CHAPTER 6

ONTOLOGY ALIGNMENT TECHNIQUE
FOR E-LEARNING

6.1 DEONTIC LOGIC BASED ONTOLOGY ALIGNMENT
TECHNIQUE FOR E-LEARNING

A deontic logic based ontology alignment technique has been proposed in this work for effective content delivery in e-learning using semantic analysis.

6.1.1 Ontology based Content Analysis

Semantic Web (Berners-Lee et al 2001) focuses on effective management of documents intelligently which are present in the Web by considering the properties of the entities (terms) and the relationships involved among them. This conceptual organization is facilitated by building ontology pertaining to a particular domain (Gomez et al 2003). One of the major areas of research in retrieving the web information intelligently is the provision of learning course contents through online (e-learning). The prerequisite of the semantic-driven resource management and content delivery in e-learning web service has been facilitated in such systems by building ontology.
6.1.1.1 Need for semantics

Automatic exchanging and reusing of data or information in the universal medium for information exchange (WWW) is very limited due to two main reasons namely the heterogeneity problem prevailing in the information resources and the non-semantic nature of HTML and URL. Information heterogeneity occurs in syntax, structure and semantics. Though enhanced techniques are developed to solve syntactic and structural heterogeneity problems (Giunchiglia Fausto and Zaihrayeu Ilya 2009), the problem of semantic heterogeneity is still prevailing to be a great challenge. When two contexts do not share the same interpretation of information, semantic heterogeneity occurs. Several approaches were proposed in the past (Doan et al 2003) to solve semantic heterogeneity problems like synonym sets, concept lattices, features and constraints. However, all these existing approaches could solve this problem only partially.

6.1.1.2 Ontology alignment

In the semantic web, ontology plays a key role in solving the problem of semantic heterogeneity. Ontology alignment aims to find semantic correspondences between similar elements of different Ontologies and has been the subject of research in various web domains and applications. Ontology is an explicit formal specification of a shared conceptualization. In the ontology, a set of concept types and a set of formal axioms are explicitly defined with both human-readable and machine-readable text (Dahab et al 2006). The ontology is also widely used as an important component in many areas, such as knowledge management, electronic commerce, e-learning, and information retrieval systems.

Ontology alignment can be carried out either manually or using automated tools (Ehrig and Staab 2004). Such alignment becomes very
critical when it is performed manually as the size and complexity of the ontology structure increases. Hence, automatic ontology alignment became a well-known technique in many practical applications including information transformation and data integration, query processing, e-commerce and e-learning. Several categories of ontology alignment techniques exist in the literature which includes String-based, Language-based, Constraint-based and Semantic-based methodologies (De Marnee and Manning 2010). However, all these existing ontology alignment techniques suffer from two main limitations:

1. They have only limited expressivity,

2. Relationships between the entities in the existing systems are retrieved based on the occurrence of only dominant words in the input text documents (Ehrig and Staab 2004; Romero 2009). These shortcomings may lead to reduction in the accuracy of evaluation in an e-learning scenario. Therefore, it is necessary to provide intelligent techniques for effective ontology alignment.

In this work, a new framework is proposed that derives deontic relations from the input text documents for identifying non-dominant words which helps to perform better evaluation in an e-learning environment. In addition, a measure for similarity/conflict resolution between two ontologies are also proposed. In this work, deontic relationships are used to perform ontology alignment instead of propositional logic. The application of deontic logic allows us to use universal and existential quantifiers in rules. Moreover, it enhances the efficiency of semantic matching techniques through the use of additional predicates such as can, could, ought, each, every, any, before, after and when. This proposed framework considers not only the predicate logic features namely equals and partially equals, but also the newly added
consistency checking deontic predicate ‘conflicts’ and hence it covers all the aspects of logic including unification, resolution, subsumption and conflict identification.

The main objective of this research work is to improve the accuracy of the performance evaluation of the learners in e-learning environments by developing ontology alignment techniques. This is achieved by resolving the conflicts between two ontologies are using the deontic relationships holding two sets of entities that belong to different discrete ontologies. There are many advantages of the proposed framework. First, it helps to evaluate the learners in an e-learning environment using not only the dominant words but also the non-dominant words in their input text documents. Second, it uses the rules from deontic logic. Therefore, the accuracy of evaluation is increased. Third, it not only considers the keywords, but also their relationships. Finally, it performs semantic analysis in addition to syntax analysis. This work is advantageous in evaluating the performance of the learners effectively compared to other existing techniques since the proposed work has increased the expressiveness through the construction of ontologies using axioms and the deontic relationships derived from the text documents. Moreover, this system considers not only the dominant words but also the non-dominant words occurring in the text documents, thus resolves the semantic limitations present in the existing systems.

6.1.2 Problem Statement

Since, ontology alignment is useful for discovering similarities between two ontologies and to determine the relationships holding two sets of entities incorporated with the domain knowledge, it is necessary to provide effective techniques for semantic analysis in ontology alignment. Semantic techniques (Giunchiglia et al 2010) attempt to map the elements (concepts) in
the two ontologies according to their semantic interpretation. The main objective of the proposed technique is to discover the similarities that exist between dominant and non-dominant terms associated with one concept. In this work, the alignment is represented in the form of axioms where, each concept is converted into a propositional validity problem. Semantic relations obtained from e-learning evaluation documents are translated into propositional connectives using the rules namely \( a \iff b \), \( a \rightarrow b \), \( b \rightarrow a \) and \( a \equiv b \). There are three kinds of relationships that are identified in this work and the mathematical relationship is of the form:

\[
\text{axiom} :: \text{rel}(\text{context}_1,\text{context}_2) \quad (6.1)
\]

where,

\[
\begin{align*}
\text{context}_1 & = \text{node elements in Ontology 1 constructed from a learner document} \\
\text{context}_2 & = \text{node elements in Ontology 2 constructed from a domain experts document called as the base ontology} \\
\text{rel} & = \text{relationship that exists between the concepts}
\end{align*}
\]

The candidate axioms that are handled in this work are

\[
equals(c_1,c_2), \text{ partial equals}(c_1,c_2) \text{ and } \text{conflicts}(c_1,c_2).
\]

**Case 1: Equals (c₁, c₂)**

As proposed by (Assawamekin et al 2009), this work has been evaluated for the equality conditions, where \( \text{context}_1 \) in ontology 1 is exactly equal to \( \text{context}_2 \) in ontology 2. The above formula turns out to be unsatisfiable when they are evaluated using the SAT library (Berre 2006). Therefore, the final relation for the given pair of concepts is equivalence.
Case 2: Partial-Equals ($c_1, c_2$)

Similarly, the partial-equals conditions have been evaluated based on the work proposed by (Assawamekin et al 2009), where, context$_1$ in ontology 1 is only partially equal to the context$_2$ in ontology 2. Some examples of this matching are superset and subset analysis and the relation is subsumption.

Case 3: Conflicts ($c_1, c_2$)

Conflicts relationship is the newly proposed relationship between two entities of different ontologies and is extracted by writing deontical relationships from the text documents using the standard deontical rules which have the unique facility of understanding the non-dominant words occurring in the text document. Conflicts between documents are due to the enormous usage of non-dominant words and are identified in this work by using deontic logic. In this proposed framework, the conflicting documents are identified by using both the dominant and the non-dominant words in the text documents and hence considers relationships which are neither fully equal nor partially equal.

6.1.3 Deontic-Based Ontology Alignment Framework

This work aims at proposing a deontic logic based ontology alignment framework for semantic matching in e-learning applications. This framework is based on XML Path expressions where the input text is preprocessed and the output is written into an XML file for further processing. Using this output, ontology is created to evaluate the learning ability of the learners in learning the ‘C’ programming language
electronically. Now, ontology is constructed to identify the commonalities between the documents given by various learners. A rule-based method is used to identify the conflicts among the documents produced by the learner and the domain expert. Unlike, the existing works where the non-dominant keywords are rejected, in this work both the dominant and non-dominant words are considered for ontology alignment. The non-dominant keywords addressed in this work are modal verbs, determiner words and adjectival time clauses where deontic rules are created. Separate ontologies called A and B are constructed for two different input text documents provided by the learner and domain expert respectively. The deontic rules created in learner ontology (A) is then matched with the deontic rules created in domain expert ontology (B). The complete framework of this proposed system is shown in Figure 6.1. This framework consists of five major modules namely co-reference resolution, parsing, dominant and non-dominant keywords resolution, deontic rule creator and constrained ontology alignment. The co-reference resolution module takes a raw input text document and performs anaphora resolution. The parsing module performs lexical analysis and provides a lexical semantic representation. The dominant and non-dominant keywords resolution module extracts the respective keywords. The deontic rule creator extracts the deontic rules for further analysis. Moreover, ontologies are created by the ontology creation module and are stored in an ontology repository. The constrained ontology alignment module takes two ontologies pertaining to a particular concept and matches them. In addition, it then identifies the degree of similarity and conflicts which are given as experimental results.
The ontology construction and Alignment algorithm proposed in this work is as follows.

**Algorithm** : Ontology Visualization and Ontology Alignment

**Input** : Raw text Documents

**Output** : Similarity and Conflict percentage among the documents

**Procedure**

Begin

For each raw text document
Begin

I. Iterate Anaphora Resolution algorithm for he/she/it kind of words

II. Reiterate Anaphora Resolution algorithm for who/where kind of words

End

For each pre-processed document

Begin

I. Split the document using sentence splitter algorithm

II. Compound words are identified

III. Perform lemmatization process to obtain the root words

IV. Identification of non-dominant keywords

V. Obtain four ontological relationships for aiding the ontology construction

   I. Resolution of deontic relationships from the POS tags
   II. Removal of redundant relationships by precedence

   (Obligatory-high, forbidden-high, permissibility-low)

End

For any two processed documents

Begin

I. Formation of context-based propositional logic for sentence pair in the text documents

   [Checking for equals, partial equals and conflict relationships]

II. Evaluation of logic and checking for unsatisfiability using SAT solver

III. Calculation of degree of similarity/conflict between the documents.

End   End
This algorithm is useful for effective ontology construction and alignment. Moreover, the time complexity of this algorithm is $O(n)$ where $n$ is the number of input documents. The space complexity of this algorithm is $\log(n)$ and hence provides an effective representation.

6.1.3.1 Co-reference resolution

In linguistics, anaphora is an instance of an expression referring to another noun (Winograd Terry 1972). Anaphora resolution helps to resolve what a pronoun or a noun phrase refers to which was previously defined in the complete text document. In other words, the referential entity is called as an anaphor and the entity to which it referred previously is called as an antecedent. The process of determining the antecedent of the anaphor is called as Anaphora Resolution. The existence of several anaphors in a document has a great impact in the construction of correct ontology. Several types of anaphora exist in documents which includes pronominal anaphora, definite noun-phrase anaphora and One-anaphora (Denis and Baldrige 2007 and Markert Katja and Malvina Nissim 2005). Therefore, in this proposed framework an “Anaphora Resolution” module has been developed which concentrates on three categories of nouns that pertain to the gender, person and grammar resolution of the text. The main advantage of this module is that it can identify the pronouns such as he/she/it and also the who/where types of words for the replacement of nouns. In this work, co-reference was performed individually on each learner document and the domain expert Professor A document during the first experiment. In the subsequent experiments, these ontologies were compared with ontologies produced by other professors.

6.1.3.2 Document parsing

The document is now ready for analysis after co-reference resolution. Now, the documents are given to the parser module which uses the
standard Stanford Parser for parsing the document (De Marnee and Manning 2010). The parser generates a parse tree for each document. These parse trees are given as input to the typed dependencies generator module of the Stanford Parser. The complete typed dependencies of the documents are generated and stored in XML files. The compound words are also identified from this document. Once the compound words are identified the other words are lemmatized to resolve the root words. On successfully finding the compound nouns and root words by lemmatization, the entire documents are now cleaned by removing the existing prepositional dependencies. These compound words and the root words are replaced in all the original documents which provide the dominant words.

6.1.3.3 Recovery of ontological relationships

The output document obtained from the previous stage is converted to a lexical semantic representation in this module. Therefore, the exact hierarchy for the ontology construction is designed in this phase. The first-order logic implementation is used in this work in order to write the facts and rules to be applied on the document. Now, the query processor finds the different kinds of structural relationships among the dominant terms in the document. The results obtained are cleaned and the following four types of structural relationships are obtained. They are categorized based on the classifications done by Assawamekin et al (2009) namely Aggregation relationship (partOf), Property relationship (propertyOf), Generalization/specialization relationship (isA), Equivalence relationship (sameAs). After these structural relationships have been identified, the connectives among the terms were easily resolved and viewed. The rules extracted for identifying these structural relationships are as follows:
Extraction Rules

1. **Noun RULE – Object:** If \( x \) is a noun, then \( x \) is an object.

2. **Verb RULE – Relationship:** If \( r \) is a verb, then \( r \) is a relationship.

3. **PartOf RULE - Aggregation:** Let \( r \) be a special verb relation (e.g., part of, belong to or subdivision of). If a noun \( x \) participates in object \( y \) with \( r \), then object \( x \) is a part of object \( y \).

4. **Includes RULE- Aggregation:** Let \( r \) be a special verb relation (e.g., have, contain, comprise, include, define, consist of, compose of, denote by, identify by, make up of or record with). If a noun \( x \) participates in a noun \( y \) with \( r \) and a noun \( y \) also participates in a noun \( z \) with another \( r \), then noun \( y \) is a part of noun \( x \).

5. **Generalization /Specialization RULE:** Let \( r \) be a special verb relation (e.g., be, kind of, type of, classify into or consider as). If a noun \( x \) participates in noun \( y \) with \( r \), then the noun \( x \) is a kind of the noun \( y \).

6. **Adjective RULE:** If a noun \( x \) is a numeric modifier of another noun \( y \), then the noun \( x \) is a property of the noun \( y \).

7. **Equivalence RULE:** If a noun \( x \) is an abbreviation for another noun \( y \), then the noun \( x \) is the same as another noun \( y \).

6.1.3.4 **Deontic rule creator**

Deontic logic is the formal study of the normative concepts of obligation, permission, and prohibition. In modern deontic logic, the notions of prohibition \( F \), permission \( P \) are usually defined in terms of obligation \( O \) as shown in Equations (6.2) and (6.3) and the basic ontology for deontic modalities are used.
\[ F A = O \neg A \]  
\[ P A = \neg F A \]

In this research work, the deontic relations from the text documents are identified in order to resolve the conflicts between the documents. When there is a conflict, the algorithm indicates the positions of conflicting words. The text documents with no conflicts are identified as “Identical/Similar Documents”. For this purpose, this work uses the properties of negation, unification and resolution. Experimental works have been carried using a number of tools and algorithms. In this process, dominant keyword resolution was carried out using Stanford Part of Speech (POS) tagger. In addition, filtering of useless tags from POS tags was also performed. The structural relationships were identified using rules and hence the relationships such as isA, sameAs, PropertyOf and PartOf have been identified. Now, the resolution of deontic relationships from the POS tags were carried out using deontic rules. The detection of transitive relationships was also performed using deontic rules. Finally, the removal of redundant relationships such as obligatory-high, forbidden-high and permissibility-low were performed.

### 6.1.3.5 Rules for detecting deontic relations

In the e-learning experiments conducted in this work, the learners were allowed to view the course contents from the service providers. In order to validate the understanding of the user on the e-learning content, the domain experts were also allowed to view the content. Both the learner and the domain expert provide a short description about the viewed course content. Separate ontologies are created and they are matched against each other. This is done in order to find out three kinds of relationships namely equals, partial-
equals and conflicts. Based on the relationships obtained, the learner levels of understating are obtained. In order to obtain these relationships, special kinds of deontic relations shown below have been used in this work.

**Rule 1** : If ‘x’ is a noun and ‘x’ is related to y by attribute or part of relationship and there exists a determiner relationship between ‘X’ and ‘Y’ then OBLIGATORY (‘X’ HAS ‘Y’)

**Rule 2** : If ‘x’ is a noun and ‘x’ is related to ‘Y’ by attribute or part of relationship and there is a modal relationship between ‘X’ and ‘Y’ then

**Rule 2.1** : If the modal relationship is MUST or SHOULD then OBLIGATORY (‘X’ HAS ‘Y’)

**Rule 2.2** : If the modal relationship is CAN then PERMITTED (‘X’ HAS ‘Y’)

**Rule 3** : If ‘X’ is a noun and ‘X’ is related to ‘Y’ by part of or attribute relationship and consists of negative modal relationship

**Rule 3.1** : If the modal relationship is MUST NOT or SHOULD NOT then FORBIDDEN (‘X’ HAS ‘Y’)

**Rule 3.2** : If the modal relationship is CAN NOT then NOT_PERMITTED (‘X’ HAS ‘Y’)

**Rule 4** : If ‘X’ and ‘Y’ are nouns and are related with Property of relationship OBLIGATORY (‘X’ is NOT NULL)

**Rule 5** : If ‘X’ and ‘Y’ are noun and are related by is A relationship OBLIGATORY (‘X’ has attribute TYPE)
6.1.3.6 Transitivity rules generation

Rule 6: If ‘X’ and ‘Y’ are related with is A relationship and ‘Y’ is related to another ‘Z’ with some deontic relationship ‘R’ then ‘X’ is related to ‘Z’ with deontic relationship ‘R’

Rule 7: If ‘X’ and ‘Y’ are related with sameAs relationship and ‘Y’ is related to another ‘Z’ with some deontic relationship ‘R’ then ‘X’ is related to ‘Z’ with deontic relationship ‘R’

Rule 8: If ‘X’ and ‘Y’ are related by a deontic relationship ‘R’ and ‘Y’ and ‘Z’ are related by deontic relationship ‘R’ then ‘X’ and ‘Z’ are also related with deontic relationship ‘R’.

6.1.3.7 Predicate calculus relations for deontic rules

RULE 1: \( \forall x, \exists y \rightarrow \text{OBLIGATORY}(x,y) \)

RULE 2.1: \( \text{MUST}(x,y) \lor \text{SHOULD}(x,y) \rightarrow \text{HAS}_\text{OBLIGATORY}(x,y) \)

RULE 2.2: \( \text{NOUN}(x) \land \text{NOUN}(y) \land \text{CAN}(x,y) \rightarrow \text{HAS}_\text{PERMITTED}(x,y) \)

RULE 3.1: \( \text{NOUN}(x) \land \text{NOUN}(y) \land \text{MUST}_\text{NOT}(x,y) \land \text{SHOULD}_\text{NOT}(x,y) \rightarrow \text{HAS}_\text{FORBIDDEN}(x,y) \)

RULE 3.2: \( \text{NOUN}(x) \land \text{NOUN}(y) \land \text{CAN}_\text{NOT}(x,y) \rightarrow \text{HAS}_\text{NOT}_\text{PERMITTED}(x,y) \)

RULE 4: \( \text{NOUN}(x) \land \text{NOUN}(y) \land \text{PROPERTY}_\text{OF}(x,y) \rightarrow \text{OBLIGATORY}(x, \text{NOTNULL}) \)

RULE 5: \( \text{NOUN}(x) \land \text{NOUN}(y) \land \text{OBLIGATORY}(x,y) \rightarrow \text{HAS}_\text{ATTRIBUTE}(x, \text{TYPE}) \)

RULE 6, 7: \( \text{NOUN}(x) \land \text{NOUN}(y) \land \text{NOUN}(z) \land \text{DEONTIC}(y,z) \rightarrow \text{DEONTIC}(x,z) \)
where

\[ \text{DEONTIC}(y,z) \rightarrow \text{MUST}(y,z) \lor \text{SHOULD}(y,z) \lor \text{CAN\_NOT}(y,z) \lor \text{HAS\_FORBIDDEN}(y,z) \lor \text{HAS\_NOT\_PERMITTED}(y,z) \]

**RULE 8** \[ \text{NOUN}(x) \land \text{NOUN}(y) \land \text{NOUN}(z) \land \text{DEONTIC}(x,y) \land \text{DEONTIC}(y,z) \rightarrow \text{DEONTIC}(x,z) \]

where

\[ \text{DEONTIC}(x,y) \rightarrow \text{MUST}(x,y) \lor \text{SHOULD}(x,y) \lor \text{CAN\_NOT}(x,y) \lor \text{HAS\_FORBIDDEN}(x,y) \lor \text{HAS\_NOT\_PERMITTED}(x,y) \land \text{DEONTIC}(y,z) \rightarrow \text{MUST}(y,z) \lor \text{SHOULD}(y,z) \lor \text{CAN\_NOT}(y,z) \lor \text{HAS\_FORBIDDEN}(y,z) \lor \text{HAS\_NOT\_PERMITTED}(y,z) \]

### 6.1.3.8 Constrained ontology alignment

The relationships and rules identified are represented in the form of ontology. The relationships are arranged based on the base ontologies of deontic rules and the input documents. Semantic ontology matching using propositional logic is followed to identify the implicit relationship among the documents. Wordnet is used for matching the elements in the documents (Miller et al 1990). Wordnet is a lexical database used to identify the synonym, antonym, hypernym and hyponym. Wordnet Similarity is used to find the similarity between two words. Wordnet distance measure returns 0 if both words are equal. The elements in the ontologies that have to be matched should be compared using wordnet and propositional logic is formed. Relationship between wordnet semantic relations and corresponding propositional logic for ontology alignment is shown in Table 6.1. The logic is then given to the SATsolver tool to solve the problem using the propositional logic. In Table 6.1, the newly proposed axioms for conflict resolution are also
included in addition to the existing axioms. To make a decision on the satisfiability, the following rule is used.

If the mathematical axiom given in Equation (6.1) is said to be unsatisfiable, then the relationship holds.

The exact algorithm for ontology alignment is as follows:

**Algorithm**: Ontology Alignment

**Input**: Deontic statements obtained from Ontology A, Da

Deontic statements obtained from Ontology B, Db

**Output**: rel

Output

Domain Set : <equals, partial equals, conflicts>

**Procedure**

Begin

For each logic statement ls1 in Da

For each logic statement ls2 in Db

Pl <- FormPropositionalLogic(ls1,ls2)

Rel<-SATSolver(pl)

End  End  Return rel
Table 6.1 Ontology Alignment Table

<table>
<thead>
<tr>
<th>Semantic Relations</th>
<th>Input Keywords</th>
<th>Propositional Logic</th>
<th>Relationships</th>
<th>Semantic-Numeric Mapping</th>
<th>Translation into CNF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Synonym a=b</td>
<td>Dominant</td>
<td>a ↔ b</td>
<td>equals(=)</td>
<td>1</td>
<td>Axioms∧(context₁ ∧ ¬context₂)</td>
</tr>
<tr>
<td>Hyponym or Meronym a ⊆ b</td>
<td>Dominant</td>
<td>a → b</td>
<td>partialequals (⊇)</td>
<td>0.5</td>
<td>Axioms∧(¬context₁ ∧ ¬context₂)</td>
</tr>
<tr>
<td>Hypernym or holonym a ⊇ b</td>
<td>Dominant</td>
<td>b → a</td>
<td>partialequals (⊇)</td>
<td>0.5</td>
<td>Axioms∧(¬context₁ ∧ context₂)</td>
</tr>
<tr>
<td>Deontic Conflict a ⊨ b</td>
<td>Dominant and Non-dominant</td>
<td>¬ (a ∨ b)</td>
<td>Conflicts(⊥)</td>
<td>-1</td>
<td>Axioms∧(¬context₁ ∧ ¬context₂)</td>
</tr>
</tbody>
</table>
**Similarity Computation**

The text documents are processed for the deontic relations obtained from the input documents. In the proposed work, any two documents to be aligned are checked for similarity or conflicts. This kind of alignment is resolved as equivalence, partial-overlap and conflict relationships. This is achieved by calculating the similarity/conflict percentage in terms of the positive matches identified by the ontology alignment algorithm described in the above section. In this work, name similarity is considered for semantic matching between two ontologies. The name similarity between two ontologies $e_{1i}$ and $e_{2j}$ is given by

$$\text{Namesim}(e_{1i}, e_{2j}) = 1 - \frac{\text{EditDist}(e_{1i}, e_{2j})}{\max(l(e_{1i}), l(e_{2j}))}$$  \hspace{1cm} (6.4)

where $e_{1i}$ = entity of ontology constructed by the learner

$e_{2j}$ = entity of base ontology (constructed by the domain expert)

$l(e_{1i})$ = string length of element in learner ontology

$l(e_{2j})$ = string length of element in base ontology

$\text{EditDist}()$ = Standard Levenshtein distance

For this kind of similarity computation, the node entities and the total number of nodes in the ontologies constructed by the domain expert called as the base ontology and the learners are considered. The distance between the entities present in the two different ontologies are found using the Standard Levenshtein distance. The degree of similarity/conflicts of the constructed ontologies is found using Equation (6.4). Several numbers of experiments were performed in order to identify the threshold values. The
threshold for the similarity computation in this application is set to be 0.5. If the similarity computation measure is equal greater than 0.8, then the documents written by the learner after e-learning and the domain expert (base ontology) are exactly equal which indicates the equivalence relationship. However, if the similarity computation measure is between 0.3 and 0.7 the documents are partially-equal, which describes the subsumption relationship. The last case is if the similarity computation measure is less than 0.3, it indicates the conflicts relationship which is assumed that the documents written the learner do not match the base ontology.

6.1.4 Performance Evaluation

The applicability of this framework is tested in real problem applications. Since, the authors’ domain of interest is concerned with e-learning, in this work the learners level of understanding in learning the ‘C’ programming language course electronically is tested. The objective of the developed framework is to obtain the degree of similarity/conflict after the text documents produced by the learners and the domain experts are compared. This objective was also tested for other existing algorithms and the results are depicted in this section.

6.1.4.1 Experimental set-up – preparation of raw text documents

The text documents were collected from the learners and domain experts. The learners provide their documents based on their learning experience that is gained from e-learning of the ‘C’ programming language from the e-learning servers namely mediawiki, moodle and joomla. The experiments are mainly based on the e-contents posted by various instructors on the mediawiki e-learning server and experiments were carried out using
First year Undergraduate learners of 4 different departments namely, Computer Science and Engineering, Civil Engineering, Mechanical Engineering and the Electronics and Communication Engineering. Thirty (30) learners from each branch were considered as target learners for the e-learning of ‘C’ programming language. Four professors from the Department of Computer Science and Engineering in Anna University were considered as experts in the ‘C’ programming language and the ontology construction and alignment were based on the documents produced by these experts as well as the learners. In this work, ontology construction was carried out by using Jena programming toolkit in Java programming language. The experiments were repeated and tested with the approaches provided in S-Match, Content-match and MUPRET, in addition to the work proposed in this work. In all these experiments, documents were processed and ontologies were constructed based on the e-learning of ‘C’ programming language concepts.

6.1.4.2 Results and discussion

The experimental results given below are obtained from the experiments conducted in this research works on evaluating the learning capability of learners in learning the ‘C’ language from e-contents. The learners were made to learn the e-contents of the mediawiki e-learning server and are asked to produce a short written document on what they have learnt for the purpose ontology construction. Moreover, for the purpose of obtaining the degree of similarity/conflict, a domain expert is also asked to produce a short written document on the same contents of ‘C’ programming language. Separate ontologies were constructed for the documents produced by the learners and domain experts. Following the ontology construction, these ontologies are aligned to check for the relationships indicated as equals, partial-equals and conflicts. Subsequently, the degree of similarity/conflict
was calculated. The experiments were carried out in several stages. In the first stage of experiments, the input documents from 30 learners and 1 domain expert were tested and these experimental results alone are shown in this work. The evaluation of the proposed framework was estimated in terms of the performance metrics namely precision, recall and specificity (Partyka et al 2008). It is found that, the evaluation accuracy in terms of the above performance metrics given by the proposed algorithm is better than the other existing algorithms and the results are shown in Figures 6.2 to 6.4. Subsequent experiments conducted with the rest of the learners and domain experts also yielded the similar results.

The inference made by the authors from the experiments is that, the learners level of understanding through e-learning of ‘C’ programming language is analyzed using ontology alignment techniques as indicated in the objectives of this work. In addition, the deontic rules derived from the documents aids in finding the degree of similarity/conflict of the documents produced by the learners and domain experts is found by considering both the dominant and the non-dominant words occurring in the text documents. Hence, it is evident that almost all the concepts of the logic are covered namely equivalence, subsumption, unification and conflicts.

6.1.4.3 Inferences

This work has been evaluated using Precision (PR), Recall (RE) and Specificity (SP) metrics. Generally, Precision is the degree to which repeated experiments yield the same results under unchanged conditions. It is computed using the formula given in Equation (6.7). In this work, Precision is measured as the ratio of the number of relationships correctly identified by the learners to the total number of relationships present in the e-learning
system considered for learning ‘C’ language. Figure 6.2 shows the precision analysis for the results obtained from this work. From this figure, it can be observed that the precision of the proposed ontology alignment technique is higher than the other existing algorithms namely MUPRET, S-MATCH and CONCEPT-MATCH. This is due to the fact that the ontology alignment technique proposed in this work uses axioms from deontic logic for resolving the structural relationships in ontology construction and alignment.

The second performance metric used in this work is Recall. In this work, recall is measured as the ratio of the number of correctly identified relationships by the learners to the total number of correct and incorrect relationships present in the e-learning document and is computed using the formula given in Equation (6.8). Figure 6.3 depicts the recall measure for the proposed algorithm and compares it with the other existing algorithms.

The third performance metric used in this work for analysis is specificity which is defined as the proportion of incorrect relationships identified correctly by the learner to the total number of correct and incorrect relationships present in the e-learning document. Figure 6.4 shows the specificity for the e-learning system proposed in this work and it is computed using the formula given in Equation (6.9). From this figure, it can be observed that the specificity metric shows that the proposed system has higher evaluation accuracy than the existing approaches in the e-learning of ‘C’ programming language. The performance metrics discussed in the e-learning application are defined as follows:

\[
\text{Precision (PR)} = \frac{TP}{TP + FP} \quad (6.7)
\]
Recall (RE) = \frac{TP}{TP + FN} \quad (6.8)

Specificity (SP) = \frac{TN}{TN + FP} \quad (6.9)

where,

FP is the False Positives (no. of incorrect relationships identified by the learner as correct)

TP is the True Positives (no. of correct relationships identified by the learner as correct)

FN is the False Negatives (no. of incorrect relationships which are not identified by the learner)

TN is the True Negatives (no. of correct relationships not identified by the learner)

Table 6.2 shows the comparison of the results obtained from this work with the existing works namely MURPET, S-MATCH and CONCEPT MATCH. In the table P denotes the Positive relationships, PR denotes Precision, RE denotes Recall, SP denotes the Specificity and N denotes the Negative Relationships. From Table 6.2, it can be observed that Deontic logic based approach is more accurate than MUPRET, S-Match and Concept-match algorithms in terms of precision, recall and specificity.
Table 6.2 Precision, Recall and Specificity Evaluation Results

<table>
<thead>
<tr>
<th>P</th>
<th>N</th>
<th>PROPOSED DEONTIC LOGIC BASED MODEL</th>
<th>MUPRET</th>
<th>S-MATCH</th>
<th>CONCEPT-MATCH</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>TN</td>
<td>TP</td>
<td>FP</td>
<td>FN</td>
</tr>
<tr>
<td>5</td>
<td>3</td>
<td>2</td>
<td>5</td>
<td>2</td>
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<td>25</td>
<td>37</td>
<td>105</td>
<td>92</td>
<td>0.53</td>
</tr>
</tbody>
</table>
Figures 6.2 to 6.4 compare the proposed work with MUPRET, S-Match and Concept-match in terms of precision, recall and specificity. From these comparisons, it is observed that the proposed deontic logic based approach shows better performance with respect to providing appropriate decisions on the recommendation and provision of more relevant learning contents and learning methodologies to the learners in the e-learning environments.

Figure 6.2 Precision Evaluation

Figure 6.3 Recall Evaluation
Figure 6.4 Specificity Evaluation

The proposed framework has achieved this performance by applying deontic logic for recovering the deontic relationships by resolving the conflicts between two documents based on both dominant and non-dominant keywords present in the documents.