Ontology Alignment using WordNet Method

Somayeh Amirian[1], Somayeh Mohammadi[2]

[1]Department of Computer and Information Technology, Kermanshah Branch, Islamic Azad University, Kermanshah, Iran.
[1]Department of Computer and Information Technology, Kermanshah Science and Research Branch, Islamic Azad University, Kermanshah, Iran.
[2]Department of Computer Engineering, Ghasr-E-Shirin Branch, Islamic Azad University, Ghasr-E-Shirin, Iran.

Abstract
Nowadays, the ontology alignment plays an important role in development of information-based systems due to the growing use of ontology in information systems. New technologies such as the Semantic Web facilitate the application of ontology in information systems. These approaches have led to the development of new ontology. The construction of new ontology from zero is not recommended; hence, the ontology mediation techniques are utilized in particular fields. Different tools and ways have been now provided for various ontology mediations. This information is not sufficient and comprehensive in some cases and there is a need for more information about the overall ontology in order to improve the result. The ontology alignment aims at creating an alignment which identifies all correct communications. We aim at implementing an algorithm for alignment of two ontologies via the WordNet background knowledge. Our research context or "the use of Semantic Web as the background information in the ontology mapping" is one of the ways to achieve this goal which is partially investigated in this article. The use of background information is one of the available methods in the field of ontology alignment. Therefore, this article is seeking to first study the Semantic Web and ontology concepts, and then discuss the existing models and methods for different mediation ontologies, and eventually it improves the available methods in ontology alignment through the background information.

Keywords:
Semantic Web, ontology alignment, background information, ontology

1. Introduction

The ontology generally means a branch of philosophy which seeks to answer the questions such as "What is the existence?" and "What common characteristics are there among all creatures?" In fact, the ontology is the basis of semantic web which can lead to the appropriate outcome only by their definition and utilization. We are seeking to make the meaning of scattered data on the Web understandable by machines. The appropriate definition and use of ontology is one of the most important measures [1].

The ontology officially expresses the existing knowledge in domain by identification of concepts and entities in a domain and description of relationships between them, and making them understandable by machines as well as utilizing a set of rules. According to official description of knowledge by ontologies, the software factors or in general the machines on the Semantic Web will be able to effectively make use of that knowledge. According to the main advantage of ontology, it is able to express the knowledge officially; and it is exactly what the Semantic Web needs. The roles of ontologies in the Semantic Web can be described as follows:

The ontology is able to process knowledge, share it among different factors and reuse it on the web. The ontology owes the official definition and description of concepts and entities and expression of their relationship for such these capabilities. The available data in Web pages can be mapped to concepts in ontologies by analyzing the content of Web pages. Such this measure enhances the synergy between human and machine in a way that the machines are prone to perform most of the human duties.

Ontologies provide a good context for activities of intelligent services. For instance, the use of ontologies can be very effective in services such as the intelligent search on the web, the information filters, the intelligent information integration and knowledge management. The ontology alignment aims at integrating the information especially in the field of bioinformatics; and this article investigates the ontology alignment using WordNet method.

In this article, we first study the Semantic Web and ontology concepts, and then review the previous studies and propose a method, Afterwards, the results and the evaluation are presented, and finally the conclusion and future studies are discussed.

2. Research background and literature

Ontology alignment is an active context in current studies with powerful society which raises a number of solutions. Euzenat and Shvaiko [2] have provided a comprehensive overview of current approaches and classified them into three aspects: clustering, input interpretation, and input type. Clustering aspect distinguishes between techniques of element level and structure differentiation level. The input interpretation aspect is divided into several sections:

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The hybrid section which only uses the ontology structure; the external section which utilizes the secondary resources out of the ontology; and semantic section which uses some formal semantic forms to justify the results. The types of input technique aspects are classified as follows: As a term which works on text strings; the structural aspect which deals with ontology structure; extensive aspect which analyzes the data samples; and semantic aspect which provides the Semantic principled interpretation of ontologies.

Rymom [3] identified the similarities in institutional description; and analyzes the samples, institutional names, taxonomic structure and limitations before the use of "Bayesian" decision theory in order to create an alignment between the ontologies; and also accepts the user input to improve mapping. Falcon-AO uses a linguistic matcher which is combined with a technique indicating the structures of ontologies that are matched as a bipartite graph. IF-Map first matches two ontologies by examining their samples in order to determine whether they are attributable to concepts of a reference ontology or not, and then performs alignment through formal concept analysis (for extraction of an alignment) [4]. The similarity filling uses a similarity sharing technique along with property relations between the categories. OLA utilizes the weighted means between matchers along with multiple properties of ontology, and provides a solution for calculating the similarities of institutional set based on the numerical analyses. An approach, which is used in ASMOV to calculate the similarities at a lexical, and structural and extensive levels, is similar to OLA, but it has utilized the flexibility to design the calculations for measuring the similarities of different characteristics.

3. Proposed approach

Despite the fact that the existing method of ontology mapping will result in good outcome based on compared similarity of structure and tag, they cannot identify the important mappings in a few cases. This section explains a new ontology mapping method which has overcome this limit by application of background information. The existing background-information -based methods usually have one or two key limitations: 1. They are dependent on a selected manual reference ontology. 2. They have the noise resulting from the use of semi-organized resources such as text corpora.

It is difficult to obtain accurate background information. Some of these methods rely on the obvious ontology, but unfortunately these ontologies are no existed in all fields; and they manifest even when they do not cover all target mappings between input ontologies. Furthermore, it is impossible to select the relevant ontologies in some cases; for instance, the mapping fields cannot be selected as a priority in application of Semantic Web such as power agua, and thus the necessary background information should be identified dynamically and in real time. To avoid the problems associated with manual selection of ontology, the background information can be obtained from the textual sources with poor structures through other techniques. However, the limits in information extraction technology have noise. The recent growth of Semantic Web has led to the increased online semantic data and the first search for data usage or Swoogle. It is assumed that despite trying to solve the disparity between the semantic web, the ontology mapping can benefit from it. In other words, the available online ontologies offer the background information sources to retain the ontology mapping and overcome the above-mentioned issues. On the one hand, they can be selected at the dynamic level, and this eliminates the need for a priority or manual selection of ontology; and on the other hand, we can avoid the noise of data mining methods by relying on the semantic resources. [5]

In this section, we review the ideas about the ontology mapping which determine the dynamics of location and apply the background information beyond the similarity-based algorithms, and then investigate the use of ontology for background information in ontology alignment.

3.1 Research methodology

Two ontologies are matched with the third type in the form of background information.Therefore, this process has two stages: Anchoring and Deriving relations.

Anchoring consists of alignment the target concepts and a source of background information. In general, this process is done with an ontology technique. Furthermore, the conceptual tags may include the use of ontology structures. Anchoring does not only pay attention to finding the concepts corresponding to the equivalent. Another type of relation with concepts can affect the background information. Deriving relations refer to the process of identifying the relations between the target concepts and source by searching the relations between the Anchor concepts in background information.

3.2 Syntactic methods by non-recognition of semantic mappings

Semantic tools such as power aqua, which deals with results of mapping techniques, require expressing the identified mappings in the forms of semantic relations between ontologies. The official languages of mapping such as C- Owl can retain a wide range of relations between ontologies, but s few available mapping techniques are able to identify these semantic mappings. An analysis of the latest mapping systems describes the limitation range of techniques which can provide the semantic mappings. It seems important that most of the systems combine a variety of non-semantic techniques because the terminological- structural and extensive methods (attachment) are only a few systems relying on the semantic techniques, so the use of mapped semantic ontology and mapping language indicate the mappings of available information. Therefore, only an algorithm is able to detect semantic mappings in the forms of subsidiary concept relations in the last OAC.

Other techniques include confidence based mappings which are obtained from the output of terminology and structural algorithms. Unfortunately, the interpretation of these types of relations is difficult with low semantics and their application in reasoning methods. In contrast, the semantic techniques should led to the significant relationships between mapped ontologies, and thus the higher reasoning can be applied. They should focus on good qualitative maps which can be justified and explained through applied information and results.

3.3 Syntactic methods which not able to identify different ontologies

The traditional methods have defects if there is low lexical interference between the ontology tags or the ontologies have weak or heterogeneous structures. This observation has been partially proven in the last OAC; and a basic ontology is applied to map the modified systematic versions. Most of the techniques have very low performance in pilot cases in which there are significant changes in ontology structures and tags.

Despite the fact that the similarities between the tag and structure can imply the significant mappings, this hypothesis is difficultly proved. For instance, the relationship between Beef and Food concepts cannot be identified on the basis of syntactic relations, but it is clear when the meaning of these concepts (semantics) has been taken into consideration. Regardless of this semantics, the syntactic techniques are ineffective to identify several important mappings.

3.4 How the background information is now applied?

In the previous sections, we discussed that the meanings of mapped concepts should be applied for identifying the meaningful mappings which cannot be identified by syntactic methods. Unfortunately, despite the fact that the meaning is expressed by ontology in the Semantic Web, it does not cover the target components and their relationships in ontology mapping. In other words, a semantic mapping between two ontologies can be interpreted only in a greater scope of these ontologies [6].

Therefore, there is a need for integration of external information as a way to cover the input ontology and filling the semantic gap between them in order to get the semantic mapping [7]. The following kinds of background information have been utilized in mapping:

WordNet: It is one of the most common sources of background information. For instance, CTxMatch converts the ontology tags into a logical formula between their components, and then these components are mapped to corresponding components in WordNet, and finally a Sat Solver is applied for identifying the semantic mappings between different concepts.

This method has recently been used to solve the problem of background information removal. Lack of information during the mapping process is identified by WordNet-based techniques as a source of information and this shortage is resolved. It should be noted that WordNet is a lexical source and makes the connection between the words through relations such as the hypernym. Therefore, it can be considered as an effective source of linguistic information in making the connections between the tags at lexical stages of an alignment method.

Source ontology is another method relies on source ontology as a semantic relation between two ontologies. Researchers have proved that the last matchers have not been successful in alignment of two words with weak structure of medical terminology. As a solution, they suggested the DICE ontology application as a background information source. The terms are mapped from two words to Anchor terms in DICE, and then their mappings are obtained based on the semantic relations of Anchor terms. Accordingly, the obtained mappings can describe a greater range of semantic mappings between terms, not just their equivalent [6].

3.5 Application of a background information ontology in ontology alignment

Ontology alignment plays an important role in development of information-based systems. New technologies such as the Semantic Web facilitate the application of ontologies in information systems. These approaches have led to the development of new ontologies which in turn need an ontology increase referring to its integration with applied system. Therefore, numerous studies have been conducted on ontology alignment.

Various methods have been developed in this regard and they mainly focus on two aspects: lexical match of ontology elements and the application of ontology structure from which the former includes the application of linguistic methods and tags to identify the relationship between components which are based on tag similarities, and the latter includes the relationships between the ontologies to identify the similarities. The ontology components which are associated with each other (but do not have any structural or lexical similarities), remain unknown. Therefore, we emphasize on the use of background information and note that the background ontology provides a solution for finding the unidentified proportions by other methods by full explanation of target and source ontologies.

4. Results and evaluation

In previous sections, we have explained that the utilization of background ontology can compensate the lack of structure and lexical interference, and thus the increase in the amount of background information improves the alignment result. In this section, we study the advantages and problems of a medical ontology and match it with another as we apply the ontology larger than a similar scope with background information. According to results of our tests, the background information can improve the alignment performance, and particularly the maximum advantage can be gained by combining different information components with background information, but these components should be carefully taken into account during the combination.

4.1 Hypothesis test through the experiment

Five tests were conducted for alignment with Crisp. In the first test, direct Mesh was conducted, but it was as the background information indirect in other four cases with FMA ontology. Direct alignment was used as a basis for comparing each indirect alignment. With the aim at increasing the value of background information application, the identified additional matches were analyzed by indirect alignment. Furthermore, several matches were found in indirect case, not in the indirect one.

4.2 Tests

Five tests were conducted. The direct match of CRISP was conducted with Mesh in the first test, but it was as indirect background information in other four tests with FMA. In the second test, the relation of "Part-of" and "is a" was separately applied in FMA. In the third test, the relation of "is a" and "Part-of" was used with their annexes. In the fourth test, these two relations were applied in combination and alignment. Their special combinations were applied for alignment in the fifth test.

4.3 First test

Direct alignment: This test was conducted at two stages: lexical and structural. At the first stage, Mesh with CRISP alignment was conducted with concept tags. Basic terms such as the, of, and, ... were ignored; and the singular and plural forms of the same words were included. According to match of two concepts of X and Y, it is concluded that if a pair of their tags are matched, then X ≡ dy. Furthermore, if X has a tag a superior set of tag words, it is concluded that X ≥ dy and X≤dy if X has the subset tag of words in a tag Y. In other words, the lexical alignment is applied in a tag by limiting the meaning of concept. Therefore:

At the structural stage, CRISP and Mesh structures were applied for alignment with combination of relations; and SRISP and Mesh were used for lexical alignment. For instance, with the following equations:

- CSP: Brain ≡d MSH:Brain

-MSH:Brain ≥ MSH:Temporal lobes

It is concluded that:

- CSP: Brain ≥d MSH: Temporal lobes

A set of lexical alignment is developed with displayed match of CRISP and Mesh structures; and the following rules are applied for development of set:

If (Xc ≤d YM) ^ (YM ≤ ZM) then (Xc ≤d ZM)
If (Xc ≤ Yc) ^ (Yc ≤d ZM) then (Xc ≤d ZM)
If (Xc ≤d YM) ^ (YM ≤ ZM) then (Xc ≤d ZM)
If (Xc ≥d YM) ^ (YM ≥ ZM) then (Xc ≥d ZM)
If (Xc ≥ Yc) ^ (Yc ≥d ZM) then (Xc ≥d ZM)

These rules also applied ≡ relations, so that X ≡ Y was written as Y ≤X and Y ≥ X .

Indirect alignment: It indicates a project which is described in methodology. It has two steps: First, Anchoring CRISP and mesh with FMA, and then Deriving relations between CRISP with Mesh and FMA as the background information. In Anchoring step, we use the same technique as direct CRISP alignment with Mesh. Old anchor of Mesh and CRISP is done with FMA, and thus a set of alignment is obtained with three types of relations: X ≡a Y ، X ≤a Y و X ≥a Y

Where, Y is a concept of FMA and X in CRISP or Mseh.

The following rules are obtained according to the relations:

$$if\ (X^C \leq^{\alpha} Y^F) \wedge (Y^F \leq Z^F) \wedge (Z^F \leq^{\alpha} Q^M) \text{include}\ (X^C \leq^{i} Q^M)$$

$$if\ (X^C \geq^{\alpha} Y^F) \wedge (Y^F \geq Z^F) \wedge (Z^F \geq^{\alpha} Q^M) \text{include}\ (X^C \geq^{i} Q^M)$$

Therefore, we apply the relations of "is a" and "part-of" for ≥, and vice versa the relations of "has-kind" and "has-past" for ≤, despite the fact that there are not any larger and smaller relations in FMA and instead there are the relations of "is a" and "part-of" and vice versa the relations of "has-past" and "has-kind". We developed four different tests of indirect alignment by application of FMA as the background information. These tests are different in terms of their application and combination of "is a" and "part-of" relations to build FMA during the achievement of larger and smaller relations, and they are applied in the above-mentioned rules and for indirect inter-conceptual match of CRISP and Mesh.

4.4 Second test

The indirect alignment is obtained through the use of "is a" and "part-of" and FMA relations without relationship annexes of FMA if a direct relationship with "is a" or part-of" is established. In this regard, we used the following rules:

$$(X^{F} isa\ Y^{F})\text{include } (X^{F} \leq Y^{F})$$

$$(X^{F} part-of\ Y^{F})\text{include } (X^{F} \leq Y^{F})$$

To obtain XF ≤ YF relation, we added their semantic equivalence or YF ≥ XF. This was done in all indirect alignment tests.

4.5 Third test

It includes the indirect alignment by application of "is a" and "part-of" relations related to FMA along with their transitive closure. The relations between two concepts of FMA are obtained by connecting the FMA concepts with transitive closure of "is a" and "part-of" relations. We used the following rules:

$$(X_1^{F} isa\ X_2^{F} isa \ldots isa\ X_n^{F})\text{include } (X_1^{F} \leq X_n^{F})$$

$$(X_1^{F} part-of\ X_2^{F} part-of \ldots part-of\ X_n^{F})\text{include } (X_1^{F} \leq X_n^{F})$$

4.6 Fourth test

It refers to indirect alignment through "is a" and "part-of" relations of FMA in combination mode. In this test, "is a" and "part-of" relations for FMA are fully combined and the obtained relation is applied. Here, we used only an inferential rule:

$$(X_1^{F}\ rel^{1}\ X_2^{F}\ rel^{2} \ldots rel^{n-1} X_n^{F})\text{where } rel^{i} \in \{isa, part-of\}\text{inlude } (X_1^{F} \leq X_n^{F})$$

According to the study on results of the fourth test, the false positives matches are obtained due to the use of "is a" relation before "part-of" in alignment conclusion process. The next test is conducted in order to eliminate this negative effect.

4.7 Fifth test

It refers to indirect alignment through "is a" and "part-of" relations associated with FMA without application of "is a" before "part-of".

This test avoids using "is a" before "part-of". A rule is only used for this test:

$$\left(X_1^{F} part-of\ X_2^{F} \ldots X_{k-1}^{F}\ part-of\ X_k^{F}\ isa\ X_{k+1}^{F} \ldots X_{n-1}^{F} isa\ X_n^{F}\right)\text{include } (X_1^{F} \leq X_n^{F})$$

In this section, we provided the test results. We first describe the figures contained in the tables, and then interpret their meanings, and eventually evaluate the results. According to an important issue in providing the alignment results, a number of alignment in combination with structures of ontologies can refer to many others. For instance, all concepts in CRISP are found more particular than the concept of stem in Mesh, while the balance between these two concepts of stem imply all these matches. Similarly, the alignment between these two concepts covers the implicit information about their Upper and Lower concepts. A set is obtained between all possible alignment in order to create an appropriate relationship between two of all only by a minimum set of matches implying the others. The following steps are taken in each test:

We started working with a set of all matches. A set of all matches was obtained for each concept of source, and then the set was minimized by removing the matches shown by the rest of set. The minimum set was not sensitive to degree and order to removing the matches. The integration of minimum sets was the final result. This set of perfect matches separately extracted the quantitative information for each concept of source.

4.8 Results of direct and indirect alignment

The direct CRISP and Mesh alignment with FMA was performed at Anchoring stage which is depicted in Table 1. The equivalent equations were shown as the one-to-one alignment, while the larger and smaller relations were shows as many-to-many relationships. The search of equations led to the successful correlation: 65.5% of CRISP and 70.6% of mesh concepts were correlated with their equivalents in FMA. This success was achieved from rich FMA. On the other hand, there were not the equivalent concepts in FMA for most of them because of the disagreement over the coverage of anatomy area. There is a CSP concept in CRISP: Muscle Movement which is not as the anatomical part of human body, and thus there is not in FMA. Furthermore, about 99% of concepts obtained from CRISP and Mesh were correlated by application of CRISP and Mesh structures. For example, CSP: Muscle Movement exists as a smaller relationship in FMA because it is smaller than CSP: Muscle in CRISP.

Table 1: Test 1 for direct alignment of CRISP and Mesh with FMA

	Anchoring concept	≡	≤	≥	Anchoring concept
Anchoring CRISP to FMA	738	483(65.5%)	607	1474	730(98.9%)
Anchoring MeSH to FMA	1475	1042(70.6%)	1545	2227	1462(99.1%)

Table 2 summarizes the results of five tests. It compares the direct and indirect alignment and it is concluded that the indirect alignment finds the further larger and smaller relations than the direct alignment. This table indicates that the concepts contained in CRISP and Mesh can be linked in many ways and they are not detectable only through the structure of these ontologies. In our example, FMA emphasizes on deleted information which has led to this development in direct type.

Table 2: Comparing the summary of results in direct and indirect alignment tests

		≡	≤	≥	≡ + ≤ + ≥	increase
Exper 1:	Direct	448	417	156	1021	
Exper 2:	Indir , isa and part-of	395	516	405	1316	29%
Exper 3:	Indir , isa and part-of closure	395	933	1402	2730	167%
Exper 4:	Indir , isa and part-of mixed and closure	395	1511	2228	4143	306%
Exper 5:	Indir , isa and part-of isa only after part-of	395	972	1800	3167	210%

The last column of Table 2 indicates the increase in indirect alignment compared to direct alignment. The indirect alignment of test 2 is 29% more than the direct alignment. Therefore, a better performance with direct type is obtained only by direct relationships of "is a" and "part-of" with FMA concepts. In the third test, "is a" and "part-of" led to an increase of 167% or about 2.7 times higher than alignment in direct mode. The combination of these relationships led to an increase of 306% or 4 times. In the fifth test, an increase of 210% was obtained and it was 3.1 times higher by combining these relationships. It is 26% less than the fourth test and 19% more than the third test.

According to these figures, the use of background information will lead to more alignment than the direct mode. This process is better than the direct method without combination of relations in the background information, and then the combination of relations in background information indicates the more alignment; and the combination of various relationships indicates the maximum number. Obviously, these figures do not reflect the quality of these matches. In particular, if the relationships are optionally combined, then the increase of alignment is created, and the false positive alignment is created. However, the correctness will be maintained and the alignment rates will be increased by combining them in a particular manner. Given the equivalent alignment, the indirect method will indicate the lower relations; and all the indirect matches show an equal number of equations because obtaining both correlated concepts with a concept in background information is the only way for indirect exploration of equations. The direct equivalents are obtained from the available concepts in CRISP and Mesh, not FMA. The indirect equations, not the direct ones, are selected in several cases because their tags are hypernym only through the background information.

To test the correctness of alignment obtained from various experiments, 30 CRISP concepts are randomly selected and their alignment is studied by manual opening the Wikipedia pages which explain these concepts.

Table 3: Correctness of alignment obtained from various tests

		≡	≤	≥	Total	Correct(%)
Exper 1:	Direct	17	18	3	38	38(100%)
Exper 4:	Indir , isa and part-of mixed and closure	14	39	59	112	105(93.7%)
Exper 5:	Indir , isa and part-of isa only after part-of	14	37	50	101	101(100%)

The last column of Table 3 shows the correctness of alignment resulted from different tests. On this basis, there were the matches with decreased accuracy of 93.7% only in the fourth test, and it was 100% in other tests. All identified matches were correct. Evaluation of second and third tests was not performed because the tests produced the subsets of the fifth test containing 100% correct matches. Obviously, 30 concepts are not enough for a complete evaluation. However, all these cases are carefully reviewed and this evaluation indicates the accuracy of tests. The number of matches for these 30 concepts is similar to the whole test.

The evaluation phase is not explicit in the absence of a gold standard. In other words, some of the matches are accurate due to the nature of "part-of" relationship. For instance, the ulnar artery is a part of elbow, but it is seen in the whole arm, so it is not only a part of elbow. These matches are called the "commonalities". However, a relationship is effective between these two. The medical literature should be searched for elbow and this artery. The matches of ≤ or ≥ are obtained in the fifth test, and we have found that there are 30 common matches, while it is not true for 57 matches. It means that the background information shows a big scale in result of alignment even by investigating the matches and removing the types of commonalities.

5. Conclusion

Nowadays, the web technology is moving towards the Semantic Web. The important role and application of ontology cannot be overlooked in this regard.

The ontology enables a structure for defining the terms related to a certain field and the accurate relations, so that different Semantic web proxies will achieve the equal and correct understanding of existing terms [8]. This enables them to use the other's information and also provides the possibility of further and efficient cooperation and interaction. Since the cooperation and interaction are very vital and important in this regard for obtaining the information, there is a need for methods of using and combining the ontologies. The subject of our study entitled "the use of Semantic Web as background information in ontology mapping" is one of the ways to achieve this goal which is partially reviewed in this article. Despite the fact that we design the ontologies to provide knowledge in a suitable form for machine, it is natural that the people directly connect with ontology. For example, the knowledge engineer, who wants to create and manage the ontology of a system, requires appropriate tools and methods for observing, searching, and manipulating the ontology. Therefore, since the volume of ontology information is usually applies high, the way of ontology display is an important issue which requires further research despite the conducted studies.

Nowadays, there may be the knowledge-based systems in a field or an organization which do not use the ontology (e.g. expert systems). There is a need for study and innovation about how we can store the knowledge in these systems to develop the ontologies or how we can establish the connection between these systems with a system based on the ontology. It is important since there are numerous knowledge-based systems which do not use the ontology. Furthermore, the tendency towards the ontology-based systems has been enhanced in recent years.

Ontology is used to represent knowledge of an area of the world. The changes in that area will usually change its knowledge. Therefore, the ontology needs to be changes in order to provide a true picture of the real world; hence, the ontology change and evolution are obvious, and thus we require methods and tools to manage these changes.

As the roles of powerful hardware and software infrastructures are undeniable in the field of relationship database, there is a need for such infrastructures to store, retrieve, and process ontologies in order to make full use of the potential of ontologies.

Since the ontology development is difficult, time consuming and professional, this question arises that how we can estimate the production cost of the ontology (as we estimate the production cost of a software)? This is important since in the case of access to an appropriate estimate, we can study whether the production of ontology for target use is economical or not. There is a need for research and innovation about estimating the cost of production and maintenance of ontologies. The method of evaluating and measuring the quality of ontology is another theoretical issue in the field of ontology production and maintenance. In this case, we need to define the criteria based on which we can assess the quality of ontology.

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