Knowledge Graph to determine the domain of learning in Higher Education

Grafo de conocimiento para determinar el dominio del aprendizaje en la educación superior

http://dx.doi.org/10.32870/Ap.v13n1.1991

Jorge Arturo Hernández-Almazán*
Juan Diego Lumbreras-Vega**
Arturo Amaya Amaya***
Rubén Machucho-Cadena****

Keywords
Knowledge Structures; Classification Systems; Students; Higher Education

ABSTRACT

The representing of a student's knowledge in an academic discipline plays an important role in boosting the student's skills. To support stakeholders in the educational domain, it is necessary to provide them with robust assessment strategies that facilitate the teaching-learning process. Student´s mastery is determined by the degree of knowledge, which demonstrates objectively, on the topics included in the different areas that make up an academic discipline. Although there is a wide variety of techniques to represent knowledge, particularly Knowledge Graph technique is becoming relevant due to the structured approach and benefits it offers. This paper proposes a method that classifies and weights the nodes (topics) of a Knowledge Graph of a disciplinary area, which is analyzed through a case study. The method has two approaches: avoid exhaustive evaluation of the nodes and weight the nodes with adequate precision. Method´s application is illustrated by a case study. As results, a Knowledge Graph is obtained with its classified and weighted nodes through the application of the proposed method, in which 100% of the topics have been impacted through the objective evaluation of 20.8% representing 10 nodes. It is concluded that the proposed method has potential to be used in the representation and management of knowledge, being necessary to improve phases' iteration to condition number of objective nodes.

Palabras clave
Estructuras de conocimiento; sistemas de clasificación; estudiantes; educación superior

RESUMEN

La representación del conocimiento de un estudiante en un área disciplinar juega un importante rol para impulsar sus habilidades. Para apoyar a los involucrados en el ámbito educativo es necesario proporcionarles estrategias de evaluación robustas que faciliten el proceso de enseñanza-aprendizaje. El dominio de un estudiante es determinado por el grado de conocimiento que demuestra, de forma objetiva, sobre los temas incluidos en las diferentes áreas que componen un campo disciplinar. Aunque existe una amplia variedad de técnicas, el grafo de conocimiento en particular está adquiriendo relevancia por el enfoque estructurado y los beneficios que ofrece. Este trabajo propone un método que clasifica y pondera los nodos (temas) de un Grafo de conocimiento de un área disciplinar, el cual es analizado mediante un estudio de caso. El método tiene dos enfoques: evitar la evaluación exhaustiva de los nodos y ponderar los nodos con precisión adecuada. Como resultados se obtiene un grafo de conocimiento con sus nodos clasificados y ponderados mediante la aplicación del método propuesto, en el cual el 100% de los temas han sido impactados mediante la evaluación objetiva del 20.8% que representa 10 nodos. Se concluye que el método propuesto tiene potencial para ser utilizado en la representación y gestión del conocimiento, siendo necesario mejorar la iteración de sus fases para condicionar la cantidad de nodos objetivos.

Received: August 12, 2020
Accepted: January 25, 2021
Online Published: March 26, 2021

* Ph.D. in Knowledge Management and Transfer by the Universidad Autónoma de Tamaulipas. Research Professor at the Universidad Politécnica de Victoria, Mexico. ORCID: https://orcid.org/0000-0003-1060-6455
** Engineer in Information Technology from the Universidad Politécnica de Victoria. Student of the Master's program in Engineering at the Universidad Politécnica de Victoria, México. ORCID: https://orcid.org/0000-0001-7249-5493
*** PhD. in International Education from the Universidad Autónoma de Tamaulipas. Research Professor at the Universidad Autónoma de Tamaulipas, México. ORCID: https://orcid.org/0000-0002-6614-4256
**** Ph.D. in Science from the el Instituto Politécnico Nacional - CINVESTAV Unidad Guadalajara. Research Professor at the Universidad Politécnica de Victoria, Mexico. ORCID: https://orcid.org/0000-0002-5731-6677

INTRODUCTION

Knowledge obtained from an information transformation process (Ramirez & Garcia, 2018), and its representation is of essence for the progress of humankind. There are different techniques to represent knowledge (Han & Ellis, 2020; Lei *et al.*, 2019; Lu *et al.*, 2020; Wang *et al.*, 2019; Yang *et al.*, 2020; Zhang *et al.*, 2020) and one of them is attracting researchers in the fields of education, communication and industry: the knowledge graph (KG) (Li *et al.*, 2019; Mosquera & Piedra, 2018; Yoo & Jeong, 2020; Yu *et al.*, 2017; Zárate *et al.*, 2019; Zhao *et al.*, 2019).

Over the last years, KG has attracted more attention in the educational field (Cope *et al.*, 2020; He *et al.*, 2019; Wang, Ding & Yu, 2019), because it is required to discover, measure or chare students' knowledge in every disciplinary area (DA) (Whi *et al.*, 2020). In this sense, KG provides a robust mathematical structure to represent knowledge of any DA, for example, mathematics, physics, chemistry, accounting, among others.

A DA is comprised of a large number of interrelated topics and based on their complexity. In accordance with the number of mastered topics it is likely to determine the knowledge degree of a student. Although efforts have been done to represent knowledge in different ways (Ivinson, 2020; Paulius & Sun, 2019; Puustinen & Khawaja, 2020), at present, it still is a challenging task which demands innovative processes and methods (Bloodgood, 2019; Guan *et al.*, 2019; Long *et al.*, 2020) aimed to prevent exhaustive assessment and ensure accuracy.

Therefore, knowledge may be represented by means of interrelated collections of topics in a specific area. In this sense, KG establishes causal relationships among previous and later topics of a DA (Rantanen, Hyttinen & Järvisalo, 2020; Shin & Jeong, 2021). Thus, no exhaustive assessment is justified by preventing assessment of every topic of a DA; that is to say, by assuming three interrelated topics due to the complexity thereof A>B>C, if, when assessing topic B, a 100% mastery is determined, then it is assumed that topic A has been completely mastered, which would also determine part of the knowledge on topic C.

In this article we show initial advances on the design of a method to classify and weigh the nodes (topics) of a KG in a DA. There are two approaches in the method: to prevent exhaustive assessment of the nodes and to examine the nodes with proper accuracy. The method is comprised of three phases based on rules, which determine the guidelines to classify and weigh a node objectively by means of evidence provided by the student on the mastery of a specific topic. Afterwards, the graph is updated subjectively, first off in a descending manner and then in an ascending manner, from the causal effects of the node mentioned above. Lastly, the three phases are iterated until a KG is obtained.

By way of illustration, a case study is presented which shows how the proposed method allows us to obtain a KG from the mathematics DA. In every phase of the method the approach is considered to prevent exhaustive assessment of the multiple topics (nodes) of DA, and ensures accuracy when weighing the nodes.

This article is organized as follows: after the introduction, literary review is presented; then, the methodology is mentioned to support the proposed method design. The results of the case study are also shown and, finally, discussions and conclusions.

LITERARY REVIEW

There is a large number of researches using KG to represent knowledge (Bellomarini *et al.*, 2020; Jia *et al.*, 2017; Krenn & Zeilinger, 2020; Lin *et al.*, 2017; Zhu *et al.*, 2019). The structure of KG enables the use of weightings that allow us to obtain new knowledge and conclusions of existing data (Chen *et al.*, 2020; Li & Madden, 2019; Wang *et al.*, 2019). KG nodes represent entities or relevant topics of a mastery and the edges (arrows) determine dependencies, prerequisites, relationships and frequency of co-occurrence among the nodes.

Most of the KG applications are aimed to extracting the association of entities, such as *is-a* and *part-of* (Seo *et al.*, 2020; Wang *et al.*, 2019). In contrast, other studies consider the differences of students' mastery as the basis to represent, in a KG, the relationship of prerequisites among knowledge points and the recommendation of exercises (Lv *et al.*, 2018; Meneses *et al.*, 2020); however, they only propose a method to examine nodes of KG based on the behavior of a student's data, collected by means of an assessment system, but which do not use the evidence provided by the student on the mastery of a DA to prevent assessment completeness.

Oramas *et al.* (2017) y Qiao y Hu (2020) proposed a method to enhance the description of nodes in a KG with semantic information. They employed two different approaches to encrypt the information of KG within a linear representation of the characteristics. Liang *et al.* (2018) highlight the design of an entity-relation scheme to model associations and properties of different objects. Starting from the scheme created by the KG, whose structure enables learning in the interior design area, by weighing its nodes.

Chen *et al.* (2018) propose a system to build a KG automatically in the educational context, it combines heterogenic sources of data to obtain instructional concepts (nodes) and infers relationships among the nodes. Wang *et al.* (2018) represent knowledge of DA on geosciences by means of a KG, where the nodes symbolize words of content and the frequency of co-occurrence is shown as an edge. In both cases, a method is proposed comprised of phases to represent knowledge by means of a KG of a DA;

each node is labeled and weighted in accordance with its influence among the relevant topics. None of them classify nodes to prevent exhaustive assessment as is the case of Lie *et al.* (2020) nor does it examine the nodes with proper accuracy (Chen *et al.* 2020).

The proposals of Chen *et al.* (2018), Long *et al.* (2020), Shi *et al.* (2020) y Wang *et al.* (2018) are focused on integrating heterogenic sources of data to mainly apply techniques to process natural language, classification or neuronal networks in accordance with the context of the problem; however, most of them are evidence of areas of opportunity regarding their practical application because weighting of nodes in the network requires long processing or training times to represent knowledge by means of KG. For this reason, a method is proposed to classify KG nodes to prevent completeness and weighs them with proper accuracy, from the evidence provided by the student on the mastery of topics of a DA specifically.

METHODOLOGY

A DA involves a large number of interrelated topics in accordance with dependency of their complexities, that may be represented as nodes and edges (arrows), respectively, in a diagram called graph expert. The proposed method classifies and weighs the topics (nodes), from the graph expert to obtain a KG that represents mastery of a student on topics of a DA.

Figure 1 shows that three iterative phases (process) comprising the proposed method. The input for phases is the graph expert, which is built by a DA expert. Interrelations of dependencies are established in this graph by means of edges (arrows), in accordance with complexity of the topics (nodes). Thus, in the upper section, that is, in the first level, the name of the DA is specified; in the second level the DA areas are determined; while the third level presents the root topics (node) of the areas because they are the least complex.

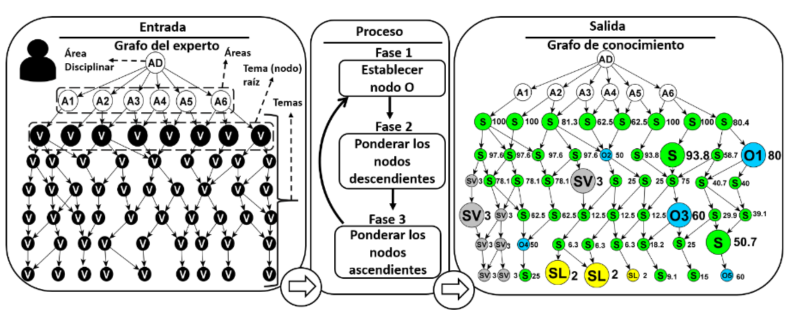

Figure 1. General scheme of the proposed method.

The topics are specified from the third level downwards, the complexity of one of them is greater the farthest away it is from its root topic (node). Once iteration of phases is completed, a KG is obtained as the method output. At the output in figure 1 some values and nodes of different types have been highlighted, with the purpose of improving the visual appreciation. Therefore, their size is not relevant.

To go from the graph expert (input) to KG (output), nodes are classified in five topics, shown in table 1. Therefore, the nodes on the KG of figure 1 are defined in table 1.

Table 1. Classification of KG nodes.

Type	Description
V	Virgin node: all nodes in the expert's graph are of type V and have no weight. This type of node has the lowest priority in the graph. It is black
SV	Virgin subjective node: in phase 1 the nodes are converted to type SV, each with a weight of 3 to represent a low degree of dominance. The SV node replaces a node of type V. It is gray.
O	Objective node: it is determined when the evidence of the domain of the subject (node) by a student is obtained through a questionnaire with a minimum value of 0 and a maximum of 100. Node O will impact its interrelated nodes in an ascending and descending way. This type of node has the highest priority in the graph; therefore, it can substitute for a node of any type: SV, S, and SL. It is blue
S	Subjective node: it is generated from the causal effect of node O. A node S is part of the ascending and descending nodes that are interrelated to node O. The value of node S is subjectively calculated from the value of node O. The node S can replace a node of type SV or SL. It's green
SL	Far subjective node: it is generated from the causal effect of node O. A node SL is part of the descendant nodes that are interrelated to node O from the fourth level of complexity downwards. Because a node SL is far from node O, its weight has more uncertainty than node S; therefore, node SL will have a constant weight of 2 to represent a low degree of dominance. The node SL can replace a node of type SV. It is yellow

Each node type, except for V, shall have a current weighting (CW) which represents mastery of a student on the topic in KG. O and S nodes may have a CW of 0 to 100. CW for node O is determined from the objective assessment of a student by means of a questionnaire with 'n' questions or problems on the topic of node O. Therefore, the CW of node O is the percentage of good answers a student has obtained from the objective assessment. For this reason, every student shall have a different KG as a function of their mastery of DA.

SV- and SL-type nodes shall have a constant CW of 3 and 2, respectively, while node V does not have a CW because it is part of the graph expert. Thus, calculation of CW is done in three phases of the method, that is, in the process shown in figure 1.

Below are the three phased of the proposed method in detail and the rules upon which it is based.

Phase 1. To establish node O

In this phase, an O-type node is determined upon which the CW obtained from the student's objective assessment is associated. The rules of this phase are:

F1.R1) Node O substitutes a node of the SV, S and SL type.
F1.R2) An O node is established at random on a node which is below the first two levels of the graph (the first level is the DA and the second level includes DA areas). Furthermore, the first three O-nodes should be before the last to levels of the graph (the most complex topics). This rule ensures that the O nodes are exclusively established on a topic (not in the node represented by the DA or on the nodes that represent DA areas). In addition, this ensures that the first three O nodes present topics of medium complexity.
F1.R3) An O-node cannot be substituted by any node type.
F1.R4) An O node is objectively assessed only one time

Below are the steps of phase 1 described that follow the previous rules:

F1.P1) V nodes turn into the SV type, each with a weighting of 3 to represent a low mastery degree.
F1.P2) A node is chosen at random.
F1.P3) If the chosen node is of the S, SL or SV type, it is substituted by the O node. Otherwise, it returns to step F1.-P1.2.
F1.P4) Node O is assigned a CW obtained from the objective assessment of the student. This way, the evidence provided by the student is obtained on the mastery of a topic (node) specifically.
F1.P5) The color of node O is established to be blue.

Figure 2 shows an example of reference on how the graph in each phase during iteration is updated. Figure 2(a) shows the initial condition of the graph expert (input). Figure 2(b) shows the transition when node O has been established with a weight of 80 (CW=80), that is, when phase 1 has been completed. The values shown are the CW of each node.

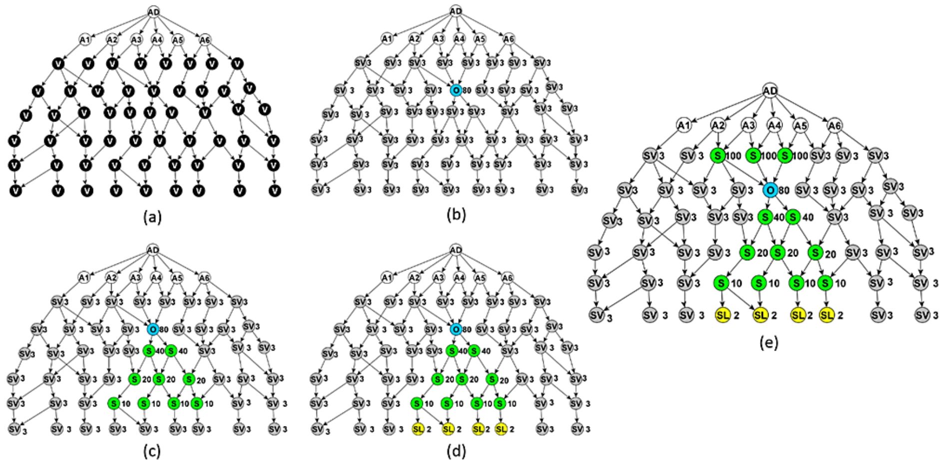

Figure 2. Graph update through the three phased of the method: example of an iteration.

In the rules of phase 2 and phase 3, the values and percentages we have proposed for the method to avoid a comprehensive assessment of the nodes are specified and weighting be done with proper accuracy. Although this is a proposal made by the authors, the causal relationship has been taken into account among the different knowledge levels of a DA with its complexity degree in respect to previous and later knowledge (Nie, Shi & Li, 2020; Rantanen, Hyttinen & Järvisalo, 2020; Shin & Jeong, 2021).

Phase 2. Weighing descending nodes

In this phase, descending nodes interrelated to node O are weighted. Thus, the causal effect of node O has an impact on the nodes (topics) with greater complexity than itself. Nodes affected shall be substituted by nodes of the S or SL type. The rules for phase 2 are:

> F2.R1) The causal effect of node O has an impact on its children, grandchildren and great grandchildren nodes. In other words, these nodes are, to the maximum, three leaps away from node O. these nodes are classified as type S.
> F2.R2) S nodes classified in the previous step, get a weighting of 50% on their father. Therefore, a child of node I gets 50% of the CW of node O. A grandchild of node O gets 50% of the CW of his father (child of node O). A great grandchild of node O gets 50% of the CW of his father (grandchild of node O). This rule is owed to the fact that nodes S, specified above, represent more complex topics than the topic of node O, consequently, from the evidence of node O, the method assumes that a student masters the node following in complexity (child of node O) by 50% of the CW of node O, and so on.

F2.R3) The CW of an S node is the average of the weightings it gets successively. Equation 1 shows the expression to compute the CW of an S node:

$$\mathrm{CW} = \frac{\sum \mathrm{W}}{\mathrm{NW}} \quad (1)$$

Where P is the weightings received in node S and NW is the number of weightings received in node S.
F2.R4) The causal effect of node O has an impact on a later node of its great grandchildren. In other words, these are the nodes from the fourth leap of node O. these nodes are classified as SL type.
F2.R5) The CW of an SL node is 2 because it is assumed that a student has a low mastery degree of this topic (node). Although node SL is interrelated with node O, the causal effect of node O has no impact on node SL as much as node S (with 50% of its father's CW). The foregoing is justified by the far distance of node SL with respect to node O.

Below are described the steps of phase 2, which respect the rules mentioned herein:

F2.P1) The paths of interrelated nodes are described, at a maximum of three leaps, to node O downwards. A path may have nodes that have been taken into account in other paths.
F2.P2) The paths are in an ascending order in accordance with their number of nodes. In this way, the path with the least number of nodes is the first one in order.
F2.P3) If there are 'n' paths with the same number of nodes, 'n' paths are ordered in a descending manner in accordance with the number of S nodes each of the 'n' paths has. In this way, the path with the most S nodes shall be the first one in the order of the 'n' paths.
F2.P4) If there are 'n' paths with the same number of nodes and the same number of S nodes, there is no order done in 'n' paths.
F2.P5) The CW is obtained of interrelated nodes in each of the paths that have been ordered by the four previous steps. The first path to weigh the nodes is the first one in the order obtained, and so on. In every path the child is weighted first, then the grandchild and lastly, the great grandchild, all of them with respect to the O node, as appropriate. This weighting is based on rules F2.R1 to F2.R3.
F2.P6) The color of node S is established to be green.
F2.P7) SL nodes interrelated to node O in a descending order are determined. SL nodes are from the fourth leap from node O.
F2.P8) Each SL node is given a CW of 2.
F2.P9) The color of node SL is established to be yellow.

Figure 2 (c) and (d) shows S and SL nodes, respectively, classified and weighted at the end of phase 2. Values shown are the CW for each node.

Phase 3. Weighting ascending nodes

Ascending nodes are weighted in this phase, which are interrelated to node O. Thus, the causal effect of node O has an impact on nodes (topics) that are less complex than this node. The nodes with an impact shall be substituted by nodes of the S type. The rules of phase 3 are:

F3.R1) A root topic (node) is found after the second level of the graph, therefore, this is the child of a DA.
F3.R2) The causal effect of node O has an impact on its parents, grandparents nodes and so on until they get to the root topic (node). In other words, they are the interrelated topics (nodes) before node O. These nodes are classified to be type S.
F3.R3) Nodes S, classified in the previous step, get a weight of 25% more than the CW of its child. Equation 2 shows an expression to compute the weighting received by an S node in phase 3.

$$RW=CWs*1.25 \quad (2)$$

Where RW is the received weight of node S during phase 3 and CW is the current weighting of the child of node S. This rule is owed that nodes S of phase 3 represent less complex topics than the topic of node O; consequently, from the evidence of node O, it is assumed that a student masters the previous node in complexity (father of node O) by 25% more than the CW of node O, and so on.
F3.R4) The CW of an S node is the average of the weightings received consecutively. Equation 1 shows the expression to compute CW of an S node.

F3.R5) If the CW of an S node is greater than 100, the CW is updated to 100 to maintain the maximum weighting limit.

Below are the steps of phase 3 described, which respect the rules mentioned herein:

F3.P1) Paths are determined of the ascending nodes from node O to the root topic (node). A path may have nodes that have been taken into account in other paths.
F3.P2) Steps F2.P2, F2.P3 are done and lastly F2.P4.
F3.P3) The CW of interrelated nodes is obtained in each of the paths, which have been ordered by means of steps F3.P1 and F3.P2. The first path to weigh nodes is the first one in the order obtained, and so on. In every path the father is weighted first and then the grandfather, both in respect to node O, and so on until reaching the root topic (node), as appropriate. This weighting is based on rules F3.R1 a la F3.R5. F3.P4. Step F2.P6 is done.

Figure 2 € shows classified and weighted S nodes at the end of phase 3. The values shown are the CW of each node.

At the end of phase 3, an iteration has been completed. Next, phase 2 is iterated to establish the following O node. After iterations of the phases have been completed a KG is obtained which represents mastery of a student on the topics of a DA.

CASE STUDY

As mentioned, educational mastery needs to represent students' knowledge by means of processes and innovative methods (Guan *et al.*, 2019; Long *et al.*, 2020), which prevent comprehensive assessment (Liu *et al.*, 2020) and ensure accuracy (Chen *et al.*, 2020). This case study describes how this problem may be studies in a simplified way.

First off, we asked an expert in mathematics to define a graph in this DA. The expert graph is comprised of the following six areas: arithmetic, algebra, probability and statistics, geometry, trigonometry, and calculus, which include a total of 48 interrelated topics (nodes) in accordance with complexity. Thus, the expert graph only includes some topics of mathematics. The topics represent nodes of the V type. Secondly, we used this expert graph as a baseline to apply ten interactions of the three phases of the proposed method. Status of the graph, when interaction 1 has been completed, is the input for phase 1 of interaction 2, and so on.

Finally, ten O nodes are established, one per interaction, to obtain the KG. the CW of the ten O nodes have been arbitrarily placed as a simulated student has been assumed.

RESULTS

Table 2 shows the results of the ten iterations, the node O established in phase 1, the evidence provided by the student on the mastery of the topic (node O) of the DA of mathematics and the percentages of each node type when completing each iteration. When completing iteration 10, the KG shown in figure 3 is obtained.

Table 2. Results of the iterations of the method.

Interaction	Node O	% of student mastery	% of nodes in the graph			
			O	S	SL	SV
1	Variables	34	2.1	35.4	2.1	60.4
2	Radicals	17	4.2	52.1	8.3	35.4
3	Triangles	63	6.3	62.5	20.8	10.4
4	Multiplication and division	80	8.3	66.7	20.8	4.2
5	Sine and cosine	87	10.4	77.1	12.5	0.0

6	Hyperbola	72	12.5	77.1	10.4	0.0
7	derivatives	91	14.6	75.0	10.4	0.0
8	Binomial distribution	76	16.7	72.9	10.4	0.0
9	Factoring	58	18.8	81.3	0.0	0.0
10	Straight	43	20.8	79.2	0.0	0.0

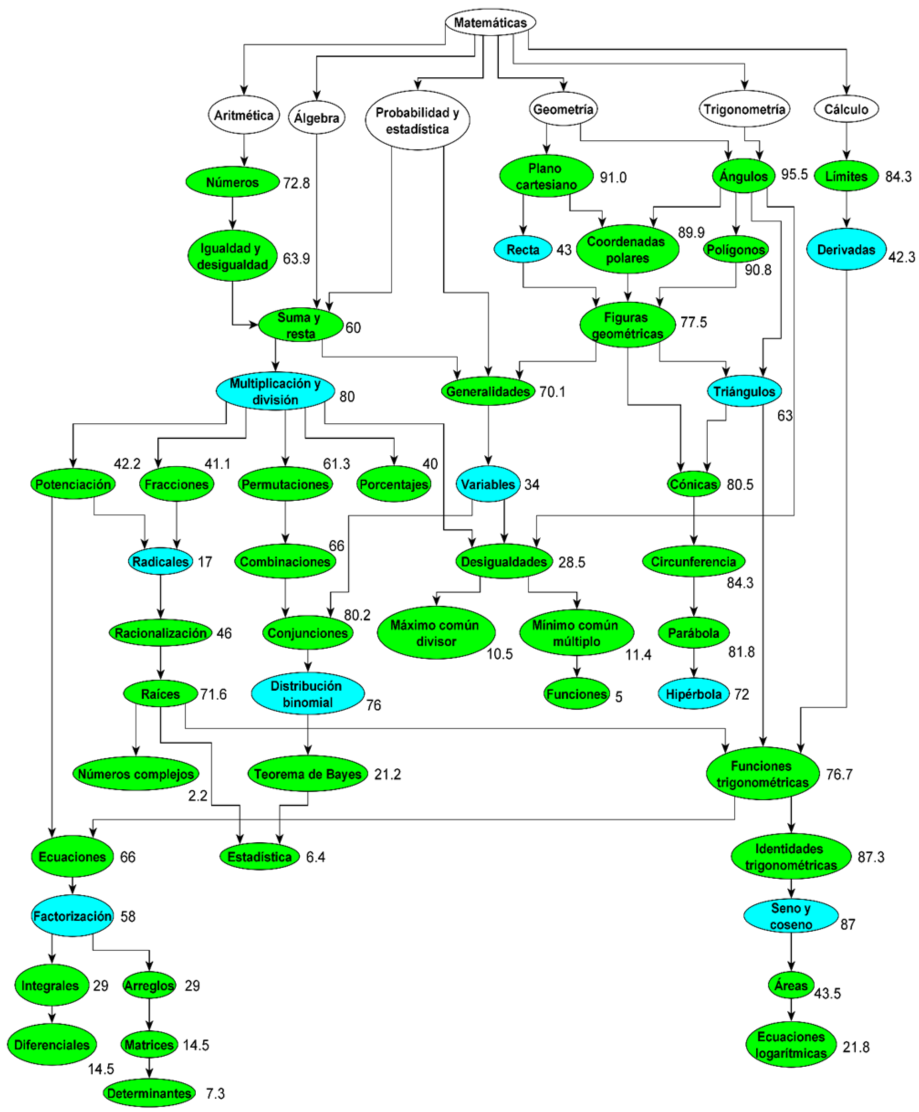

Figure 3. Segment of the knowledge graph.

In table 2, you can see that, upon completing iteration 1, only 2.1% of the SL nodes were registered, which represents one node; this is due to the fact that statistics is the only one node from the fourth leap of node O variables (figure 3). Furthermore, the CW of node O Variables allows us to classify and weigh 18 interrelated nodes in a subjective manner, from the first objective assessment on the mastery of the student's topic. This approach prevents comprehensive assessment of the topics of the KG and allows us to weigh the nodes in a proper manner, because it is based in the objective assessment, that is, the CW of node O.

Upon completion, an O node has been established per iteration. As a result, the assessment of the first five O nodes has allowed us to classify and weight 100% of the nodes of the KG, from which 89.6% has been impacted by the causal effect of O nodes. In this sense, when completing the iteration of the fifth O node (sine and cosine) there are no SV nodes in the KG. Iteration 9 of table 2 shows the removal of the SL nodes, whereas in the last iteration it is specified that the objective assessment of 20.8% of the nodes in the graph has had a subjective impact on the remainder of the nodes, as shown in figure 3. Therefore, figure 3 is the KG which represents mastery of a student on topics in the DA of mathematics.

Although the proposed method allows us to classify and weigh the nodes of KG in a systematic manner and in accordance with topic complexity, it seems that figure 3 does not show proper accuracy. For example, the Conjunctions node has a greater CW than that of tis two parent nodes, combinations and variables. In other words, it could be confusing because the student has more mastery on a topic (node) of greater complexity than on a topic (note) of less complexity.

The foregoing is due to the fact that the Conjunctions node was impacted by the causal effect of the O nodes. The first one, Variables node, has a low CW (34), whereas the second, the Multiplication and Division node and the third one, Binomial Distribution Node, have a greater CW, 80 and 76, respectively. Therefore, the CW of the Conjunctions node (node S) is updated once per each of the paths considering it, which is determined in phase 2 and phase 3 of the proposed method.

The method is focused in classifying topics only. For this reason, figure 3 of the node of the first level (DA) and the six nodes of the second level (areas of the DA), are neither classified nor weighted in the KG obtained. Lastly, the number of S and SL node types in each iteration depends on the established O node. Therefore, if more assessments are conducted with different students, each student shall have an independent instance of the KG in accordance with his/her mastery on the topics of the DA.

DISCUSSION AND CONCLUSIONS

Although KG are broadly used and applied in current research of diverse areas, there still is work to do in the educational field. In this article, we present our initial contribution by means of a method aimed to classify and weigh nodes (topics) of a knowledge graph of a disciplinary area. In the method, a baseline of the expert graph is taken so that this is the input of the three iterative phases. At the end of the iterations, the KG is obtained which represents mastery of a student on the topics of the DA.

The comprehensive assessment of the KG nodes is prevented by means of the causal effect of the O-type node, which has an impact on ascending and descending nodes interrelated therewith. In addition to classifying interrelated nodes when taking advantage of the subjective assessment of the O-type node, they are also weighted with proper accuracy as they consider the basis of the CW of the O-type node. To be fair, the case study describes the test of the method by the evidence of a simulated student. Our purpose is to show the application of each phase of the method with its respective rules to demonstrate its potential in the educational mastery.

The case study has shown that the proposed method prevents a comprehensive assessment of nodes (topics) of the DA, and gets proper weighting. In this sense, with the objective assessment only of 20.8% of the nodes, the method has allowed us to obtain a KG which shows the mastery degree of a student on the DA. Based on this precedent, the proposed method may be used in other educational scenarios. For example, at the medium-higher and higher level in the DA, such as chemistry, physics, accounting, among others. To do so, we recommend to follow previously established phases and rules. However, in complex DA, and with intrinsically interrelated topics, the difficulty to weigh and classify the nodes would increase; this is due to the fact that when following the above rules, you would have to determine the 'n' paths of the nodes interrelated to the O node.

There are several aspects to be improved in this method and in the implementation thereof. First off, the iteration process of phases is not a solid one yet because a pattern is not specified regarding the number of O nodes to be established. As a method that prevents comprehensive assessment, we expect to implement an intelligent module based on Bayesian networks that infers when to finish iterations. We have included different sources of heterogenic data to improve weighting accuracy of the nodes. For example, the results of the students' tests before entering university and their behavior in technological platforms which manage the learning activity.

Secondly, because each student shall have a different KG as a function of its mastery of the DA, it is necessary to automate the process by means of a system to manage the knowledge of students on a DA, which is based on the approach of the proposed method. In this same direction, we are planning to develop modules aiming four types of final users: expert, student, professor and administrator.

Thirdly, the proposed method may potentiate the learning activity in university education because the KG represents mastery of a student on a DA. Once the degree of knowledge is known of a student, the development of his/her disciplinary and professional competencies may be enhanced by means of the detailed attention of topics (nodes) with deficiency.

Finally, we intend to do research on the most effective ways to determine learning paths in accordance with the KG of each student from recommendations. Specifically, managing knowledge by means of a KG aimed to educational mastery is our research perspective.

REFERENCES

Alea, L.; Fabrea M.; Roldan, R. & Farooqi, A. (2020). Teachers' Covid-19 Awareness, distance learning education experiences and perceptions towards institutional readiness and challenges. *International Journal of Learning, Teaching and Educational Research, 19*(6), 127-144. https://doi.org/10.26803/ijlter.19.6.8

Bawden, D. (2002). Revisión de los conceptos de alfabetización informacional y alfabetización digital. *Anales de documentación* (5), 361-408. https://revistas.um.es/analesdoc/article/view/2261

Berry, B. (2020). Teaching, learning, and caring in the post-COVID era. *Phi Delta Kappan, 102*(1), 14-17. https://kappanonline.org/teaching-learning-and-caring-in-the-post-covid-era/

Bustos-López, H. G. y Gómez- Zermeño, M. G. (2018). La competencia digital en docentes de preparatoria como medio para la innovación educativa. *Revista de Investigación Educativa,* (26), 66-86. http://www.scielo.org.mx/pdf/cpue/n26/1870-5308-cpue-26-66.pdf

Cabrales, A. *et al*. (2020). *Enseñanza de emergencia a distancia: textos para la discusión*. Perú: The Learning Factor.

Cepeda, M. P. y Paredes-García, M. L. (2020). Competencias TIC en docentes de un Programa de Ciencias de la Salud de Bogotá. *EDUTEC. Revista Electrónica de Tecnología Educativa,* (73), 157-173. https://doi.org/10.21556/edutec.2020.73.1607

Giráldez, J. R. (2020, septiembre 28). *Covid-19 y adaptación de la enseñanza obligatoria y formación permanente. #DiálogosUNIA Seminario 8: COVID-19 y adaptación de la enseñanza obligatoria y formación permanente*. Málaga, España. www.unia.es/dialogosUNIA

Hernández, C. A. S.; Arévalo, M. A. D. y Gamboa, A. A. S. (2016). Competencias TIC para el desarrollo profesional docente en educación básica. *Praxis & Saber*, *7*(14), 41-69.

Hodges, C.; Moore, S.; Lockee, B.; Trust, T. & Bond, A. (2020). The difference between emergency remote teaching and online learning. *Educause Review*, *27*. https://medicine.hofstra.edu/pdf/faculty/facdev/facdev-article.pdf

Lagunes, R. C. (2017). Recomendaciones sobre los procedimientos de construcción y validación de instrumentos y escalas de medición en la psicología de la salud. *Psicología y salud, 27*(1), 5-18. https://psicologiaysalud.uv.mx/index.php/psicysalud/article/view/2431/4279

Martínez-Garcés, J. y Garcés-Fuenmayor, J. (2020). Competencias digitales docentes y el reto de la educación virtual derivado de la Covid-19. *Educación y Humanismo*, *22*(39), 1-16. https://doi.org/10.17081/eduhum.22.39.4114

Morales, V. G. (2013). Desarrollo de competencias digitales docentes en la educación básica. *Apertura,* *5*(1), 88-97. http://www.udgvirtual.udg.mx/apertura/index.php/apertura/article/view/367/307

Niemi, H. M. y Kousa, P. (2020). A Case Study of Students' and Teachers' Perceptions in a Finnish High School during the Covid Pandemic. *International Journal of Technology in Education and Science (IJTES),* *4*(4), 352-369. https://doi.org/10.46328/ijtes.v4i4.167

Noticias ONU. (2020). Diez recomendaciones para estudiar a distancia durante la emergencia del coronavirus. https://news.un.org/es/story/2020/03/1471342

Ozkara, B. O. y Cakir, H. (2018). Participation in online courses from the students' perspective. *Interactive Learning Environments,* *7*(26), 924-942. https://doi.org/10.1080/10494820.2017.1421562

Picón, G. A.; González de Caballero, G. K. y Paredes Sánchez, J. N. (2020). Desempeño y formación docente en competencias digitales en clases no presenciales durante la pandemia Covid-19. *Scientific Electronic Library Online*, 1-16. https://doi.org/10.1590/SciELOPreprints.778

Román, F. *et al*. (2020). Resiliencia de docentes en distanciamiento social preventivo obligatorio durante la pandemia de Covid-19. *Journal of Neuroeducation,* *1*(1), 76-87. https://doi.org/10.1344/joned.v1i1.31727

Suárez, N. M. (2020). Formación docente universitaria y crisis sanitaria Covid-19. *CienciAmérica,* *9*(2), 1-6. http://dx.doi.org/10.33210/ca.v9i2.299

Trujillo, J. M. T.; López, J. A. N. y Pérez, E. N. (2011). Caracterización de la alfabetización digital desde la perspectiva del profesorado: la competencia docente digital. *Revista iberoamericana de educación,* *55*(4). https://www.researchgate.net/profile/Juan_Manuel_Torres2/publication/283509645_Caracterizacion_de_la_alfabetizacion_digital_desde_la_perspectiva_del_profesorado_la_competencia_docente_digital/links/563c7fe708ae34e98c4a374c.pdf

UNESCO. (2019). *The ICT Competency Framework for Teachers (ICT CFT).* Francia: UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000265721

HOW TO CITE:

Hernández-Almazán, Jorge Arturo; Lumbreras-Vega, Juan Diego; Amaya Amaya, Arturo y Machucho-Cadena, Rubén. (2021). Knowledge Graph to determine the domain of learning in Higher Education. *Apertura*, *13*(1), pp. 118-133. http://dx.doi.org/10.32870/Ap.v13n1.1937