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A NOVEL APPROACH FOR TEST PROBLEM ASSESSMENT USING COURSE ONTOLOGY (75 pp.)

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Semantic analysis of educational resources is a very interesting problem with numerous applications. Like any design process, educational resources also have basic elements of design and reproduction. In the process of designing test problems, these elements are in the form of information objects. Course knowledge can be represented in the form of prerequisite relation based ontology using which, assessment and information extraction from test problems is possible. We propose a language schema based on Web Ontology Language (OWL) for formally describing course ontologies. Using this schema, course ontologies can be represented in a standard and sharable way. An evaluation system acts as the backend for the design and re-engineering system. This research aims at automating the process of intelligent evaluation of test-ware resources by providing qualitative assessment of test problems. Some synthetic parameters for the assessment of a test problem in its concept space are introduced. The parameters are tested in some real world scenarios and intuitive inferences are deduced predicting the performance of the parameters. It is observed that the difficulty of a question is often a function of the knowledge content and complexity of the concepts it tests.

A NOVEL APPROACH FOR TEST PROBLEM ASSESSMENT USING COURSE ONTOLOGY

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by

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Chapter 1.

Introduction and Background

Since the advent of the Web a great optimism has been created about online sharing of course material. Many educators worldwide today maintain course websites with online accessible teaching materials. The primary use of these web-sites is for dispensing lecture materials to immediate students. There have been many organized attempts as well to create large digital courseware libraries to promote sharing. Some of the significant efforts in this direction are NIST Materials Digital Library Pathway [2, 3], NSDL Digital Libraries in science, technology, engineering and mathematics (STEM) [10], OhioLink [4], ACM Professional Development Centre with over 1000 computer science courses [5], etc. Most universities, colleges and even schools now actively encourage online course material dispensing through portals. MIT's Open Course Ware (OCW) project [7] has more than 1000 course materials freely available, Universia [6] maintains translated versions of OCW courses in 11 languages, China Open Resources for Education (CORE) has a goal to include Chinese versions of the OCW for over 5000 courses, NSDL has focused on collecting specialized learning materials and currently has more than 1000 such collections [8], Centre for Open and Sustainable Learning [9] at the Utah State University, etc. the amount of digital courseware content available online is

huge. Surprisingly, the real sharing of the materials among the educators is still very low. In OCW it has been noted that only 16% of the users are educators out of which not more than 26% use it for planning their course or teach a class [10]. The actual reuse for most sites is mostly unreported and possibly lower. Surprisingly despite such massive intention, organized efforts and the market, effective sharing of courseware among teachers is almost non existent. A fresh and critical look has to be undertaken to tackle the central problem of sharing learning objects. It seems good courseware is the product of complex design [12, 13]. The process of teaching requires continuous innovation, adaptation and creative design on the part of the teacher. Unfortunately the current form and status of courseware doesn't aid to this process at all. Teaching is a high level cognitive activity of knowledge organization and dissemination and requires complex and continuous customization.

Most courseware today, on the web or otherwise, is not accompanied with a conceptual design. Any composition, engineering design or courseware or an art work always takes place in the context of a conceptual design space. The conceptual context is the most important factor in any formative learning process. Consider a lecturer giving a presentation on some topic. If the lecturer simply talks about the presentation topic without giving any reference to a slide or a diagram, it is very difficult to understand. Conversely if the lecturer just presents the slides without explaining them in some context, the presentation remains incomplete. There is no well formed encoding principle for capturing and sharing this invisible design without which the course materials significantly loose much of their reusability. In desperate cases, teacher has to manually

reverse engineer the design from the courseware. Therefore, it is not surprising that instructors and educators find it easier to build the course materials from scratch rather than reusing online available resources. The background design of the course material is vital for creation and reengineering of courseware. It is very unlikely that without the design, finished courseware available will ever be used creatively.

Currently the web is huge repository of assorted digital resources without much reusability. Most educational content is scattered, replicated and not linked to each other by any kind of relationship. To make this digital content reusable, sharing the metadata associated with it is necessary. A clear distinction has to be made between knowledge and information. Knowledge is the means by which intelligent design and sharing of test-ware and other web resources is possible. The main problem of information on the web is that it is hardly machine usable [11]. To make the data on the web reusable it is necessary to have information about the data itself. Thus the Meta information associated with the actual data is just as important as the data. Palazzo et.al. [13] address this problem and propose a system for courseware authoring taking into account the student learning style, technical background, presentation preferences and other inclinations.

Traditionally concepts maps are used to represent the backend context for the course knowledge. Many efforts [16, 17, 18, 19] have gone into representing course knowledge using concept maps. In the recent past ontologies progressively are being used to represent structured information in a hierarchical format. Concept maps offer a means to represent hierarchical knowledge; however they are too expressive and consequently contain more information and semantic relationships than necessary for effective

computation. Ontologies provide a means to effectively map this knowledge into concept hierarchies. Course ontology, particularly, can be roughly defined as a hierarchical representation of the topics involved in the course, connected by relationships with specific semantic significance. Using ontologies for course concept hierarchies in the domain of education is only obvious. Currently the process of designing of test problems is completely manual, based on human experience and cognition. Design of test problems also follows the basic principles of any engineering design process. The primary elements of design in this case are the information objects. Much effort has been put in the creation and reusability of these information objects called as the learning objects. The Learning Object Metadata (LOM) [26] standard for the representation of information about educational resources is the product of this effort. Recent standardization of semantic representation standards like RDF and OWL offers great technical platform to represent the concept knowledge space symbolized by ontologies. The representation of meta data for educational resources greatly improves it machine usability. These progressive steps taken in the field of knowledge and metadata representation now provide a great platform for researchers and theorists to create resourceful and innovative applications which effectively utilize the background knowledge in a particular domain to intelligently and automatically design, compose, evaluate, reengineer and share information rich resources like courseware, web resources, educational materials etc.

1.1. Related Work

There have been numerous attempts to quantify the complexity of problems [14, 15, 16, 17, 21]. The approaches to problem difficulty assessment can be distinguished into two types, knowledge based approaches and cognition based approaches. Researchers which follow knowledge based approach generally present mathematical models for calculating difficulty of a problem based on the knowledge it tests. The cognitive researchers look at the problem from learning point of view and try to find answers from the student and education perspective.

Li and Sambasivam [17] experiment with static knowledge structure of computer architecture course to compute problem difficult. The difficulty is calculated based on normalized weights of the concepts connected to and from the question. Kou, et.al. [14, 15] propose a very innovative technique to represent concept maps using information objects. These objects act as input to a system which calculates difficulty. Difficulty is considered a function of numerous factors like, number of attributes, learning sequence of concepts, concept depth, number of unknown parameters, and number of given attributes mathematical complexity etc. However the system does not calculate difficulty for complex problems, i.e. problems based on more that one concept. Palazzo, et. al. [12] provide a great representation for course knowledge. Though they do not consider the problem of difficulty assessment, they provide an excellent means for course ware authoring based on course ontologies linked with prerequisite relationships. The main problem with these approaches is that no solid course representation technique is used

consistently. The representations used are often rigid, incomplete and incomputable. Li and Sambasivam's static knowledge structures are intuitively generated structures where weights are allocated on parent child relationship without any external considerations. Kou et.al. use a number of other factors the values for which are calculated mostly empirically and are highly subjective.

The other group is the one of cognitive and educational researchers. Lee, F-K and Heyworth R., attempt to calculate the difficulty of a problem based on factors like, perceived number of difficult steps, steps required to finish the problem, number of operations in the problems expression and students degree of familiarity with the question. Studies by Croteau, Heffernan & Koedinger (2004), Koedinger & Nathan, (1999), [24, 25, 26, 27] try to figure "why algebra word problems are difficult?" They propose difficulty measures which are based on arithmetic and symbolization in a problem. The reasoning behind this is that, greater the number of symbols in an arithmetic problem, greater is the difficulty. Cognitive research also reason that much of the difficulty children experience with word problems can be attributed to difficulty in comprehending abstract or ambiguous language [44].

This thesis follows a purely knowledge based approach to assessment of problem difficulty. The main problem with previous works is that they fail to give a coherent representation of the knowledge domain. We present a novel approach to course ontology representation which is standard and coherent, and propose some assessment parameters for problem complexity computation.

1.2. Thesis contribution

In this thesis we present a novel approach to course knowledge representation using course ontologies, in an expressible and computable format using *has-prerequisite* relationships where concepts involved in teaching a course are arranged in hierarchical order of their importance. It differs from traditional ontologies most significantly in that, it is not IS-A relation based and it is not a directed acyclic graph (DAG) as most traditional ontologies. A schema language is developed called, Course Ontology Description Language (CODL) for representing course ontologies which can provide a framework for encoding and sharing courseware. It is based on OWL and provides a powerful framework for representing course ontologies in a standard and sharable way. Another original approach for specifically pointing out areas in ontologies of maximum relevance is given. This approach allows for the effective processing of only the relevant part of the ontology by which the computation time and resources are effectively saved.

This thesis investigates the properties of test problems by following a purely knowledge based approach for assessment using course ontologies. Here assessment refers to evaluation of test problems for their knowledge content and complexity. We isolate the main pedagogical challenge as finding measurable quantities that can provide guidance in the process of automatic evaluation. We reason that the qualitative assessment of problems in their concept space is a very important step in making online testing, e-learning or web based pedagogy even remotely effective. Standardizing problems by evaluating the complexity can be a backend system with immense potential

for test-ware composition and sharing applications. It has the potential to make the already available test-ware resources on the web reusable. These evaluation parameters are calculated by applying mathematical formulations to the course ontology. The parameter performance is also tested in real world test scenarios and it is shown that they are very good indicators of problem complexity. Interesting logical inferences are made from the observed behavior of evaluation parameters with respect to the knowledge a problem tests and the observed performance of the students. The semantic evaluation system can intuitively be applied in varied application areas like automatic test and question generation and solution grading. We present a few possible applications of this system.

Chapter 2.

Course knowledge representation using ontologies

Automated design and evaluation involve formal mathematical assessment models unlike cognition based models in humans. These cognition based assessment models for design and evaluation are developed by the human mind over a period of time, by learning and collecting and assessing information from corpora of incoming knowledge. Recently great deal of research is being done to make these corpora of knowledge available for machines. A machine understandable and computable assessment system therefore is essential. This body of knowledge is represented using techniques from knowledge representation like semantic networks and ontologies. Ontology is a method for representing elements in a domain or corpus of knowledge in a hierarchical fashion and links these elements with semantic relationships.

The corpus of course knowledge is hypothetically divided into two tiered description framework namely, concept space and resource space. The course ontology is the conceptual representation of the concept space graph, where in concepts are linked to each other using semantic relations. The resource space gives the description of actual resources for the corresponding concepts from the concept space. The course concept

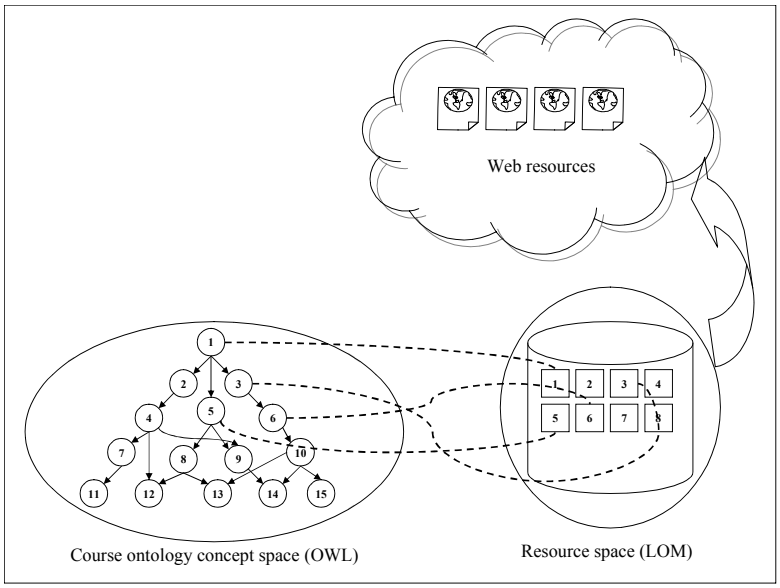


Figure2. 1: Two tired representation of concept space and resource space

space, symbolized by course ontology, is built using a language variant of Web Ontology Language, OWL [31]. The language is designed to harness maximum computability at the cost of reduced expressive power. The types of relations and properties are kept at minimum. The second tier of description, the resource space, requires more expressiveness. LOM [28] developed for learning object classification is used to provide the base elementary description for the learning objects, the resources. In this section we discuss in detail the definition, specification, and constructs for the language used to represent course ontologies.

2.1. Knowledge Representation Issues

In computer science and artificial intelligence, knowledge representation is a technique by which knowledge about a particular domain is structured to increase its usability. Knowledge representation techniques are used in AI, cognitive science, and other fields for problem solving, logical reasoning, data mining, question-answering, theorem proving, neural networks, expert systems etc. Davis, Shrobe and Szolovits define knowledge representation as a "set of ontological commitments" and "a medium of pragmatically efficient computation" [45]. It means that knowledge representation is set of vocabulary agreed upon, to represent knowledge which is practical and computable at the same time. It is important for the knowledge representation to be expressible and computable. This in turn brings us to the problem of granularity of information in course ontology. The granularity of the ontology is an important factor to consider while building the course ontology. The ontology can range from being fine-grained to coarse-grained. A finer grained ontology will contain more concepts in detail and more implicit relationships between unrepresented concepts can be discovered. Finer the ontology, the application will have more knowledge to work with giving better results. But defining a finely grained expressive ontology is costly in terms of computation. As more and more concepts and relationships are defined and represented, more is the information to be processed. At the same time, though coarse grained ontologies are computable, they do not have enough information needed for better results. The depth of the knowledge to be represented is therefore an important question in representing any kind of knowledge. Most available finished materials today are coarse granular. Unfortunately, this is not suitable for semantic evaluation. Any design system requires the basic ability to

transcend between multiple levels of granularity. In other words the mechanism of decomposing as well as re-composition is fundamental.

2.2. Course Ontology

Ontologies derive their roots from philosophy. In philosophy ontologies are used to represent the account of what exists. In computer science they are generally defined as "a specification of a conceptualization" [46]. Ontology is a data model that represents a domain and is used to reason about the objects in the domain and the relations between them. In the context of this research the domain is that of a "*course*", the objects are "*concepts in the course*" and the relations between the concepts are that of "*has-prerequisite*". Simply put, ontology is a group of concepts organized to reflect the relationships between the concepts. It is a method of specification and speculation about information. In recent past ontologies are increasingly being used to represent information in various domains like biological sciences, accounting and banking, intelligence and military information, geographical systems, language based corpus, cognitive sciences, common sense systems etc. The applicability of computer science is in the efficient representation of these ontologies and the subsequent algorithmic processing. Most ontologies today are so extensive in the breadth of knowledge that processing of these ontologies becomes almost impossible and a gargantuan computation task. There needs to be a way to efficiently process the relevant information in these

ontologies to give optimum results in minimum time and complexity of computation. We present a method which points out to a portion of the ontology which is of maximum relevance and then start processing on this portion. The size of this portion of the ontology, which we call as the projection graph, can be changed according to the desired semantic significance.

Ontologies are made up of individuals, classes, attributes and relationships. Individuals, the instantiations of classes, form the basic elements of ontology. Classes are abstract concepts which define and may contain other classes or individuals or both. Attributes are the properties of individuals or relationships. The name of the property is the attribute under consideration while the values of attributes can take form in various data types ranging from integers, strings, boolean etc. An individual is also allowed to have multiple attributes in the definition. Relationships are the way the concepts in the ontology are structured with respect to each other. Relations can be thought of as attributes whose value is another object in the ontology and is used to define the relationship between two or more different objects. Semantic relations particularly important in the context of ontologies are: Meronymy (part-of), Holonymy, Hypernymy, and Hyponymy. The has-prerequisite relationship is like holonymy relationship, where in the child node is a part of the parent node. However, in the context of course ontology, the *part-of* semantics refers to the prerequisite understanding of the child node needed to understand the parent node. On the whole the course ontology is constructed in such a hierarchical fashion that the children of node represent the knowledge required to understand the parent node, and their children represent the knowledge required to

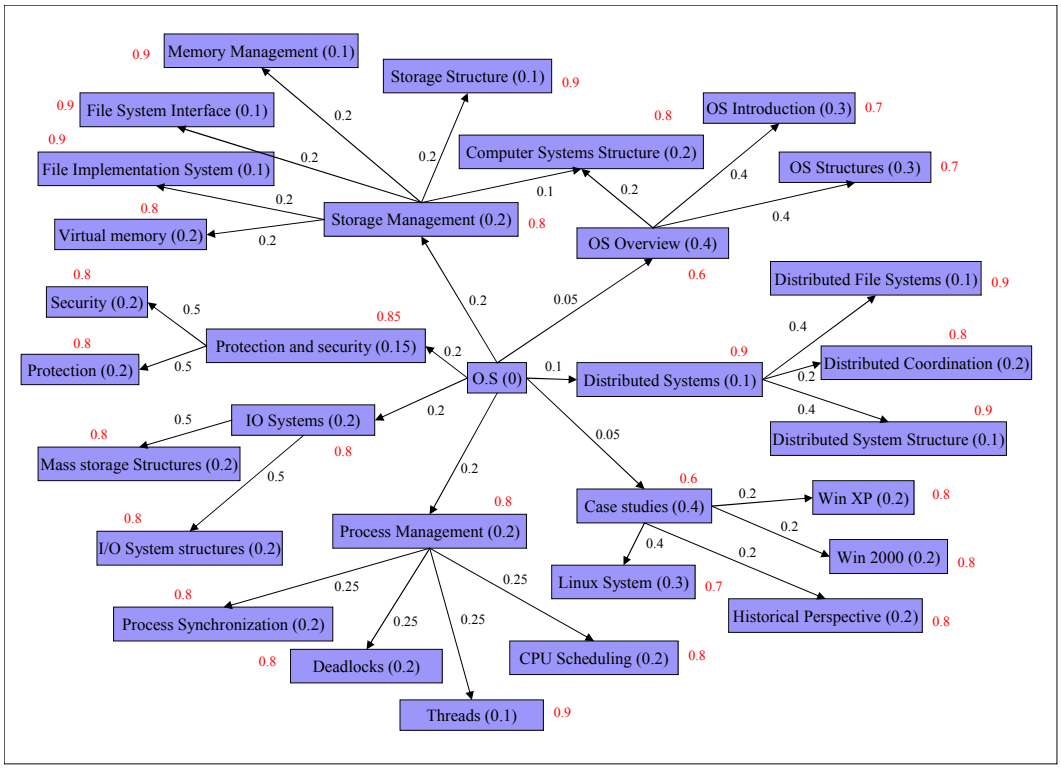


Figure2. 2: View of Operating Systems ontology 2 level deep

understand them, so on and so forth. The ontology is created using the principle of "constructivism" borrowed from learning theory. The theory states that any new learning occurs in the context of and on the basis of already acquired knowledge. We use this theory to practically implement the has-prerequisite relationship based course ontology. See in Figure 2.2. "Process Management" is the prerequisite of "OS".

A node is characterized by two values namely, self-weight and pre-requisite weight. The self-weight of a concept node is the value or the knowledge which is inherent to that node itself. It means that, the self-weight is the numerical realization of the knowledge required to grasp the concept, not in its entirety, but in partiality with respect

to itself. To understand the concept entirely, knowledge of the prerequisite concepts is also required, which is given by the prerequisite weight of the node. It gives the numerical realization of the importance of the understanding of the prerequisite concepts in the absolute understanding of a parent concept. Another value which characterizes the course ontology representation is the link weight. The link weight again is the numerical realization of the semantic importance of child concept to the parent concept. Child concepts imperative in the understanding of parent concepts will have a greater link weights than the others. Thus the course ontology representation is a collection of concepts nodes with self-weights and prerequisite weights and has-prerequisite relationships linking these nodes with a value attribute given by the link weight.

2.3. Representation Standards

The recent advances in Semantic Web representation languages such as RDF, RDF schema [35], and recently OWL [29, 30] now provide a promising technology basis for metadata representation. The course ontology is represented using OWL. OWL offers a convenient platform for the representation of hierarchical concepts like that in the course ontology. There are 3 sub categories of the OWL language namely, OWL Lite, OWL DL and OWL Full. Among these profiles OWL Full offers maximum expressiveness but it does not guarantee computability. OWL Lite offers computability by restricting expression power of the language. OWL DL (OWL Description Logic)

offers a balance between the expressiveness of OWL Full and the computability of OWL Lite. It has all the language constructs from OWL Full, but can only be used with restrictions. The differences between the three categories are explained below.

1. OWL Full: It contains all the OWL language constructs and provides free unconstrained use of RDF constructs. In OWL Full the construct `owl:Class` is equivalent to `rdfs:Class`, unlike in OWL Lite and OWL DL where `owl:Class` is a proper sub class of `rdfs:Class`. Most importantly, in OWL Full, individuals can be treated as classes. It means that, individual of class `TypeOfCarSedan`, `HondaAccord`, can also be a class, containing all Honda accord cars. In OWL Full data values can also be considered as individual. Thus `ObjectProperty` and `DatatypeProperty` are not disjoint and in fact the latter is the sub class of the former. A `rdfs:Resource` is equivalent to `owl:Thing` in OWL Full, which means that any `Thing` can be a resource. OWL Full provides the expressivity of OWL with flexibility and meta modeling feature of RDF.
2. OWL DL: It has the same constructs as in OWL Full but governed by some additional restrictions. In OWL DL an individual cannot be treated as a class, which means that all classes, data types, data type properties, object properties, annotation properties, ontology properties, individuals, data values etc. are all disjoint. This means that data type properties in OWL DL can never be inverse, inverse functional, symmetric and transitive. Also no cardinality can be placed on transitive properties, to maintain decidability of reasoning [31]. Most RDFS

vocabulary cannot be used in OWL DL. Axioms must be well formed and always refer to class names. In particular, the OWL DL restrictions allow the maximal subset of OWL Full against which current research can assure that a decidable reasoning procedure can exist for an OWL reasoner [30].

3. OWL Lite: OWL Lite abides by all the restrictions OWL DL puts on the use of the OWL language constructs. In addition, OWL Lite forbids the use of `owl:oneOf`, `owl:unionOf`, `owl:complementOf`, `owl:hasValue`, `owl:disjointWith`, `owl:DataRange`. The subjects of all axioms in OWL Lite must be identifiers or restrictions. The idea behind the OWL Lite expressivity limitations is that they provide a minimal useful subset of language features that are relatively straightforward for tool developers to support. The language constructs of OWL Lite provide the basics for subclass hierarchy construction: subclasses and property restrictions. In addition, OWL Lite allows properties to be made optional or required. The limitations on OWL Lite place it in a lower complexity class than OWL DL. This can have a positive impact on the efficiency of complete reasoner for OWL Lite. Implementations that support only the OWL Lite vocabulary, but otherwise relax the restrictions of OWL DL, cannot make certain computational claims with respect to consistency and complexity.

```
<?xml version="1.0"?>
<rdf:RDF
  xmlns:owl = "http://www.w3.org/2002/07/owl#"
  xmlns:rdf = "http://www.w3.org/1999/02/22-rdf-syntax-ns#"
  xmlns:rdfs= "http://www.w3.org/2000/01/rdf-schema#"
  xmlns:xsd = "http://www.w3.org/2001/XMLSchema#">
<owl:Ontology rdf:about="###">
        <rdfs:comment>A schema for CODL (Course Ontology Description Language)</rdfs:comment>
        <rdfs:label>Course Ontology</rdfs:label>
</owl:Ontology>
<owl:Class rdf:ID="Concept">
        <rdf:comment>Course ontology concept</rdfs:comment>
        <rdfs:subClassOf rdf:resource="http://www.w3.org/2002/07/owl#Class"/>
        <rdfs:subClassOf>
                <owl:Restriction>
                        <owl:onProperty rdf:resource="#hasPrerequisite"/>
                        <owl:allValuesFrom rdf:resource="#Relation"/>
                </owl:Restriction>
        </rdfs:subClassOf>
</owl:Class>
<owl:Class rdf:ID="Relation>
        <rdfs:subClassOf>
                <owl:Restriction>
                        <owl:onProperty rdf:resource="#connectsTo">
                        <owl:allValuesFrom rdf:resource="#Concept">
                </owl:Restriction>
        </rdfs:subClassOf>
</owl:Class>
<owl:ObjectProperty rdf:ID="hasPrerequisite">
        <rdfs:range rdf:resource="#Relation"/>
</owl:ObjectProperty>
<owl:ObjectProperty rdf:ID="connectsTo>
        <rdfs:range rdf:resource="#Concept">
</owl:ObjectProperty>
<owl:DatatypeProperty rdf:ID="hasLinkWeight">
        <rdfs:domain rdf:resource="#Relation"/>
        <rdfs:range rdf:resource="xsd:float"/>
</owl:ObjectProperty>
<owl:DatatypeProperty rdf:ID="hasSelfWeight">
        <rdfs:domain rdf:resource="#Concept"/>
        <rdfs:range rdf:resource="xsd:float"/>
</owl:DatatypeProperty>
<owl:DatatypeProperty rdf:ID="hasPrerequisiteWeight">
        <rdfs:domain rdf:resource="#Concept"/>
        <rdfs:range rdf:resource="xsd:float"/>
</owl:DatatypeProperty>

<Concept rdf:ID="MemoryManagement"/>

<Concept rdf:ID="OS">
        <hasPrerequisite>
                <Relation rdf:ID="relation_1">
                        <connectsTo rdf:resource="#MemoryManagement"/>
                        <hasLinkWeight rdf:resource="#0.2"/>
                </Relation>
        </hasPrerequisite>
        <hasSelfWeight rdf:resource="0.39"/>
        <hasPrerequisiteWeight rdf:resource="0.61"/>
</Concept>

</rdf:RDF>
```

Figure2. 3: CODL schema

2.3.1 Course Ontology Description Language (CODL)

It is the language we define to represent course ontologies. The schema for the course ontology description is mostly adherent to OWL Lite, with a few extensions. OWL Lite is used because it supports basic classification hierarchy and simple constraint features and due to its computational advantages over the other sub languages. However, representing the schema for our course ontology in OWL is an extremely non trivial issue as we will see in the explanation for the schema. The CODL schema is shown in the Figure 2.3. The elements of CODL defined course ontology are header information, class definitions, property definitions and individuals.

1. `owl:Ontology`:

It is a collection of assertions about the course ontology. This section can contain comments, version information and imports for inclusion of other ontologies. For example, the course ontology for a specific course, say "Operating Systems", can include another separate ontology for a course on "Calculus" from Mathematics. The CODL schema provides a method for conformant exchange of course ontologies. Ontological information about individuals appearing in multiple documents can be linked in a principled way.

```
<owl:Ontology rdf:about="###">
      <rdfs:comment>A schema for CODL (Course Ontology
                        Description Language)</rdfs:comment>
      <rdfs:label>Course Ontology</rdfs:label>
</owl:Ontology>
```

The `owl:priorVersion` element can be used to reference the previous version of the ontology. Versioning can effectively be done to different levels of granularity of the ontology. The `owl:import` element, which takes rdf:resource element as its subject, is used to import another ontology in to one ontology.

2. `class:Concept`:

The course ontology is structured in the form of individual concepts arranged in a hierarchy. All the individuals in the OWL representation are the instantiations of the class `Concept`. The class `Concept` is the super class which defines all concepts in the course ontology, including the restrictions on the values of the properties they can take. The class `Concept` has the rdfs construct of `rdfs:subClassOf`. The sub class axiom is used to define the necessary conditions for belonging to a sub class or a property restriction. OWL Lite requires the subject of the `rdfs:subClassOf` statement to be a class identifier. The instances of the class `Concept` are also instance of the universal class `owl:Class` in OWL, which comprises of all the classes which can be legally defined in the vocabulary of OWL language. The object of the sub class axiom is a property restriction. It describes an anonymous class, namely a class of all individuals which satisfy the restriction.

```
<owl:Class rdf:ID="Concept">
      <rdf:comment>Course ontology concept</rdfs:comment>
      <rdfs:subClassOf
rdf:resource="http://www.w3.org/2002/07/owl#Class"/>
      <rdfs:subClassOf>
            <owl:Restriction>
                  <owl:onProperty rdf:resource="#hasPrerequisite"/>
                  <owl:allValuesFrom rdf:resource="Relation"/>
            </owl:Restriction>
      </rdfs:subClassOf>
</owl:Class>
```

For example, in the above property restriction, the statement `owl:Restriction` defines an anonymous class, all of whose instances satisfy the restriction on properties `hasPrerequisiteWeight`. The property restriction states that, for all instances of class `Concept`, if they have a prerequisite (`hasPrerequisite`) then it must belong to extension of `Relation`. The extension of `Concept` means the set of all the members of the class `Concept`.

3. `class:Relation`:

The class `Relation` is used to give values to the `hasLinkWeight` property. In our representation, two instances of class `Concept` are connected by the property `hasPrerequisite` which has a link weight value. Accordingly, we want to be able to link an individual to another individual with a value and semantic relationship. These kinds of relationships are called as *n-ary* relationships [33]. There are two types of properties in the OWL world, object properties which connect instances of classes to each other, and data type properties which connect instance to data values. OWL does not offer means to link individuals with data values. Therefore we make a very important abstraction in the schema to form a separate class for `Relations`. The main objective of the class `Relation` is to link two individuals of the class `Concept` with a data value. We first link instance of the class `Concept` to an instance of `Relation`, and then link that instance again to instance of `Concept`.

```
<owl:Class rdf:ID="Relation>
      <rdfs:subClassOf>
            <owl:Restriction>
                  <owl:onProperty rdf:resource="#connectsTo">
```

```
                    <owl:allValuesFrom rdf:resource="#Concept">
                </owl:Restriction>
        </rdfs:subClassOf>
</owl:Class>
```

Thus by defining relationships between individuals as another class, *n-ary* relations can be defined in the schema and property restrictions can be applied.

4. `ObjectProperty: hasPrerequisite`

In our representation, `hasPrerequisite` property links an instance of `Concept` and instance of `Relation`. The semantic relationship of `hasPrerequisite` between two individuals is defined as an `ObjectProperty`.

```
<owl:ObjectProperty rdf:ID="hasPrerequisite">
      <rdfs:domain rdf:resource="#Concept"/>
      <rdfs:range rdf:resource="#Relation"/>
</owl:ObjectProperty>
```

The `rdfs:domain` is a property feature which is used to limit the domain of the individuals in which the property applies. If a property relates an individual to another individual, and the property has a class as one of the domains, then the individual must belong to that class. Here the property is applicable in the domain of class `Concept`. It is possible to have more that one domain. The `rdfs:range` feature limits the individual the property may have as its value. This means that if a property has range as a class, the instance of only that class can have the property. In other words, if a property relates one individual to another, and the property has class as its range, then the other individual must belong to range class. When an instance of the concept class has the property of

hasPrerequisite, the other individual to whom it relates to, must be from class Relation. Domain and range both are global restrictions.

5. ObjectProperty:connectsTo

```
<owl:ObjectProperty rdf:ID="connectsTo>
      <rdfs:range rdf:resource="Concept">
</owl:ObjectProperty>
```

This property is used to link instance of Relation to instance of Concept. The property restriction on connectTo, implies that all members of class Relation which connectsTo another member, the other member must be an individual of class Concept.

6. DatatypeProperty: hasLinkWeight

A data type property links individual to data values. Link weight is a characteristic of a relation therefore hasLinkWeight applies to instances of class Relation. The range of the property is set by the resource xsd:float. For the purpose of computational ease we set the values for all the concept and link properties between 0 and 1. In OWL Lite the range of a property must be a class identifier. ObjectProperty and DatatypeProperty are not disjoint in OWL Full unlike in OWL Lite and DL and are both sub classes of the rdf:Property class. The hasLinkWeight property links an instance of class Relation to a data value.

```
<owl:DatatypeProperty rdf:ID="hasLinkWeight">
      <rdfs:domain rdf:resource="#Relation"/>
      <rdfs:range rdf:resource="xsd:float"/>
</owl:ObjectProperty>
```

7. DatatypeProperty: hasSelfWeight

`hasSelfWeight` is used to define the self weight of a node. It too is applicable in the domain of the class `Concept` and range of values can be between 0 and 1.

```
<owl:DatatypeProperty rdf:ID="hasSelfWeight">
      <rdfs:domain rdf:resource="#Concept"/>
      <rdfs:range rdf:resource="xsd:float"/>
</owl:DatatypeProperty>
```

8. `DatatypeProperty: hasPrerequisiteWeight`

This property is used to relate an individual of the class `Concept` to its prerequisite weight values. By definition, the summation of self weight and prerequisite weight for a node is 1. Therefore this property is actually redundant as the prerequisite weight values doesn't need to be explicitly specified and can be calculated from the self weight values. However this property is included in the definition language, to incorporate the structural changes needed in an ever growing ontology. Nodes can be added and subtracted from the ontology, which may affect the prerequisite weight. Therefore this property is included to explicitly specify the values in such cases.

```
<owl:DatatypeProperty rdf:ID="hasPrerequisiteWeight">
      <rdfs:domain rdf:resource="#Concept"/>
      <rdfs:range rdf:resource="xsd:float"/>
</owl:DatatypeProperty>
```

9. `Individuals`:

```
<Concept rdf:ID="MemoryManagement"/>
<Concept rdf:ID="OS">
      <hasPrerequisite>
            <Relation rdf:ID="relation_1">
                  <connectsTo rdf:resource="#MemoryManagement"/>
                  <hasLinkWeight rdf:resource="#0.2"/>
            </Relation>
      </hasPrerequisite>
      <hasSelfWeight rdf:resource="0.39"/>
      <hasPrerequisiteWeight rdf:resource="0.61"/>
</Concept>
```

This is an instance of a typical individual in course ontology. Here the concept instance "MemoryManagement" is a prerequisite for "OS". Individuals are generally described by facts about their class membership and their property values. Individual member "OS" is a member of class `Concept` and has the property values for `hasLinkWeight` as 0.2, `hasSelfWeight` as 0.39 and `hasPrerequisiteWeight` as 0.61.

The most important part of the course ontology structure is the semantics between parent and child concepts. The representation should be able to not only define prerequisite relationship between them, but also define the value strength of this relationship. OWL does not have provision to relate two individuals using data values. In CODL, we define these kinds of *n-ary* relationships by defining a separate class of relations. Therefore the tool which uses CODL defined course ontology should be able to infer that, since `connectsTo` links `relation_1` and MemoryManagement and `hasPrerequisite` links OS to `relation_1`, MemoryManagement is prerequisite of OS.

Characteristics of `hasPrerequisite` and `connecsTo` properties are as follows:

1. Transitivity:

```
hasPrerequisite(a,r), hasPrerequisite(r,c) iff  hasPrerequisite(a,c)
connectsTo(a,b), connectsTo(b,c) iff connectsTo(a,c)
```

Both `hasPrerequisite` and `connectsTo` are transitive.

2. Symmetric:

```
hasPrerequisite (a, b) ≠ hasPrerequisite (b, a)
connectsTo (a, b) ≠ connectsTo (b, a)
```

Both `hasPrerequisite` and `connectsTo` are not symmetric.

3. Functional Property:

`hasPrerequisite (a, b) and hasPrerequisite(a, c) does not imply b=c`

`connectsTo(a, b) and connectsTo(a, c) does not imply b=c.`

Both `hasPrerequisite` and `connectsTo` are not functional.

4. Inverse of: The inverse properties of `hasPrerequisite` and `connectsTo` are `isPrerequisiteTo` and `connectsFrom` repectively.

`hasPrerequisite(a, b) iff isPrerequisiteTo(b, a) and;`

`connectsTo(a, b) iff connectsFrom(b, a)`

5. Inverse Functional:

`hasPrerequisite (b, a) and hasPrerequisite(c, a) does not imply b=c`

`connectsTo(b, a) and connectsTo(c, a) does not imply b=c.`

Both `hasPrerequisite` and `connectsTo` are not inverse functional.

Property Characteristic	CODL Properties			
	hasPrerequisite	rootEquivalentTo	equivalentTo	connectsTo
Transitivity	Yes	No	Yes	Yes
Symmetry	No	Yes	Yes	No
inverseOf	isPrerequisiteTo	-	-	connectsFrom
Functional	No	No	No	No
Functional Inverse Of	No	No	No	No

Figure2. 4: CODL Object property characteristics

2.3.2 Extensions to CODL

In this section we define some more properties to make extensions which can be incorporated in to the CODL schema for making some powerful inferences from the language.

1. `ObjectProperty:rootEquivalentTo`

```
<owl:ObjectProperty rdf:ID="rootEquivalentTo">
      <rdf:range rdf:resource="#Concept"/>
</owl:ObjectProperty>
```

The namespace declarations in OWL ontology provide a means to reference names defined in other OWL ontologies. The `owl:import` element can be used to import the entire set of assertions made by the imported ontology into the current ontology. However no current definition of import allows us to specify a node as an entirely different ontology. The `rootEquivalentTo` property provides a mechanism to expand a node in course ontology to a completely new ontology. That means that, a node in course ontology is allowed to be a root node of any other ontology.

```
<Concept rdf:ID="OS">
      <rootEquivalentTo rdf:resource="#OperatingSystem"/>
      ...
</Concept>
```

This means that “OS”, which is an instance of the class `Concept`, and is `rootEquivalentTo` the individual “OperatingSystem”, which is a member of the class `Concept` specified by the range. The equivalence property for individuals’ `owl:sameAs`

can be used to the same effect. However, defining the property as restriction on relations rather than concepts, allows for more freedom of expression in the schema.

2. `ObjectProperty:equivalentTo`

```
<owl:ObjectProperty rdf:ID="equivalentTo">
      <rdf:range rdf:resource="#Concept"/>
</owl:ObjectProperty>
```

This property provides a mechanism to equate all the nodes within ontology, so that ultimately the whole ontology is one node. It is important to note that relating all nodes by `equivalentTo` property doesn't actually mean that they are semantically equal. The purpose of `equivalentTo` property is only to unify the whole ontology as just an instance of the class `Concept`. This has very powerful implications for importing and sharing ontologies with different schemas. More power can be attributed to the representation by interspersing different kinds of relationships within ontology. Thus the ontology need not be based solely on `hasPrerequisite` relationship, but can also have other relationships like those stated above.

2.4. Mathematical representation of Concept Space Graph (CSG)

The course ontology is mathematically defined in the form of a concept space graph (CSG). A CSG is a view of the concepts space distribution in the domain of a particular course.

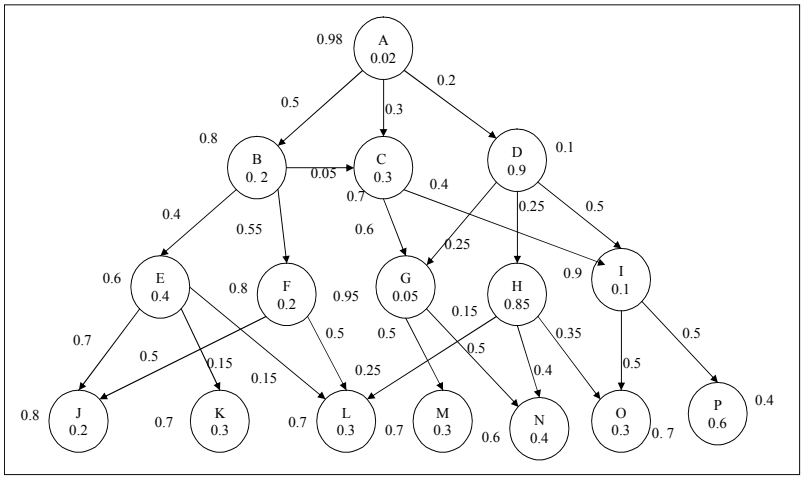


Figure2. 5: CSG rooted at concept A

A concept space graph T(C, L) is a projection of a semantic net with vertices C and links L where each vertex represents a concept and each link with weight l (i, j) represents the semantics that concept c_j is a prerequisite for learning c_i, where (c_i, c_j) Є C and the relative importance of learning c_j for learning c_i is given by the weight. Each vertex in T is further labeled with self-weight value $W_s(i)$ *cumulative prerequisite set weight* $W_p(i)$.

The self-weight $W_s(i)$ represents the relative semantic importance of the root topic itself with respect to all other prerequisites. The prerequisite weight $W_p(i)$ represents the cumulative, relative semantic importance of the prerequisite topics to the root node. Link weight is the strength of the prerequisite relationship between the parent and the child. A CSG with root A is represented as T (A) in Figure 2.5. For any

node, c_o, in the CSG, the sum of self-weight and prerequisite weights and the sum of the prerequisite link weights to its child node set $[c_1, c_2 \ldots c_n]$ are both always 1:

$$W_s + W_p = 1 \qquad \ldots(1)$$

$$\sum_{j=1}^{n} l(c_0, c_j) = 1 \qquad \ldots(2)$$

2.4.1 Node Path Weight

It is the propagated prerequisite effect of a subject node along a particular path to a root node. The notion of node path weight is introduced to compute the effect a prerequisite node has on a root node through a specific path. A single node, therefore, can have different prerequisite effect on a root through different paths.

When two concepts x_0 and x_t are connected through a path "p" consisting of nodes given by the set $[x_0, x_1 \ldots, x_m, x_{m+1}, \ldots, x_t]$ then the node path weight between these two nodes is given by:

$$\eta(x_0, x_t) = W_s(x_t) \prod_{m=t}^{1} l(x_{m-1}, x_m) * W_p(x_{m-1}) \quad \ldots (3)$$

The node path weight for a node to itself is its self weight.

$$\eta(x_1, x_1) = W_s(x_1) \qquad \ldots(4)$$

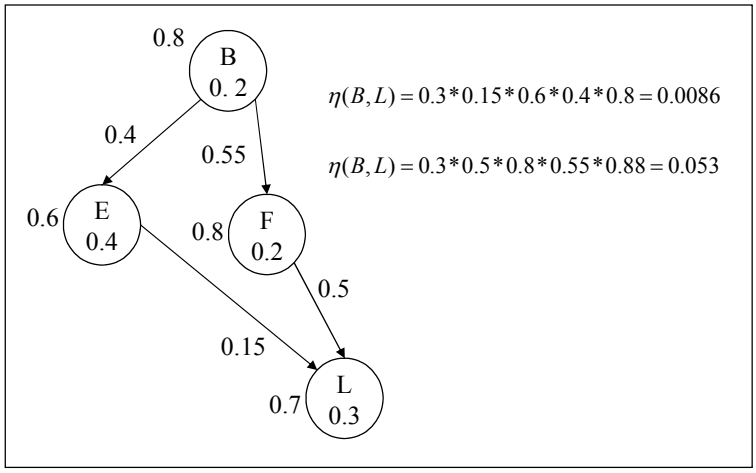


Figure2. 6: Example of Node path weight calculation

In the Figure 2.6 concept L is connected to concept B through E and F. Therefore the prerequisite effect it has on B is dependent on the prerequisite effect both E and F have on B respectively. Node path weight calculates the prerequisite effect a node has on another node. Therefore the factors of self weight of subject node and prerequisite weights of all the nodes in the path are included in the formula.

From the node path weight calculations we can see that L has a stronger prerequisite effect on B through F rather than E. This is because, L is more important to F (0.5) than E (0.15), prerequisite importance of L is more to F (0.8) than E (0.6) and subsequently F (0.55) is more important to B than E (0.4). Thus node path weights takes into consideration not only the singular effect a node has on its immediate parent but also the combined prerequisite effect a node would have to a root, B in this case, along a certain path.

2.4.2 Incident Path Weight

Incident path weight is same as node path weight except that it does not include the factor of self weight of the subject node. By doing this, we can compute the prerequisite effect the node may have on a root node, excluding the factor of knowledge of the subject node. It is defined as, the *absolute prerequisite cost required to reach the root node from a subject node.*

$$\gamma(x_0, x_n) = \frac{\eta(x_0, x_n)}{W_s(x_n)} = \frac{\eta(x_0, x_n)}{\eta(x_n, x_n)} \qquad \text{...(5)}$$

From Figure 2.6, the incident path weight calculations for paths between B and L are given by,

$\gamma(B, L) = \eta(B, L) / W_s = 0.0528 / 0.3 = 0.176$

$\gamma(B, L) = \eta(B, L) / W_s = 0.00864 / 0.3 = 0.0288$

Chapter 3.

Educational resources and Test Problems

Most of the educational resources today are not accompanied with metadata which makes it very difficult for machine processing. For educational resources to be machine processable, they have to be presented in the proper context [11]. In the last chapter we described semantic representation standards and formal mechanism to represent the *concept space* in detail. In this chapter we look at *resource space* which is made up of educational resources and the mapping between the *resource space* and the *concept space*. One aspect of research in educational technology is the development of technology in standards and practices for educational material research, design, reuse, development, and reengineering. Though educational resources can hardly replace the instructor, they can be very helpful in providing the context of the subject matter. Therefore educational resources need to be precise and intelligible.

A problem/question is one type of educational resource. The commonly observed properties of testware are difficulty or simplicity, breadth and depth of knowledge required to answer, relevance of the question to the root topic, the semantic distance between the concepts tested, ability of the question to test varying populations of students, applicability of the topics taught to a problem, etc. While designing a test, an

educator always tries to come up with questions which have maximum coverage of desired topics, diversity among the topics, good testing capabilities with respect to student knowledge, relevance to the material taught, overall generality or specificity. There are many other factors too; however the sub division of those factors almost always leads to the above given basic properties of a good question. It is important to understand these properties for better design and reengineering of test problems. In this thesis, we attempt to visualize and understand these properties of test problems by qualitative evaluation.

3.1. Problem concept mapping

The mapping between the *resource space* and the *concept space* is called as the problem concept mapping. All educational resources, including test problems are based on a few selected concepts from the ontology. When an educator creates test problems, although instinctively, there is a complex cognitive designing process behind the whole task. The educator has a mental map of the concepts taught in the course and depending on this map, the problems are composed. We define a rudimentary version of this mental map in the form of course ontology. The problem points to certain concepts from the ontology on which it is based. This is called as the problem concept mapping. This is a highly cognitive process which takes place in the human brain and needs a lot of research

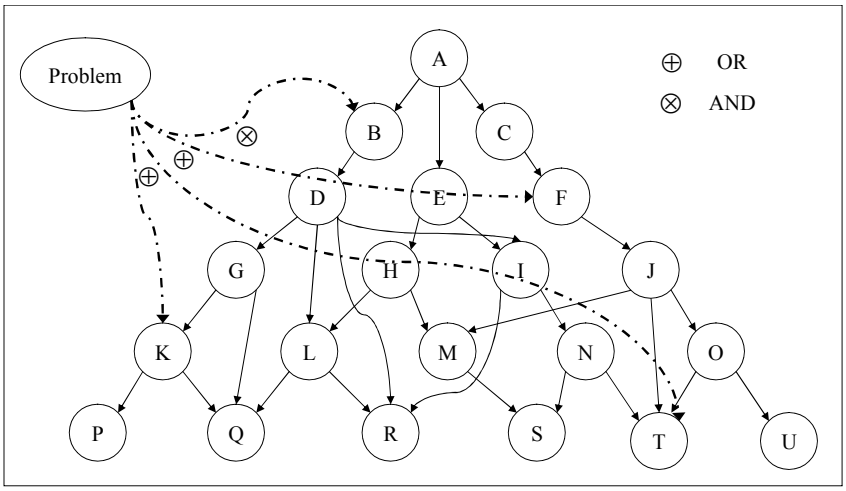


Figure3. 1: Problem-concept mapping

work to be able to explain it properly and formally. The research problem of mapping a problem to concepts from ontology automatically is an extremely non-trivial problem which involves research in natural language processing, knowledge representation etc. We limit our research to using of the problem-concept mapping in semantic evaluation. A mapping signifies the concepts which are used to form the question, which also are the same concepts required to answer a particular question.

The connection of the concepts to the testware resource entity can be in the form of an "*and*" relationship or "*or*" relationship. An "*and*" relationship is used to define concepts which are imperative to answer the particular problem. While the "*or*" relationship defines an alternative between concepts to answer the problem. Example of problem-concept mapping is shown in Figure 3.1. The dotted lines represent the concepts which the problems maps to. The angle between the dotted lines is used to represent "*and*" or "*or*" relations. If there is an "*or*" relation between two or more mapped concepts

then it means that, knowledge about any of the concepts is enough to answer the problem. An "*and*" relationship between two or more concepts means that, problem cannot be answered without the knowledge of all "*anded*" the concepts. From the figure 3.1, concept B and F are and'ed while concepts T, K and F are *or'ed*.

These implicit relationships between concepts can be effectively used in evaluating mathematics related problems. It is observed that math problems generally involve a very well defined ontology and numerous ways can be formulated to solve the problems. These solutions can be conceptualized and mapped using or mapping. Whereas a more prose based problem may require combined knowledge from various concepts to form a single solution. These can be mapped as *and* concepts.

Chapter 4.

Test Problem Assessment

Educational resources must be accessible and intelligible to varied groups of populations for consumption and reuse. Currently there is no formal method for evaluating the utility of an educational resource. We propose an assessment system which attempts to evaluate an educational resource like test problem for its knowledge content and complexity. The system is a framework based on assessment parameters. These parameters can give guidelines for setting up a standard for test problem assessment. This chapter describes in detail the assessment approach and assessment parameters.

4.1. Approach

The assessment process is essentially a two step approach. The first main step is the extraction of the relevant concepts from the CSG and is called as "*CSG extraction*". As seen in the previous chapter, each and every problem maps to some concepts from the course ontology. The set of mapped concepts act as the input to the assessment system hence the concept set has to be precise and methodically selected. The mapping of the

concepts signifies that to answer that particular question, the set of mapped concepts are required. However, the course ontology being a prerequisite relation based ontology, knowledge required for understanding a concept, and consequently answering a question, is represented as its prerequisite child concepts. Thus to comprehend a concept, say A, all child node concepts of A have to be understood first, and to understand all the child node concepts, their child node concepts have to be understood, and so on. Therefore for better understanding of a concept, we have to go as far down the ontology as possible. However, most ontologies are vast and there is virtually no limit to how deep one can go in the ontology. Therefore there needs to be a limit set for controlling the propagation. This limit is set by a variable called as the *threshold coefficient* and the process of extracting this relevant piece of sub graph, called as the *projection graph*, is called as *CSG extraction*. These concepts are further explained in the later sections.

The second step in the assessment process is applying algorithms to the individual projection graphs of each of the mapped concepts to calculate the assessment parameters. In the subsequent sections we define some assessment parameters which can help us in understanding the relationships concepts have with a test problem, the knowledge content required to answer a problem and properties of associations which concepts have with each other and the ontology root. Figure 4.1 shows the assessment process. In the first step the CSG extraction module is given the input i.e. the course ontology, the problem concept mapping and the threshold coefficient value. Using these inputs the CSG extraction process outputs individual concept projection graphs. In the next step the

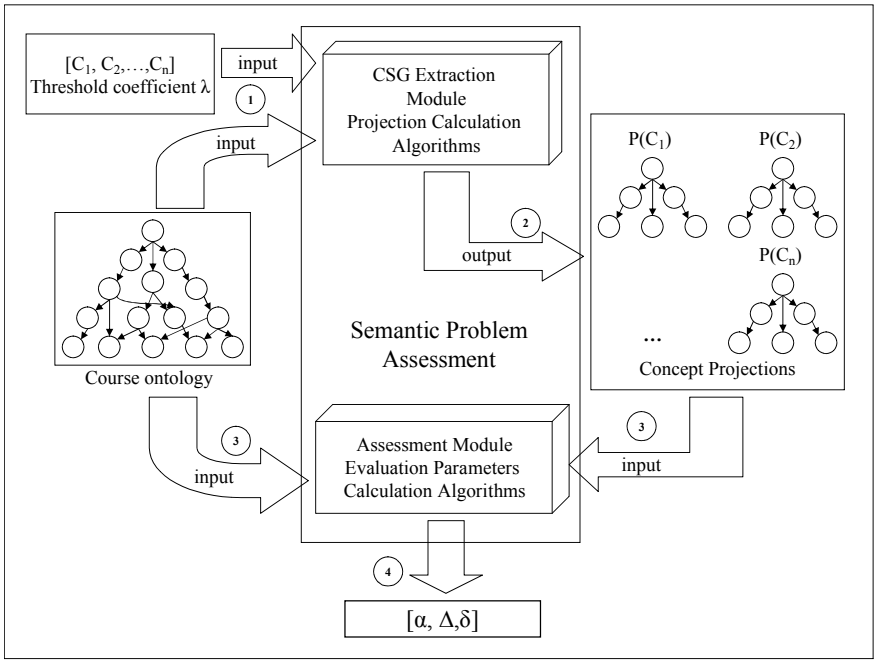


Figure4. 1: Problem assessment approach

projection graphs and course ontology act an input to the assessment module which calculates the values of assessment parameters.

4.2. CSG Extraction

A generalized CSG can be vast. Therefore we define a pruned sub-graph called as *projection graph* which cuts the computation based on a limit on propagated semantic significance. The process of selecting projection graph nodes from the Concept space graph is called as *CSG extraction*. There are quite a few reasons to apply CSG extraction to ontology. The most important reason for CSG extraction is computability. It is

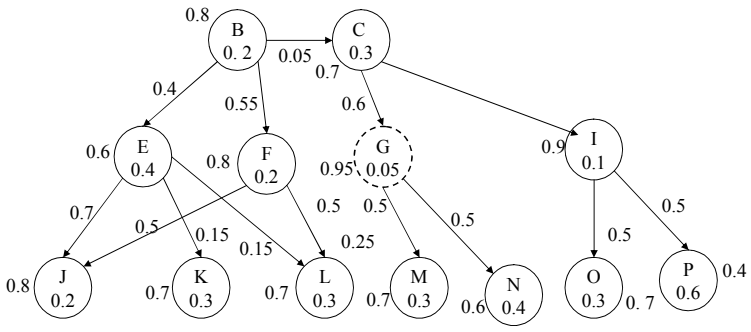
computationally very expensive to work on big ontologies. Nowadays ontologies used range from thousands to millions of concepts. Therefore processing the whole ontology is very expensive and also doesn't logically make sense. The concepts which the question maps to are relatively very less as compared to the total number of concepts in the whole ontology. More over, say if the mapped concepts are very distant from each other in the ontology. This implies that the knowledge required to understand these concepts is very diverse in the concept space. Therefore it would be a squandering of computational resources to process the whole ontology instead of just the relevant portions.

The concept space graph gives the layout of the course in the concept space with a view of course organization, involved concepts and the relations between the concepts. Examples of large CSG's include WordNet (150,000) an English language ontology, CYC (47,000 concepts, 30,000 assertions) a well known common sense knowledge mapping project using ontology, LinKBase (1 million in English, 3 million in other languages) a comprehensive medical/clinical ontology, Gene Ontology (now known as GO, over 19000 concepts) the genome mapping project, ThoughtTreasure (27,000 concepts, 51,000 assertions) another common sense mapping project, and so on. Thus defining a workable area of ontology is of the utmost importance from the perspective of semantic relevance and computability. The pruning is achieved by introducing a variable called as the projection threshold coefficient (λ).

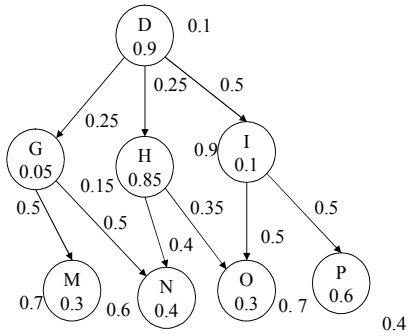
4.2.1 Threshold Coefficient (λ)

By varying the threshold coefficient the size of the computable projection graph can be varied and thus the semantic significance. Since the projection graph is a sub-graph of the concept space graph, it is necessary to have pre-requisite weights for the leaf nodes too, although most times the pre-requisite weight for the leaf nodes is zero. Flexibility for optional pre-requisite weights for the leaf nodes allows the CSG to be extensible and easily extractable for the projection.

Threshold coefficient is a kind of virtual limit by which the size of the projection can be controlled. Greater the coefficient more is the screening for the nodes to be added to the projection and thus smaller is the graph. Less coefficient value means more concepts will be included in the projection. The threshold coefficient can be thought of as a parameter which can set the depth to which the topic has been taught. If a topic is not taught in its entirety, a greater coefficient is assigned so that the depth of the projection graph will be less. Conversely, if a topic is pretty well covered, the value assigned to the threshold coefficient is low, so that the projection graph for the concept is large, encompassing more prerequisite concepts. By varying the threshold coefficient the exact semantic relevance of the question to the whole graph can be computed, the result of which is the projection graph, on which we operate. Threshold coefficient sets the limit to how far one should go down the ontology.



(a) Projection of concept B; P(B, 0.001)



(b) Projection of concept D; P(D, 0.001)

$P(B, \lambda = 0.001)$			
Local root "r"	Node "n"	$\eta(r,n)$	$\eta(r,n) \geq \lambda$?
B	E	0.128	✓
	F	0.088	✓
	C	0.012	✓
	J	0.027/0.035	✓
	K	0.00864	✓
	L	0.0086/0.053	✓
	G	0.00084	×
	I	0.00112	✓
	M	0.0024	✓
	N	0.003192	✓
	O	0.001512	✓
	P	0.003024	✓

Table 1. P(B) calculations

$P(D, \lambda = 0.001)$			
Local root "r"	Node "n"	$\eta(r,n)$	$\eta(r,n) \geq \lambda$?
D	G	0.00125	✓
	H	0.02125	✓
	I	0.005	✓
	M	0.00357	✓
	N	0.00475	✓
	L	0.00028	×
	O	0.00034 (H) 0.00675 (I)	× ✓
	P	0.0135	✓

Table 2. P(D) calculations

Figure4. 2: Projection calculation example

4.2.2 Projection Graph

Given a CSG T(C, L), with local root concept x_0, and projection threshold coefficient λ, a projection graph P (x_0, λ) is defined as a sub graph of T with root x_0 and all nodes x_t where there is at least one path from x_0 to x_t in T such that node path weights $\eta(x_0, x_t)$ satisfies the condition: $\eta(x_0, x_t) \geq \lambda$.

The projection set consisting of nodes $[x_0, x_1, x_2 \ldots x_n]$ for a root concept x_0 is represented as, $P(x_0, \lambda) = P^{x_0} = \left[x_0^{x_0}, x_1^{x_0}, x_2^{x_0} \ldots x_n^{x_0}\right]$; where x_i^j represents the ith element of the projection set of node *j*.

The projection graph points to that area of the ontology of maximum semantic relevance. Consider an example CSG as in Figure 2.5. We find the projection of the local root concepts B and D given the threshold coefficient of λ=0.001. The projections and calculations are shown in Figure 4.2 (a) and (b) and Tables 1 and 2. All nodes that satisfy the condition of node path weights greater than threshold coefficient are included in the projection. Nodes can have multiple paths to the root (J, L, and O). For node J and L, both the path satisfies the condition, whereas for O only one path satisfies the condition (O-I-D-A). Still, O is considered in the projection of D, because it still wields some prerequisite effect on D through one of the paths. If the condition for the threshold coefficient is satisfied then the node is included in the projection.

4.3. Assessment parameters

The main objective of the assessment parameters is to assess the overall knowledge content and the perceived complexity of a test problem. In this section we describe three such assessment parameters namely, coverage, diversity and conceptual distance.

4.3.1 Coverage (α)

The coverage of a question gives a quantitative effect of the selected projection set on the knowledge required to answer a particular question. Coverage of a concept is a direct indicator to the scope of the question in context of the concept space of the course. Formally, "*coverage of a node x_0 with respect to the root node r is defined as, the product of the sum of the node path weights of all nodes in the projection set $P(x_0, \lambda)$ for the concept x_0 , and the incident path weight $\gamma (r, x_0)$ from the root r*".

If the projection set for concept node x_0, $P(x_0, \lambda)$ is given by $[x_0, x_1, x_2 \ldots x_n]$ then the coverage for node x_0 about the ontology root r is defined as,

$$\alpha(x_0) = \gamma(r, x_0) * \sum_{m=0}^{n} \eta(x_0, x_m) \qquad ...(6)$$

where $\gamma(r, x_0)$ is the Incident Path Weight.

Total coverage of multiple concepts in a problem given by set [C_1, C_2 … C_n] is,

$$\alpha(T) = \alpha(C_1) + \alpha(C_2) + ... + \alpha(C_n) \qquad \ldots(7)$$

In eq.6, it is seen that the main factor contributing to the coverage is the summation of the node path weights of all the nodes in the projection of a concept. From the definition of node path weight, we know that it defines the semantic importance of a node to its designated root. Therefore the summation of the node path weights of all the nodes in the projection set gives the cumulative semantic importance of the node in the projection graph on their respective mapped concept roots. The concepts in the projection graph in turn are the concepts which are required to understand a particular concept, controlled by the threshold coefficient. The summation of the node path weights is the amount of knowledge required to answer or rather understand a particular concept. The reason why the factor of summation of node path weights is propagated to the ontology root using the incident path weight is because the questions are asked about the ontology root even though they do not directly point towards it.

Suppose a question tests concepts B and D, Figure 4.2, calculate the coverage of the question given threshold coefficient λ=0.001. The first step is to calculate the individual projections of the concepts as seen in the projection calculation example. The coverage of a concept is then the summation of the node path weights of all the concepts in its projection, propagated to the ontology root. According to the formula,

$$\alpha(B) = \gamma(A,B) * \sum_i \eta(B, P_i^B) = (0.5 * 0.98) * (0.335882) = 0.16458218$$

$$\alpha(D) = \gamma(A,D) * \sum_i \eta(D, P_i^D) = (0.2 * 0.98) * (0.0560625) = 0.01098825$$

$$\alpha(total) = \alpha(B) + \alpha(D) = 0.17557043$$

4.3.2 Diversity (Δ)

Diversity tests the extent of the knowledge domain required to answer particular question. If the projections of some of the mapped concepts overlap with each other, i.e. they have some concepts in common; it means that they are less diverse as both indirectly depend upon some common ground for their complete understanding. Whereas when no two concepts are common it means that, the question has high diversity. Diversity is calculated by measuring the effect of common and uncommon prerequisite concepts from the projections of the mapped concepts. It is dependent on the uncommon concepts rather than the common concepts because the disparate concepts attribute the diversity to a question rather than the common concepts. Prerequisite concepts in the projection sets of two or more of the mapped concepts, i.e. the common concepts, only help in reinforcing the requirement for those concepts, rather than contributing towards the diversity. A question has high diversity value if the concepts it tests are distinct in the context of knowledge space.

Alternatively diversity measure can be thought of as an inverse of similarity measure. There have been numerous attempts to quantify the similarity between two concepts in ontology. Different measures based on information content [36, 40, 42], distance [41], mutual information, etc. have been studied. Our concept of diversity between two concepts can give some insight into the similarity measures. It can be thought of as an inverse similarity measure. We present a definition of diversity which is not node based, link based or information based, but rather a knowledge based approach which renders it uniqueness.

Diversity is formally defined as "*the ratio of summation of node path weights of all nodes in the non-overlapping set to their respective roots, and the sum of the summation of node path weights of all nodes in the overlap set and summation of node path weights of all nodes in the non-overlap set*."

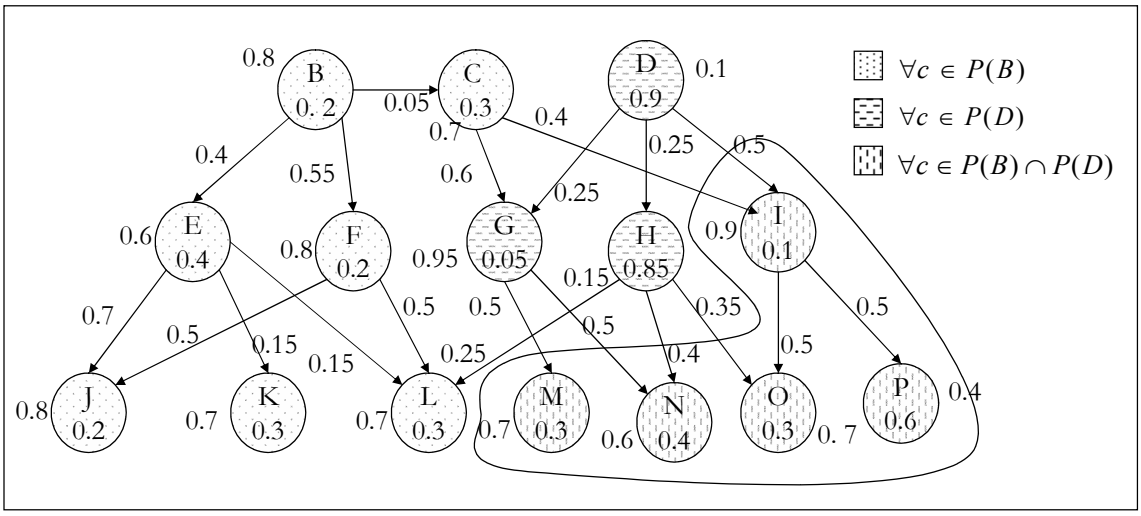


Figure4. 3: Diversity calculation

Consider a question asks a set of concepts, $C=[C_0, C_1, C_2 \ldots C_n]$. The respective projection sets are given by,

$$\left\{P(C_0,\lambda)=\left[x_1^{C_0}, x_2^{C_0} \ldots x_a^{C_0}\right], P(C_1,\lambda)=\left[x_1^{C_1}, x_2^{C_1} \ldots x_b^{C_1}\right] \ldots, P(C_n,\lambda)=\left[x_1^{C_n}, x_2^{C_n} \ldots x_c^{C_n}\right]\right\}$$

The non-overlapping and overlapping sets are, $N=\left[N_0, N_1, N_2 \ldots N_p\right]^i$ and $O=\left[O_0, O_1, O_2 \ldots O_q\right]^j$, where i and j are the local root parents of any element from N and O respectively and $\forall\ i\ ,\ j \in C$.

Cardinality restriction:

$\forall\left[O_0, O_1 \ldots O_q\right] \in [P(C_0,\lambda) \cap P(C_1,\lambda) \ldots \cap P(C_n,\lambda)]$ and $\forall\left[N_0, N_1 \ldots N_p\right] \in \left\{\begin{matrix}[P(C_0,\lambda) \cup P(C_1,\lambda) \ldots P(C_n,\lambda)] \\ -[P(C_0,\lambda) \cap P(C_1,\lambda) \ldots \cap P(C_n,\lambda)]\end{matrix}\right\}$

Diversity is given by,

$$\Delta=\frac{\sum_{m=1}^{p}\eta\left(i, N_m^i\right)}{\sum_{m=1}^{q}\eta\left(j, O_m^j\right)+\sum_{m=1}^{p}\eta\left(i, N_m^i\right)} \quad where \forall\ i, j \in C \qquad \ldots(8)$$

Figure 4.3, shows the nodes in the projections of B & D, and the shaded area shows the nodes in the overlapping region. Diversity can be calculated by the means of the formula as,

$$\Delta=\frac{1.44714}{0.0448045+1.44714}=0.97$$

This means that the diversity between concepts B and D is 97%. The concepts have high diversity.

4.3.3 Conceptual Distance (δ)

Conceptual distance is a measure of distance between two concepts with respect to the ontology root. According to one of the definitions of similarity between nodes in taxonomy by Resnik, it is the distance of the nodes from the subsuming parent [36]. Alternatively conceptual distance measures the similarity between two concepts by quantifying the distance of the concepts from the ontology root. Formally it is defined as "*the log of inverse of the minimum value of incident path weight (maximum value of threshold coefficient) which is required to encompass all the mapped concepts from the root concept*".

The conceptual distance parameter is designed in such a way that it should be sensitive to the depth of the concepts. Hence it is a function of maximum threshold coefficient required to cover all the nodes from the ontology root. Incident path weight (γ) of a concept to the root is equivalent to the threshold coefficient (λ) required to encompass the node. If question asks concept set $C = [C_0, C_1, C_2 \ldots C_n]$ then the conceptual distance from the root concept *r* is,

$$\delta(C_0, C_1 \ldots C_n) = \log_2\left(\frac{1}{\min[\gamma(r, C_0), \gamma(r, C_1) \ldots \gamma(r, C_n)]}\right) \qquad \ldots(9)$$

Calculation of conceptual distance for concept set [E, F, and M] is shown in Figure 4.4. Different types of arrows represent the paths to the root from the respective

nodes. In case on multiple paths (M) the lowest values of incident path weight is considered.

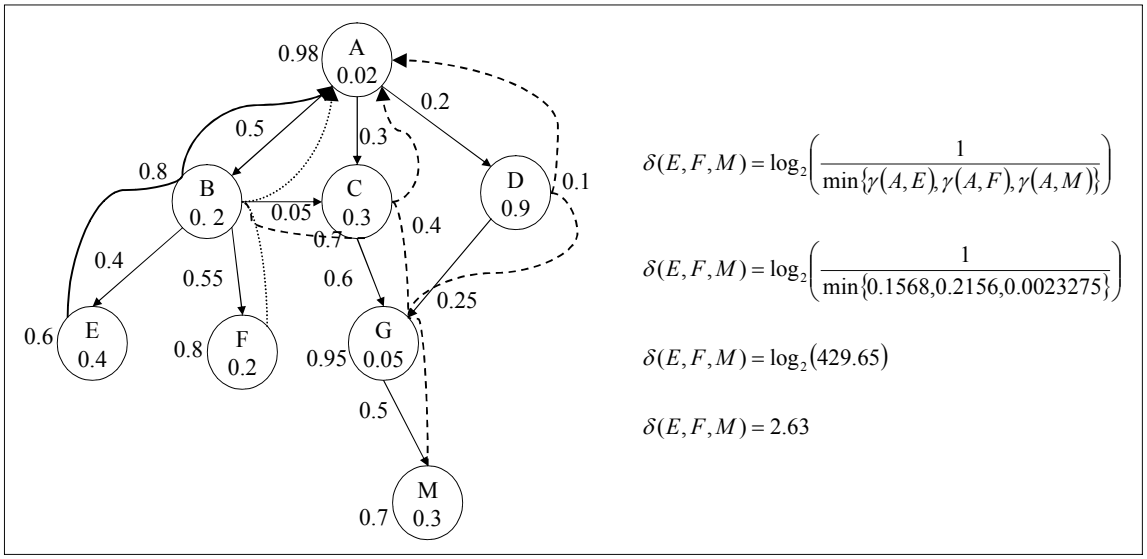


Figure4. 4: Conceptual distance calculation

Chapter 5.

Performance analysis and results

The performance analysis of assessment parameters is two fold. In section 5.1 and 5.2 we analyze the assessment parameters for their ability to be factors for reasoning about the perceived complexity of problems and their knowledge content. In section 5.3, we analyze the data qualitatively and make deducible inferences from the data.

For complexity analysis of assessment parameters we use an extensive course ontology comprising of around 1500 concepts, for the course "Operating Systems" taught as graduate level course at KSU. The ontology was created for the course by consulting the related instructor and referring to standardized textbooks. The node weights and link weights, which form an important constituent of the ontology, were assigned by intuition and guidance from the course instructor. Concepts with more intrinsic importance for understanding were assigned more self-weight and those which depended on many other prerequisite concepts were assigned more prerequisite weights. Consequently it is observed that concepts higher up in the ontology have lower self-weights, and self-weights of nodes go on increasing further down the ontology, reaching the maximum for leaf nodes. However, for the CSG to be extensible, the leaf nodes are also allowed to have prerequisite weights in case more prerequisite concepts are added later on. Keeping

the ontology extensible allows for inclusion of newer concepts, results, researches, etc. adding to the inherent knowledge base, making the course ontology an ever changing and improving repository of course knowledge. The link weights were assigned based on the semantic importance and contribution of the child topic to the understanding of the parent topic. If the understanding of the child concept is detrimental to the understanding of parent concept than the other, then it was assigned a greater link weight. Although by definition, the summation of the link weights for a node should add up to 1, it is generally not observed consistently. Most of the times, some space is left for the inclusion of newer links for prerequisite concepts which are newly added or already existing in the ontology. Again it is seen that higher up in the ontology there is no need to actually leave this space, as the probability of addition of newer links to higher level concepts is less than that to the concepts lower in the ontology.

For the purpose of evaluation, several problems were composed by the course instructor each mapping to some concepts from the ontology. The problem concept mapping was provided by the instructor in most cases with some inputs from students. These test problems were administered by undergraduate and graduate students, the results from which were used for the performance analysis. The answers to the problems were graded by a minimum of three graders per question, and the averages of the scores were considered for the analysis to remove anomalies. The coverage and diversity of the concept set changes according to the changing values of λ because they are the functions of node path weight which is relative to the projection set, which in turn depends upon λ.

Accordingly we experimented with changing the threshold coefficient values and observing the result for different projection graphs.

5.1. Parameter performance against average score

In this section we evaluate the performance of all the assessment parameters against the average score per question. The coverage analysis for each question with varying threshold coefficient can be explained by the graph shown in Figure 5.1. It is observed that the coverage has an inverse relationship with the average score. As the average score increases the coverage for that particular question decreases and vice versa. For all values of λ the coverage has the same relationship; however this relationship becomes more and more evident with decreasing values of λ. As λ decreases, the projection graph increases, thus increasing the coverage values. Hence if the inverse correlation of the coverage graph with average score graph is more for decreasing values of λ, we can infer that more concepts are required to answer that particular question. Coverage gives an approximation to the knowledge required to answer a particular question. From the graph it is seen that most of the times, coverage is inversely correlated to average score.

Diversity is also inversely correlated to average score. Diversity graph characteristics are similar to coverage graph, Figure 5.2. In the case of diversity it is observed that as the threshold coefficient λ decreases, the diversity values for all the

questions also go on decreasing. This is because as the λ decreases the projection set for each concept in the concept set increases. As the projection set increases the probability of having more common concepts increases, thus increasing the coverage of overlap set and decreasing the diversity. In some cases however the diversity increases with decrease in λ. This happens because, sometimes when the threshold coefficient decreases, the projection obviously increases; however instead of having more overlapping nodes, the non overlapping node set increases consequently increasing the diversity.

The performance of conceptual distance versus average score is observed in Figure 5.3. Although not directly dependent on projection graph, distance is also inversely correlated to average score. This means that distance is a very good indicator of the similarity between concepts. As the distance between two nodes decreases, the similarity increases. As the similarity increases, the knowledge required to answer the concepts decreases, consequently increasing the average points scored. As conceptual distance is not a factor of projection graph, behavior in the graph is constant for all threshold coefficients. Distance is a logarithmic function as *log* gives the inverse behavior of an exponential function, which is observed here. Similar to coverage and diversity the conceptual distance is also inversely correlated to average score with good correlation. As seen from the behavior of all three assessment parameters, the average score has an inverse correlation with the parameters. This means that the parameters are pretty good indicators of the perceived difficulty of test problems.

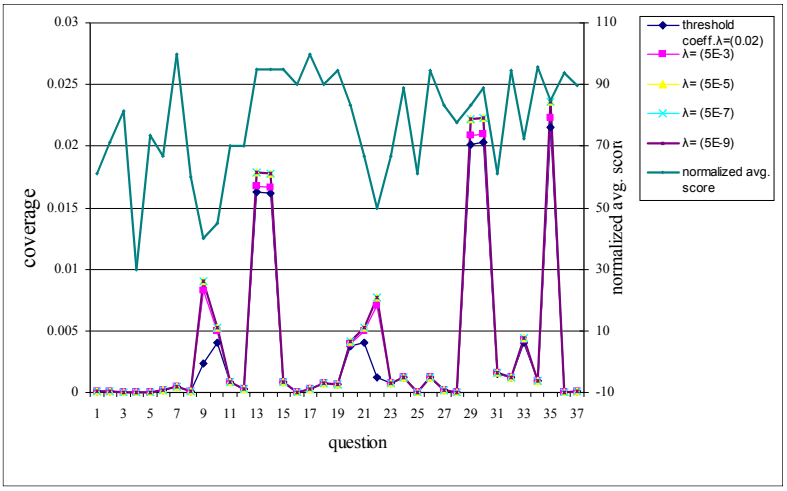


Figure5. 1: Coverage vs. Average score

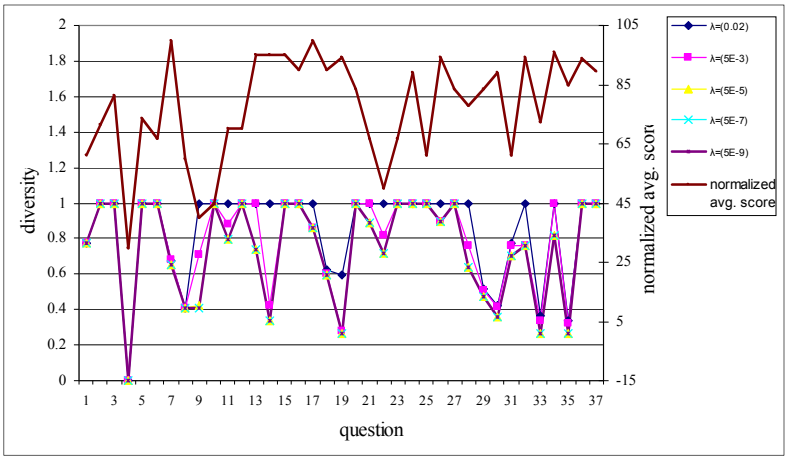


Figure5. 2: Diversity vs. Average Score

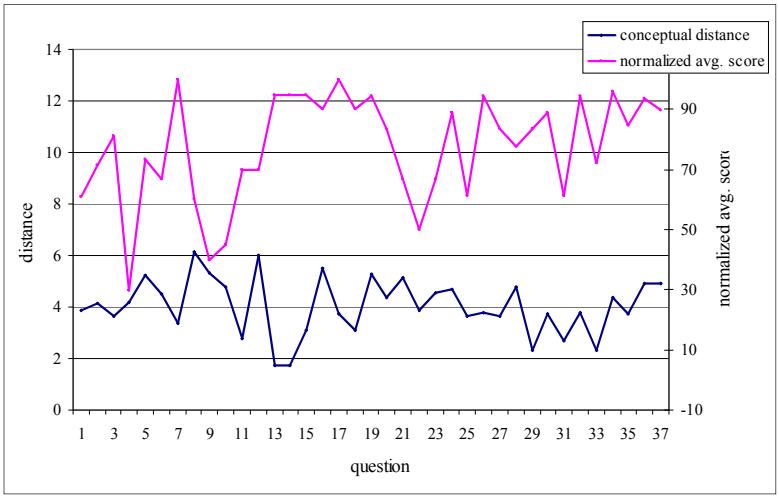


Figure5. 3: Conceptual distance vs. Average Score

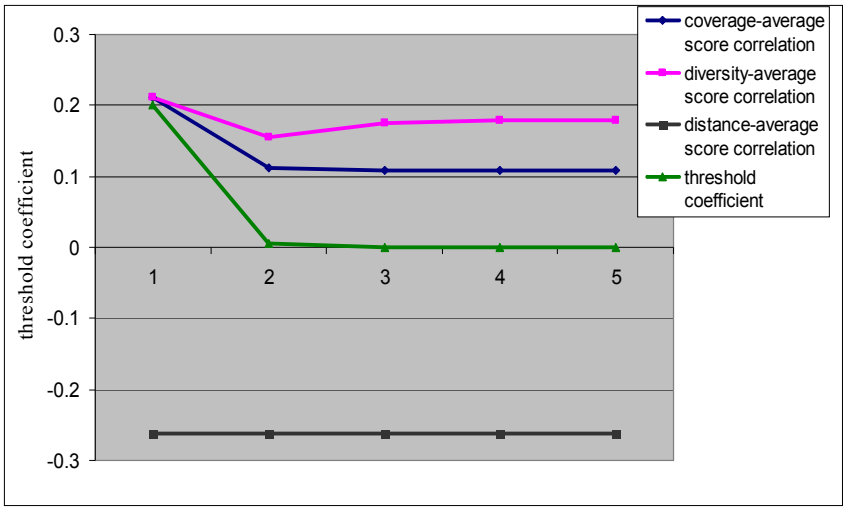


Figure5. 4: Correlation analysis

5.2. Correlation Analysis

In this section we study the correlation between the parameters and average score for varying threshold coefficient values. A high degree of inverse correlation is desired, so that as average score increases, the values of the assessment parameters go down, and vice versa. From Figure 5.4 it is seen that as the threshold coefficient value decreases, the correlation for coverage and diversity with average score also decreases and then remains constant for lower values of threshold coefficient. The reason for this behavior is that, when the threshold coefficient decreases, the projection sets of the respective concepts increase as more and more nodes are added. However the average score for a particular problem remains constant. Hence if a problem has a high average score, it means that originally the coverage and diversity for that problem was lower, but since the projection

set has increased, now their values have also increased. Due to this the correlation between coverage and diversity and average score decreases. Similarly, if a problem has low average score, it means that originally the coverage and diversity for that problem were high, but since the projection has increased, their values increase too. In this case the correlation has decreased in the reverse direction. After some value of threshold coefficient though, the projection set remains constant, and so does the correlation between coverage and diversity and average score. The correlation between conceptual distance and average score remains constant throughout because, conceptual distance is independent of the projection graph and therefore the threshold coefficient.

5.3. Qualitative Data Analysis

5.3.1 Test based analysis

Though most of the times coverage and diversity values are inversely proportional to average score, it is important to observe and measure the percentage variation to draw inferences.

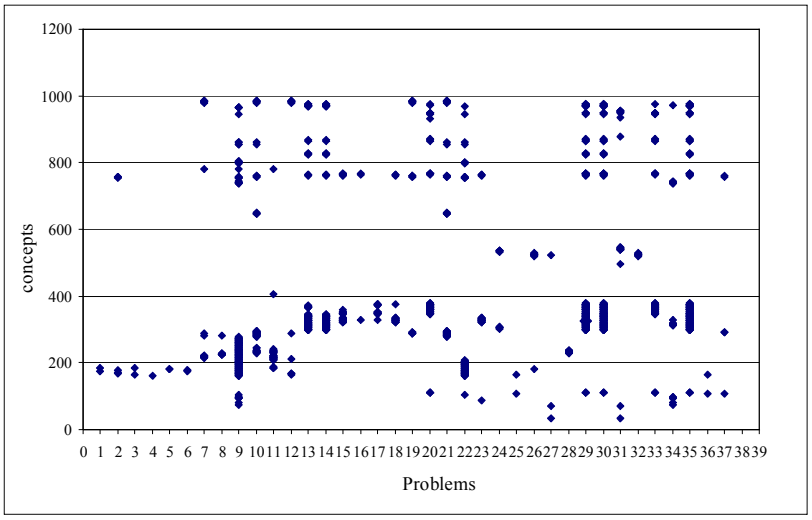


Figure5. 5: Problem-concept distribution by tests

Figure 5.5 shows the distribution of concepts according to the concept mapping of the problems according to the tests. Problems 1-6 are in test a, 7-12, 13-18, 19-37 are in tests b, c and d respectively. A simple scatter plot of question-concept can give a lot of information. Observations and Inferences:

1. Questions 13, 14, and 29, 30, 33, and 35 ask almost similar concepts. Out of these 13, 14, 33 and 35 have good inverse correlation with average score, but 29 and 30 don't. This implies that these questions have some implicit factors other than the mapped concepts which made them difficult, which in turn decreased the average score correlation.
2. Most questions are based on or relate to concepts from 100-400 and 750-1000. That means that most of the tests were based on that part of the ontology. This inference has a very interesting implication. It means that, the instructor chose to set the problems only on select topics from the course ontology. The obvious

inference is that; those were the only topics covered in the course from the ontology. The exact portions of the ontology which were taught and tested can be pointed out using this analysis.

3. Test "*a*" asks concepts only around 200, but the distribution of concepts increases with the tests. As more and more topics are taught from the ontology, tests are increasingly based on more concepts than the previous.
4. There is a small clustering of concepts followed by a slightly bigger clustering, between concepts 50-250. Since the concepts were numbered levels wise it means that the small cluster are the mapped concepts, while the rod is the projection of the mapped concepts. This behavior is seen through out the graph. Clustering following smaller clustering usually means projections of mapped concepts.

5.3.2 Correlation based analysis

In this analysis, we separate out the problems which do not show good correlation with average score from those which do. In the context of assessment parameters and average score, an inverse correlation between the two is considered good, and vice versa. These problems are then analyzed to make intuitive inferences as to why the observed correlation is good or bad. In Figures 5.6, 5.8 most of the problems have high inverse correlation with average score, while in Figures 5.7, 5.9 most have very low inverse correlation as seen in the plots. For correlation based qualitative data analysis, the

problems which have an inverse correlation between coverage and average score were separated out from those which don't.

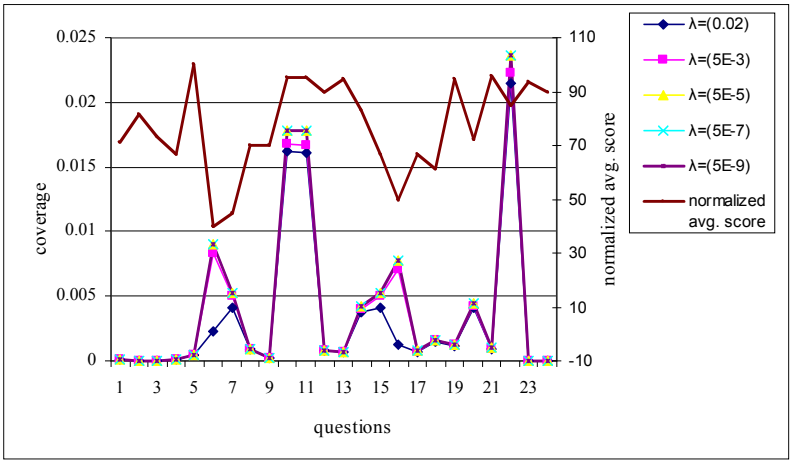


Figure5. 6: Problems with high coverage-score inverse correlation

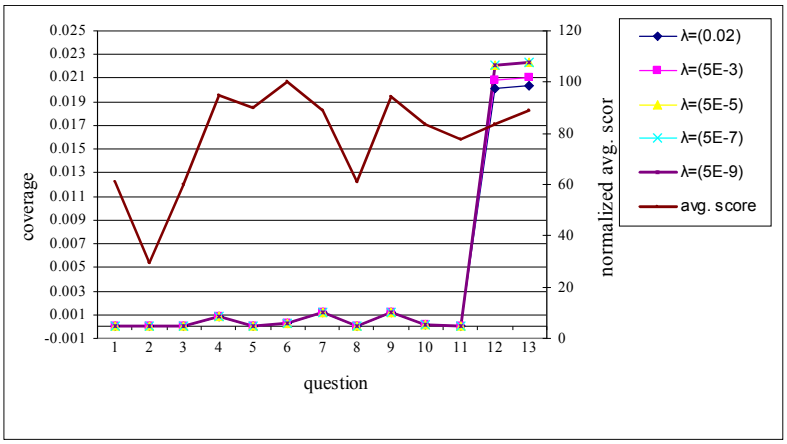


Figure5. 7: Problems with low coverage-score inverse correlation

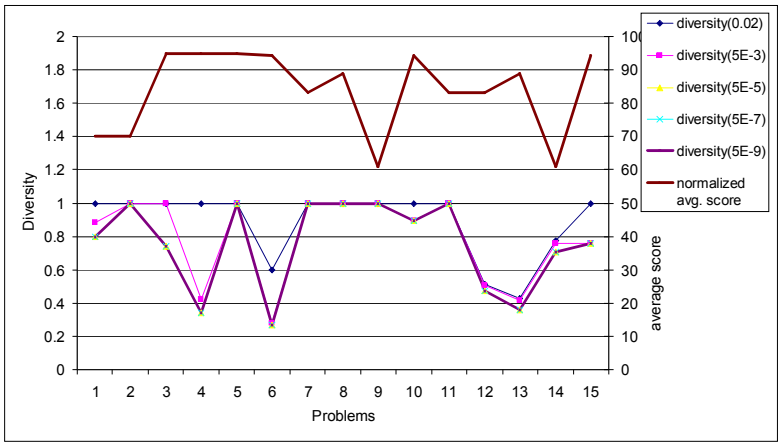


Figure5. 8: Problems with high diversity-score inverse correlation

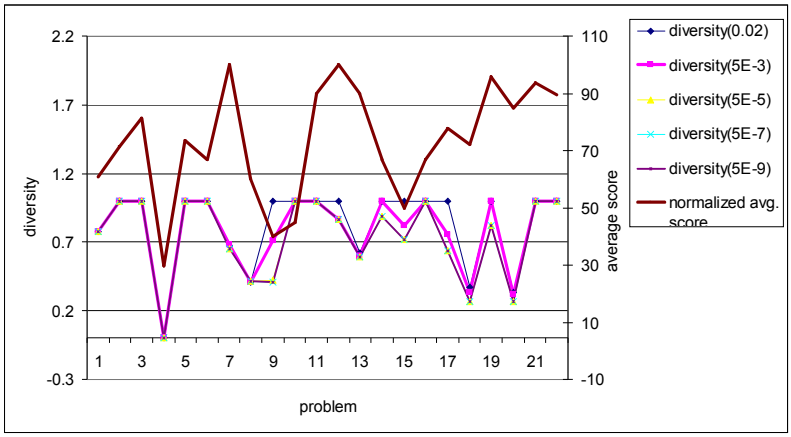


Figure5. 9: Problems with low diversity-score inverse correlation

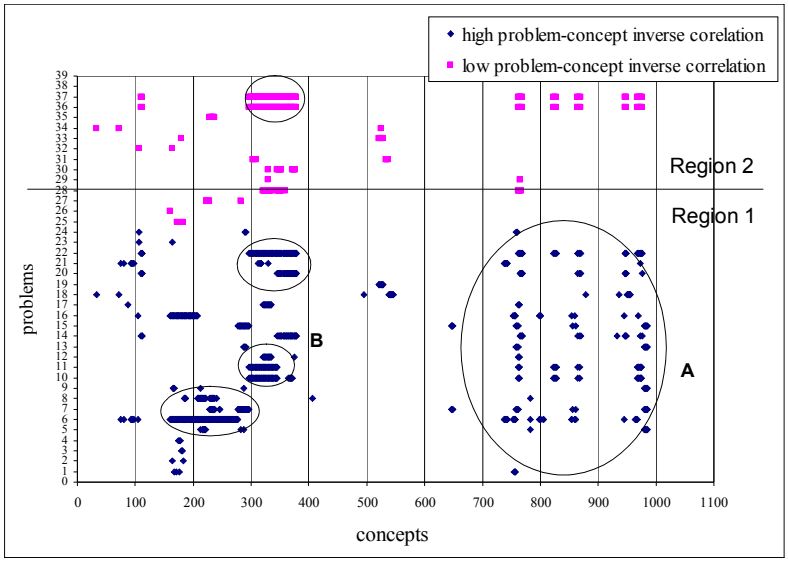


Figure5. 10: Problem-concept mapping by high/low inverse correlation with average score

On carefully observing the set of concepts to which these problems map to, it is seen that there are surprisingly high number of common concepts and among the problems with good and bad correlation. It is important to note here that, rather than just considering the mapped concepts, the projections of the mapped concepts were considered as they would give a better understanding of the whole set of prerequisite concepts required to answer the question. Figure 5.10 shows the problem-concept distribution separated for the questions with high inverse and low inverse correlation between coverage/diversity and average score. Interesting inferences can be made by observing the graph.

1. In area A there is similar concept distribution across problems with a good correlation. From this we can infer that students know those concepts well, or the problems based on these concepts were fairly easy to answer, or these concepts are intrinsically easier to understand and answer. However it is seen that, for the same concepts, there are a few problems (36-37) which have bad correlation with average score. This again could mean that these problems were harder because of some other parameters, or these problems required knowledge from out of the scope of this ontology. If similar clustering behavior is observed in problems which have bad correlation with average score, then it can almost conclusively be said that, those concepts or that part of the ontology needs more attention i.e. either the course instructor should teach the concepts again, or if the concepts are intrinsically difficult to understand then they should be somehow be simplified for the students.

2. It is observed that in problems with low inverse correlation, concepts are more dispersed (as in, not clustered) around the ontology as compared to those with high inverse correlation.
3. The small clusters in area B, mean that problems usually ask concepts near and around a primary concept. These small clustered concepts mostly are those concepts which come in the primary concepts projection itself. Two small clusters near each other mean two primary concepts projections which are very near to each other.
4. Concepts around 200-400 and 750-1000 are frequently asked among the questions with high and low inverse correlation equally. This means that the tests were based on those concepts and not specifically on others and the concepts which appear scattered around the plot are those which are needed to answer the specific problem. The concepts which do not form the part of the cluster are most definitely concepts, which are distant from the primary concept, however still necessary to answer the particular problem completely.
5. Another interesting observation is that, in the questions which have low inverse correlation, the projections of the primary concepts are very small (dots) compared to those in the questions with high inverse correlation (rods). This means that even though the same concepts are asked, with smaller or bigger set of prerequisite concepts required to answer it, the question composition itself has some properties other than the asked concepts which attribute difficulty/simplicity to it. In this vein, a lot of information can be gathered and inferences can be made.

Chapter 6.

Applications and Future Work

The assessment framework can be intuitively applied to a number of applications. It provides a system for qualitative assessment of a test problem and gives values of desired coverage, diversity and conceptual distance to work with. To enable automatic assessment of any kind, it is important to have numerical values to realize intangible aspects of a problem like its difficulty. We present a few applications where the assessment framework can be employed. Much of the formal development of these applications is a future work. In this thesis we simply put forth the ideas for possible applications.

6.1. Automatic test generation

We propose an algorithm which can select problems from a database with specific difficulty values and compose a test with desired complexity and desired area of testing. Most of the tests composed by educators today are composed manually. Also the final product, the test, is not associated with any characteristics like difficulty and area of

testing. It is important to know these characteristics of a test to be able to more efficiently teach, grade and analyze. The task of selecting a proper set of problems, which is complete in coverage and precise in difficulty, is a mechanical task which can be put in an algorithm. Difficulty values for problems can be calculated using function of coverage, diversity and conceptual distance. The output is a test with a specific set of problems which cover certain topics from the area and also amount to a specific level of difficulty. The test composition algorithm is a minimalist binary knapsack algorithm, where in the composer has to select questions and also weigh the selection against difficulty value constraint. The input to the algorithm is a set of concepts on which the test is based. The problems in the database have a difficulty value and problem concept mapping. The algorithm selects problems from the database depending on the problem concept mapping and difficulty values until all the desired concepts are included in the test and a specific difficulty value is met.

This algorithm can be used to create variations of difficulty for a test, a relatively hard test, a relatively easy test and a test with difficulty centered on a specific value. If the algorithm starts by selecting only the more difficult or lesser difficult problems form the test we can ultimately compose a test which is harder or easier respectively. To compose a test around a specific difficulty the algorithm can be easily modified to select a question with difficulty value as close to the desired difficulty value as possible, instead of selecting the first question from the question set every time.

6.2. Semantic Problem Composition

To design a question we should first be able to properly evaluate the perceived difficulty of a question. Semantic problem composition uses the assessment framework to compose a problem automatically. A problem composer must be aware of the difficulty/ease of a problem, the student knowledge/prerequisite and understanding, relevancy of the problem to the topics being taught, student evaluation capability of the problem, etc. Also the problems selected for the test have various properties like hardness/ease, time required to answer, mathematical complexity, the length and breadth of the topics it covers, the relevancy of the topics, etc. Most of these considerations can be accounted for in the problem assessment parameters. The architecture of the composer is shown in Figure 6.1. The two main modules are the problem assessment module and the problem generation modules. The inputs to the problem assessment module are the desired set of concepts, the desired maximum coverage and minimum diversity. Based on these concepts and the values, the algorithm finds out the projections of the concepts and thus the amount of knowledge required to compose the problem with the constraints on coverage and diversity. All these selected concepts then act as input to the problem generation module. This module puts the concepts in fixed problem templates created by analyzing a variety of problems, and puts them into sentences using propositions from the database. The final product is a problem which requires a specific set of concepts to answer and with a desired coverage and diversity, composed using problem templates and sentence construction algorithms.

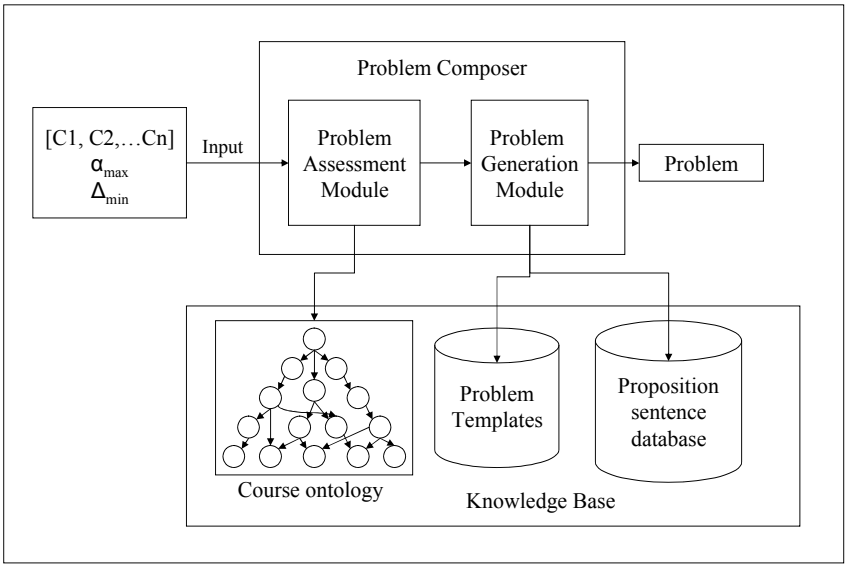


Figure6. 1: Semantic Problem Composer

6.3. Semantic Grader

If the cognitive process of problem composition can be automated with the necessary knowledge support given by course ontologies, then we can have an efficient system that can not only create courses and tests automatically considering various factors but also evaluate the tests. At present the process of grading or assessment of answers is mostly manual barring a few good exceptions. Automatic grading of answers has been an interesting research problem for a long time in the educational technology research community. Most of the work in automatic grading is in grading programming assignments. One of the prominent examples is KASSANDRA [48]. E-rater at ETS has experimented with automated evaluation of answer [47]. In this thesis we propose an

approach for automatic grading of answers irrespective of the format of the answer. We propose an initial architecture for the system and plan to develop a completely automated system for grading answers in the future.

From, Chapter 2 and 4 we understand that problems can be mapped to concepts from the ontology. Based on these mapped concepts, we generate projection graphs for the individual concepts, and calculate the assessment parameters based on them. With the same reasoning, we can apply a CSG extraction procedure to the solutions. A grader initially points out the concepts from the ontology which the solution includes. If we know this, "*solution concept mapping*", we can apply the same procedures for CSG extraction to the solution too and obtain a cumulative projection graph of the solution. Once we have the cumulative projection graphs for the problem and the solution, we can apply graph comparison algorithms to determine parameters which can guide through the process on grading of answers.

This method of grading is more comprehensive and non-trivial. The grading is more knowledge oriented. Once the solution projection graph (SPG) is obtained, the exact concepts contained in the solution can be pointed out and hence the knowledge gained by the student. The SPG can contain more concepts or fewer concepts than the required set, governed by the PPG, and the solution is graded accordingly. Figure 6.2 shows the working of the semantic grader. The problem concept mapping, solution concept mapping and course ontology act as the preliminary inputs to the CSG extraction module. The outputs of this stage, i.e. SPG and PPG then act as input to the module which applies graph comparison algorithms on them to finally give parameters needed for

grading. Based on these parameters the final grade is computed. The parameters give an estimation of how different are the SPG and PPG, does the SPG contain any extra concepts which are not needed to answer but are still relevant to the question, are there any new relationships between the concepts in the SPG which are significant, etc. As a part of the future work we propose to implement this system for a more complete course ontology based semantic grader.

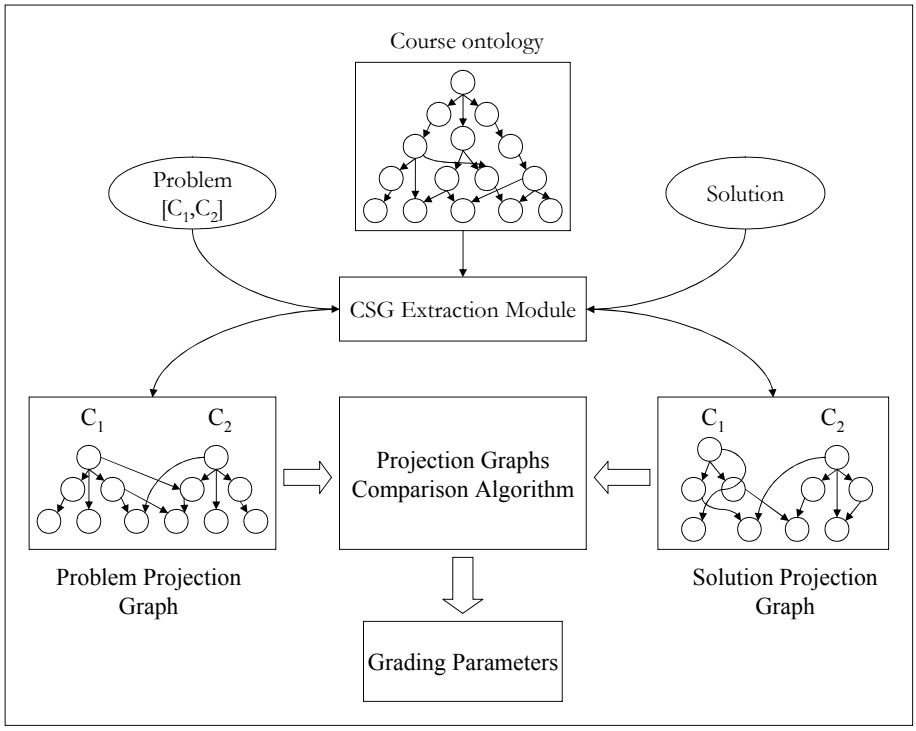


Figure6. 2: Semantic Grader

Chapter 7.

Conclusion

In computer aided automated design of educational resources, specifically test problems, a backend system for the assessment of these test problems is an absolute must. We propose a system for the assessment of test problems based on a few synthetic parameters. The knowledge support for the system is provided by course ontology. Course ontology is a formal description of the concept knowledge space associated with a course. It is described in a specifically customized language, called as Course Ontology Description Language and is written in OWL. The course ontology representation is expressible and computable at the same time. We present a novel approach to extract relevant information from course ontology depending on the desired semantic significance. Using this method computation cost for processing ontological information can be greatly reduced. Finally we propose some parameters for evaluating the knowledge content and the complexity of a test problem using the concept knowledge from the course ontology. The parameters are formulaic and derived from real world understanding of the factors which attribute complexity to a problem like, coverage, diversity and conceptual distance. The parameters are then tested in the real world scenario of tests, and it is observed that they perform very well. These parameters maybe

used for the standardization of test-ware which can further the development of fundamental applications in reuse and engineering of digital content on the web. Interesting observations are made in regards to the information which can be extracted and used from these ontologies. The assessment framework can be employed to create automatic design and evaluation systems like test composition, problem composition, semantic grading etc. Further more the ontology expression language can be extended to incorporate more information from the course, and thus try to infer more interesting results.

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