جامعة الشـرق الأوسـط MIDDLE EAST UNIVERSITY

Measuring the Quality of Online Learning Material Using Semantic Similarity Measures

قياس جودة مواد التعليم الإلكتروني باستخدام مقاييس دلالات التشابه

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LIST OF ABBRIVATIONS

- MOOC : Massive Open Online Courses.
- LO : learning object.
- ILOs : learning outcomes.
- KAON : Karlsuhe Ontology.
- WS4J : WordNet Similarity for Java.
- WuP : Wu and Palmer.



- LCH : Leacock & chodorow.
- HSO : Hirst & St-Onge.
- IC : Information Content.
- LESK : Michael E. Lesk
- LIN : Dekand Lin.
- NLP : Natural Language Processing

Abstract

Deciding the quality of the online learning material is an important factor and aspect in choosing which material to study by the stakeholder since it ensures a good learner experience. One approach is to make sure that the content of the learning material covers their Intended Learning Outcomes (ILOs). Many educational institutes are creating or adapting quality assurance tools such as standards and criteria regarding their learning material.

This research utilizes semantic similarity measures and ontology to define the quality of the learning material by calculating the coverage percentage of the ILOs in the learning material and deciding which measure gave the best coverage percentage of the ILOs in the



learning material. Online learning material and their ILOs were collected from well-known educational institutes with a good reputation and due to their interest in developing online courses as a primary learning method. Three subjects were collected; E-commerce, Software engineering and Networks those particular courses were selected due to them being available in text format. KAON (Karlsruhe Ontology and Semantic Web infrastructure) was utilized to extract the concepts from the data. As this research is based on experiments three cutting points were chosen 70%,80% and 90%. Semantic similarity measures are used to calculate the similarity among concepts. Eight semantic similarity measures were selected to cover all semantic measures families. The measures were applied using WS4J (word similarity for java) tool to calculate semantic matching between the ILOs and the learning material concepts.

This research also, used Root Mean Square Error (RMSE) to calculate the difference between the chosen semantic measures and the educational experts. Research concluded that from the eight measures (LIN) was the best measure that gave the quality of the learning material at cutting point 90%. It generated the minimum RMSE (2.5%) for ecommerce and (5.8%) for the software engineering course. The average error for network course was (19%) the network course was selected to prove that when the ILOs concepts for a certain topic are different from the learning material concepts the error percentage will be high.

Keywords: Learning material, intended learning outcome, concept, extracted concepts, semantic similarity measures.



الملخص

تقييم المواد التعليمية الإلكترونية على الانترنت يعتبر عامل مهم في العملية التعليمية لمعرفة مدى جودة تلك المواد وللتأكد من انها ستعطي مخرجات تعليمية جيدة. يقوم هذا البحث باستخدام المقاييس الدلالية لتحديد جودة تلك المواد التعليمية عن طريق مقارنتها بأهداف تعليمية موثوقة وصادرة عن مؤسسات تعليمية رائدة ومعتمدة عالميا. يستخدم هذا البحث المقاييس الدلالية لقياس مدى تشابه وتقارب المفاهيم في المعرفة. يهدف هذا البحث الى معرفة مقدار تغطية تلك المواد التعليمية لأهداف ومخرجات التعلم باستخدام المقاييس الدلالية.

لإجراء التجارب تم استخدام مواد تعليمية من جامعات ومؤسسات تعليمية لديها مكتبات للتعليم الالكتروني او التعلم عن بعد وهي التجارة الالكترونية وهندسة البرمجيات والشبكات. تم اجراء العديد من التجارب لإيجاد اي مقياس من المقابيس الدلالية التي تعطي أفضل نسبة مقدار تغطية المادة التعليمة لأهداف ومخرجات التعلم. تم استخراج المفاهيم الاساسية من كل من المواد التعليمة ومن اهداف ومخرجات التعلم. ثم تم تطبيق ثمانية مقابيس دلالية على هذه المفاهيم المستخرجة، ثم تم استخراج قيم رقمية تمثل مقدار التشابه والتقارب في معاني تلك المفاهيم.

هذا البحث يستخدم متوسط مربع الخطأ لحساب الفرق بين تقييم المقاييس الدلالية وتقييم الخبراء.



اظهرت النتائج ان من ثمانية مقاييس دلالية، كان أفضل مقياس اعطى جودة المواد التعليمة بنسبة خطأ (2.5 %) هو

.(LIN)

كلمات البحث: التعليم الإلكتروني، المفاهيم، الخبراء، المفاهيم المستخرجة، المقاييس الدلالية، اهداف، مخرجات.



CHAPTER ONE

Introduction



1.1 Introduction

The use of e-learning is opening doors for a lot of opportunities for different categories of people globally. And as the demand grows, so does the competition between educational institutes which in turn invest in numerous resources to stay in the market. Part of these resources is the high quality online learning material that achieves the desired educational goals. The online learning material is critically important to develop because it is a major factor in the implementation of any e-learning initiative. To create a proper online learning material to various social and educational levels, the online learning material should be designed in a way that is centrally focused on the learners' flexibility and in a "user-friendly" manner.

An example of the e-learning initiatives is the Massive Open Online Courses (MOOCs) which have grown in significance as a new model in education. MOOCs are accessible to everyone and offer educational materials for learners who can connect to the Internet. In recent years, educational institutes became aware of the various aspects of MOOCs including their forms, concepts, and challenges (**Saadatdoos et al., 2015**). The Quality of the online learning material is an important aspect of ensuring a good learner experience. The general definition of quality is that it's "the standard of something as measured against other thing of similar kind"¹. Therefore, the quality of the online learning material is the degree to which it measures up to a good learning.



1 https://www.oxforddictionaries.com/

As systems on their own are not enough, quality assurance tools are now considered essential in most of the established educational institutions. Conducting quality audits for the institution in general is driven by the goal of supporting and improving both the teaching and the learning processes to achieve the best quality. That led to having tasks such as quality assurance audits and external reviews being mandatory for the institution to conduct in a quite good number of countries (**CONOLE**, **2015**).

Another important component is the Intended Learning Outcomes (ILOs) "which are statements placed at the beginning of online learning material aiming to inform learners

About its content". ILOs assist the designer of e-learning to create the online learning materials according to the stakeholder requirements, needs, and learning objectives (Anderson et al., 2001).

The learning material is designed as a response to the need of the learning seekers. The degree of how clear the ILOs is related to the needs of the learning seekers. Those needs are expressed in a form of demand. d'Hainaut (1983) mentioned an interesting point which is if the learning seekers didn't have the necessary information of the ILOs they will not be able to formulate a valid opinion on the quality of the course and if this particular course fits their needs.

The ILOs of any learning material is important as it helps the learning seekers to have a general idea of what to expect to learn from the course they are intending to take also, if the course has any activities (i.e. mathematical course, computer science courses.... etc.)



the ILOs prepares the seeker for those type of activities. Another reason why the ILOs are important is in case the learning material will be taught by an instructor since ILOs asset the instructor to develop the proper learning material for the course to be more efficient. The ILOs service as a criteria standard for the choice of the courses aids which can be a collections of texts, volumes, films and audio files. The instructor must ensure that the courses materials and aids are proper and fit the ILOs.

This research will assist stakeholders to determine the most suitable learning martials which cover the required (ILOs) using semantic similarity measures and ontology.

1.1.1 Semantic similarity measures and ontology

Semantic similarity measure research revealed a growing attention to Natural Language Processing (NLP). Semantic similarity measures are essential in artificial intelligence, psychology and cognitive science. It has been broadly used in information retrieval, word sense disambiguation, text segmentation, question answering, recommender system, information extraction etc. While Syntax measure is another type of measure and it is the study of sentence structure therefore, the measure operates on the notion that the meaning of a sentence is made up of not only the meanings of its individual words, but also the structural way the words are combined also, the measure takes into consideration the grammatical accuracy of the text. It's utilized in information retrieval systems and in text summarization.

In latest years, the measures based on WordNet have gained a huge interest since they make the application in those fields more intelligent and work in better manner. Having an



organized knowledge illustration that is at the same time accessible via ontologies, which are (explicit specification of conceptualization). Resemblance between concepts or terms that exist in a certain source of information aiming at coming up with approximations is calculated using semantic similarity measures (**Slimani, 2013**). According to literature, semantic measures can be classified into different families based on their theoretical principles. Some examples of semantic measures from each family include but are not limited to:

- 1. Path Length Family (Wu and Palmer Measure. Leacock & Chodorow Measure)
- 2. Information Content Family (Resnik Measure, LIN Measure)
- Semantic Relatedness Family (LESK Measure. Hirst & St-Onge Measure (Michelizzi ,2005).

Sunitha and Aghila presented a study to find the semantic relatedness between learning objects and they defined LO "as standalone educational resources meant to satisfy a specific objective". They presented a comparison among semantic relatedness measures (usage context based measure, Meta data based measure, lexical co-occurrence based measure and path based measure). They highlighted the advantage and the disadvantage of each measure. They just listed the comparison, advantages and disadvantages without any implementation of these measures for e-learning materials (**Sunitha & Aghila, 2013**).

Al Kayed et.al. introduced a coverage measure to measure the quality of concept description for specific domain knowledge but instead of focusing on words the measure focused on concepts where higher coverage value meant better quality for the description (**al kayed et.al., 2013**).



This research deployed different measures from each family of semantic measures to find how much of the ILOs is covered in the learning material. The research depended on semantic similarity measures families since they work with individual words not sentences hence, the syntax measure wasn't utilized in this research since it's based on the notion that the meaning of the sentence is made up of not only the meanings of its individual words, but also the structural way the words are combined.

1.1.2 Ontology

Different authors have defined ontology differently. Gruber is one of them. He described the ontology as a proper, explicit specification of a shared conceptualization (**Gruber**, **1993**). Zhang et al., on the other hand, stated that ontology provides a set of concepts and their interrelationships in a specific domain to assist understanding and automatic processing of text (**Zhang et al., 2012**). Furthermore, (**Jiang et.al. , 2013**) defined the ontology as an abstract description system for knowledge composition in a specified domain. An ontology presents elements in the domain by providing a well-structured vocabulary. To do that, ontology labels relations among terms and organizes concepts in a hierarchal space via limited relational descriptors.

Ontologies can be classified according to their purpose to general ontologies and domain specific ontologies. Wordnet¹ which is an online lexical and can also be considered as an ontology is used to compute the similarity between concepts by most of the semantic similarity researches (**Boonyoung & Mingkhwan, 2015**).



1.1.3 WordNet

"WordNet¹ is an online lexical database designed for the use of under program control. English nouns, verbs, adjectives, and adverbs are organized into sets of synonyms, each representing a lexicalized concept. Semantic relations link the synonym sets" (Miller ,1995).

Similarity measures utilize information available in the form of a hierarchy of concepts (or synsets). In addition, they also quantify the resemblance between concepts. In other words, how similar is a concept X to a concept Y. An example can be that an automobile is more similar to a ship rather than a tree. That is caused by having the automobile and the ship having in common the word vehicle in the form of an ancestor in the WordNet noun hierarchy. WordNet 2.0 contains 115,700 different synsets. These Synsets contains 80,000 nouns, 13,500 are verbs, 18,500 are adjectives and 3700 are adverbs. Since WordNet is a lexical database it has a huge number of nouns, adjectives, verbs and adverbs they are organized in a form of synonym sets (Synsets) by semantic relation they represent one concept. Also, each Synset may contain one or more synonymous word and it has a brief definition "gloss" to define the meaning of Synset. For example, synonymy, autonomy, hyponymy, member, similar, domain and cause. They are relations used to form word relation and they are relations used to form semantic relation. These relations assemble a hierarchy structure which makes WordNet a useful tool for natural language processing and since most language semantics depend on nouns when calculating semantic similarity.

1 https://wordnet.princeton.edu/



Four common usage of nouns are hyponym/hypernym (is-a) example cucumber is a vegetable. Part meronym/part holonym (part-of) example microphone is a part of the telephone. meronym/member holonym (member-of) example Saturn is part of solar system. Substance meronym/substance holonym (substance-of) example Feather is a substance of Bird. The is-a relation is the most common and most used relation in WordNet since it interprets 80% of all relations and the hypernym/hyponym relation is considered about how two concepts are similar (Michelizzi 2005; Boon young & Mingkhwan 2015; meng et al., 2013).

There are several recognized ontological tools that can be used to extract concepts from the text that al kayed et al discussed, KAON², Swoogle³, and Protégé⁴. KAON which is an ontology management targeted for business applications. It includes a comprehensive tool suite allowing easy ontology creation, storage, retrieval and maintenance of ontologies. Swoogle on the other hand is an indexing and retrieval system for the semantic web. Swoogle computes the rank for each semantic web document and provides online system to check the availably of ontologies in any domain. Protégé is another tool which lets the user to build domain ontology, alter data entry forms, and enter data.

This research utilized KAON due to its availability, ease of use, and user interface. KAON was used to extract concepts from both the ILOs and the learning materials (Maedche, 2001; Kayed et. al., 2013).

² http://kaon2.semanticweb.org/

³ http://swoogle.umbc.edu/

⁴ http://protege.stanford.edu/



1.2 Problem Statement

E-learning is increasingly considered an important and emerging educational tool. Many educational institutes are using e-learning systems. There is a need to evaluate the quality of learning material .Finding the most suitable learning material is a challenging task. Educational experts believe a good learning material covers their ILOS. Semantic similarity measures will be used to compute the similarity and relatedness among concepts and terms in online learning material and their ILOS .This research will use semantic similarity measures to find how much the online learning material covers their ILOS. It will also define which measure or measures best compute the coverage for the ILOS in the online learning material.

1.3 Problem Statement Questions

This research will answer the following questions:

- Which semantic similarity measures are the best to evaluate the coverage of ILOs in the learning material?
- How can these semantic similarity measures be used to decide the span coverage of ILOs in the learning material?
- How can the extracted concepts be utilized to support measuring quality of learning material without human intervention?



1.4 Limitations

This research utilized semantic similarity measures to figure how much of the ILOs is covered by its learning material. Since semantic similarity measures only works with textual data any multimedia teaching tools such as videos and pictures in the learning materials had to be converted into text. Punctuation had to be deleted from the learning material data to enable the researcher to get the best results when extracting concepts from the learning material and the ILOS.

In the software engineering course the code symbols and java language had to be deleted since the semantic similarity measures only works with defined textual data.

The courses were chosen in English language only. Arabic courses couldn't be used since not all semantic similarity measures work with Arabic language.

1.5 Objectives:

Finding the most suitable learning material is very important for learning seekers therefore evaluating the online learning material is crucial. This research aims to:

- Evaluating the learning material by figuring how much the ILOs is covered in the learning material by utilizing semantic similarity measures.
- Deciding which measure give the best coverage of the ILOs in the learning material by experimenting with semantic similarity and relatedness measures on the concepts of the learning material and the ILOs.



1.6 Motivation of the study

The demand for e-learning in educational institutions is growing, competition is increasing, and academic institutions are investing to improve the quality of their e-learning resources. Thus, effective quality measures are urgently requited for e-learning material. There are challenges associated with setting the quality for a certain learning martial in e-learning. For the stakeholder to find the best learning material online is a challenging task the can be both time and effort consuming. Therefore, there is a need to find a good methodology to evaluate the quality of the learning material by measuring how much does it cover their ILOS. This motivates the researcher to deploy the semantic similarity measures to test the quality of e-learning material as far as we know there is no implementation for semantic similarity measures in the literature to find the quality of e-learning materials.

1.7 Contribution of the study

This research contributed in the following:

- 1- Finding the most suitable semantic similarity measures to determine the coverage of the ILOs in the learning material.
- 2- Deploying the best semantic measures to find how much of the ILOs are covered in the learning material.
- 3- Finding the quality of the learning material by deploying semantic similarity measures and finding the highest percentage of coverage by mapping the learning material to the ILOs.



1.8 Organization of the Thesis

The organization of the thesis identifies the structure we followed through this research. The thesis contains five chapters, references, and appendices. The following part explains a brief description for each chapter:

Chapter 2 presents the literature review of the online learning material and MOOC (Massive open online course), semantic measures and ontology. A description of the semantic similarity measures family is provided.

Chapter 3 presents the flowchart of the research. How the concepts were extracted from the learning material and the ILOs. A brief description of the learning material source. Also, the calculation process of the similarity between the learning materials and the ILOs using the semantic measures.

Chapter 4 explains the experiments in details. Its presents the matching process in details and how much the learning materials cover their ILOs using semantic measures.

Chapter 5 presents the discussion, the conclusion and the future work of the thesis.



CHAPTER TWO

Literature Review



Overview

This chapter presents a theoretical background and literature that relates to our study, we classified the literature into five parts: First part provides an explanation of each of measure and how does the measure calculate the similarity between each concepts and term. Second part is MOOCs and how important they are in the e-learning world. Third part is semantic similarity measures and how they can be used to compute the relation between concepts and terms. Fourth part covers the ontology. Fifth part describes the tools the researcher utilized and used to complete the research.

2.1 Semantic Measures

If the Concepts of any text are expressed by two similar word senses, the sense would be semantically similar. The degree of similarity of the word sense is computed by the semantic similarity measures. These measures can be categorized in two groups based on their theoretical principles: Semantic similarity measures and semantic relatedness measures. The measures of semantic similarity work with noun-noun or verb-verb since only nouns and verbs can be classified into is-a hierarchies while relatedness measures work on all open class parts of speech since they are not limited to is-a hierarchies. We will experiment with different measures to cover all kinds of semantic measures. The following will list all the measures which the researcher will experiment with.



- 1. Path Based Family
 - Wu and Palmer Measure.
 - Leacock & Chodorow Measure.
 - The Shortest Path Measure
- 2. Information Content Family
 - Resnik Measure.
 - LIN Measure.
 - Jiang's Measure
- 3. Semantic Relatedness Family
 - LESK Measure.
 - Hirst & St-Onge Measure.

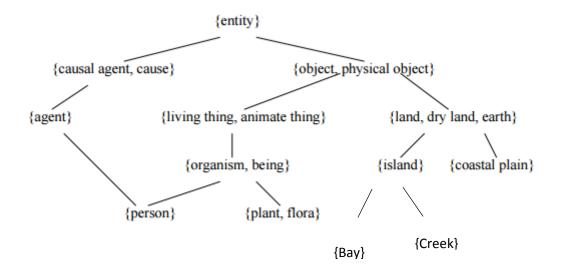


Figure 2.1: WordNet hypernyms adapted from (Michelizzi, 2005)



2.1.1 Path Length Family

"Path-based measures compute the similarity between two concepts as the function of the length of the path linking the concepts and the position of the concepts in the taxonomy."

One of the methods to measure the similarity is to handle the taxonomy as undirected graph and use the distance as a path length between the synsets as similarity measure. As the distance gets further between the synsets the, similarity percentage gets less. For example, the Synset sun is closer to planet, Galaxy and light than it is to car or bus. Computing the distance between two synsets can be done using edge counting or using node counting. Edge counting relies on the number of links between the two synsets. Node counting relies on the number of nodes along with the shortest path between the two synsets are path (Michelizzi, 2005).

1-Path Measure

Michelizzi illustrate the path measure depends on the distance length to measure the similarity of synsets. Using node counting the measure calculates the similarity between two synsets.

 $Dist_{node}$ is the definition of similarity where (s1; s2) is the distance between synset s1 and synset s2 using node counting.

 $\frac{1}{dis node(S1, S2)}$ (1)



For example, the distance between person and living thing, animal is three, so the similarity score is 1/3. Using node counting, the distance between two synsets is always greater-than or equal-to 1. If we take the synsets person and person, the distance between the synsets is 1. Therefore, similarity is always greater-than 0 but less-than or equal-to 1 (Michelizzi, 2005).

1- Wu and Palmer Measure

Michelazzi explain WuP similarity measure as the depth of two concepts and the depth of the least common subsume(LCS).

According to Baader et al, (LCS) is the most precise concept which is the ancestor of both concept X and concept Y. Where the concept tree is defined by is-a relation. A concept is defined to be an ancestor of other concept, which is the parent of the other concept (**Baader et al., 2007**).

For example, figure 2.1 the subsumers are (object, physical object) and (entity) for nodes (living thing, animate thing) and (land, dry land, earth). Finding the least common subsumer for these two nodes require the researcher to search for the most specific subsmer of the two synsets. The LCS for these two synsets are (object, physical object) (Michelizzi, 2005).

$$Sim_{wup} = \frac{2 * depth(LCS)}{depth(concept_1) + depth(concept_2)}$$
(2)

Equation (2) shows how to calculate the WuP measure, which is the node depth of LCS for the two nodes divided by the sum of the depth of first node and the depth of the second



node. To compute the similarity of the two nodes (Bay) and (Creek) using WuP in figure 2.1; the node counting (Bay) and (Creek) is 5 for both, the depth for their LCS which is (Island) is 4. Thus, the result using equation (1) is $\frac{2*4}{5+5} = \frac{8}{10} = 0.8$

2- Leacock & Chodorow Measure

LCH measure depends on distances and depths to compute the similarity by counting nodes.

LCH measure equation is shown in (2).

Where dist. is the distance between concept1 and concept2. the depth for a given taxonomy where the concepts are existing.

For example, using figure 2.1, for the two synsets (Bay) and (Creek). The distance between them is 3, and the depth is 5. Thus, the score using measure LCH by equation (3) is:

 $-\log 3/(2 * 5) = 0.5$ (Michelizzi, 2005).

2.1.2 Information Content Family

Information content (IC) measures use the concepts information content to compute the semantic similarity measure between two concepts. The value of the concept depends on how many times the concept occurs. Furthermore, a concept that occurs frequently in a document would have low information content and a concept that rarely occurs in the document would have high information content. "High information content means that the concept conveys a lot of meaning when it occurs in a text. A concept with high information



content is very specific, but a concept with low information content is very general; therefore, information content corresponds to specificity" (Slimani, 2013; Michelizzi, 2005).

The information content for a given concept equation is shown in (3):

IC(concept) = -log P(concept).....(4)

Where $\mathbf{P}(\text{concept})$ is the probability of the concept.

1- Resnik Measure

Resnik measure has been defined as information content measure. It takes into account the LCS information content which return the information content of the LCS of two concepts.

Resnik measure equation is shown in 4:

$$Sim_{res} = IC(LCS)$$
 (4)

The maximum similarity value for the Resnik measure occurs when the frequency of an LCS is one. When the frequency is one, the information content of the LCS is logN, where N is the sum of the frequencies of all the top-level nodes of the given part of speech. One characteristic of the Resnik measure is that it is a rather coarse-grained measure. All pairs of synsets with the same LCS will have the same similarity score. For example, {object, physical object} is the LCS of many synset pairs in Figure 2.1, including {plant, flora} and {island}, {plant, flora} and {land, dry land, 13 earth}, and {plant, flora} and {object, physical object}. Since these pairs have the same LCS, by Equation (4) they will have the same similarity score.



2- LIN Measure

Lin measure calculates the similarity score based on three assumptions. The more similar the concepts the more they have in common. Second rule is the less the two concepts have in common the less similar they are. Third rule maximum similarity happens when the concepts are identical. Equation (5) shows Lin measure equation. By equation (5), we can note that the similarity based on the information content for the least common subsume. And the information content for both concepts. LIN measure and WuP measure look alike, but the WuP measure based on the depth of the LCS, where LIN measure based on the information content of LCS (Corley & Mihalcea, 2005; Michelizzi, 2005).

$$Sim_{lin} = \frac{2 * IC(LCS)}{IC(concept_1) + IC(concept_2)}$$
(5)

The information content of the LCS will always be less-than or equal-to the information content of both s1 and s2; therefore, the similarity score can be at most one. The score is zero only if the information content of the LCS is zero. The score is undefined if the information contents of s1 and s2 are zero. The Lin measure is similar to the measure of Wu and Palmer, except that depth is replaced with information content. In fact, information content is a type of depth because synsets that are deeper in a taxonomy will also have a greater information content. Information content is a measure of specificity, and specificity increases as depth increases.

3- Jiang & Conrath

Jaing & Conrath presented a measure of semantic distance that uses information content.

$$Dist_{jcn}(c1, c2) = IC(c1)IC(c2) - 2 * IC(LCS(c1, c2))....(6)$$



The distance measure changed to a similarity measure through its multiplicative inverse.

 $Sim_{icn}(s1, s2) = 1/Dist(s1, s2)$ (7)

Consider a case where the synset s1 has the following distances from synsets s2, s3, and s4

		distance
s_1	s_2	2
s_1	s_3	3
s_1	s_4	4

The corresponding similarity scores are

		similarity
s_1	s_2	0.50
s_1	s_3	0.33
s_1	s_4	0.25

2.1.3 Semantic Relatedness Family

Semantic relatedness has a much wider view than semantic similarity. For example, an engine is related to vehicle the two are related but are not similar since engine is not a kind of a vehicle and the vehicle is not a kind of engine. Semantic similarity is a special case of semantic relatedness but only the is-a relation is taking into account. LESK measure and the Hirst & St-Onge are well known semantic relatedness measures.



1- LESK Measure

LESK measure is a gloss overlap measure it depends on the sense of the target words in the text. It compares the glosses of difference senses with those of the words in text. The sense of the target word whose gloss has the most words in common with the glosses of its nearby words is chosen as the most fitting sense.

When computing the relatedness of two synsets, s1 and s2, relation functions are used to determine which glosses are to be compared.

Each pair of functions specifies the glosses that are to be searched for overlaps. For example, the pair hypehype means the gloss for the hypernym of s1 and the gloss for the hypernym of s2 are searched for overlaps.

The pair hype-hypo means that the gloss of the hypernym of s1 is compared to the gloss of the hyponym(s) of s2. If there is more than one hyponym for s2, then the glosses for each hyponym are concatenated into a single gloss. The pair glos-hype means that the gloss of s1 is compared to the gloss of the hypernym of s2.

Each pair of relation functions generates a score, and the overall relatedness score is the sum of the scores for each relation function pair. The scoring mechanism takes into account both the number of words in the overlaps and the length of the overlaps. The motivation is that a four-word overlap (i.e., an overlap consisting of four consecutive words in both glosses) is more significant than four one-word overlaps because longer overlaps are less likely to be incidental. The score for a single relation function pair is the sum of the squares of the length of each overlap found:



$$pairscore = \sum_{i}^{\#overlaps} length^2(overlap_i)$$

The overall relatedness score is simply the sum of each of these pairwise scores:

$$Relatedness(s_1, s_2) = \sum_{j}^{\# pairscores} pairscore_j$$

(Banerjee & Pedersen 2003).

2- Hirst & St-Onge Measure

The Hirst & st-Onge measure is path based measure. The relations are classified as having directions. "It establishes the relatedness between two concepts by trying to find a path between them that is neither too long nor that changes direction too often."

weight = C - path length - k. #changes in direction.....(9)

where C and k are constants. In WordNet::Similarity, the values for C and k are 8 and 1 respectively. Thus, the maximum relatedness value in case of medium-strong relatedness is 8.

To illustrate how this measure of relatedness works, consider the word senses car#n#1 (an automobile) and jet#n#1 (an airplane with jet engines). There is a path in WordNet that links these two word senses as shown in Figure 3. The word sense hood#n#5 is a meronym of car#n#1 since a hood is part of a car. Because an airplane can contain a hood, airplane#n#1 is a holonym of hood#n#5. Since a jet is a type of airplane,jet#n#1 is a hyponym of airplane#n#1.



The length of the chain linking car#n#1 and jet#n#1 is 3 (counting the relations that link the word senses).

The meronym relation is an upward relation, and the holonym and hyponym relations are downward relations

(see Table 3); therefore, there is one change in direction. The relatedness score using Equation (16) is score = $8 - 3 - 1 \cdot 1 = 4$ (**Pedersen et al., 2004**).

2.2 E-learning and MOOCs

According to (**Ehlers, 2004**) it is crucial to find solutions for the challenges when it comes to the e-learning quality keeping in mind that these challenges can be in the theory or in the practice if in the future e-learning is going to be treated equally with the traditional educational qualification measures system. He also studied gradually conceptualizing complicated concepts in terms of quality. In addition, an experimental model was built and used to come up with the research results which can be summarized by saying that learners could differentiate the quality preference of theirs in the e-learning domain. Those learners are part of the experimental model. In fact, learner preferences are expressed in thirty dimensions on top of 4 preference profiles that are analyzed and described.

(Marshall, 2013) presented both sides of MOOCs in which it has features that both attractive and threatening. The main attraction is that they are very large scale and very low-cost learning material. However, the threat is competition which can lead to the degradation in higher education as a product of large scale experiences delivered by



institutions internationally without comprehensive awareness of the local student culture, values and needs.

(Sunitha & Aghila , 2013) carried out a study in finding the semantic relatedness between Learning Objects (LO) in the context of E-learning. They gave the general meaning of semantic relatedness as it specifies the degree of relatedness between two concepts. They defined Learning Objects as small instructional chunks of learning elements which can be archived, extracted and shared in the learning process. They used path length measures and information contact measures and the text based measures. They carried out a comparison of mechanics among the three measures in e-learning and detailed the advantages and disadvantages among them. They just listed the comparison, advantages and disadvantages without any implementation of these measures for e-learning materials.

(Morrsion, 2015) discussed that quality in higher education was measured by what the course is consisted of and what are the learning objective as this approach has shifted to a process oriented system where a combination of activities contributing to the education experience are considered. Activities that include: student desires and use of data and information for decision-making and department contributions as well as better learning objectives. She presented 5 steps to measure the quality of the online learning material.

- 1. Asses Using a Rubric or Other Tool to Consider Basic Course Elements
- 2. Analyze Course from a Student Perspective
- 3. Assess Course Artifacts, Materials, & Feedback
- 4. Take into consideration the interaction such as student to student and student to instructor.



5. Results: Are Students Learning? Learning by having assignments demand that students prove what they know and are required to apply course concepts.

2.3 Semantic similarity measures

Scientists and well known researchers have been experimenting with semantic similarity measures for years. The semantic similarity measures and ontology filed has many useful and valuable references. Tom Gruber an American researcher have been working and developing ontology since the 90s. The researcher couldn't find any previous work related to applying semantic similarity measures to evaluate the content of the learning material. However, one research was found but it discussed applying semantic similarity measures on the learning object not the content of the learning material.

This part discusses different types of semantic measures and the importance of semantics measures in many domains. Several studies use semantic measures to find which measure that gives the best result.

(Li et al., 2003) discussed that the similarity between words and concepts had become a difficult problem that is encountered by many applications. They tried to predict the determination of semantic similarity by a number of information resources that contain semantic information from lexical taxonomy. They also indicated how information sources could be used effectively by using variety of strategies for using various possible information resources. However, authors argued that all first-hand information sources need to be processed in similarity measure. Besides that, word resemblance comparison is achievable by human beings even though the interval is limited when it comes to similarity.



(**Pedersen et. al., 2004**) Explained both semantic relatedness and semantic similarity within WordNet. Since similarity measures are only used for pairs of nouns, verbs, adjectives and adverbs they calculate how much two terms or concepts are similar. However, measures of relatedness calculate the relatedness between pairs of concepts. The main difference between the similarity and relatedness measures is that the relatedness measures can be used on a wider area.

According to (Wang& Buckley ,2011) knowledge from lexical recourses can be used as input to quantify words relatedness which is basically a measurement of semantic similarity or simply the distance between words. Existing hybrid methods had some limitations that Wang et. al., attempted to deal with, using the internet in their proposed hybrid method. This proposed method relies on WordNet to obtain the semantic similarity among both the words and the structure information. The accuracy of estimating semantic relatedness among words increased as the results of the experiment they conducted show. This is caused by utilizing the knowledge available on the internet to WordNet-based semantic similarity measures.

(Meng et. al., 2013) stated that while relations can be used to create relations from words, they can also be used to create semantic relations. Upon being connected with words, relations become hierarchical structures. This leads to it being very valuable when it comes to natural language processing and computational linguistics. A lot of semantic measures related to similarity were studied according to an is-a relation through WordNet. They covered hybrid, feature based, information content based, and Path based measures. In



addition, various measures were studied from different aspects; principles, characteristic, pros, and cons.

(Mittal & Jain ,2015) studied the ambiguity in search query which is the process of retrieving irrelevant documents due to the user uncertainty in query. Another reason for ambiguity is words that have more than one meaning. For example, the word 'bank' can mean two different things based on the context. If we say "I want to meet the bank manager" and "I went to the bank to watch the sunrise". The first phrase refers to the financial bank where the second phrase refers to the river bank. To solve this problem, they present a method by using semantic similarity and relatedness between the unclear terms. They applied leacok & chodorow and wu & palmer similarity measures on noun only because compared to other types of words in a language nouns communicate most of the information.

(Al-Khiaty & Ahmed, 2016) Studied matching model for its importance in various model management operations. An example would be the model evaluation and retrieval. They also covered the importance of accessing and reusing available software models efficiently using a systematic method. They recognized the matching models and found the similarities and differences in each one. They experimented in UML diagrams (Unified Modeling Language) class diagram. They utilized semantic similarity for concepts comparison according to WordNet in class diagram. The concepts were (Classes names, operations name and attributes names). They used the semantic path-based measure. Path length and Wu & Palmer are the two measures supported by WordNet.



2.4 Ontology

"Ontology is defined as an abstract description system for knowledge composition in a certain domain" (**Jiang R., 2013**). It presents an explanation of concepts or terms. Ontologies have been used in different domains; each domain has its own vocabularies, concepts or terms.

(Kayed et. al., 2010) discussed the ontology concepts and the ability to build a shared concept. They experimented with software requirements by extracting different components from the software requirements. The components didn't include only concepts but also terminologies and definitions. They figured if there are enough semantics in the concepts which are generated through the process of condensing semantic definitions, a common understanding can be reached. They developed a new ontology in requirement engineering process using KAON tool. This will allow developers to share a general concepts and terms.

(**Kayed et. al., 2013**) demonstrated several experiments to show how ontological concepts can be used to test the quality of a description for a software component. They built ontologies concepts with WordNet relationships. These concepts have been used to check whether some component's description is suitable for the software component or not. They proposed a coverage measure which computes the distance between any domain definition and its domain ontology. This coverage measure along with a non-parametric statistical method will define the goodness of an ontology or a description with a 95% confidence rate.



2.5 concepts tools (Extracting and organizing concepts tools)

We utilized many tools in this research, for concepts extraction and arrangement and for computing the semantic similarity between the concepts. A description for each tool as well as a justification for why was this specific tool were chosen are given below.

2.5.1 KAON TextToOntoTool

There are widely available tools for building an ontology and to help in generating ontology concepts. KAON is a well-known tool for building and operating an ontology. Maedche defined TextToOnto as "a tool suite built upon KAON in order to support the ontology. Engineering process by text mining techniques; providing a collection of independent tools for both Automatic and semi-automatic ontology extraction" (Maedche A. 2001). KAON was utilized in this research for the below mentioned reasons.

- Easy to use.
- A friendly user interface.
- Easy to handle.
- Open source tool.

The process of extracting concepts from both the ILOs and the learning material started with collecting ILOs and learning material from well-known educational institutions. That data was converted to text files. Then the text files were imported into TextOnTo (Corpus). As shown in figure (2.2). Then we chose the (New Term Extraction) so the concepts can be extracted from the corpus as shown in figure (2.3-2.4).



This tool extracts concepts using parameters, there are many frequency thresholds available in the KAON ontology tool.

🛓 KAON Workbench	-
File Edit View Procee	lures
Load Workspace	
Save Workspace	
Open Ol-model	
Create <u>N</u> ew Ol-model	
<u>C</u> opy To New Ol-model	Nev
Duplicate Ol-model	
<u>Save Ol-model</u>	
Import	
<u>E</u> xport	
New Corpus	
New Term Extraction	
New Instance Extraction	
New <u>A</u> ssociations Extrac	tion
New <u>R</u> elation Learning	
New <u>P</u> runer	
New <u>T</u> axo Builder	
New <u>O</u> ntoEnricher	
New Ontology Compariso	n
<u>E</u> xit	Alt-F4

Figure 2.2 The front-end of the kaon TextToOnto tool



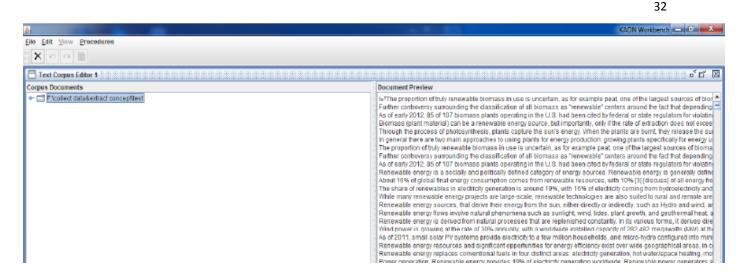
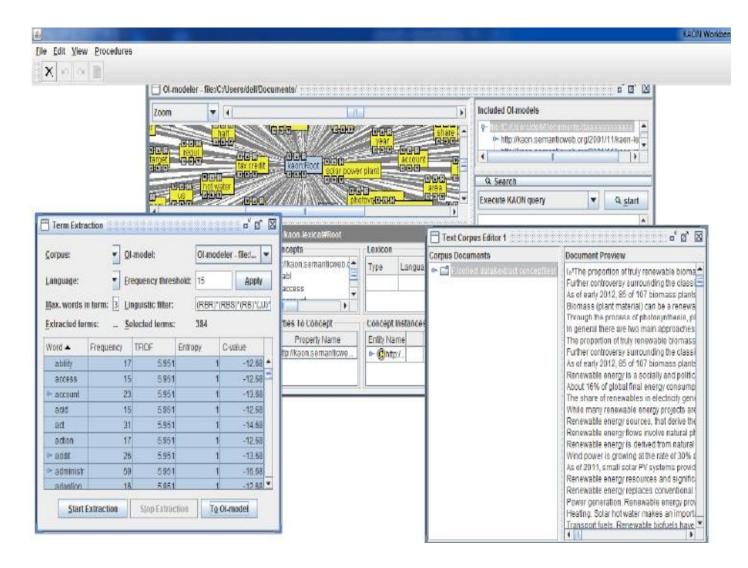


Figure 2.3 Create new corpus function using KAON TextToOnto tools



2.4 New term extraction function using KAON TextToOnto tool



2.5.2 WordNet Similarity for Java (WS4J)

 $WS4J^1$ is an online tool to find the similarity between concepts using the published semantic similarity measures. It's a JAVA API tool which depends on WordNet relations between concepts then applying the semantic similarity measures it generates the similarity

between the concepts. The online demo gives the user two options the first option is to find the match between two words only. The second option lets user match multiple words with each other at the same time.

S4J	(WordNet Simil	arity for Java) measures semantic similarity/relatedness between words.
ord	Net loading state	JS: C
/pe	in texts below, o	or use: example words example sentences
1.	Input mode	Word Sentence
1. 2.	Input mode Word 1	Word © Sentence the first word

WS4J demo is maintained by Hideki Shima.

Figure 2.5: WS4J Tool Front End

1 <u>http://ws4jdemo.appspot.com/</u>



2.5.3 Sporkforge

Sporkforge² is an online tool which analyze a set of texts. It gives the user the ability to have an analytical overview of their text as it can show the word count and list all the words used in the text and how many did a specific word occurred and if the word was repeated also, it gives a list of both the recurring sequences and consecutively repeating words.



Figure 2.6: The front-end of the sporkforge

2 http://sporkforge.com/index.php



CHAPTER THREE

Research Methodology



Overview

Chapter three presents the methodology that the researcher followed to get the results. Each phase and its steps are explained in detail. These phases are: collection of learning material, concepts extraction and applying the semantic similarity measures on the extracted concepts. Finally evaluating the results of each measure by computing the error of each one. The aim is to assist stakeholders determine the most suitable learning materials which covers their (ILOs).

3.1 Introduction

This research followed a descriptive, quantitative and qualitative approach. Our methodology will be based on performing multiple experiments to select the best semantic similarity measures. For the descriptive part, ILOs along with their concepts will be collected. Also, learning material will be collected from different online resources and well-known educational institutes. For the quantitative part, this data will be transformed from textual data into numeric values using different semantic similarity measures to determine the best measures. To be able to know the quality of the learning material, human evaluation is required to be compared with the results of semantic similarity measures. Thus, part of the evaluation process will be based on human. The other part will be done by our experiment and this will depend on the error calculation which is the difference between human evaluation and measures results.



The main idea of this research is to find which semantic measure that give us the quality of the learning material by extracting the main concepts for both learning material and ILOs using KAON software; then matching those concepts by applying different types of semantic measures, through these measures the quality coverage will be defined.

Flow chart for proposed work

The following will illustrate the main steps of the research methodology as showing in figure 3.1:

- 1- Collecting data.
- 2- Extracting the concepts.
- 3- Experimenting with several semantic measures.
- 4- Evaluate the results.



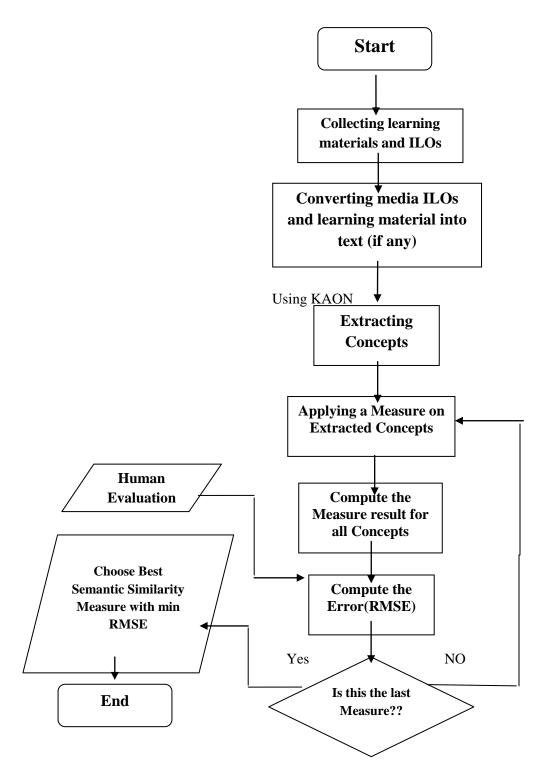


Figure 3.1: Flowchart of the proposed methodology



3.2 Collection of (learning materials and ILOs)

Good learning material and ILOs are essential in this research. Therefore, they were collected from different educational institutes.

e-commerce course was selected due the researcher background in the subject and availability on the e-learning websites. After the researcher ran the experiments on the courses a noted resemblance was found in the results hence, an accurate decision couldn't be made. This is due the e-commerce learning materials being similar in characteristics and the way it was being presented in the course even though it was collected from different universities. Further search and investigation for more textual learning material was required and after a very intensive research introduction into software engineering and introduction into network courses were selected due to their large textual data and its characteristics and the presentation of it being different from one university to another.

The researcher chose those particular universities since they have a good reputation. Also, they have an interest in developing online courses as a primary learning method and they are shifting most of their courses to E-learning. Finally, they have a huge library of online courses in text format and other learning tools.

Three subjects were selected E-commerce, Software engineering and network. The ILOs for e-commerce were collected from Harvard University and for software engineering were collected from Saylor Academy.



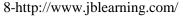
The learning materials for the e-commerce were collected from different educational websites. METU¹ open course ware, San Jose University², Arab academy³ for science and technology and northern university⁴. Software engineering learning materials were collected from the University of Cambridge⁵, tutorials points⁶ and the University of Lugano⁷. Finally, the network learning material was collected from Jones and Bartlett learning website⁸. For more details about ILOs, *see appendix 1.2*.

3.3 Concepts Extraction

The next step following collecting ILOs and learning materials, is to convert the learning materials into text file and to extract concepts from all texts. An easy to use open source ontological tool, KAON, was used to perform this process as explained in detail in chapter two. If we consider the first file (Introduction to e-commerce) referred to as (C1) as a shortcut file name. The file was converted to text and fed into KAON to extract concepts.

The extraction process for (C1) started with setting the frequency parameter to three however, the results were four hundred concepts with many unnecessary concepts. Accordingly, the frequency was set to four then five then six. At frequency six the results were acceptable but the best frequency had to be chosen. To achieve that, the lists of extracted concepts for frequency four, five and six were presented to an educational expert.

1- http://ocw.metu.edu.tr/ 2-http://www.sjsu.edu/ 3-http://www.aast.edu/ 4-http://www.northern.edu/ 5-https://www.cam.ac.uk/ 6- https://www.tutorialspoint.com 7-http://www.usi.ch/en





They decided to go with frequency six as it has a group of terms that are important in the field. Sporkforge, an online tool to analyze a set of texts, was used to perform the elimination process for stopping words and characters hoping to ultimately refine the results of extraction ontology concepts. Final results show 165 concepts for the file (C1). The same steps were followed with the e-commerce's ILOs.

The same process was implemented on all textual learning materials. Four E-commerce learning materials and their designated ILOs, Three Software Engineering learning materials and their designated ILOs and network learning material. For a sample list of the concepts that has been extracted from the learning material please refer to table 3.1 and for the sample ILOs that has been extracted from the learning material refer to table 3.2. *For the complete of concepts refer to appendix 3*.



1	access	40	government	79	control	118	revenue
2	accuracy	41	group	80	shop	119	practice
3	advantage	42	help	81	experience	120	procedures
4	analyses	43	horizontal	82	software	121	important
5	auction	44	industry	83	speed	122	operate
6	book	45	inform	84	character	123	infrastructure
7	Business	46	instance	85	store	124	resource
8	commerce	47	inventories	86	subscription	125	agreement
9	relationship	48	status	87	supply	126	improvement
10	catalog	49	mail	88	support	127	track
11	chain	50	rebates	89	time	128	package
12	management	51	manual	90	trade	129	enhancement
13	channel	52	manufacture	91	traditionalist	130	implementation
14	communication	53	market	92	Traffic	131	broker
15	Companies	54	model	93	type	132	price
16	web	55	merchant	94	value	133	media
17	site	56	sale	95	voice	134	report
18	computer	57	offer	96	wall	135	provider
19	confirmation	58	order	97	mart	136	payment
20	connection	59	organ	98	demand	137	quality
21	cost	60	Participate	99	structure	138	maintenance
22	service	61	popularity	100	transaction	139	application
23	Cycle	62	post	101	facilitating	140	promotion
24	process	63	power	102	activity	141	survey
25	data	64	presences	103	customer	142	interaction
26	deliveries	65	privacy	104	opportunities	143	dynamic
27	employee	66	procurement	105	cooperation	144	saving
28	result	67	product	106	share	145	request
29	environment	68	profit	107	information	146	refill
30	exchange	69	Purchase	108	program	147	invoice
31	expertise	70	recognition	109	organization		
32	extensibility	71	regularity	110	publishing		
33	markup	72	fulfillment	111	distributing		
34	language	73	administration	112	material	165	shipping
35	figure	74	announcement	113	establishment		
36	function	75	trend	114	training		
37	goal	76	search	115	bank		
38	goods	77	security	116	retailer		
39	example	78	sell	117	reduce		

Table 3.1: Sample of learning material Text Extracted Concepts



No.	Concept	No.	Concept
1	Advertisement	18	Outcome
2	Business	14	Request
3	Environment	15	Charge
4	commerce	16	Limitations
5	Market	17	challenges
6	Content	18	Applications
7	Contribution	19	Categories
•••••		•••••	
17	Driver	34	Framework

Table 3.2: Sample Extracted Concepts from ILOs

Table 3.3 presents the names for learning materials and the number of concepts which was extracted from each one.

Table 3.4 presents the number of extracted concepts for the ILOs. One ILOs for ecommerce learning material and one for software engineering learning material.



No.	Learning material name	File shortcut	Number of learning material Concepts
1	Introduction into electronic commerce	C1	165
2	Introduction into e-commerce	C2	163
3	Overview of electronic commerce	С3	140
4	E-commerce	C4	169
5	Fundamentals of software engineering	S1	200
6	Introduction into software engineering	S2	175
7	Software engineering	S3	185
8	Introduction into network	N1	116

 Table 3.3: Number of Extracted concepts of all learning materials

Table 3.4: Number of Extracted concepts of ILOs

No.	Learning material ILOs Name	File shortcut	Number of Concepts
1	ILOS of E-commerce	ICc	34
2	ILOS of software engineering	ICs	66

3.4 Applying the Measures

The next stage is applying the extracted concepts to the measures. WS4J tool is utilized at this point. The following will discuss and presents in details how this operation was done. It should be mentioned here that since we are experimenting with eight different measures and with a large data corpus that this operation required a long time and efforts to be completed.



3.5 Upload Concepts in WS4J

Concepts from ILOS and learning material have been extracted. As we explained in chapter 2 WS4J has two input options. To save time and effort we chose to match all the concepts at once. Figure 3.1 shows how this is done. For example, file (C1) has 165 concepts so 165 concepts were uploaded to WS4J and compared with 34 ILOS concepts.

WS	54J Den	0	
WS4J	(WordNet Simil	rity for Java) measures semantic similarity/related	Iness between words.
Word	Net loading stat		
Туре	in texts below, o	use: example words example sentence	s
1.	Input mode	Word Sentence	
2.	Sentence 1	dictator confusion hospital room arrest rule legality move supporter extraditio immunity extradition outcome request ch surgery death court government	n request
з.	Sentence 2	defense minister priest magistrate murd embassy police source insult team claim warrant attorney envoy extradition requ term rally week boss government officia	arrest est opinion *
4.	Submit	Calculate Semantic Similarity	

Figure 3.2: Calculate Concepts Semantic Matching



3.6 Calculate the Results for all Measures

After data collection and concept extraction is done for the ILOs and the learning material. Next step is applying the measures to the extracted concepts from learning material and ILOs. Table 3.5 shows a sample from the results which researcher concluded after applying the semantic similarity measure WuP to the extracted concepts for the first learning material file (C1). The table's column represents ILOs concepts where the table's row represents the learning material concepts. Table fields represent the matching value between two concepts.

All eight measures (WuP, LCH, LIN, Resnik, HSO, JSN, Path and LESK) were applied to all learning materials. Appendix 4 will include the samples of eight tables for (C1) learning material.

LC	IC1	IC2	IC3	IC32	IC33	IC34
	Advertisement	security	application	 companies	payments	issues
advantages	0.4286	0.5333	0.4286	 0.5333	0.4	0.4286
advertisement	1	0.625	0.7143	 0.4286	0.4	0.4286
affiliate	0.4286	0.6667	0.4706	 0.8571	0.4	0.7619
auction	0.3333	0.48	0.7	 0.3333	0.8182	0.75

 Table 3.5: Sample of Semantic Matching for WuP Results



For example: the two concepts matching from the (c1) file, first ILOS concept IC1 is Advertisement and first learning material LC1 is advantage, the result as shown in the table 3.5 using WUP measure is: 0.4286.

3.7 Evaluation

The evaluation process target is determining the quality of the learning material by comparing it to their designated ILOs. Educational expert evaluation of the learning material quality is considered first then a comparison is performed between the educational expert evaluation and semantic similarity measures results. After that, a calculation process for the errors of each measure is performed to figure which measure gave the minimum error. Descriptive statistical Root Mean Square Error (RMSE) will be used to evaluate the final results.



CHAPTER FOUR

Experimentation and Evaluation



Overview

This chapter will explain in details the proposed solution followed by the researcher. In the previous chapter, we showed from where the data was collected and how it was extracted. Several semantic measures have been identified to be employed in our experiments. This chapter will explain which measure gave the minimum error. The error will be computed by calculating the difference between the semantic measure result and the expert's evaluation. Hence, the researcher made two types of evaluations, which are the expert's evaluation and the semantic similarity measures' evaluation.

4.1 Proposed Model

Our proposed model contains the following phases:

- 1. Extracting concepts from the ILOs.
- 2. Extracting concepts from the learning material.
- 3. Calculating semantic measures among concepts.
- 4. Finding the best semantic measure with a minimum error.

As explained in the previous chapter, the data has been collected for both the learning materials and ILOs: three online courses consisted of eight learning materials and two ILOs.

In order to get accurate results, the learning materials and the ILOs were collected from different educational institutions. ILOs concepts were extracted first. Then, the concepts were extracted for each learning material individually. For example, the number of the extracted concepts from the first learning material of e-commerce (C1) is 165, while the number of extracted concepts from the ILOs (IC) is 34.



Eight measures have been applied on the extracted concepts to compare each concept from the learning material with the concept from the ILOS. From these measures, we will just demonstrate an example for WuP measure on the 165 concepts against the 34 concepts for the learning material and ILOs respectively. Table 3.5 shows a sample of the obtained results.

The first field of the Table 3.5 represents the concepts of the learning material (LC), where the concept in this example is "advantages". At the same table, the first row represents the ILOs concepts (IC). For each concept of the 165 concepts, we computed the WuP measure value with 34 ILOS concepts. This step has been repeated for all learning materials (four learning materials for e-commerce, three learning materials for software engineering and one for network). This step has been also repeated for the eight measures (WuP, LCH, LIN, Resnik, HSO, JSN, Path and LESK). *For full results see appendix number 4*.

4.2 Calculating the Maximum for Each Concepts

The maximum value is important to see how far these concepts are closed to each other. At first, we need to define the maximum value for each semantic measure (SM). Some of the semantic measures have an identified maximum value, whereas the maximum value needs to be calculated for some other measures. The maximum value for WuP, LIN and PATH is "1", while HSO measure maximum value is "16" (**Pedersen et al., 2004**). RES, JNC, LCH and LESK maximum value is infinite. Therefore, the maximum value needs to be calculated. The aim of this research is to find how much of the ILOs are covered in the learning material. For example, the ILOs were 34 concepts and the e-commerce learning material (C1) were165 concepts. This leads to the question which concepts out of the 34



gave the maximum value. We can also accept it if the maximum go beyond a certain point, which is called the "cutting point". As shown in Table 4.2, the maximum value is between concepts "auction" and ILOS concept "**payments**", which has the value (0.8182) using WuP measure.

LC	IC	IC2	IC3		IC32	IC33	IC34
	Advertisement	Security	Application		Companies	Payments	Issues
Advantages	0.4286	0.5333	0.4286		0.5333	0.4	0.4286
Advertisement	1	0.625	0.7143		0.4286	0.4	0.4286
Affiliate	0.4286	0.6667	0.4706		0.8571	0.4	0.7619
Auction	0.3333	0.48	0.7		0.3333	0.8182	0.75
•••					•••	•••	
Maximum values	0.9231	1	1	0.9412	0.875	0.9091	0.9524

 Table 4.2: Calculate Maximum Value Example using WuP

4.3 Calculate the Maximum for Each Semantic Measure

As previously mentioned, some measures do have a maximum value and some measures do not. WuP, LIN and PATH have a maximum value that is greater or equal to zero and less than or equal to one. The maximum value of HSO measure is greater than or equal to zero and less than or equal to 16. The maximum value is of great importance, as it helps us calculate the cutting point. The cutting point defines whether the semantic measure between two concepts is above or below a certain point. If yes, it will be accepted and it will be rejected if the answer is not. Thus, the maximum value will assist us in making sure whether the result is below this certain point. In this case, the result is rejected. For



example, LIN measure maximum value is "1". Calculating the accepted concepts for a certain point, which is for example "80%", allows us conclude that all semantic matching results achieving or overpassing "0.80" will be considered accepted, and that all other matching results below "0.8" will be rejected.

The remaining four measures (LESK, LCH, JCN and Resnik) have no maximum value. This means that the mximum value cannot be calculated, and that the percentage of the cutting point cannot be set. (Al kayed and Zaniab , 2015) presented four different techniques to calculate the maximum value for each semantic measure: max average, average for all results, trimming average for all results with 5% and trimming max average with 5% which they found it as the best technique. The best technique has been chosen to apply it into these measures Then, a cutting point can be set for each of those semantic measures. We applied the trimming max average method with 5% after the maximum values of semantic measure were sorted from low to high.

For example, in file (C1) extracted concepts from the ILOs were 34 and the extracted concepts from the learning material were 165. The semantic measures matching were computed for all extracted concepts. The maximum results were calculated as well. Sorting the maximum values was in ascending order. 5% trimming from 34 is "2" concepts. Therefore, 4 concepts were removed as follows: 2 concepts were removed from above and 2 other concepts were removed from below. The average of the remaining concepts "30 concepts" was calculated after trimming and the average was 8.8 (RES measure).



4.4 Semantic Matching with Different Cutting Points

In this part of the thesis, we shed light on the reasons behind the researcher's preference to choose multiple and various cutting points. It also indicates the outcomes resulting from using each one of them. Cutting points are mainly used to examine if two particular concepts are close or far and to what extent. In this study, we will choose three distinct cutting points: (70%, 80%, and 90%). The aim is to determine whether we accept or reject the matching results. After that, we will apply them to all semantic measures. Choosing multiple values is crucial, because we need to find out the best cutting point, which is critical to the success of the study. Another aspect related to the selection of the cutting point is how high the cutting points are as shown in the previous selected points. This is due to the fact that we aim at calculate the similarity between the learning material and the ILOs.

For each learning material and their ILOs, we measure these cutting points for the eight semantic measures. Equation (8) shows how the acceptance rate is calculated for a certain measure. Therefore, we apply this against the four e-commerce learning materials, the three software engineering learning materials and the learning material of network for the eight measures.

Acceptance Rate % =
$$\frac{\text{No. of ILOS concepts above cutting point \%}}{\text{No. of ILOs concepts}} 100\% \dots (8)$$

Different cutting points are used to check the coverage of ILOs within the subjects. Each measure has three different cutting points. The next section illustrates an example for some semantic measure with different cutting points.



Cutting point percentage calculation based on how the learning material cover ILOS concepts with threshold value. If we consider the first file (C1) for e-commerce learning material for instance, and if we calculate 90% from the maximum value of WuP measure, the result of the 90% cutting point for WuP measure is 73.5. As indicated earlier, the maximum value for WuP is 1. Hence, the value for 90% is 0.9. We conclude that all concepts with a maximum that is equal or greater than 0.9 is counted.

In the same file, we will go over the calculation performed using the 90% cutting point with WuP measure. Our goal is to determine how much of the ILOS are covered by the learning materials. The number of extracted concepts form ILOs is 34 concepts and that the number of extracted concepts from the learning material is 165.

We need then to calculate to what extent the ILO covers the learning material. The researcher chooses various points to accept or reject the results. The total number of concepts with a maximum value that is greater than or equal to 0.90 is 25 concepts. This means that the 25 ILOs concepts are covered within 165 learning materials concepts.

In order to calculate the coverage percentage, we divided the covered concepts from ILOS, which are 25 concepts, by the total number of the original extracted ILOS concepts, which accounts for 34 concepts. As shown in Table (4.3), the result from equation (8) is 73.5 for the first file(C1) using WuP measure. As for the second file (C2), the result is 82.3.

Acceptance Rate in 90% (c1) = 25\34 * 100% = 73.5



Learning material name	File	
	shortcut	"90%" cutting point
Introduction to electronic commerce	C1	73.5
Introduction to e-commerce	C2	82.3
Overview of electronic commerce	C3	88
E-commerce	C4	91.1

 Table 4.3: Sample of Result for the 90% Cutting Point in WuP Measure in E-commerce

As seen in Table (4.3), the course name is mentioned (E-Commerce) and the results of the 90% cutting point using WuP measure are indicated as well. A brief explanation will be presented later on to explain how the average error is calculated for each cutting point.

Table (4.4) shows another example using a different measure. We used HSO measure. As mentioned before, the maximum value for HSO is 16. Thus, we need to measure the degree of acceptance and rejection results to be above 80% cutting point, 80% from 16 is equal 14. Basically, all concepts with the maximum equal or greater than 14 are counted.

The results showed that concepts with maximum value above 14 are 22 concepts, which means that 22 ILOs concepts are covered in the Introduction into electronic commerce (C1). The final result is 64.7 using HSO measure.

Acceptance Rate in 80% (c1) $=\frac{22}{34}$ * 100% =64.7



Learning material name	File	
	shortcut	80% cutting point
Introduction into electronic		64.7
commerce	C1	04./
Introduction to e-commerce	C2	64.7
Overview of electronic commerce	C3	73.5
E-commerce	C4	76.4

 Table 4.4: Sample of Result for the 80% Cutting Point in HSO Measure for E-commerce

4.5 Result for Different Cutting Points

The following explains why different cutting points were applied. For each learning material, eight different measures were applied along with three different cutting points. The experiments for the course (E-commerce) contained four learning materials (4*8*3=96 experiments), while the course (software engineering) contained three learning materials (3*8*3=72 experiments) and the network course contained one learning material (1*8*3=24 experiments).

Table (4.5) presents a mockup of the results using different cutting points in WuP measure. By picking a high value cutting point such as 90%, we require a high coverage between the ILOs and the learning material, which means that the learning material achieved the most of ILOS. From Table (4.5), we can see the relation between the cutting point and the results. we notice that the lower cutting point value the higher result. The second text corpus (C2) using the 80% cutting point meaning the maximum value above 0.8 is counted. The result was 100 (34 concepts with the value above 0.8 divided by the total number of the original extracted concepts, which are (34). The result for the same text



corpus (C2) by applying a different 90% cutting point is 82.3 (28 concepts that have value above 0.9 divided by the total number of ILOs concepts (34).

Learning material name	File shortcut	70% cutting point	80% cutting point	90% cutting point
Introduction into electronic commerce	C1	100	100	73.5
Introduction into e-commerce	C2	100	100	82.3
Overview of electronic commerce	C3	100	100	88
E-commerce	C4	100	100	91.1

Table 4.5: Sample of Result for all Cutting Points in WuP Measure

4.6 Different Evaluation Rate

This research used human evaluation of the learning material coverage of ILOs. The experts will evaluate how much of the ILOs are covered in the learning material. They will decide which course gave a good coverage, which means that the learning material covers most of the content of its ILOs. Also, they will decide which course gave a bad coverage, which means that the learning material does not cover the ILOs. Their evaluation is important to the research, as it will be compared to the results of the semantic similarity measures, in order to help the researcher, decide which measure will be used to evaluate the quality of the learning material. The evaluation is divided into four sections: high coverage percentage (90), average coverage percentage (80), low coverage percentage (70) and (0) for no matching between ILOs and learning material. The courses on which the researcher applied the semantic measures will be evaluated by educational experts in those courses. They have an excellent background about the courses and they teach those courses in well-known universities. *For more*

details, refer to Appendix 6.



Learning material name	File shortcut	Expert Evaluation %
Introduction into electronic commerce	C1	70
Introduction into e-commerce	C2	80
Overview of electronic commerce	C3	80
E-commerce	C4	90
Fundamentals of software engineering	S1	70
Introduction into software engineering	S2	90
Software engineering	S3	70
Introduction into network	N1	0

 Table 4.6: Expert Evaluation Percentage for all Learning Materials

Table 4.6 presents the percentage of expert's evaluation for all learning materials. The expert evaluation was 90% for file (C4). This means learning material (C4) covers most of the content of their ILOs. As for file (C1), the expert finds that the coverage of the ILOS is 70%, which means that the learning material has low coverage comparing with their ILOs.

The expert's evaluation part is performed for all learning materials. In this experiment, we need to find which measure can give a result that is close to expert's evaluation. Also, we need to find which measure can give the minimum error. Besides, this experiment needs different cutting points to compute the coverage of the ILOs.



4.7 Experiment result and analysis

To find the quality of learning material, the researcher has to explore which one of the semantic measures gives the minimum error. Through the results, the best measure is the measure that can give minimum error.

This research uses the Root-Mean-Square Error (RMSE), which is a measure type of error. It is a very frequently used measure of the differences between the values predicted by an estimator or a model and actual observed values. In this research, RMSE was used to compute the average error of each semantic measure, where each measure will have three RMSE results, as each one of the semantic similarity measures has three cutting points (Chai and Draxler, 2014).

$$\mathsf{RMSE} = \sum_{1}^{n} \sqrt[2]{\frac{(human \, evaluation - cutting \, point \, result)^{2}}{n}} * 100\%.....(9)$$

Where n is a number of samples.

To calculate the RMSE for a certain cutting point, we need to calculate the difference between human and a given cutting point. The formula is as follows:

Error square for a cutting point = (Expert Evaluation - Cutting point result)²

For example, in e-commerce learning material (c1), the result using WuP measure in the cutting point 90% is 12.2. To calculate the error for the cutting point 90%, the result is the difference between the human evaluation, which is here 70, and the result for 90% cutting



point, which is here 73.5. Thus, the result for the error using WuP measure in 90% cutting point is as follows:

Error square cutting point $90\% = (70 - 73.5)^2 = 12.2$

To compute the RMSE, we must record the error between the human evaluation and the result obtained for each cutting point. This process is performed for different cutting points (70%. 80% and 90%) and for each semantic measure (WuP, Path, JCN, LCH, LIN, Resnik, HSO and Lesk). For further details, please refer to Appendix 5.

Table 4.7: Result for error square at Cutting Point 70%, 80% and 90% in WuP with Expert

Evaluation

Learning material name	File shortcut	Expert Evaluation %	70% cutting point	Error 70%
Introduction into electronic commerce	C1	70	100	900
Introduction to e-commerce	C2	80	100	400
Overview of electronic commerce	C3	80	100	400
E-commerce	C4	90	100	100
Fundamentals of software engineering	S1	70	77.2	51.84
Introduction into software engineering	S2	90	78.8	125.44
Software engineering	S3	70	74.2	17.64
Introduction into network	N1	0	77.2	5959.8



Learning material name	File shortcut	Expert Evaluation %	80% cutting point	Error 80%
Introduction into electronic commerce	C1	70	100	900
Introduction into e-commerce	C2	80	100	400
Overview of electronic commerce	C3	80	100	400
E-commerce	C4	90	100	100
Fundamentals of software engineering	S1	70	72.7	7.29
Introduction into software engineering	S2	90	74.2	249.64
Software engineering	S3	70	68.1	3.61
Introduction into network	N1	0	63.6	4044.9

Learning material name	File shortcut	Expert Evaluation %	90% cutting point	ERROR 90%
Introduction into electronic commerce	C1	70	73.5	12.25
Introduction into e-commerce	C2	80	82.3	5.29
Overview of electronic commerce	C3	80	88	64
E-commerce	C4	90	91.1	1.21
Fundamentals of software engineering	S 1	70	62.1	62.41
Introduction into software engineering	S2	90	65.2	615.04
Software engineering	S3	70	56	196
Introduction into network	N1	0	28.7	823.6

Table 4.7 shows the results for the cutting points "60%, 80% and 90%" respectively in WuP with human evaluation rate. It also shows the error for each cutting point. To calculate the error for each cutting point, we need to find the difference between the human evaluation and the result for each cutting point as previously mentioned. For example, in the first learning material from software engineering (S1), the expert evaluated the coverage of the learning materials by comparing it with its ILOS. The result of the expert's evaluation was 70. The calculation using WuP measure in the 90% cutting point is 62.4. Therefore, the error between the result of the expert's evaluation and the result of the expert between both.



The result is as follows:

Square error in $90\% = (70 - 62.1)^2 = 62.4$

This is performed for all cutting points. For example, Resnik measure has three different cutting points. The same is performed on the rest of semantic measures. Through these experiments' results, we need to figure which measure of the eight measures gives minimum error in a certain cutting point. For that we need to calculate RMSE at different cutting point.

1- Result for E-commerce learning materials:

The results for the expert's evaluation came with different percentage based on the coverage of the main content of learning material with its ILOs. As we have previously mentioned, this experiment used the expert's evaluation to evaluate the quality of the learning material. This is done by performing a comparison with their ILOs. To compare the result of the expert's evaluation and results of semantic measures, concepts were extracted from both learning material and ILOs. Then, eight measures were applied on the extracted concepts. A calculation process was carried out to figure the average error for each one of the semantic measures. Since the research requires a high coverage percentage between the ILOs and the learning material which leads to the conclusion that the learning covered most of the ILOs. A high cutting point value 90% were chosen and since our research is based on experiments the researcher picked another high value cutting point 70% and 80% to figure which measure gave the minimum error in the chosen courses.



each e-commerce and software engineering we conclude that the best measure to evaluate the quality of learning material. Meaning if a certain cutting point gave the least error for a certain measure in the chosen courses that measure is considered the best measure.

Both cutting points 70% and 80% gave different measure which has the minimum error however, the 90% cutting point gave the same measure which is LIN.

The results showed in e-commerce subject that LIN at the cutting point 90 has the minimum error with (2.5%) average errors. Table 4.8 and Figure 4.1 present the results at the cutting point 90%. It is clear that LIN measure has the minimum average error's value.

Measures	RMSE at the 90%Cutting point
WuP	5.0
LCH	8.5
LIN	<u>2.5</u>
Resnik	17.5
HSO	11.5
LESK	28.5
Path	13.0
JCN	15.0

 Table 4.8: RMSE in the 90% Cutting Point for E-commerce Learning Materials



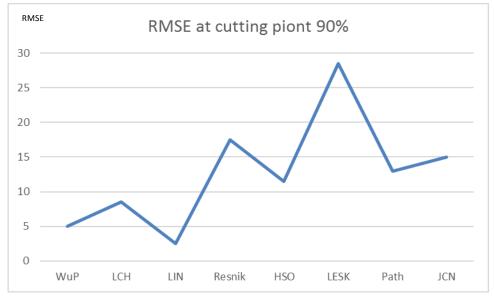


Figure 4.1: Average Error for RMSE in the Cutting Point 90%

Measures	RMSE at the cutting point 70%	RMSE at the cutting point 80%	RMSE at the cutting point 90%
WuP	21.5	21.5	5.0
LCH	21.5	5.5	8.5
LIN	15.0	11.5	<u>2.5</u>
Resnik	18.5	16.5	17.5
HSO	11.5	11.5	11.5
LESK	16.0	26.5	28.5
Path	13.0	13.0	13.0
JCN	15.0	15.0	15.0

Table 4.9: RMSE in all (Cutting Points for E-commerce	Learning Materials



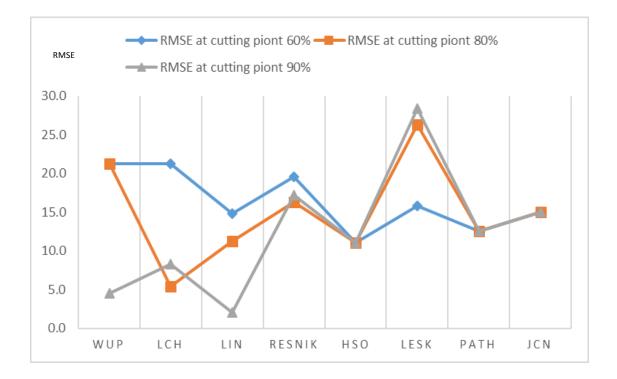


Figure 4.2: RMSE in all Semantic Measures for E-commerce Learning Material

2- Result for Software Engineering Learning Materials:

This research used three subjects. The first subject, which is e-commerce, contains four learning materials and its ILOs. We applied our experiments in the first subject, but to evaluate the results, we used another subject software engineering, which contains three learning materials and its ILOs. We also used a third subject, which is computer networks, to prove that the research model will reject this learning material when it is compared with the software engineering's ILOs and will give a low percentage for covering. Similar to the e-commerce, the error is calculated by computing the difference between an expert's evaluation and the results for each measure. Then calculate the RMSE for each cutting point.



The results showed in the subject of software engineering that (LIN) has the minimum error with (5.8) average errors at the cutting point 90%. Table 4.10 and Figure 4.3 present the results at the cutting point 90%. It is obvious that LIN measure has minimum error value.

The calculations and results for e-commerce and software engineering courses showed that LIN measure gave the minimum error at the cutting point 90%. In both topics, the error's percentage was a minimum at the cutting point 90%. The error's percentage began to drop from the cutting point 60% to reach the minimum at the cutting point 90%, which is good for the research, as it requires a high similarity percentage between the learning material and the ILOs.

Measures	RMSE at cutting point 90%
WuP	17.1
LCH	9
LIN	<u>5.8</u>
Resnik	10.4
HSO	27.8
LESK	28.5
Path	33.1
JCN	33.5

 Table 4.10: RMSE in the Cutting Point 90% for Software Engineering Learning Materials



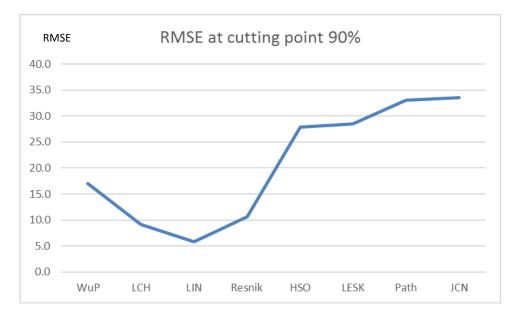


Figure 4.3: RMSE in the Cutting Point 90% for Software Engineering Learning Materials

Table 4.11: RMSE in all	Cutting Points for	Software Engineering	Learning Materials
	8	0 0	0

Measures	RMSE at cutting point 70%	RMSE at cutting point 80%	RMSE at cutting point 90%
WuP	8	9.3	17.1
LCH	9.2	8.4	9
LIN	6.6	5.9	<u>5.8</u>
Resnik	8.2	7.8	10.4
HSO	27.8	27.8	27.8
LESK	19.4	23.3	28.5
Path	33.1	33.1	33.1
JCN	33.5	33.5	33.5



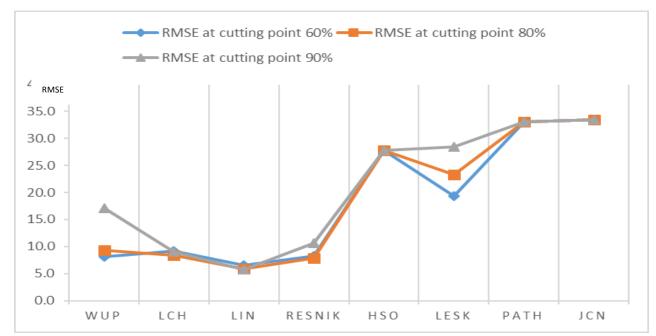


Figure 4.4: RMSE of all Semantic Measures for Software Engineering Learning Materials

3- Result for Network Learning Material:

In this experiment, the researcher wants to prove that when the ILOs concepts for a certain topic are different from the learning material concepts the similarity percentage will be very low at a certain cutting point. Table 4.12 shows that the expert evaluated the network topic by zero, as its concepts differ from the ILOs concepts for the software engineering topic.

As shown in Table 4.12, when comparing the concepts of network learning material with the concepts of software engineering's ILOs, the result of matching in all cutting points is very low using LIN measure. This means that the learning material does not sufficiently cover the software engineering's ILOs. We conclude that the learning material is rejected.



LIN					
File name	File shortcut	Expert evaluation	70% Cutting point	80% Cutting point	90% Cutting point
Network	N1	0	60.6	36.3	<u>19.6</u>

Table 4.12: RMSE in all Cutting Points for Network Learning Material



CHAPTER FIVE

Conclusions and Future work



Overview

Chapter five summarizes the work of this research. It presents the conclusion obtained from the results of the experiments. Also, it presents the future work of this research.

5.1Conclusion and Contributions

This research concluded in determining the best measure that gave the minimum error for measuring the quality of learning material.

The researcher had educational experts in the courses evaluating the coverage of the ILOs in the learning material. Then, the semantic similarity measures were applied to both the learning material and the ILOs. The results obtained from the experiments show that LIN measure has the best coverage, as it gave the minimum error's percentage. If any educational institute or student wants to determine the coverage of the ILOs in the learning material, they can use LIN measure.

This research evaluated the semantic measures and showed how these measures can be utilized to evaluate the quality of learning material. It helped in defining the best semantic measures with minimal error that computes the coverage of the ILOs in the learning material.

Below are the main outcomes of this research:

1- This research presented a method in how to determine the quality of the learning material using eight different semantic similarity measures, which are as follows: WuP, LCH, LIN, Resnik, HSO, Path, JCN and LESK to achieve semantic matching as well as to cover all families of semantic measures.



2- This research computed the coverage of the ILOs by utilizing three different cutting points for each measure. Picking a different cutting point helped the research determine how close learning materials concepts to the ILOs concepts.

3- The final results of the experiments showed that LIN measure is the best measure to evaluate the coverage of the ILOs in the learning material.

5.2 Future work

There are several issues that can be further explored from this thesis. These issues are as follows:

- 1) Using other semantic measures.
- 2) Measuring the quality of Arabic learning material.
- Using the semantic measures to experiment with other fields in the educational domain.



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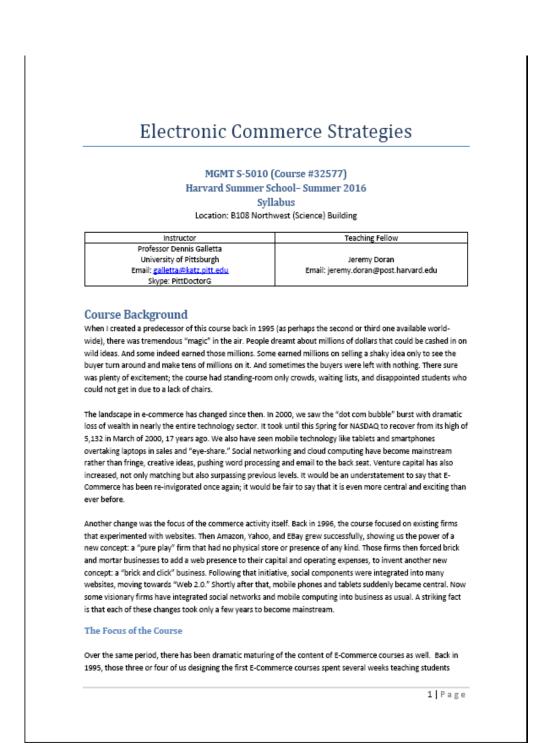
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Appendix

1. Harvard university syllabus and learning outcomes (e-commerce):





Final Course Outline

_		Part 1: Introduction	
1	June 21	Introduction	Chap 1
		Group Formation	Galletta (2009)1
		Strategic Models	,
2	June 23	e-Commerce Business Models and Concepts	Chaps 2, 3
		e-Commerce Infrastructure	Cummings ² and
		Creative Applications	Kay ³ articles
		Group adjustments/reformation	
		Part 2: Technology Infrastructure for E-Business	
3	June 28	Uber case analysis due (individual) - see the last section of	Chap 3 (continued), Chap 8
		this syllabus for all case questions!	(sec 1 only)
		E-Commerce Infrastructure	
		Ethical Issues	
3	June 30	Lands End case analysis due (group)	Chap 5
		E-Commerce Security	
4	July 5	iPremier case analysis due (individual)	Chap 5 (continued)
		E-Commerce Security	
		Quiz 1	
		Part 3: Business Concepts and Social Issues	
5	July 7	Orbitz case analysis due (group) (pp. 242-245)	Chap 5 (conclusion)
		Building an E-Commerce Presence	Chap 4 pt. 1
6	July 12	Twitter vs Facebook case analysis due (brief class discussion	Chap 4 pt. 2
		only; nothing written) (text Chaps 2 pp. 53-56; plus Chap 7	Google Adwords Infographic ⁴
		pp. 421-423)	Chap 6 pt. 1
		E-Commerce Marketing and Advertising Concepts	
		Failures analysis due (group)	
7	July 14	Amazon case analysis due (individual)	Chap 6 pt. 2
		E-Commerce Marketing and Advertising Concepts	Loiacono ⁵
		Part 4: E-Commerce in Action	
8	July 19	New York Times case analysis due (group)	Chap 7
		Social, Mobile, and Local Marketing	Elberse ⁶
		The Long Tail	
		Quiz 2	
9	July 21	Etsy case analysis (individual)	Chaps 8, 9 pt. 1
		Ethical, Social, Political Issues	
		Online Retailing and Services	
10	July 26	Threadless case analysis due (group)	Chap 9 pt. 2, Chap 10
		Crowdsourcing	Bonabeau ⁷
		Online Retailing and Services	
		Online Content and media	
11	July 28	eBay case analysis due (individual) (text Chap 11 pg 742-744)	Chaps 11, 12
		Social Networks, Auctions, and Portals	
		B2B, Supply Chain, Collaborative Commerce	
Final	Aug 2	Online Entrepreneurship Project - Presentations (group)	
	1	Quiz 3	

Note: All case analyses are due online (Word or PDF format are preferred) by the minute class begins. For each 5 minutes or fraction thereof, 1 point is deducted until the score becomes zero (this occurs in less than a half hour).

6 Page



E-commerce , learning outcomes(ILOS) from Harvard university:

- 1. Define electronic commerce (EC) and describe its various categories.
- 2. Identify and describe the unique features of e-commerce technology and Discuss their business significance.
- 3. Describe the major types of e-commerce.
- 4. Discuss the origins and growth of e-commerce.
- 5. Describe and discuss the content and framework of EC.
- 6. Describe the digital revolution as a driver of EC.
- 7. Describe the business environment as a driver of EC.
- 8. Describe some EC business models.
- 9. Describe the benefits of EC to organizations, consumers, and society.
- 10. Describe the limitations of EC.
- 11. Describe the contribution of EC to organizations responding to environmental pressures.
- 12. Identify some of the major challenges that companies must overcome to succeed in ecommerce
- 13. Describe some of the current uses and potential benefits of m-commerce
- 14. Identify several e-commerce applications
- 15. Outline the key components of technology infrastructure that must be in place for ecommerce to succeed
- 16. Discuss the key features of the electronic payments systems needed to support ecommerce
- 17. Identify the major issues that represent significant threats to the continued growth of ecommerce
- 18. Outline the key components of a successful e-commerce strategy
- 19. Recognize business models in other emerging areas of e-commerce.
- 20. Understand key business concepts and strategies applicable to e-commerce.



2- Software engineering, learning outcomes(ILOS) from saylor academy¹:

- 1. explain and define software engineering.
- 2. identify the differences between software engineering and computer science.
- 3. relate software by characteristics, responsiveness, and type.
- 4. incorporate the attributes of good software.
- 5. interpret the three major methodologies in software engineering.
- 6. show an understanding of software engineering code of ethics in professional practice.
- 7. illustrate the software development life cycle (SDLC).
- 8. prepare the sequence of activities and deliverables in a sequential life cycle model.
- 9. prepare the sequence of activities and deliverables in an iterative life cycle model.
- 10. compare and contrast the two categories of life cycle models.
- 11. interpret the context appropriate for five commonly used UML artifacts.

12. apply abstraction to the UML artifacts to arrive at essential object-oriented modeling concepts.

- 13. choose data types.
- 14. interpret data/requirements gathering techniques.
- 15. compare and contrast data gathering techniques most appropriate for each application type.
- 16. prepare request for proposal and evaluation of proposal regarding hardware and software.
- 17. interpret fundamental software requirements and analysis terms.
- 18. practice the four activities of software requirements and analysis.
- 19. use requirements elicitation techniques.

20. interpret the conceptual foundation underlying data-oriented, process-oriented, and objectoriented methodologies.

21. show the analysis activities and their major representations in data-oriented, processoriented, and object-oriented methodologies.

22. use software design principles.



23. interpret architectural design in terms of decisions, system organization, modular decomposition, and flow-and-control.

24. employ design activities and their major representations in data-oriented, process-oriented, and object-oriented methodologies.

25. interpret programming.

26. identify the characteristics and selection of programming/implementation languages.

27. interpret the concepts for purchasing of hardware and software.

28. demonstrate basic software testing terminologies.

29. compare and contrast the use of various testing strategies, including black-box, white-box, top-down, and bottom-up.

30. design a test plan to include unit, integration, and system levels of test coverage.

31. compare and contrast the role of the project manager relative to the software engineer.

32. identify the three areas of responsibilities of a project manager.

33. illustrate the concepts of project management in terms of the project (i.e., planning, scheduling, execution, etc.).

34. apply the concepts of project management in terms of the people (i.e., hiring, motivating, evaluating, firing, etc.).

35. employ the concepts of project management in terms of change management (i.e., application, software, configuration, etc.).

1 https://learn.saylor.org



No.	Concepts	No.	Concepts	No.	Concepts	No.	Concepts	No.	Concepts
1	advantages	30	discount	59	management	88	purchase	117	Partial
2	advertisement	31	drive	60	market	89	reduction	118	forms
3	affiliate	32	earn	61	marketplace	90	resource	119	degree
4	auction	33	economic	62	mass	91	response	120	digitization
5	benefits	34	electric	63	material	92	revenue	121	Dimensions
6	broker	35	employee	64	model	93	revolution	122	agent
7	business	36	empowerment	65	mortar	94	role	123	link
8	buy	37	enterprise	66	name	95	sale	124	retailing
9	category	38	environment	67	network	96	seller	125	bid
10	chain	39	evaluation	68	online	97	service	126	purposes
11	classification	40	failure	69	organization	98	shopper	127	train
12	commerce	41	fee	70	partner	99	site	128	citizens
13	community	42	framework	71	peer	100	society	129	finance
14	company	43	good	72	people	101	standard	130	actions
15	computer	44	government	73	plan	102	items	131	barter
16	concept	45	group	74	policy	103	maintenance	132	improvement
17	consumer	46	growth	75	pressure	104	method	133	requests
18	control	47	improvement	76	price	105	Specialization	134	case
19	corporation	48	individually	77	process	106	superbly	135	Limitations
20	cost	49	information	78	product	107	supplier	136	Тах
21	customer	50	infrastructure	79	project	108	technology	137	Permits
22	definition	51	integration	80	proposition	109	tender	138	Pure



23	delivery	52	issue	81	public	110	time	139	subscription
24	description	53	knowledge	82	mortar	111	transaction	140	system
25	develop	54	learn	83	name	112	value	141	portal
26	device	55	limitation	84	network	113	viral	142	Communication
27	digitally	56	major	85	online	114	virtually		
28	strategy	57	facilities	86	supports	115	web		
29	structure	58	Categories	87	Quantities	116	trading		



4- semantic matching results for "introduction into electronic commerce" (C1samples):

	LC	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9	IC10	IC11	IC12	IC13	IC14	IC15	IC16
		Advertisement	security	application	component	features	significance	revolution	driver	consumer	market	growth	strategy	contribution	vision	factors	framework
1	access	0.5	0.6667	0.7368	0.7619	0.7619	0.7	0.6316	0.6667	0.5556	0.6316	0.6154	0.6667	0.6	0.5263	0.7619	0.7619
2	accuracy	0.4615	0.5714	0.4615	0.5455	0.4	0.6667	0.4615	0.3333	0.3077	0.4615	0.4706	0.375	0.4286	0.4286	0.4615	0.5714
3	advantage	0.4286	0.5333	0.4286	0.5	0.375	0.625	0.4286	0.3158	0.2857	0.4286	0.4444	0.3529	0.4	0.4	0.6667	0.5333
4	analysesS	0.6154	0.7059	0.7619	0.5455	0.625	0.6667	0.6667	0.5	0.3077	0.7778	0.5556	0.6957	0.7368	0.6	0.5217	0.5217
5	auction	0.3333	0.48	0.7	0.381	0.5	0.4	0.7	0.2609	0.2222	0.7368	0.5263	0.381	0.75	0.5263	0.4762	0.381
6	book	0.6667	0.7059	0.6667	0.5455	0.8421	0.7143	0.4615	0.5455	0.5263	0.6154	0.7692	0.375	0.4286	0.4286	0.5333	0.6667
7	BusinessP	0.4615	0.6316	0.8235	0.6316	0.6316	0.6667	0.7778	0.3333	0.3077	0.875	0.625	0.7273	0.9091	0.625	0.6316	0.6316
8	commerce	0.5333	0.8	0.7059	0.4615	0.5882	0.5714	0.8235	0.4	0.2667	0.7059	0.625	0.4444	0.8571	0.625	0.5556	0.4444
9	relationship	0.5	0.7143	0.5	0.8	0.4286	0.5455	0.5	0.3636	0.3333	0.5	0.5882	0.4	0.6154	0.4615	0.5	0.5714
10	catalog	0.625	0.5556	0.625	0.4444	0.7273	0.6667	0.375	0.48	0.4545	0.5217	0.4706	0.3158	0.3529	0.3529	0.4348	0.5714
11	chain	0.4	0.8	0.4444	0.6667	0.6316	0.4286	0.4	0.7273	0.7273	0.7368	0.7273	0.3333	0.375	0.375	0.8235	0.6316
12	management	0.4	0.5263	0.7059	0.4615	0.5882	0.4706	0.8235	0.3	0.2667	0.7059	0.625	0.4444	0.6667	0.625	0.5556	0.4444
13	channel	0.4	0.6316	0.75	0.5333	0.75	0.4706	0.75	0.5455	0.5263	0.75	0.625	0.4444	0.7826	0.625	0.5556	0.6667
14	communication	0.7273	0.6154	0.8	0.7273	0.625	0.4706	0.8	0.5	0.3636	0.8	0.6667	0.4706	0.75	0.6667	0.5882	0.5
15	CompaniesS	0.4286	0.7368	0.4706	0.5	0.5	0.4706	0.4286	0.7619	0.7619	0.7059	0.5714	0.3529	0.4	0.4	0.7273	0.5
16	web	0.4615	0.8	0.4615	0.7273	0.75	0.5	0.4615	0.6087	0.5556	0.6316	0.8	0.375	0.4286	0.4286	0.5333	0.7059
17	site	0.2667	0.7619	0.3529	0.5714	0.6	0.2857	0.2667	0.5833	0.4762	0.5455	0.6154	0.2222	0.25	0.25	0.4545	0.6
18	computer	0.2857	0.8	0.5	0.5	0.6316	0.3077	0.2857	0.8	0.8	0.5714	0.5333	0.2353	0.2667	0.2667	0.7619	0.6316
19	confirmation	0.7143	0.625	0.7368	0.5263	0.5556	0.7692	0.7059	0.4211	0.2857	0.7778	0.5882	0.5263	0.7368	0.5882	0.5263	0.5263
20	connection	0.5	0.7778	0.7778	0.8	0.7059	0.5556	0.6667	0.8	0.8	0.6667	0.6154	0.5263	0.6316	0.7368	0.8696	0.7059
21	cost	0.4	0.8	0.4	0.6154	0.3529	0.5556	0.4	0.3	0.2667	0.4	0.4211	0.3333	0.7059	0.375	0.4	0.5

A) WuP measure:

B) -Resnik measure:

		LC	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9	IC10	IC11	IC12
			Advertisement	security	application	component	features	significance	revolution	driver	consumer	market	growth	strategy
		access	3.0718	4.6003	8.5877	4.5549	4.5549	4.0582	2.6044	8.5877	1.3696	2.6044	4.093	4.0582
	1	accuracy	0.7794	2.3982	0.7794	0.7794	0.7794	4.1033	0.7794	0.7794	0	0.7794	2.3982	0.7794
	2	advantage	0.7794	2.3982	0.7794	0.7794	0.7794	4.1033	0.7794	0.7794	0	0.7794	2.3982	0.7794
	3	book	4.0382	4.6933	4.6003	1.1692	5.6543	4.0382	0.7794	4.6003	1.3696	2.8722	5.254	0.7794
	4	BusinessP	0.7794	3.8937	4.7636	3.3927	3.3927	3.3927	4.5251	0.7794	0	6.1203	2.8722	5.823
	5	commerce	3.0718	7.5173	3.0718	1.7798	3.0718	3.0718	4.5251	3.0718	0	3.8937	2.8722	1.7798
	6	relationship	0.7794	3.1688	0.7794	3.1379	0.7794	2.3982	0.7794	0.7794	0	0.7794	3.1688	0.7794
	7	process	3.0718	6.0586	4.6003	2.7753	3.7607	3.0718	2.6044	4.6003	0.6144	3.3826	4.093	2.7753
	8	catalog	4.0382	4.0382	4.0382	1.1692	5.6543	4.0382	0.7794	3.0718	1.3696	2.4934	1.1692	0.7794
	9	management	0.7794	3.5267	2.6044	1.7798	2.2541	1.7798	4.5251	0.7794	0	3.5267	2.8722	1.7798
	10	channel	0.7794	2.6044	2.6044	1.7798	3.7607	2.3982	4.5251	2.4934	1.3696	2.6044	2.3982	1.7798
	11	communication	3.0718	3.1379	3.0718	3.1379	3.0718	3.0718	2.6044	3.0718	0	2.6044	2.2541	1.7798
	12	CompaniesS	0.7794	4.7838	1.8747	1.1692	1.3696	2.3982	0.7794	1.9033	1.9033	3.8937	3.1688	0.7794
	13	web	0.7794	4.3676	0.7794	1.1692	3.7607	0.7794	0.7794	3.4451	1.3696	2.8722	2.8722	0.7794
	14	site	0	4.3676	0.6144	1.1692	2.4934	0	0	3.4451	1.3696	2.4934	1.1692	0
	15	computer	0	4.3676	1.8747	1.1692	2.4934	0	0	3.4451	1.9033	2.4934	1.1692	0
	16	confirmation	4.0382	4.0382	4.0382	2.7753	3.0718	4.0382	2.6044	3.0718	0	3.3826	2.2541	2.7753
	17	connection	0.7794	4.1005	4.1005	3.1379	2.7753	2.7753	2.6044	3.4451	1.9033	2.6044	3.1688	2.7753
	18	cost	0.7794	5.4027	0.7794	3.1379	0.7794	6.2564	0.7794	0.7794	0	0.7794	2.3982	0.7794
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	LC	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9	IC10	IC11	IC12
		Advertisement	security	application	component	features	significance	revolution	driver	consumer	market	growth	strategy
	access	0.0625	0.0633	0.0694	0.1329	0.1286	0.0923	0.064	0.0689	0.0827	0.0857	0.0728	0.1012
1	accuracy	0.0628	0.0782	0.0651	0.0917	0.07	0.1124	0.0603	0.0567	0.0613	0.0629	0.0823	0.065
2	advantage	0.0681	0.0865	0.0708	0.1034	0.0767	0.1306	0.0652	0.0609	0.0663	0.0683	0.0916	0.0706
3	analysesS	0.0733	0.0981	0.1323	0.1025	0.0899	0.0839	0.0849	0.0606	0.0659	0.1049	0.0807	0.0817
4	auction	0	0	0	0	0	0	0	0	0	0	0	0
5	book	0.0942	0.1267	0.0863	0.0952	0.1621	0.1125	0.0618	0.0712	0.0861	0.0894	0.0755	0.0667
6	commerce	0.0757	0.077	0.1112	0.1222	0.1047	0.0871	0.1572	0.067	0.0736	0.1051	0.0924	0.0937
7	relationship	0.0676	0.0988	0.0703	0.1676	0.0761	0.0895	0.0647	0.0606	0.0659	0.0678	0.1054	0.0701
8	process	0.0842	0.0857	0.1217	0.1672	0.1605	0.1206	0.095	0.0852	0.0961	0.1145	0.2795	0.1361
9	catalog	0.0926	0.0799	0.085	0.0813	0.0959	0.1102	0.0557	0.0546	0.063	0.0647	0.0596	0.0596
10	chain	0.0614	0.0622	0.0636	0.0888	0.0906	0.0687	0.059	0.0555	0.063	0.0944	0.0712	0.0635
11	management	0.0695	0.0705	0.0982	0.1067	0.0931	0.0789	0.1324	0.0621	0.0677	0.0935	0.0833	0.0843
12	channel	0.0579	0.0694	0.0763	0.0817	0.1174	0.0719	0.0699	0.0618	0.0673	0.0734	0.0726	0.0677
13	communication	0.177	0.184	0.1512	0.192	0.1166	0.2549	0.092	0.0837	0.0942	0.0982	0.1031	0.1031
14	CompaniesS	0.0689	0.0822	0.0717	0.1053	0.0777	0.0782	0.0659	0.0662	0.0729	0.0939	0.0867	0.0715
15	web	0.0633	0.0642	0.0657	0.0929	0.0852	0.0711	0.0608	0.0571	0.0646	0.0803	0.0738	0.0656
16	site	0.0614	0.0622	0.0636	0.0888	0.0724	0.0687	0.0591	0.0658	0.0783	0.0685	0.0714	0.0635
17	computer	0.0539	0.0546	0.0556	0.074	0.0645	0.0595	0.0521	0.0586	0.0684	0.0704	0.0615	0.0555
18	confirmation	0.0884	0.0767	0.0815	0.089	0.087	0.1043	0.0634	0.0531	0.0571	0.0663	0.0637	0.0793

c)- JCN measure:

D)- LCH measure:

		LC	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9	IC10	IC11	IC12
			Advertisement	security	application	component	features	significance	revolution	driver	consumer	market	growth	strategy
		access	1.4917	1.743	1.8971	1.8971	1.8971	1.743	1.6094	1.6094	1.4917	1.6094	1.8971	1.6094
	1	accuracy	1.6094	1.743	1.6094	1.8971	1.3863	1.8971	1.6094	1.4917	1.3863	1.6094	1.6094	1.291
	2	advantage	1.4917	1.6094	1.4917	1.743	1.291	1.743	1.4917	1.3863	1.291	1.4917	1.4917	1.204
	3	analysesS	1.8971	1.8971	1.8971	1.8971	1.743	2.0794	1.743	1.4917	1.3863	2.0794	1.6094	1.6094
	4	auction	1.1239	1.1239	1.743	1.291	1.291	1.204	1.743	1.0498	0.9808	1.8971	1.3863	1.0498
	5	book	1.8971	1.8971	1.8971	1.8971	2.3026	2.0794	1.6094	1.4917	1.3863	1.8971	2.3026	1.291
	6	commerce	1.6094	1.8971	1.8971	1.6094	1.6094	1.743	2.3026	1.291	1.204	1.8971	1.743	1.291
	7	relationship	1.743	2.0794	1.743	2.5903	1.4917	1.8971	1.743	1.6094	1.4917	1.743	1.743	1.3863
	8	process	1.6094	2.3026	2.3026	2.0794	2.5903	1.8971	2.0794	2.0794	1.8971	2.5903	2.9957	1.743
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E)- LIN measure:

LC	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9	IC10	IC11	IC12
	Advertisement	security	application	component	features	significance	revolution	driver	consumer	market	growth	strategy
access	0.0625	0.0633	0.0694	0.1329	0.1286	0.0923	0.064	0.0689	0.0827	0.0857	0.0728	0.1012
accuracy	0.0628	0.0782	0.0651	0.0917	0.07	0.1124	0.0603	0.0567	0.0613	0.0629	0.0823	0.065
advantage	0.0681	0.0865	0.0708	0.1034	0.0767	0.1306	0.0652	0.0609	0.0663	0.0683	0.0916	0.0706
analysesS	0.0733	0.0981	0.1323	0.1025	0.0899	0.0839	0.0849	0.0606	0.0659	0.1049	0.0807	0.0817
auction	0	0	0	0	0	0	0	0	0	0	0	0
book	0.0942	0.1267	0.0863	0.0952	0.1621	0.1125	0.0618	0.0712	0.0861	0.0894	0.0755	0.0667
commerce	0.0757	0.077	0.1112	0.1222	0.1047	0.0871	0.1572	0.067	0.0736	0.1051	0.0924	0.0937
relationship	0.0676	0.0988	0.0703	0.1676	0.0761	0.0895	0.0647	0.0606	0.0659	0.0678	0.1054	0.0701
process	0.0842	0.0857	0.1217	0.1672	0.1605	0.1206	0.095	0.0852	0.0961	0.1145	0.2795	0.1361
catalog	0.0926	0.0799	0.085	0.0813	0.0959	0.1102	0.0557	0.0546	0.063	0.0647	0.0596	0.0596
chain	0.0614	0.0622	0.0636	0.0888	0.0906	0.0687	0.059	0.0555	0.063	0.0944	0.0712	0.0635
management	0.0695	0.0705	0.0982	0.1067	0.0931	0.0789	0.1324	0.0621	0.0677	0.0935	0.0833	0.0843
channel	0.0579	0.0694	0.0763	0.0817	0.1174	0.0719	0.0699	0.0618	0.0673	0.0734	0.0726	0.0677
communication	0.177	0.184	0.1512	0.192	0.1166	0.2549	0.092	0.0837	0.0942	0.0982	0.1031	0.1031
CompaniesS	0.0689	0.0822	0.0717	0.1053	0.0777	0.0782	0.0659	0.0662	0.0729	0.0939	0.0867	0.0715
web	0.0633	0.0642	0.0657	0.0929	0.0852	0.0711	0.0608	0.0571	0.0646	0.0803	0.0738	0.0656
site	0.0614	0.0622	0.0636	0.0888	0.0724	0.0687	0.0591	0.0658	0.0783	0.0685	0.0714	0.0635
computer	0.0539	0.0546	0.0556	0.074	0.0645	0.0595	0.0521	0.0586	0.0684	0.0704	0.0615	0.0555
confirmation	0.4166	0.3204	0.3968	0.3306	0.3258	0.4573	0.184	0	0	0.1909	0.1849	0.3057
cost	0.0777	0.1825	0.0812	0.319	0.0891	0.301	0.0739	0.0685	0.0754	0.0779	0.0918	0.0811
customer	0.06	0.0608	0.0621	0.086	0.0704	0.067	0.0578	0.0766	1	0.0687	0.0695	0.062
service	0.0692	0.0702	0.1179	0.1061	0.083	0.0927	0.0787	0.0619	0.0674	0.0956	0.0819	0.0759
CycleP	0.0589	0.076	0.0679	0.1282	0.0686	0.0655	0.0776	0.0575	0.0668	0.0688	0.082	0.0637
time	0.0761	0.1	0.0998	0.1232	0.1124	0.1051	0.1221	0.0673	0.0739	0.0949	0.1334	0.0998
dataS	0.0714	0.0725	0.0874	0.1233	0.1196	0.096	0.079	0.0636	0.0695	0.0836	0.0796	0.1055

F)- Path measure:

	LC	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9	IC10	IC11	IC12
		Advertisemen t	security	application	component	features	significance	revolution	driver	consumer	market	growth	strategy
1	access	0.1111	0.1429	0.1667	0.1667	0.1667	0.1429	0.125	0.125	0.1111	0.125	0.1667	0.125
2	accuracy	0.125	0.1429	0.125	0.1667	0.1	0.1667	0.125	0.1111	0.1	0.125	0.125	0.0909
3	advantage	0.1111	0.125	0.1111	0.1429	0.0909	0.1429	0.1111	0.1	0.0909	0.1111	0.1111	0.0833
4	analysesS	0.1667	0.1667	0.1667	0.1667	0.1429	0.2	0.1429	0.1111	0.1	0.2	0.125	0.125
5	auction	0.0769	0.0769	0.1429	0.0909	0.0909	0.0833	0.1429	0.0714	0.0667	0.1667	0.1	0.0714
6	book	0.1667	0.1667	0.1667	0.1667	0.25	0.2	0.125	0.1111	0.1	0.1667	0.25	0.0909
7	commerce	0.125	0.1667	0.1667	0.125	0.125	0.1429	0.25	0.0909	0.0833	0.1667	0.1429	0.0909
8	relationship	0.1429	0.2	0.1429	0.3333	0.1111	0.1667	0.1429	0.125	0.1111	0.1429	0.1429	0.1
9	process	0.125	0.25	0.25	0.2	0.3333	0.1667	0.2	0.2	0.1667	0.3333	0.5	0.1429
10	catalog	0.1429	0.1111	0.1429	0.1111	0.1429	0.1667	0.0909	0.0833	0.0769	0.0909	0.1	0.0714
11	chain	0.1	0.2	0.1	0.2	0.1667	0.1111	0.1	0.1429	0.1429	0.1667	0.25	0.0769
12	management	0.1	0.1	0.1667	0.125	0.125	0.1111	0.25	0.0909	0.0833	0.1667	0.1429	0.0909
13	channel	0.1	0.125	0.2	0.1429	0.2	0.1111	0.2	0.1429	0.125	0.2	0.1667	0.0909
14	communicati on	0.25	0.1667	0.25	0.25	0.1429	0.3333	0.25	0.1429	0.125	0.25	0.1667	0.1111
15	CompaniesS	0.1111	0.1667	0.1111	0.1429	0.1	0.125	0.1111	0.1667	0.1667	0.1667	0.1429	0.0833
16	web	0.125	0.2	0.125	0.25	0.2	0.1429	0.125	0.1667	0.1429	0.1667	0.3333	0.0909
17	site	0.0833	0.1667	0.0833	0.1429	0.1111	0.0909	0.0833	0.1111	0.1	0.0909	0.1667	0.0667
18	computer	0.0909	0.2	0.1111	0.125	0.125	0.1	0.0909	0.2	0.2	0.1	0.1429	0.0714
19	confirmation	0.2	0.1429	0.2	0.1429	0.1111	0.25	0.1667	0.1	0.0909	0.2	0.125	0.1



LC	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9	IC10	IC11	IC12	IC13	IC14
	Advertiseme nt	security	application	component	features	significance	revolution	driver	consumer	market	growth	strategy	contribution	vision
access	44	53	61	72	47	55	31	34	31	39	74	38	42	43
accuracy	39	51	46	60	58	108	30	34	20	44	56	35	27	51
advantage	71	96	76	90	72	98	64	56	38	63	111	68	34	62
analysesS	73	78	91	102	75	75	51	54	32	63	103	50	30	56
auction	17	20	23	25	21	19	22	10	7	24	36	19	12	21
book	138	158	148	168	153	118	104	87	49	102	265	97	47	123
commerce	85	114	102	95	96	76	72	51	36	317	127	67	57	81
relationship	52	62	45	203	57	48	47	36	26	47	93	43	26	47
process	106	148	140	175	288	117	72	80	44	91	463	94	38	97
catalog	37	44	35	52	37	31	33	32	23	33	50	28	22	34
chain	98	170	132	160	138	121	115	88	40	105	284	94	43	113
management	61	82	98	94	60	94	64	47	37	54	102	60	39	55
channel	96	160	133	157	133	115	92	85	41	98	251	88	42	105
communicatio n	97	115	86	123	85	198	67	50	29	69	135	79	37	72
CompaniesS	86	182	84	117	72	87	74	69	38	95	145	79	35	74
web	64	82	54	83	96	58	56	42	33	59	162	47	33	60
site	68	111	79	120	96	89	67	54	22	72	132	60	30	69
confirmation	50	65	52	76	49	64	39	41	20	49	81	45	23	58
connection	73	142	101	241	87	80	47	69	43	59	111	59	56	62
consumer	34	36	33	38	30	25	26	60	686	43	35	37	22	32
cost	61	92	81	87	58	82	55	49	59	97	111	67	38	54

G)- LESK measure:

H)- HSO measure:

_	LC	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9	IC10	IC11	IC12	IC13	IC14	IC15	IC16	IC17	IC18	IC19
-		Advertisemen t	security	application	component	features	significance	revolution	driver	consumer	market	growth	strategy	contribution	vision	factors	framework	categories	concepts	types
1	access	0	0	2	2	2	0	0	0	0	0	2	0	0	0	2	2	3	5	3
2	accuracy	0	0	0	2	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0
:	advantage	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0
4	analysesS	2	2	2	2	0	3	0	0	0	3	0	0	2	2	0	0	0	0	2
5	auction	0	0	0	0	0	2	0	0	0	2	0	0	0	0	0	0	0	0	0
(i book	2	3	2	4	4	3	0	0	0	2	4	0	0	0	0	0	5	0	2
1	commerce	0	2	2	0	0	0	4	0	0	6	0	0	5	0	0	0	0	0	0
8	relationship	0	3	0	5	0	2	0	0	0	0	0	0	2	0	0	0	2	0	0
9	process	0	4	4	3	5	2	3	3	2	5	6	2	4	4	0	0	2	3	2
1 1 1	D catalog	0	0	0	5	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1 chain	0	3	0	3	3	0	0	0	0	3	4	0	0	0	4	2	0	0	0
1 1	2 management	0	0		0	0	0	4	0	0	2	0	0	0	0	0	0	0	0	0
1	3 channel	4	0	3	0	4	3	3	0	0	3	2	0	2	0	0	0	0	0	2
1	4 communication	5	3	5	4	3	6	4	0	0	4	2	0	3	2	2	0	3	0	5
1	5 CompaniesS	0	2	0	0	0	0	0	2	2	3	0	0	0	0	0	0	2	0	2
1	5 web	0	3	0	4	3	0	0	2	0	2	5	0	0	0	2	2	3	0	3
1 1 1 1	7 site	0	2	2	5	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
1	B computer	0	3	2	6	2	0	0	3	3	2	2	0	0	0	2	2	0	0	3
1 2	9 confirmation	3	0	3	0	0	4	2	0	0	3	0	0	2	0	0	0	0	0	0
		0	0	0	0	2	0	0	3	16	2	0	0	0	0	2	0	0	0	3
2	1 cost	0	4	0	2	0	4	0	0	0	0	0	0	2	0	0	0	0	0	0
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WUP								
file name	text	human evaluation	70% cutting point	80%cutting point	90%cutting point	error 70%	error 80%	error 90%
Introduction to electronic commerce	C1	70	100	100	73.5	900	900	12.25
Introduction to E- commerce	C2	80	100	100	82.3	400	400	5.29
Overview of Electronic Commerce	C3	80	100	100	88	400	400	64
E-commerce	C4	90	100	100	91.1	100	100	1.21
average						450	450	21
RMSE						21.5	21.5	5

5- Results for learning materials with different cutting points & RMSE(E-commerce) :

RES								
file name	text	human evaluation	70% cutting point	80%cutting point	90%cutting point	error 70%	error 80%	error 90%
Introduction to electronic commerce	C1	70	100	97	85.2	900	729	231.04
Introduction to E- commerce	C2	80	97	91.1	64.7	289	123.21	234.09
Overview of Electronic Commerce	C3	80	97	85.2	61.7	289	27.04	334.89
E-commerce	C4	90	97.1	76.5	70.6	50.41	182.25	376.36
average						382.5	265.5	294.5
RMSE			_			20	16.5	17.5



JCN								
file name	text	human evaluation	70% cutting point	80%cutting point	90%cutting point	error 70%	error 80%	error 90%
Introduction to electronic commerce	C1	70	55.8	55.8	55.8	201.64	201.64	201.64
Introduction to E- commerce	C2	80	61.7	61.7	61.7	334.89	334.89	334.89
Overview of Electronic Commerce	C3	80	70.5	70.5	70.5	90.25	90.25	90.25
E-commerce	C4	90	73.5	73.5	73.5	272.25	272.25	272.25
average						225	225	225
RMSE						15	15	15

LCH								
file name	text	human evaluation	70% cutting point	80%cutting point	90%cutting point	error 70%	error 80%	error 90%
Introduction to electronic commerce	C1	70	100	76.4	76.4	900	40.96	40.96
Introduction to E- commerce	C2	80	100	82.4	82.4	400	5.76	5.76
Overview of Electronic Commerce	C3	80	100	88.2	73.5	400	67.24	42.25
E-commerce	C4	90	100	91.1	76.4	100	1.21	184.96
average						450	29	68.5
RMSE						21.5	5.5	8.5



LIN								
file name	text	human evaluation	70% cutting point	80%cutting point	90%cutting point	error 70%	error 80%	error 90%
Introduction to electronic commerce	C1	70	94.1	88.2	70.5	580.81	331.24	0.25
Introduction to E- commerce	C2	80	91.2	91.2	79.4	125.44	125.44	0.36
Overview of Electronic Commerce	C3	80	91.2	85.3	76.5	125.44	28.09	12.25
E-commerce	C4	90	97.06	94.1	88.2	49.8436	16.81	3.24
average						220.5	125.5	4.5
RMSE						15	11.5	2.5

РАТН								
file name	text	human evaluation	70% cutting point	80%cutting point	90%cutting point	error 70%	error 80%	error 90%
Introduction to electronic commerce	C1	70	61.7	61.7	61.7	68.89	68.89	68.89
Introduction to E- commerce	C2	80	61.7	61.7	61.7	334.89	334.89	334.89
Overview of Electronic Commerce	C3	80	73.5	73.5	73.5	42.25	42.25	42.25
E-commerce	C4	90	76.5	76.5	76.5	182.25	182.25	182.25
average						157.5	157.5	157.5
RMSE						13	13	13



LESK								
file name	text	human evaluation	70% cutting point	80%cutting point	90%cutting point	error 70%	error 80%	error 90%
Introduction to electronic commerce	C1	70	55.8	47	44	201.64	529	676
Introduction to E-commerce	C2	80	82.3	73.5	73.5	5.29	42.25	42.25
Overview of Electronic Commerce	C3	80	97	55.8	50	289	585.64	900
E-commerce	C4	90	67.6	50	50	501.76	1600	1600
average						249.5	689.5	805
RMSE						16	26.5	28.5

HSO								
file name	text	human evaluation	70% cutting point	80%cutting point	90%cutting point	error 70%	error 80%	error 90%
Introduction to electronic commerce	C1	70	64.7	64.7	64.7	28.09	28.09	28.09
Introduction to E-commerce	C2	80	64.7	64.7	64.7	234.09	234.09	234.09
Overview of Electronic Commerce	C3	80	73.5	73.5	73.5	42.25	42.25	42.25
E-commerce	C4	90	76.4	76.4	76.4	184.96	184.96	184.96
average						122.5	122.5	122.5
RMSE						11.5	11.5	11.5



6- Experts Details:

Name of expert	Job title	Educational institution
Prof Ahmad alkayed	Dean of IT college	MEU university -Jordan
Dr. Moutaz Saleh Mustafa Saleh	Lecturer, College of Engineering and computer science	Qatar university-Qatar
Dr. Amna khadeja	Academic planning & curriculum development coordinator.	Qatar university -Qatar

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