ASSESSING THE DISTRIBUTION OF COURSE CONCEPTS IN LEARNING MATERIALS

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ABSTRACT: *This paper describes a simple scheme to assess the distribution of course concepts in a learning material. The scheme uses relations in the WordNet lexical knowledge-base as the basis for four proposed metrics; size, usability, complexity and cohesion. The metrics are formed according to the existing ontology metrics, and they are for educators to comparably assess the distribution of course concepts in learning materials. Using this scheme, educators could author learning materials that covers course concepts without constructing concept maps and without the involvement of domain experts. Inexperienced educators could ensure that their learning materials which are obtained from the Web meet their courses objectives. We conducted a quantitative study to determine the feasibility of the scheme to assess the distribution of concepts in an Information System course. The metrics was computed on a three-page case study provided by the Information Systems Audit and Control Association (ISACA). Then, the learning material was evaluated by 55 undergraduates at the end of a 36-contact-hours course. Both results from the metrics computation and the learners' perception are agreeable in term of the size, usability, and cohesion.*

Keywords: Education, Information Communication, Educators' Decision Making, Learning Material Authoring

1. INTRODUCTION

Educators need to ensure that the learning materials they author match the course topics. The learning materials should emphasize concepts with importance in the course being taught [1]. Learning materials adopted from the Web have the tendency to omit important course concepts due to the educators' ignorance and subjectivity [2,3,4]. This omission is even unexceptional for experienced educators [5]. As a consequence, learners may be presented with reading assignments which do not address the course topics.

In order for educators to understand the distribution of course concepts in learning materials, they commonly construct concept maps for course topics, contents, and assessment materials [3,4,5]. A concept map provides visual and semantic representation of concepts and their relations. This semantic representation use meta-data labelling such as *is Prerequisite For,isClassification Of,isSuper Topic For, Same As,hasProperty, hasType,* and *hasLearningType* for the course concepts [3].

However, labelling the semantic is a heavy task for educators as it requires the educators' judgement of the concepts and relation importance. The labelling typically involves domain knowledge experts [6,7], and could involve as many as eighteen experts for a course [5]. Another way to construct concept maps is by calculating the frequency of concepts occurrence and relations strength [3,4] known as a corpus-based ontology construction [8]. In order to understand the distribution of course concepts, this approach is still is a heavy task for educators. This approach requires information on the frequency of occurrence that each concept has over all terms in a large, complete collection of a domain related texts, or a corpus [9]. In either approach, the process of constructing a concept map is challenging, time consuming and costly for educators [10].

In this paper, we propose a simple approach for educators to assess the distribution of course concepts in a learning material. This approach utilizes the relations among concepts in the publicly available lexical knowledge-base, WordNet.

2. RELATION IN LEXICAL KNOWLEDGE-BASE

The lexical knowledge-base, WordNet provides taxonomy of English lexical as term senses connected by the is-a and part-of relations [11]. In specific, there are hypernym, hyponym, and synonym in the is-a relation; meronym and holonym in the part-of relation. For example, "work" is hypernym of "consulting service", and "consulting service" is a hyponym of "work" (Fig. 1); "car" is a meronym of "wheel", and "wheel" is a holonym of "car"; and "work" is a synonym of "occupation".

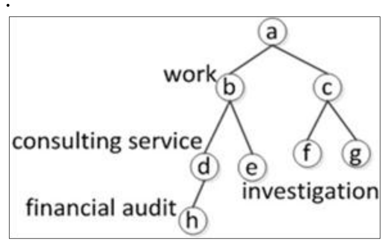


Fig (1) Order of relation in the lexical knowledge-base

In each relation, any two term senses can be classified either as a generic value or a specific value [12]. To illustrate, let X be a subset of an ordered set S in the lexical knowledge-base; $a, b, c, d, e, f, g, h \in X$ (Fig. 1), and $\prec$ is the order of relations.

There are four categories of relations between a concept (C) in a course topic, and a word (W) in a learning material. In the first category, the course concept (for example, financial audit) is transitively generalized (TG) by the word ("work") in the learning material ($b_{work}{:}W \prec h_{financial\_audit}{:}C$). Second, the course concept (work) is transitively specialized (TS) by the word (financial audit) in the learning material ($b_{work}{:}C \prec h_{financial\_audit}{:}W$). Third, the course concept ("work") is replicated (R) by the word (work) in the learning material ($b_{work}{:}C = b_{work}{:}W$). Fourth, the course concept ("consulting service") is associated (A) with the word (investigation) in the learning material ($b_{work}{:}W \prec d_{consulting\_service}{:}C$ *and* $b_{work}{:}W \prec e_{investigation}{:}W$), by a another common ancestor in the learning material.

TG, *TS*, *R*, and *A* are the four categories of course concepts (*C*) distribution in a learning material. The distribution is determined by the number of words (*W*) in the learning material that belong to each category (Fig. 2).

The words in the learning material are represented as $W = \{w_1, w_2,.., w_i\}$. The concepts to be learned in the course are represented as $C = \{c_1, c_2, ..,c_j\}$. Each word, w_i in the learning material is compared to each concept, c_j in the course in terms of their semantic relatedness.

The semantic relatedness algorithm by Wu and Palmer [13] determines the most related concept-word pairs and the relative depth of the path distinguishes pairs that are more strongly related [14]. A stronger relation is depicted by concept-word pair that has lower abstraction, in which their Least Common Subsumer (*LCS*) is deeper in the taxonomy of the knowledge-base, and the concept-word are closer to *LCS*.

When a particular word, w_i in the learning material finds its most semantically related course concept, c_{max}, we increase the distribution in one of the four categories, *TG*, *TS*, *R*, or *A* for the course concept, c_j. The category to be increased is determined by the *LCS* obtained from the lexical knowledge-base. The *LCS* is either the word, w_i, the related concept, c_{max}, some other word which is in or not in the set *W*.

For example, let w_i = company, C = {information_technology, organization, governance, audit, investigation}; c_{max} = organization, and *LCS* (w_i, c_{max}) = organization.

If the semantic relatedness is greater than a threshold, then the count is increased in the *TG*, *TS*, *R* or *A* category. $LCS = w_i$ indicates that the word precedes the concept in the lexical knowledge-base, or $w_i \prec c_{max}$. In such case, the *TG* count is increased by one for the related c_j. $LCS = c_{max}$ indicates that the concept precedes the word in the lexical knowledge-base, or $c_{max} \prec w_i$. In such case, the *TS* count is increased by one for the related c_j. $LCS = wi$ and $LCS = c_{max}$ indicate that the concept is similar to the word in the lexical knowledge-base, or $w_i = c_{max}$. In such case, the R category is increased by one for the related c_j. There is a possibility where $LCS \neq w_i$ and $LCS \neq c_{max}$ but *LCS* is other word, w_x in the learning material. In such case, the *A* category is increased by one for the related cj. There is also a possibility where $LCS \neq w_i$ *and* $LCS \neq c_{max}$ and *LCS* is not a word in the learning material. In such case, the count in *A'* is increased by one.

$W = \{w_1, w_2, .. , w_i\}$, $C = \{c_1, w_2, .. , c_j\}$
For each w_i , For each c_j
$SemanticRelatedness_{Wu\&Palmer}$ (w_i , c_j)
$c_{max} = c_j$
$_{LCS\ =}$ w_i or c_{max} or W or W'
If $SemanticRelatedness_{Wu\&Palmer94}$ (w_i , c_{max}) > 0.7 Then
If ($w_i \prec c_{max}$) Then $TG(c_j)$++
Else-if ($c_{max} \prec w_i$) Then $TS(c_j)$++
Else-if($w_i = c_{max}$) Then $R(c_j)$++
Else-if (LCS (w_i, c_{max}) $\in$ W) Then $A(c_j)$++
Else $A'(c_j)$++
End If
End loop

Fig(2) Pseudocode to categorize the distribution of course concepts in a learning material

The learned distribution of course concepts in the learning material is used in four proposed metrics. The metrics, namely *size*, *usability*, *complexity*, and *cohesion* (SU2C) aim to comparably assess learning materials. The definition of the metrics is adopted from the ontology metrics, which measure taxonomic knowledge representations [15].

The structural-based ontology metrics measure *size* in number of classes, instances or properties [16,17,18]. The size of a learning material can be determined by the number of distinct words in the learning material, which are semantically related to the course concepts. These are the words which form the concept-word pairs in the *TG*, *TS*, *R* or *A* relation categories.

Size = number of distinct words in a learning material semantically related to course concepts
= TG + TS + R + A, where '+' operator is the addition in regular mathematical equation

The pragmatic-based ontology metrics measure *usability* in terms of usefulness or task relevance. The usability of an ontology is determined by the number of units which are relevant to the task at hand [19]. Adaptively, the usability of a learning material can be determined by the number of distinct words in the learning material which are semantically related to the course concepts over total occurrence of words in the learning material.

Usability = number of distinct words in a learning material semantically related to course concepts / number of distinct words in a learning material
= (TG + TS + R + A) / (TG + TS + R + A + A'), where A' is a complement set of A

The complexity-based ontology metrics measure complexity as a ratio between edges and nodes [20], or a ratio between the number of relations and the number of classes. The complexity of a learning material can be determined by a ratio between the distinct words which are semantically related to the course concepts, and the number of concepts.

Complexity = number of distinct words in a learning material semantically related to course concepts / number distinct concepts in a course
= (TG + TS + R + A) / number of distinct concepts in a course

In ontology representation, cohesion is determined by the ability to describe a specific sub-domain related concepts. Ensan and Du [21] measure cohesion by an average of the local dependencies, over the number of all potential local dependencies. The cohesion of a learning material can be determined by the average of number of semantically related words in a topic, over the number of all semantic relations. This metrics would determine the learning material ability to describe a focused course topic.

Cohesion = Average [number of distinct words in a learning material semantically related to course concepts in a local chapter / number of distinct words in a learning material semantically related to course concepts
= t=1 ∑t=n [(TGt + TSt + Rt + At) / (TG + TS + R + A)] / n, where t is the local chapter

3. EXPERIMENTAL DESIGN

We obtained quantitative results from two means; metrics computation and learners' perception. The experiment allowed us to test the feasibility of the metrics computation.

Materials:

A case study is the chosen learning material for evaluating the proposed metrics. There are a few factors for using a case study. First, case study is a common learning tool across any pedagogical approaches [22] and its content may vary, for example as dilemma, issue, or analysis [23]. Second, it is important for the case study to be relevant to the course [24] in order to promote effective case-based teaching and learning [25][26][27][28].

The case study used in the experiment is a three-page educational material (Fig. 3) prepared by the Information Systems Audit and Control Association [29]. The case study has been used as a reading material in an undergraduate Information Systems Auditing course. The course has twelve chapters which contain concepts such as audit, financial audit, database, and controls in the course topics (Table 1).

Tampa Bay Office Inc. (TBOF) is a public company that manufactures office furniture. The company has two sales offices and a manufacturing plant in the Tampa Bay area. The company has an IBM AS/400-based accounting system that was implemented three years ago. An IT audit team is performing an independent audit on TBOF. They are to review and evaluate the IT general controls over Access to the System, Program Change Procedures, and Computer Operation… (continued)

Fig(3) An excerpt from the reading assignment

Table 1: List of chapters and course topics

Chapters	*Course Topics*
1	IT governance and audit
2	Conducting IT audit
3	Legal and ethical issues in IT
4	Frameworks and standards
5	IT risks and controls
6	IT deployment risks and controls
7	Managing IT function
8	Network risks and controls
9	Database risks and controls
10	E-business risks and controls
11	Auditing IT projects
12	Fraud and forensic auditing

Procedure:

First, nouns were extracted from the reading assignment and the course topics. This step revealed 172 words from the reading assignment and 95 concepts from the course topics. The words and the concepts were labelled as $\sum_{i=1}^{172} w_i$, and $\sum_{j=1}^{95} c_j$ respectively. Then, the Word-Similarity-for-Java (WS4J) Application Programming Interface (API) [30] calculated the similarity between each word and each concept. This step produced the semantic relatedness between each possible pair of the word and the concept. Next, the distribution of the course concepts in the reading assignment was determined following the pseudocode (Fig. 2). Lastly, the distribution in each category was used to calculate the *size*, *usability*, *complexity*, and *cohesion* metrics.

Participants:

The participants were asked to assess the above experiment material. They have been introduced to the case study at the beginning of a 36 contact-hour course. All participants have 3.03 GPA on average and are novices with regards to the domain knowledge presented in the case study. At the end of the course, the participants were required to estimate the number of words related to the course concepts, number of course concepts addressed by the reading assignment, complexity of the reading assignment, and its ability to address individual chapter in the course. The participants were asked to estimate these elements only at the end of the course rather than directly following the introduction of the reading assignment. This arrangement is influenced by the time it requires for semantic integration [31], in which the gap allows the participants to have acquired better integration of the semantically related words.

4. DATA ANALYSIS, RESULTS AND DISCUSSION

The results are presented in two sections; computation of the metrics, and perception of the participants.

Metrics computation:

The extraction of nouns from the course topics revealed 95 concepts from the twelve chapters in the course. Some concepts such as "audit" appeared in more than one chapter. Therefore, there were 48 distinct concepts excluding those repeatedly occurring. The extraction of nouns from the reading assignment revealed distinct 172 words, excluding stop-words, suffixes and prefixes.

The running of WS4J [30] determined a concept with the highest semantic relatedness for each word. The concept is either transitively generalized (*TG*), transitively specialized (*TS*), replicated (*R*), or associated (*A*) by the words. Table 2 shows the distribution of words in each course chapter. For example, from Chapter 1, the case study generalizes 2 concepts, specializes 5 concepts, replicates 1 concept, and associates 8 concepts from the course.

Table 2: Concepts distribution by each chapter

Category	Chapters												
	1	2	3	4	5	6	7	8	9	10	11	12	∑
TG	2	0	2	0	0	0	1	1	2	1	0	2	11
TS	5	0	0	0	1	4	6	2	2	1	2	0	23
R	1	0	2	2	2	6	3	2	4	2	1	2	27
A	8	0	0	0	0	0	0	0	0	0	0	8	16
∑	16	0	4	2	3	10	10	5	8	4	3	12	77

The learned distribution of course concepts (Table 2) was used to calculate the following metrics.

Size *= number of distinct words semantically related to course concepts*

= TG + TS + R + A, where '+' operator is the addition in regular mathematical equation = 77

Usability *= number of distinct words in a learning material semantically related to course concepts / number of distinct words in a learning material*

= (TG + TS + R + A) / (TG + TS + R + A + A'), where A' is a complement set of A = 77 / 172 = 0.44767

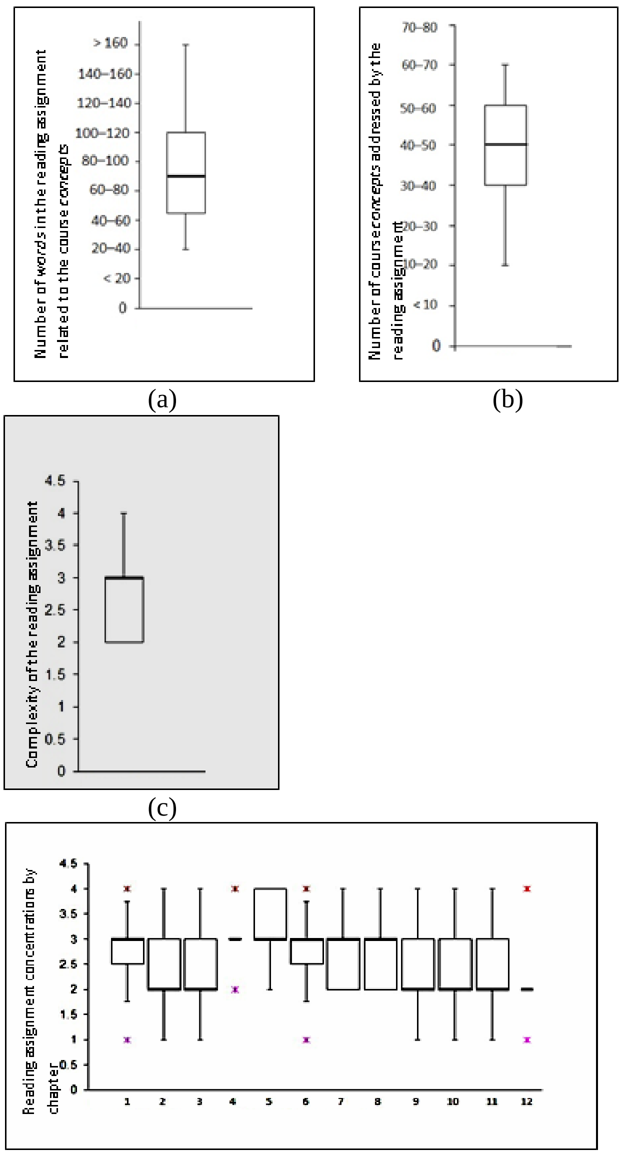
Complexity *= number of distinct words in a learning material semantically related to course concepts / number of distinct concepts in a course*

= (TG + TS + R + A) / number of distinct concepts in a course = 77 / 48 = 1.60417

Cohesion *= Average [number of distinct words in a learning material semantically related to course concepts in a local chapter / number of distinct words in a learning material semantically related to course concepts]*

$= \sum_{t=1}^{t=n} [(TG_t + TS_t + R_t + A_t) / (TG + TS + R + A)] / n$, *where t is the local chapter*

$= [16/77 + 0/77 + 4/77 + 2/77 + 3/77 + 10/77 + 10/77 + 5/77 + 8/77 + 4/77 + 3/77 + 12/77] / 12 = 0.083333$



(a) (b) (c) (d)

Fig(3) The participants' rating of the reading assignment to determine the (a) size, (b) usability, (c) complexity and (d) cohesion.

Participants' perception:

The learners provided their perception of the learning material. Their responses were summarized as median scores. According to the participants' rating, the case study has 80 occurrences of words that are semantically related to the course concepts (Fig. 4a), and has 40–50 occurrences of concepts from the course topics (Fig. 4b). In a scale of 1 to 4, the participants rate the reading assignment complexity at 3 (Fig. 4c). The participants rate that the reading assignment concentration is focusing on Chapters 1, 4, 5, and 6 (Fig. 4d).

DISCUSSION:

Comparison of the results from the learners' perception and computation shows the viability of the metrics. The learners' estimation shows 80 words in the learning material are related to the course concepts (Fig. 4a), which is close to the computed value, 77 (Table 2). The learners' estimation shows 40–50 course concepts are addressed by the learning material (Fig. 5b), which matches the computed value, 48 (Table 2).

The learners' estimation on the complexity of the learning material is 3 (Fig. 5c), comparable to the computed value 1.60417 (or ≈ 2). The above estimations support the computation for the *size*, *usability* metrics and *complexity* metrics.

The learners' estimation of the cohesion partially agrees with the computed cohesion by 0.5. The learners perceive that the learning material concentrates on Chapters 1, 6, 7, and 12 (Fig. 5d). Computationally, the learning material shows high concentration on Chapters 1, 4, 5, and 6 (Table 2). Both the estimation and the computed metrix indicate high cohesion on two chapters 1 and 6.

We found that the learners' perception is comparable to the metrics computation of the learning material. The metrics are based on the concepts distribution formerly determined by the concepts' relations in the lexical taxonomy. The concepts hierarchy contains schematic representation that depicts concepts relatedness within human memory [32][33], whereby short semantic distance between the concepts facilitates the recall of semantic relation between them [34]. Therefore, the derivation of the metrics depicts the way learners see the learning material. It is feasible for educators use the metrics in order to understand the course concepts distribution in learning materials that they author.

5. CONCLUSION

The goal of this study is to provide a simple method for educators to assess the distribution of course concepts in a learning material without having to rely on concept maps or semantic judgments. As the strength of relation depicts the accuracy of recall in human memory, we assessed a learning material based on the distance and the order of semantic relation between the learning material and course concepts. The information obtained from the semantic relation is used in computing the *size*, *usability*, *complexity*, and *cohesion* metrics. We found that the metrics computation on the learning material is aggregable with how learners perceive the learning material. Moreover, the metrics computation does not burden educators to formerly construct course concept maps. Rather, the metrics utilizes the publicly available lexical knowledge-base, WordNet. We hope that our results will contribute in helping educators to adopt learning materials from the Web which match the courses.

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