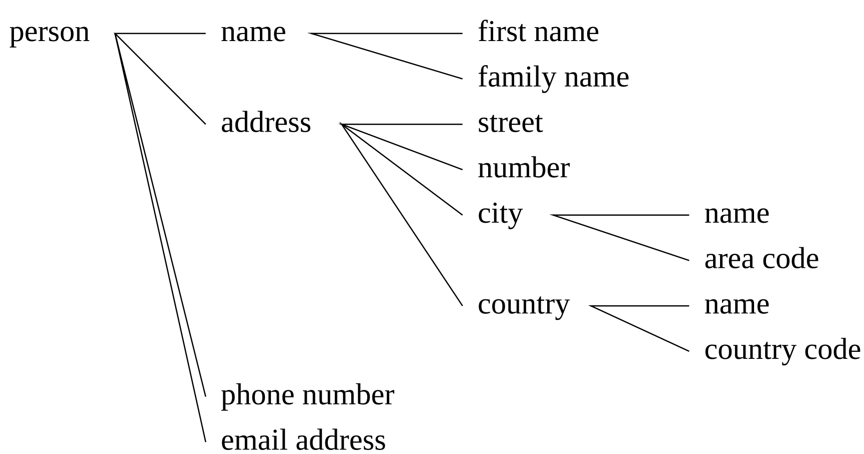
Semantic heterogeneity concerns the intended meaning of described information. Information about, for instance, persons can be described by different ontologies. The ontologies may have different (semantic) structures, *structural conflict*, and different names may be used for the same information or the same name for (slightly) different information, *naming conflicts*. The following two ontologies illustrate semantic heterogeneity.

Ontology 1



In ontology 1, 'street' also describes the house number and 'phone number' describes the country code, the area code, and the local number.

Ontology 2



In ontology 2, 'phone number' only describes the local number. The 'area code' and the 'country code' are stored with the city respectively country.

Each ontology clearly has a different structure. Ontology 1 is flat while ontology 2 has a hierarchical structure. This structural conflict can be solved relatively easy because ontology 2 more or less extends ontology 1. When the two ontologies have completely different hierarchical structures, the structural conflict becomes more severe.

The naming conflicts between the two ontologies form a more severe problem. Different concept names are used for the same type of data; e.g. 'first name' and 'christian name'. Moreover, the same concept name is used for slightly different types of data; e.g.

‘street’. In ontology 1 ‘street’ denotes both the street name and the house number while in ontology 2 it only denotes the street name. Hence, in order to reach interoperability, we must be able to split and merge data fields.

We can conclude that in order to reach interoperability we have to find a mapping form the concepts of one ontology to the concepts of another ontology while instances of the concepts can be split and merged.

3 Problems in current approaches

To deal with semantic heterogeneity, several solutions have been proposed. Many of the proposed solutions try to derive a common ontology by some (semi) automatic process, see for instance [1, 3, 5, 7, 12]. These approaches heavily rely on assumptions such as:

- concepts are defined using a set of shared primitive concepts,
- different ontologies are the result of differentiations of one initial ontology,
- a human specifies relations between concepts of different ontologies and resolves possible conflicts.

Beside the problem that the above mentioned assumptions often cannot be met, ontology and (in database terms) schema integration is an indirect way of establishing a mapping between two ontologies. An approach that addresses the problem of establishing a mapping directly has been proposed by Papazoglou et al. [6]. They assume that the same naming conventions are used in different databases and that for each database an abstract description model describes the types of relations that hold between concepts are specified. The possible relation types are common knowledge. From this information a mapping between the databases can be derived. The disadvantage of this approach is that it cannot handle naming conflicts.

In a recent survey of existing approaches [11], Wache et al. point out that establishing a mapping between two ontologies is still an important open problem. In this paper, we propose a new approach that solves part of the problem. Our approach handles naming, structural and representational conflicts fully automatically. We only require that there are a number of instances of the concepts making up the ontology that are known by the two agents that wish to communicate. In terms of the two ontologies of Section 2, there must be several persons whose data are represented in both ontologies.

4 Learning ontology mappings

Suppose that agent 1 wishes to know the phone number and email address of some persons. Agent 1 knows that the information is (probably) available in a database managed by agent 2. Therefore, agent 1 contacts agent 2. In order for agent 1 to put forward its request, the agents first have to establish whether both use the same ontology or whether they use an ontology of which the other agent knows how to map it on its ontology. If the agents use different ontologies and if no mapping is known, the agents should try to establish a mapping.

Language games We propose that agents play a *language game* in order to establish a mapping. Language games were developed by Steels to investigate how a population of agents can develop a shared communication system from scratch [8]. In a language game two agents – a speaker, agent 1, and a hearer, agent 2 – try to communicate about some topic, for instance some real world object as is the case in [10]. In that experiment agent 1 names the categorization (or meaning) of a light source. In turn, agent 2 tries to interpret this name. Initially both the agents' (private) ontologies and lexicons are empty. When some part of the game fails, the lexicon is adapted to improve communication on future occasions. When it succeeds, the lexicon is adapted such that the effective elements of the lexicon are more likely to be selected in the future than ineffective ones. This way, after a number of games the lexicon will become shared by the different agents of the population.

The language game model has been tested successfully in simulations and on physical robots, see e.g. [9, 10]. However, the language always dealt with either perceptually grounded meanings or 'simulated' meanings. It would be interesting to see whether the ideas of the language games will work in an information retrieval task using agents that have different ontologies. These different ontologies serve as the meaning of the language to be developed. That this would be an interesting approach lies in the fact that the different robots used in the experiments have no knowledge about each others internal representations of the meanings. So, these representations can and do differ from agent to agent.

Using language games for learning an ontology mapping The idea behind using language games for ontology mapping is the following. We assume that the agents wish to communicate about a concept such as a 'person' and that some instances of this concept are known by both agents. A concept such as a 'person' may consists of a hierarchy of sub-concepts. For the *leaf* concepts in this hierarchy, an instance specifies the actual values. For example, an instance could be a person called 'Haddock', who lives at 'Castle lane 1, Marlinspike', with phone number '421'. By finding such an instance of the concept 'person' of interest known by both agents, the agents determine *joint attention*. This joint attention will be the basis of the language game.

To establish the joint attention, one agent produces an utterance containing a unique representation of a concept and instance of the concept. The other agent, upon receiving the utterance, investigates whether it has a concept of which an instance matches to a certain degree the communicated instance. For this the agent measures the proportion of words that two instances have in common. The instance with the highest proportion of corresponding words, forms, together with the communicated instance, the joint attention — provided that the correspondence is high enough.

After establishing joint attention, one of the agents tries to establish a mapping between the leaf concepts (in database terms: the fields) that make up the concept. For this the agent establishing the mapping needs an utterance from the other agent and itself. Each of these utterances uniquely represents the leaf concepts of the concept followed by instances of these leaf concepts. The used representations of the leaf concepts can be any symbol, in principle, even Egyptian hieroglyphs. The only thing that is required is that each representation uniquely represents a leaf concept. Hence, the structure of the ontology plays no role. We may use, for instance, the term 'pnfn' or a term representing the place of a leaf concept in the ontology 'person.has.name.has.first name' to denote a person's first name in a communication.

It makes sense, however, to use a representation that describes the place of a leaf concept in the ontology of an agent. Though it is not necessary for learning a mapping between leaf concepts that can be used for communication, it will enable agents to derive a more accurate mapping between their ontologies. If, for instance, both ontologies have a a similar hierarchical structure for a person's name, e.g.

person.has.name.has.christian name:Archibald
person.has.name.has.family name:Haddock

and

person.has.name.has.first name:Archibald
person.has.name.has.family name:Haddock

the agent might derive from the learned associations that the concept 'name' is used in both ontologies to denote a persons name. The derivation of a more accurate mapping may, however, be limited by structural conflicts.

If agent 1 and 2 use the ontology 1 respectively 2 of Section 2, agent 1 might formulate the following utterance:

person.has.christian name:Archibald
person.has.family name:Haddock
person.has.street:Castle lane 1
person.has.city:Marlinspike
person.has.country:Belgium
person.has.phone number:06229–421
person.has.email address:haddock@herge.be

Agent 2 receiving this utterance might formulate its own utterance about the subject of joint attention:

person.has.name.has.first name:Archibald
person.has.name.has.family name:Haddock
person.has.address.has.street:Castle lane
person.has.address.has.number:1
person.has.address.has.city.name:Marlinspike
person.has.address.has.city.area code:06229
person.has.address.has.country.name:Belgium
person.has.address.has.country.county code:32
person.has.phone number:421
person.has.e-mail:haddock@herge.be

Next, agent 2 tries to establish associations between the different concepts. Agent 2 generates associations between the concepts of the two utterances on the basis of the proportion of corresponding words in concepts pairs, one from each utterance. Possible associations are:

field $x \leftarrow$ field y
field $x \leftarrow$ field y, split(s), first
field $x \leftarrow$ field y, split(s), last
field $x \leftarrow$ field y, field z, merge (s)
field $x \leftarrow$ field y, split(s), last, field y, split(s), first, merge(s)
$\vdots$

Here, x, y and z represent leaf concepts, and s denotes a separator such as ‘ ’, ‘,’, ‘;’, or a type change (i.e., a change from letters to digits or vice versa).

Agent 2 has to search through a space of possible associations guided by the proportion of words that instances of concepts have in common. Each new utterance from agent 1 enables agent 2 to update the strength of the associations. After having received a number of utterances, agent 2 may accept certain associations as being correct. When this point is reached the agents are able to communicate.

The final mapping consists of a mapping from leaf concepts of agent 1 to leaf concepts of agent 2 containing split and merge operators. Note that the mapping is asymmetric in that it enables communication in one direction. For full communication, agent 2 also must establish a mapping in the other direction.

Search through the association space In the previous section we have seen that we may have to combine several leaf concepts in order to establish a mapping. If we determine a mapping from agent 1 to agent 2, then for each leaf concept of agent 2, we must consider all combinations of the leaf concepts of agent 1. This gives us $n2^m$ possible associations, where m and n are the number of leaf concepts of agent 1 and agent 2 respectively. The number of possible associations is even higher since we may also split instances of concepts and, even worse, splits can be done in various ways. To reduce this complexity the agent only considers combinations that have a high proportion of words in common.

5 Experiments

We have conducted experiments for *a proof of principle*. The experiments did not involve communicating agents; we focused on the process of finding the mapping. Further research will be embedded in an agent context.

In our experiments, we tried to establish a mapping between two address databases. For this we used the address database of our department and two small artificial address databases. The structure of the ontology of the address databases used was not very complex. It is even simpler than the example ontologies of Section 2. This does not weaken our results since, as was pointed out in the previous section, we only need unique references to leaf concepts. Structural conflicts therefore do not play a role. The difficulty in establishing a mapping between the ontologies, lays in finding an association between the references of concepts and in combining and splitting instances of these leaf concepts.

The departmental database (DDB) that we used in the experiment had 13 fields and contained 502 records. The first artificial database (ADB1) had 4 fields (identical to the first 4 of ontology 1 in Section 2) and 23 records, and the second artificial database (ADB2) had 5 fields and 5 records.

In ADB1 and ADB2 there were three matching instances, which were all found by the system. For 4 out of 5 fields, the mapping from ADB1 to ADB2 was correct for all records. The algorithm cannot match the abbreviated christian names in ADB1 to the full christian names in ADB2, therefore the christian name field mapping is left empty. The results of the reverse mapping, ADB2 to ADB1, were similar. However, the system failed to match properly names of the form 'van den Herik' to 'Herik, van den'. Merging poses no problem (using split(','), merge(' ')), but *splitting* compound names requires knowledge on Dutch names.

In ADB1 and DBB there were two matching instances, which were found both. The mapping from ADB1 to DBB was correct for all fields for all records. The reverse mapping showed some problems with foreign addresses, which are structured differently from Dutch addresses. Again, special knowledge would be required to solve this shortcoming. The ADB2–DBB results were equal to the ADB1–DBB results.

6 Conclusions

We introduced an approach to learning mappings between the ontologies of two agents. The agents engage in a dialogue where utterances are exchanged that are formulated using the agents' own ontologies. The approach requires that both ontologies have at least some instances in common.

The approach was tentatively tested with a system that made mappings between three small address databases. The results showed that our concept works. The shortcomings identified were due to missing knowledge about the structure of names and addresses. Since our approach aims to be a generic solution, we do not plan to add this knowledge.

Future work will focus on embedding the system in a real MAS, since that is the intended application of our approach. Moreover, we will generalize the system to deal with ontologies in which instances are organized differently from databases.

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