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ENTROPY BASED PERSONALIZED LEARNING MANAGEMENT SYSTEM (PELMS) – AN APPROACH TOWARDS BUSINESS AND IT EDUCATION

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Development of personalized e-Learning Management Systems (PeLMS) using advance modelling techniques is crucial to achieve personalization and adaptation in content deliveries. This paper delves on some important issues related to the integration of PeLMS with Semantic Overlay Networks (SON). Developing a prototype for a Business Statistics course delivery, a Semantic Web based PeLMS using Topic Maps, Ontology, Classification rules, and ISA Algorithm has been prescribed. Considering classification as one of the important aspects in the content organisation in PeLMS, this study proposes a new classifier, based upon the maximum entropy principle. It is argued that the most similar items in a learning object repository space can be classified together, on the statistical basis, to build a PeLMS. The ISA algorithm has been proposed to enable this classification. The paper also presents three key Learning Object Models for the organization of contents and suggests how an optimal level of personalization that can be ensured by maintaining the entropy within the system. Mechanisms such as normalization and time complexity have also been suggested to ensure personalized and optimal content delivery.

Key words: Personalized Learning Management System (PeLMS), Semantic Web (SW), Learning Content Model, Semantic Overlay Network (SON), Learning Object Repositories (LOR), Entropy, Ontology and Annotation, Business and IT Education.

1 INTRODUCTION

SWT E-learning systems have witnessed a series of evolutionary stages [40, 29]. Each evolution has brought over a mix of benefits and challenges. [15] Classify these evolutions into generations from 'monolithic – the first generation' to 'customizable – the current generation'. These evolutions focus the need to improve web-based education systems [17][32] – mainly in terms of adaptivity and intelligence – which are expected further to support federated exchange between services (information and control), various levels of interoperability (intra-domain and inter-domain), and service composition (orchestration and choreography) [15]. Using a case of Business Statistics course, this paper proposes some improvements in the existing *Personalised e-learning Content Management Systems* (PeLMS) by capitalizing on ontological and entropy based support.

A PeLMS is aimed to assist both instructors and learners in designing and delivering course contents, respectively, in a web-based learning environment. Two of the most important characteristics of a PeLMS are that (i) it heeds to students' personal characteristics, which can be measured and stored in properties; (ii) it allows content designers to define and set conditions for adapting the learning design to learner's characteristics, during runtime [36]. In other words, PeLMS offers personalized services to the learners while providing them with different sets of contents according to their choice of subjects, learning outcomes, or activities. Thus, a PeLMS satisfies individuals or peers – who have different aspirations, preferences and abilities – differently, even if they all take the same course with similar or different options. PeLMS can intelligently provide remedial activities, additional learning objects, and examples to different students, who either possess a certain prior knowledge or have some gaps therein. However, these PeLMSs are not without limitations, for several issues affect their performance. First of all, inaccessibility of relevant content, which is caused by the poor mapping of personalization needs, affects the retrieval time. Secondly, search results do not necessarily match the learner's profile. Thirdly, knowledge profiles of the learners are not personalized. This paper suggests addressing these issues by embedding an intelligent layer in the system that consists of agents, rules, topic maps and annotations, and retrieves the relevant content using aggregation and classification.

Stating some problems in the current adaptive educational information systems, [18] also stresses the need for deploying advanced user modelling techniques to achieve the goals of personalization and adaptation. According to [18] the user models of adaptive systems fail to take account of the prior knowledge of the first-time users, which is necessary to devise the delivery of relevant content [33]. Furthermore, the user models based solely on analysis of learner-system interaction may lead to inaccuracy in assessing the learners' results and performance. Semantics and course-goals followed by the course-author and the learner, if different, may generate inaccurate learner diagnosis. Finally, the adaptive systems fail to capture the dynamics of user system interaction as the learners' goals, preferences, and knowledge evolves.

Whilst the availability of a huge distributed set of data on the Web has offered several learning resources to learners at one hand, the rapid growth in its accumulation has also caused an information overload [4, 5]. Consequently, Web-based learners, sometimes, are unable to find the information they require [2, 23]. The Web-based learners rely heavily on search engines, which provide personalized mechanisms enabling users to filter out uninteresting or irrelevant search results. However, search engines do not deliver accurate contents always. To overcome the weaknesses associated with search engines, [14] introduced the concept of a Semantic Overlay Network (SON). SONs organize content in peer-to-peer (P2P) networks, from thematically focused peer groups using peers with similar content, and support content-retrieval by forwarding queries selectively to the relevant peer groups [21]. However, SONs connect loosely with each other. A system using SONs cannot quickly and accurately forward a query to other SONs when any one SON fails to meet the conditions of a query [48]. Thus, it becomes difficult to improve search efficiency further.

A similar situation affects the domain of Web-based learning, which highlights a need for some sort of a personalized mechanism to help learners learn effectively. To cater to varied information needs of learners, many researchers have ventured into the area of developing personalized mechanisms for Web-based learning [7, 9, 30, 34, 24, and 27].

However, the development of PeLMS has got different focus and attention in their recommendations. Most of the recommendations [37] consider learner's preferences, interests, and browsing behaviours as a key to developing personalized services. However, a focus to learner's ability, for devising personalized learning mechanisms, have been neglected by many, which has been highlighted by a few researchers – attributing that personalization should consider different levels of a learner's knowledge [10, 26, 28, 30]. As the abilities of individuals are based on major specialization of their study and subjects undertaken by them in the past, considering this along with learner's ability can predict personalized learning needs better.

One of the key requirements in the development of learning systems is the aggregation and reusability of contents, which is largely implemented by ensuring granularity. The Reusable Learning website sponsored by the U.S. National Science Foundation (NSF), defines aggregation as “the degree to which a digital learning resource is made up of other digital learning resources” and granularity as “the size, decomposability and the extent to which a resource is intended to be used as part of a larger resource." According to the Reusable Learning website [26], “The higher the aggregation levels the deeper the hierarchical structure.” In the following sections, an effort has been made, first, to define the key technologies associated with learning management systems and web semantics; and, second, to suggest the level of personalization that can be secured by maintaining the entropy within the system.

2 LEARNING CONTENT MODELS (LCMs)

Learning content models provide a framework for defining the structure of the contents in terms of the level of aggregation and granularity of learning objects [38]. LCMs can be implemented by different models such as the Sharable Content Object Reference Model (SCORM) [1] the IEEE LTSC LOM standard [26] the Cisco Systems RLO [11.12], and the Learnativity content model [39, 40]. A brief coverage of these models is given below for the sake of clarity.

2.1 SCORM Model

SCORM offers specifications and standards that help in creating “interoperable, accessible, durable, affordable, and re-usable learning content” [1, 22]. Rather than introducing a new set of standards, SCORM uses established technical standards, specifications, and guidelines as promulgated by IMS, the IEEE LTSC, ARIADNE, and AICC. SCORM mainly suggests content aggregation model, runtime environment; and navigation and sequencing. The main components of the SCORM content model include Assets, SCOs and Content organizations [1].

The content aggregation model is the most relevant to this study as it defines the content components used in creating a learning experience and their aggregation into units of learning. SCORM proposes content aggregation based on Assets – the smallest re-usable piece of learning content – to build other assets and SCOs. A *content organization,* which is normally restricted to a hierarchical tree structure, presents a structured map of the learning resources, just like a table of contents. To develop a unit of learning, SCORM suggests packaging of assets, SCOs, activities, content organization, and metadata as a single content aggregation.

However, there are two issues associated with the SCORM. First, SCORM neither prescribes the actual size of an SCO nor the size of the unit of learning. Second, although SCORM provides an opportunity to the content writer to structure the learning content hierarchically, it does not specify any specific taxonomy, vocabulary, or heavyweight ontology for representing the structure of contents, for example, of a course, module, or lesson.

2.2 IEEE LTSC Model

The IEEE LTSC model [26], suggests four levels of aggregation based on: material such as raw media data or fragments; lessons; learning objects, such as a course; and modules, such as a collection of courses, whereby modules witness the largest level of granularity. Learning objects have been prescribed by an internationally recognized standard data model known as Learning Objects Metadata. Developed by IEEE, learning objects are described in terms of relevant attributes such as type of object; author; owner; terms of distribution; format; and pedagogical attributes, such as teaching or interaction style. However, [6] attribute these aggregation levels as general and vague. Their objection is mainly about the explicit specification or description of various aggregation levels, despite their use of Learning Object Model (LOM) standards for specifying the functional granularity of learning objects. According to [32] the lack of explicit definitions and explanations regarding the use of the general aggregation level and general structure elements and their corresponding LOM vocabularies makes the specific metadata elements and values difficult to be used by metadata creators.

2.3 Cisco Model

Cisco's reusable learning object content model aggregate learning objects into smaller and reusable units in order to meet specific learning needs [11,12]. The Cisco model is divided into five aggregation levels for structuring the learning content: subtopic, topic or RIO (reusable information object), lesson or RLO (reusable learning object), module, and course. Subtopics contain small pieces of information like definitions, examples, tables, and guidelines. A topic consists of subtopics revealing information such as assessment, practice activities, and metadata. A lesson contains a single learning objective, an overview, a summary, and a collection of topics, as well as practice activities, assessment, and metadata. A module includes a collection of lessons, forming multiple courses and learning knowledge categories, while a course includes finally a collection of modules. All these five components are reusable information objects. [3] Suggests that a learning object can combine five to nine reusable information objects. Both the lessons and topics components can be represented in different media formats such as text, audio, pictures, animation, videos, Java codes, and other multimedia objects [12]. The latest versions of Cisco model consider each aggregation level as an object and without following any hierarchical classification.

2.4 NETg Learning Model

This learning content model consists of topic, lesson, unit, and course as independent components. This model follows the Semantic Web principle which aims at converting the unstructured or semi-structured content to data that can be easily shared and reused across applications, enterprises, and community boundaries. Semantic web technology facilitates searching, aggregating and combining of the Web content, particularly by adding new data and metadata to existing Web documents, by using RDF (Resource Description Framework).

RDF interacts with Web pages, applications, and databases to *provide a* structure to the basic Web-data, which can be aggregated at different levels to deliver the contents. RDF and DAML+OIL were the key enablers to the Semantic Web which contributed towards the development of the Web Ontology Language (OWL)[46].

The above models offer an insight into the organization of content for personalizing the learning process. Contents can be organized according to the learner's profile, which can be either retrieved from the databases or can be created afresh for a new learner. In latter case, a learner either can be involved in automated interactions assessing the ability and knowledge level or can take an automated test. Based on computerized assessments, the requirements of a learner can be mapped to an appropriate aggregation level as defined by the hierarchical components discussed above. The system is expected to match the learner's requirements with appropriate contents and to record the interactions – in the form of a user model or knowledge base – to personalize future deliveries. This learning scenario is exhibit in Figure 2 where a learner's requirements to study Business Statistics has been illustrated. The traditional LCMs could not bring this personalization in learning. The emerging technologies, based on web semantics, can integrate different technologies for delivering a personalized content.

3 SEMANTIC WEB-BASED EDUCATIONAL SYSTEMS

The following section gives a descriptive account of semantic Web-based educational systems, and the way integration of technologies can be attained for personalized deliveries.

The Semantic Web Based Educational Systems (SWBES) belong to the third generation of e-Learning systems. In the domain of e-learning, where there is a large amount of content residing in the Learning Object Repository, the conceptual structure of the content is an essential part of the learning material. Without this contextual information, the learners will not be able to contextually integrate the concepts that they are trying to learn [42]. SWBES helps in contextualizing information crucial to match the content with the learner's requirement.

Ref. [19] Suggest that SWBES need to interoperate, collaborate, exchange, or re-use content. According to them, interoperability can be achieved by capitalizing on ontologies and semantic conceptualization, common standardized communication syntax, and large-scale service-based integration. The Semantic Web is an advance technology for improving semantic interoperability of e-learning mechanisms. The Semantic Web is created using domain ontologies, which are formal descriptions of a shared domain conceptualization and are used in organizing contents [4]. The Semantic Web can be seen as an opportunity to enhance the metadata associated with learning contents. In other words, the metadata expressed in terms of ontologies describe the concepts and associations of the learning contents. The Semantic Web is enabled by Resource Description Framework (RDF), Web Ontology Language (OWL), and Extensible Markup Language (XML) to provide descriptions to the Web documents using contents, which represent descriptive data stored in Web-accessible databases [5, 8].

3.1 Semantic Web Technology (SWT) for LCMS

SWT has been recognized by several researchers using different approaches to integrate new technologies with the metadata. The use of standards proposed by this technology helps in improving the annotative capabilities as well as the reusability of the metadata and its content. These technologies are now shifting from the complex metadata extensions [47] to the use of Semantic Web technologies such as Topic Maps [20, 35].

Ontologies are becoming popular due to their power to influence annotations allowing, therefore, a shared and common understanding of a domain, which in turn enables communication between people and applications [16]. Ontologies describe the semantics of the e-learning process, structure content, activities and communication facilities, and define the knowledge category and the environment of e-learning. [19] Classifies Ontology-building into two categories – ontological engineering and ontology development. While the former covers processes such as knowledge elicitation, knowledge structuring, knowledge formalization, ontology mapping, and ontology merging, the latter involves ontology generation and extraction, manual ontology development, and ontology development support.

Ontologies for learning processes can be built in different ways, which include a dictionary explaining different terms, and their relationship with each other. In a given knowledge domain, Ontologies support learning processes by providing conceptual descriptions to a specific content and identifying appropriate items and associations [13]. According to [41] the role of Ontologies in web-based learning is often underestimated. Ontology cannot only be support interactive and interoperable systems but also the development process itself, primarily in context of reusability, reliability and specification. to the above cited benefits, this paper explains next how ontologies can be effective in developing effective PeLMS.

4 PERSONALIZED PeLMS

LCM ontology and Course ontology help in setting up an explicit vocabulary as well as the structure and aggregation level of learning contents, respectively [43, 44, and 45]. Both the ontological approaches address discrete portions of a learning content hierarchy. For example, the LCM ontology defines a learning object as a collection of content fragments and content objects, but it does not specify the role and position of a learning object in the learning content hierarchy. On the other hand, the Course ontology identifies the components of a whole course, but it does not expose the specific nature of a learning object. Because of these two contrasts, there is a need to build a PeLMS, which not only defines a learning object, but also specifies its role and position within the learning hierarchy. The architecture of a PeLMS proposed in Fig. 1 illustrates the use of LCM and Course ontology to enable personalized content delivery. This figure explains the role of SONs in personalizing the learning contents using web interface, browser agent, and ontology. Topic maps and metadata association helps in classifying the LCOs. The intelligent layer use classifiers based on the maximum entropy principle that help in retrieving relevant metadata and domain content objects according to the learner profiles, which is updated dynamically from time to time. Figure1 explains the mechanism of personalization that can be achieved.

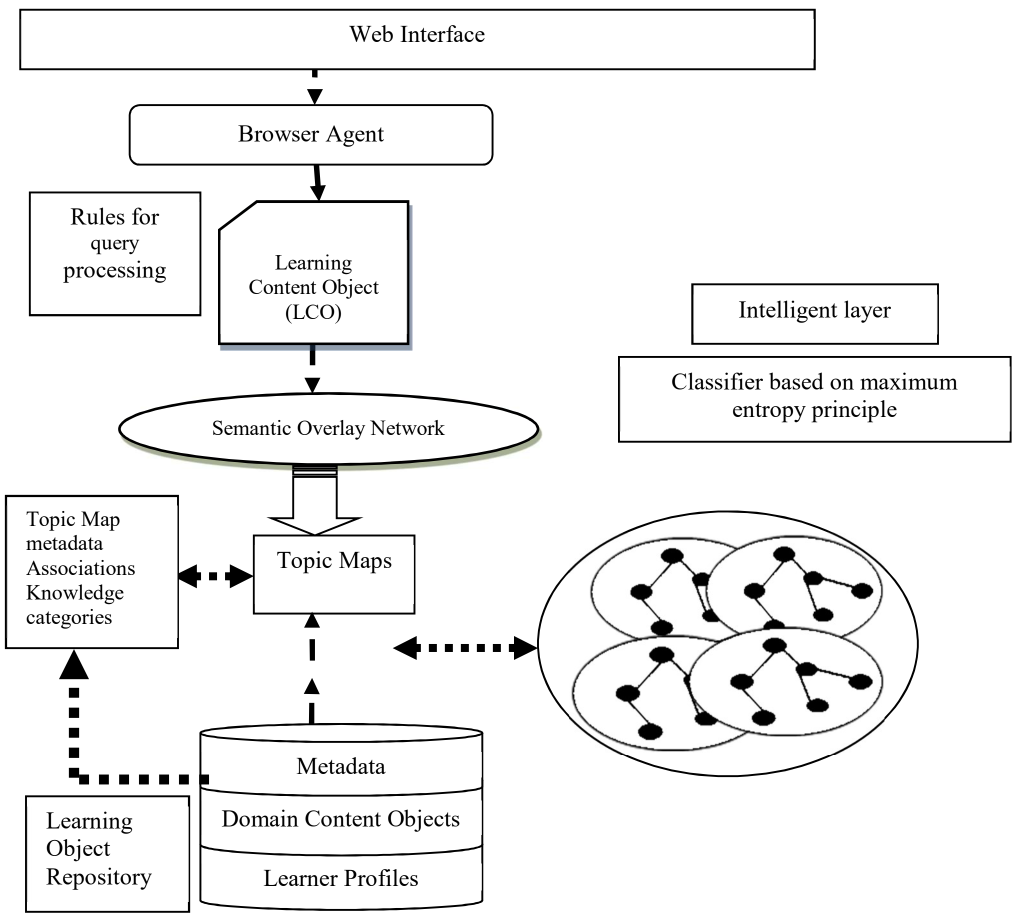

Figure 1. Creating Ontologies to Conceptualize Aggregation Level of Learning Contents

Figure 2 illustrates how a course on Business Statistics can be delivered using PeLMS. The content is expressed on the right side which is aggregated from subtopics to modules on the basis of the principle of granularity. The figure also displays the overall context of PeLMS by mentioning entities such as students, teachers, and LCM systems and their general interactions with the PeLMS. A detail of domain ontology matching the semantic and domain contents is illustrated in Figure 3.

In the following section, a discussion is built on the use of entropy in measuring and sustaining the performance of PeLMS so that the effectiveness in terms of personalized delivery of content can be ensured to the optimal level. We start with the mathematical model for creating associations between LOs and the topics in an LOR is detailed in the following section.

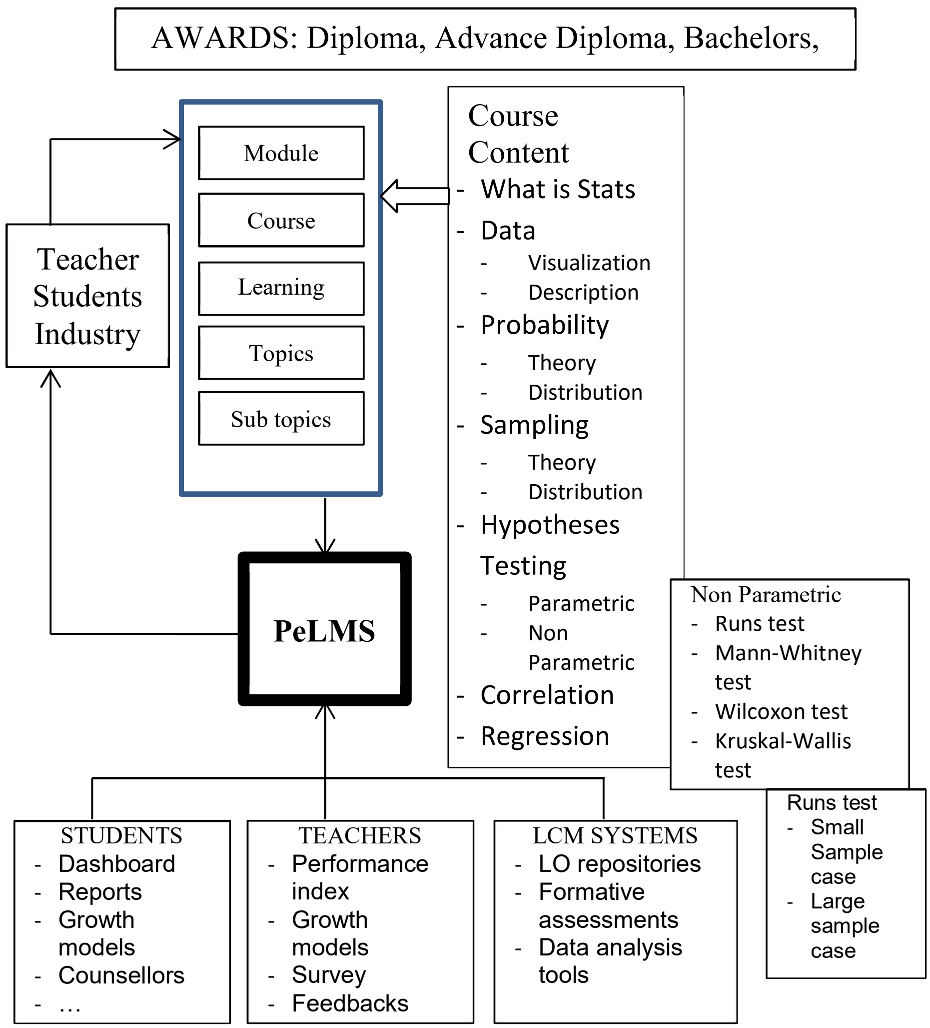

Figure 2. A Prototype of Personalized Learning Management System for Business Statistics

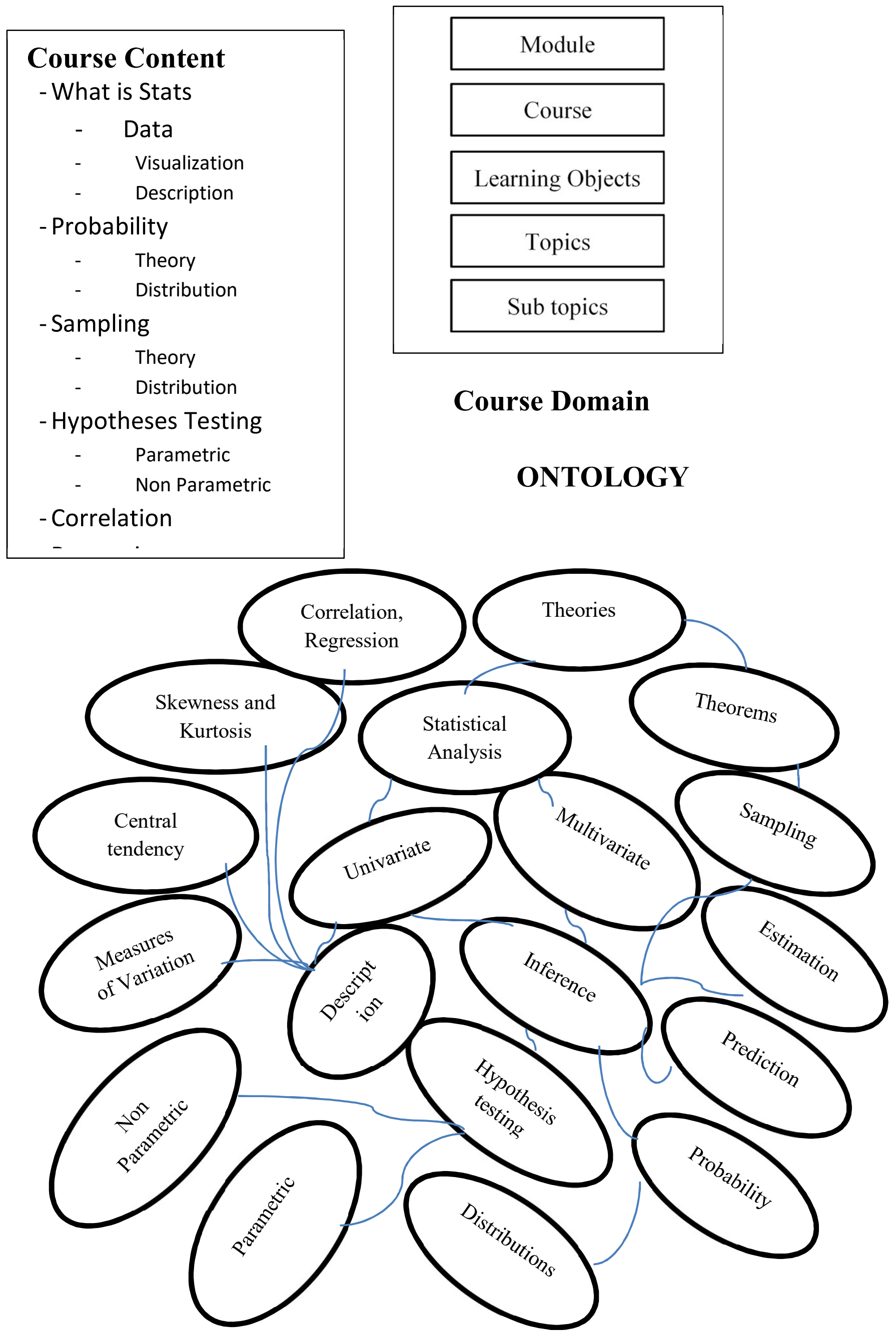

Figure 3. An Illustration of Ontology for Business Statistics

5 Entropy and PeLMS

Let Lo = $\{lo_1, lo_2, lo_3, lo_4 \ldots\ldots\ldots, lo_n\}$ be the set of learning objects that can appear in a particular query and Tc = $\{tc_1, tc_2, tc_3, tc_4, \ldots tc_n\}$ be a set of n number of topics. Let a set Q = $\{q_0, ,q_1, q_2, q_3, \ldots\ldots q_n\}$ be the set of all possible query transactions that can be made by the user entities in the LOR.

The training dataset tc_m, $0<m<n$, is the learner's topic of desire. A query from the learner, say T, can be classified as a learning element tc_m, for which the probability $p(tc_m|Tc)$ is maximum. Bayes formula allows us to compute this probability from the prior probability $p(tc_m)$ and the class conditioned probability $p(tc_i|Tc)$ as follows:

$p(tc_i|q) = \frac{p(p|tc_m)*p(tc_m)}{p\ (q)}$, $p(tc_m)$ is the relative frequency of topic tc_m in training set T.

We can calculate the probability $p(tc_m|Tc)$ by directly measuring the frequency of Tc in the transactions T. which belongs to topic class Tc. There may be a possibility of non-existence, which will return a zero. A Most Frequent Item (MFI) classifier helps the system to estimate $p(Tc/tc_m)$.

Let S (learning component) = $\{St_1, St_2, \ldots, St_n\}$ be the union of the frequency item sets extracted from each class Tc,

$$S = \{s_m \mid \exists tc_m \, s.t. P(s_m \mid tc_m) \geq \sigma\} \qquad \textit{(Equation 1)}$$

where $P\ (s_m|tc_m) = \sum_{x \in X} p(q \mid tc_m)$, where $P\ (s_m|tc_m)$ denotes the support of s_m in class tc_m and σ is the learner support threshold.

Each $s_m \in S$ is called a set. The learning components in set S are used as parameters to model each class (e.g., sub topic, topic, lesson, module, and course, in chronological order) ,such that each itemset s_j together with its support $P\ (s_m|tc_m)$ in class tc_m forms a constraint that needs to be satisfied by the statistical model for that particular class. Thus for each class tc_m we have a set of constraints.

$C_m = \{(s_m, P(s_m \mid tc_m)) \mid s_m \in S \}$.

The probability distribution that we build for class tc_m, must satisfy these constraints. However, there is a possibility of having multiple distribution sets satisfying these constraints.

The maximum entropy principle is used here to select that distribution set which has the highest entropy. This is referred to as the maximum entropy model which is unique and can be expressed in the following product form:

$$p(q \mid tc_m) = \prod_{j=1}^{|Ci|} \mu f \qquad \textit{(Equation 2)}$$

where $f_m(x) = 1$ if $s_m \sum_{Tc \in X} p(q \mid tc_m) \subseteq x$ =0 otherwise

The normalization constant Π (Pi), which ensures $\sum_{x} \in X$ p(Tc|c_m) = 1. Iterative algorithms are defined above to compute $\in S$. In Equation 2, $\prod$ is a normalization constant which ensures that $\sum_{Tc \in X} p(q \mid tc_m) = 1$.

Normalization is aimed to reduce redundancy in the selection process. Several algorithms exist to compute μ_m; however Iterative Scaling Method (ISA) algorithm was used in this paper. The model given in Equation 1 is referred to as the classical *Maximum Entropy* model, but as a limitation this model does not differentiate between a class-variable and a normal variable. The model given in Equation 2 is called the conditional maximum entropy model as it models the domain for each class variable. The following discussion drops the conditional in P(s_m | tc_m) in favor of P(s_m) wherever required.

The above coverage reveals the classification process in a learning phase by finding the set of constraints S and computing μ values for the classes representing different learning components. The computed μ values for each component class are stored and used at the time of classification. The process to classify a given transaction T is to first extract all the learning component classes in S that are subsets of T, and then to use Equation 2 to maximize the performance by selecting that class which maximizes the value of Equation 2.

In the following section, a mechanism explaining iterative scaling using the Maximum Entropy Model is presented, which can be used to justify the learning content selection to enable optimization of the search outcomes.

5.1 Computing Parameters of the Maximum Entropy Model

Maximum entropy is a probability distribution estimation technique that can be used in classification of multimedia based learning contents. Iterative scaling (IS) methods are popular in training Maximum Entropy models. There are many popular models which all share the same property of solving a one-variable sub-problem at a time [25]. By using these methods, it can be rest assured that the selection of the learning content is the optimal one, and it meets to the desire of the learner most satisfactorily. The following lines give a descriptive analysis of ISA algorithm. We start with the μ_m's as derived in *Equation 2* in the previous section, using *Iterative Scaling*. Iteration, using this method, improves the estimation of the parameters. The algorithm stops when no significant changes in the μ_m's values are further observed.

The ISA algorithm runs with the constraint set S on the domain Tc and computes the optimal entropy while satisfying all the constraints. We call Tc and S, the parameters of the ISA. The ISA algorithm first initializes all the μ_ms to 1 and executes the following procedures until convergence.

$$\mu_m^{(n+1)} = \mu_m^{(n)} [P(s_m)/P^{(n)} (s_m)]$$

$$P^{(n)} (s_m) = \sum_{Tc \in X} p^n(Tc) f_m Tc \qquad \textit{(Equation 3)}$$

$$p^{(n)}(Tc) = \Pi \prod_{m=1}^{S} (\mu_m^{(n)})^{f_m(Tc)}$$

The variable n in the above system of equations denotes the iteration number. $P^{(n)}(s_m)$ denotes the expected support of s_m in the n^{th} iteration and the P(s_m) the actual support of (s_j). The expected and the actual support of every s_m should be nearly equal to attain the convergence. However, further to convergence, there is a concept of time complexity, which highlights the runtime that the algorithm takes before convergence. When Equation 3 is executed, $P^{(n)}(s_m)$ is also calculated from the distribution of $P^{(n)}$. This process consumes O(|X|) of time, which accumulates to O(|X|*|C|) for all s_m. Alternatively, if the algorithm performs m iterations for the distribution of $P^{(n)}$ to converge, the time complexity of the ISA can be calculated as O(m*|X|*|C|). However, in real life the number of iterations m is told in advance, and the algorithm is forced to stop once it reaches the count, thereby prevent the full convergence [39].

5.2 Exceptions caused by the Non-Closed Itemsets

The classical Maximum Entropy model is not a guarantee for success, for it is unable to converge sometime. If the frequency of an itemset is similar to the frequency of any one of its supersets, then the selection will not close. A non-closed itemset has been defined as under.

An itemset $s_m \in S$ is non-closed if $P(s_m) \neq 0$ and
$\exists s_v \in S$ such that $s_m \subset s_v \wedge P(s_m) = P(s_v)$

The presence of s_m in a transaction Tc means that s_v will also be present in Tc. This pair (s_u, s_v) is called a fully confident itemset pair. It is clear that there will be no solution when there are non-closed itemsets. This will lead to the non-convergence in case of ISA and prevent the system from obtaining any solution. The modification is therefore required in the maximum entropy model to deal with the situation of non-closed itemsets and to arrive at the convergence.

There is one more exception beyond the situation imposed by then non-closed items. If a learner quits searching facing this situation but wants to continue the search for the knowledge content by changing the content of the search. Now, it becomes important to the system to provide some sort of generalized information as the categorisation of knowledge disciplines. There exists an approach for computing maximum entropy for assessing the performance of the PeLMS.

5.3 Knowledge categorization using Maximum Entropy Model

Knowledge categorization can be ensured by obtaining a positive probability for a transaction. Using the Maximum Entropy Model, this probability can be explained by the following notations:

p(x) = 0 if $\exists$ [sm, s_v] **s.t.** $s_m \subseteq x \exists \wedge s_v \not\subset s_{Tc}$

$$= \Pi \prod_{i=1}^{|S'|} \mu_i^{fi(Tc)} \quad \text{(Equation 4)}$$

S' denotes the set of closed constraints in S. The non-closed constraints in S are only used to check for the zero probabilities.

To boost the performance further, a modified maximum entropy model is suggested below, which computes some key performance indicators and ensures the convergence.

5.4 Modified Maximum Entropy Model and Measurement of Parameters

Under this approach, the ISA algorithm uses S' on the domain X' instead of the usual parameters X and S. The μ_m s are first initialized to 1 in C', and the ISA procedure is followed until the convergence.

$$\mu_m^{(n+1)} = \mu_m^{(n)} \, [P(s_m)/P^{(n)}(s_m)] \;\; \mu_m \in \; C' \qquad \textit{(Equation 5)}$$

$$P(n)\,(s_m) = \sum p^{(n)}(x')\, fm\,(x')$$

$$p^{(n)}(Tc') = \Pi\prod(\mu_m^{(n)})^{fm(Tc')} \forall Tc' \in X' \quad \text{(Equation 6)}$$

The Equations 5 and 6 that express the ISA model converge to the desired Maximum Entropy Model. The time complexity of the modified ISA algorithm is estimated by O(m*|X'|*|S'|). It has been found that the modified ISA algorithm as exhibited by Equations 5 and 6 computes not only the correct entropy but also runs faster than the ordinary ISA algorithm as exhibited by Equations 1 and 2.

6 CONCLUSION

The discussions in this paper reveal that the study of PeLMS, entropy, time complexity is important for developing the learning management systems and enabling them to offer personalized services. The= existing Learning Content Systems lack personalization of content delivery in a true sense. To personalize the content delivery, there is a need for content aggregation and content extraction based on learners' profiles. The classification based on concepts such as subtopic, topic, learning objects, course, and module is important to match the supply side, i.e., the content management systems with the demand side, i.e., elements in the learning domain. This personalization can be achieved further through the application of ontology and annotations using advanced modelling algorithms like ISA. Concepts such as Maximum Entropy Principle and time complexity can help in improving and sustaining the entropy of the PeLMS, which can help finally in optimizing and improving content delivery and personalization.

7 LIMITATIONS

There is no doubt that the concepts of classification, aggregation, annotations, ontologies, and mapping & optimization mechanisms would lead to a better personalization of content delivery and the concepts of entropy and time complexity would help in ensuring the sustainability of the learning content management systems. However, the findings of this paper have not been experimented and tested. Therefore, a test bench for the proposed system needs to be developed and the model needs to be verified for its performance

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