Knowledge Graph-based Framework for Domain Expertise Elicitation and Reuse in e-Learning

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***Abstract*—Reusing knowledge expertise of different domains in e-learning is an ideal approach to sustain knowledge and disseminate it throughout the different organizations' processes. This approach generates a valuable source for instruction which can enrich significantly the quality of teaching and training as it uses effortlessly expertise from its original sources. It is also very useful for teaching activities since it connects learners with real-life scenarios involving field experts and reliefs instructors from the tedious task of authoring teaching material. In this paper we propose a framework that allows gathering automatically expertise from domain experts while doing their activities and then represents it in a form that can be shared and reused in e-learning by different types of learners. The framework relies on knowledge graphs that are knowledge representation structures which facilitate mapping expertise to e-learning objects. A case study is presented showing how inspector reports are handled to generate on-demand e-courses specifically adapted to learners' needs.**

Keywords—Knowledge graph; domain expertise; e-learning; knowledge elicitation; learning web

I. Introduction

Expertise is a valuable asset in today's competitive world. Organizations are striving to safeguard and make the most of their expertise to sustain development and maintain an advantage with competitors. Expertise is retained by human experts; it is the set of know-how and skills developed through practicing and experiencing their knowledge in a specific domain [1]. Identifying, representing and sharing expertise requires the development of knowledge management systems that are able to sustain knowledge and disseminate it through the different organizations' processes. These two requirements represent a twofold challenge facing the development of knowledge management systems. First, acquisition of expertise is not a straightforward task; it requires specific settings and work context to obtain it from experts. Most of the methodologies that have been proposed to acquire expertise relied mainly on eliciting expertise manually or by using elicitation systems that rely on the availability of experts where meetings are organized to acquire their expertise [2]. This ends up generally with additional load for experts which is not always in line with their daily commitments and duties resulting in less involvement and motivation. Second, transferring and reusing expertise requires that the representations of knowledge have the articulacy and flexibility to smoothly transfer it from an initial domain to another domain and to adapt it to different contexts and users. The ability to reuse expertise remains the ultimate goal of organizations. e-Learning systems can contribute a great deal to reuse expertise by mapping it to e-courses for on demand learning and training [3]. In order to provide such e-learning environment for organizations, these systems should be able to handle expertise in a mechanistic way so that to not add a burden on experts while transferring their expertise and also on instructors while preparing e-courses for learners.

In this research we propose a framework that is designed to transfer domain expertise through e-learning systems which can generate and adapt the learning material to different target learners. The framework maps conceptual representations of expertise acquired during normal experts' activities while on duty into learning material that can be used by different types of learners. Expertise is represented as knowledge graphs that are knowledge representation structures which facilitate mapping expertise to e-learning courses. Knowledge graphs capture the expertise concepts and their relationships offering a semantic organization of concepts which allow a fluent mapping into an e-learning course where concepts are prerequisite of other concepts. Also, accessing concepts over the web is facilitated by available technologies that allow querying remotely knowledge graphs which opens the possibility to share and reuse all knowledge graphs on the web. The transition from knowledge graph representation to a e-course is made possible by the learning web constructor algorithm, proposed in this research, which is used to structure e-learning material as a tree of concepts that are adapted to fit the learner's context and profile. A case study is presented to illustrate a real life application of the proposed framework. It shows a company that employs experts who write inspection reports that are automatically represented as knowledge graphs during the report elaboration phase. Domain knowledge and reports are stored into a knowledge graph base that is used to generate on-demand e-courses specifically adapted to learners' needs. The knowledge graph base is then queried to retrieve the necessary concepts which are used to generate a e-course for two types of learners: inspection trainees and new recruits.

This paper is organized as follows: Section 2 provides a background on knowledge engineering and knowledge graphs. Section 3 presents research works in relation to the present research. The following section presents the knowledge management framework and explains the different stages to handle expertise. Section 5 details the inspector report case study that illustrates how expertise is acquired and reused. Finally, we conclude this research and provide future potential research paths to investigate.

II. Background

A. Knowledge Engineering

Knowledge engineering is a critical task and a bottleneck facing any knowledge management system aiming to handle human expertise. During this task expertise is acquired from domain experts by specialized knowledge engineers. Many methodologies have been suggested and used to perform this task and the majority relies on the availability and willingness of experts to transmit their tacit knowledge to the knowledge engineer who encodes it into the knowledge base of a knowledge management system [4], [5]. Unfortunately, experts are not always available and experience has shown that classical knowledge engineering could not be applied at large scale. Indeed domain dependence of the developed systems was not easy to bypass towards flexible and domain independent systems. In order to circumvent this difficulty and make this phase at large scale, knowledge engineering should be transparent to experts relieving them from the burden of eliciting knowledge for every domain from scratch [6], [7]. Also knowledge engineers should focus more on the development of knowledge management systems which serve the daily tasks of experts and at the same time can detect, acquire and represent knowledge into knowledge bases that can be reused and shared effortlessly. Such systems can be developed with the widespread of mobile technologies and context-aware mobile systems which are able to adapt to complex context situations and recommend sophisticated solutions to users. This has been the target of many research such as in the medical, engineering and manufacturing fields [8]. In these domains experts have mobile applications that facilitate their work and at the same time perform a great management work on the background such as efficient storage and retrieval of information, efficient context management to adapt information to users and recommendation systems to guide them through the best and optimal solution [9].

B. Knowledge Graphs

Knowledge graphs are graphs of data intended to accumulate and convey knowledge of the real world [10]. Knowledge Graphs involve interlinked descriptions of entities – objects, events or concepts. These are semantic graphs which can capture subtle meanings that can enhance inference in knowledge management systems. The implementation of knowledge graphs and their use in different applications can also foster the development of intelligent systems able to reason and recommend knowledge. Knowledge graphs can use ontologies to provide an abstract representation of a domain where graph concepts and relationships are concisely defined. Besides, available technologies allow accessing concepts over the web which facilitates sharing and reusing remotely knowledge graphs. Also, query languages, such as SPARQL, have been defined to query knowledge graphs which opens the possibility to search and retrieve knowledge graphs easily [11].

A knowledge graph is defined as a graph G = {E, R, F}, where E is a set of entities, R a set of relations and F a set of facts that have the form of a triple (e, r, e') [12]. For instance, (Tom, FriendOf, Jerry) is a triple denoting a relationship FriendOf between two objects Tom and Jerry. This simple fact can be represented in predicate calculus as: FriendOf(Tom, Jerry). Predicate calculus is a language which handles knowledge graph representations in the form of facts, rules for inferring new knowledge and allows expressing queries for retrieving knowledge. For instance, the query FriendOf(Tom, X) retrieves all friends of Tom by instantiating X with all objects that match similar predicates and hence knowledge graphs.

III. Related Work

Sharing and reusing expertise is a broad research field which involves many disciplines such as knowledge management to elicit knowledge of experts, artificial intelligence to represent knowledge and use it in reasoning, computer information systems to develop applications able to diffuse knowledge to the right user in the right context. e-Learning is an ideal application domain that can contribute to reuse expertise as it transfers tacit knowledge to explicit knowledge through learning, training, coaching, or mentoring [2]. e-Learning systems developed for education or training implement instructional material into user-friendly sophisticated systems that have the ability to adapt to learners in need of domain expertise in a specific context [9]. Knowledge representations are naturally used in teaching and learning in the form of concept maps and taxonomies to categorize concepts and to illustrate them through concept visualization. In this section we present research works that have used concept graphs in education from different perspectives.

Shi et al. in [13] propose a learning path recommendation model which uses specific semantic relationships and knowledge graphs to propose learning objects to learners. The objective of the proposed framework is to increase learning efficiency and recommend personalized learning paths. This framework has been applied to learn machine learning algorithms. Learning objects are categorized into three classes namely: basic knowledge, algorithm, and task. A recommendation algorithm is then used to recommend the optimal learning path for learners based on scores of learning algorithms features such as publication time, citation count, search frequency and impacts of the publisher and author. While this approach seems to work well in the specific domain of machine learning algorithms, it has two major limitations: i) it needs a manual elicitation of the domain knowledge to identify and categorize learning objects for every domain, and ii) some of the semantic relationships defined to link learning objects such as: Ori-algorithm (current LO was improved from an original algorithm), ApplyToAlgorithm and ApplyToTask, are local to this particular domain and can hardly applied to another domain. In [14] a system is developed based on knowledge graphs to provide personalized learning content to learners that are categorized by their learning abilities skill set. Knowledge graphs are constructed based on the concepts extracted from learning objects and relationships are set between concepts. Based on the core concepts and the relationships semantic of the knowledge graph, graphs are generated automatically to the three categories of learners. Accordingly, slow learners are given only the core concepts, then additional graph relationships are considered to generate learning content for moderate learners, and finally highly skilled learners are offered more learning objects based on an extended knowledge graph. In [15] authors developed a learning path generator based on knowledge graphs to provide guidance for learners. The method uses a topological ranking algorithm to generate a topological structure of the learning path and then learning objects are serialized using ant colony optimization. Evaluation of the method shows that the generated learning path is comparable to expert learning path in terms of learning outcomes. Authors in [16] propose KnowEdu, a system that construct educational knowledge graphs that can be used for online learning in school. The system uses pedagogical data and learning assessment data to extract instructional concepts of courses and then identifies significant relations holding between these concepts. Concepts and relations are extracted using respectively neural sequence labeling algorithm on pedagogical data such as textbooks and course tutorials, and association rule mining on learning assessment data to identify the relations such as prerequisite and inclusion. The authors present a case study where the system was used to build a knowledge graph for mathematics course.

IV. Knowledge Management Framework

The framework depicted in Fig. 1 shows the different stages that allow handling knowledge from its source till its utilization in e-learning systems. The framework exhibits four main phases namely: Elicitation, Management, Reuse and Sharing, for converting knowledge expertise as it is acquired from experts till it is shared by learners in various learning systems.

A. Knowledge Elicitation

Knowledge is sought through daily expert activities such as coaching, auditing, brainstorming, training, consultation and mentoring. Knowledge undergoes a four step process: Identify, Extract, Validate, and Represent. Knowledge identification is done from resources such as videos, audios, manuals, reports, regulations, procedures, etc. produced by the expert and made available for performing the activities. These resources are either available internally within the organization and are queried from databases or are retrieved using web services for activities that are posted on the web or online social networks. Knowledge is then extracted automatically from these resources and then validated to make sure that it fits with the objectives set for reusing and sharing learning content. In the last process step knowledge is represented into the knowledge base for further use. This process is supported by the Elicitation Model which specifies what knowledge is sought, from where to get it and how to extract it and validate it. It is also supported by the knowledge representation language which allows representing knowledge into the knowledge graph base.

B. Knowledge Management

Knowledge Management step handles mainly the storage of knowledge in the knowledge graph base and provides a reasoning engine to infer new knowledge or to adapt knowledge according to the user’s context. For this purpose, context is constantly gathered and updated to allow adaptation of learning content. Knowledge is also scored which is necessary in order to retrieve quality knowledge in response to requests of learners.

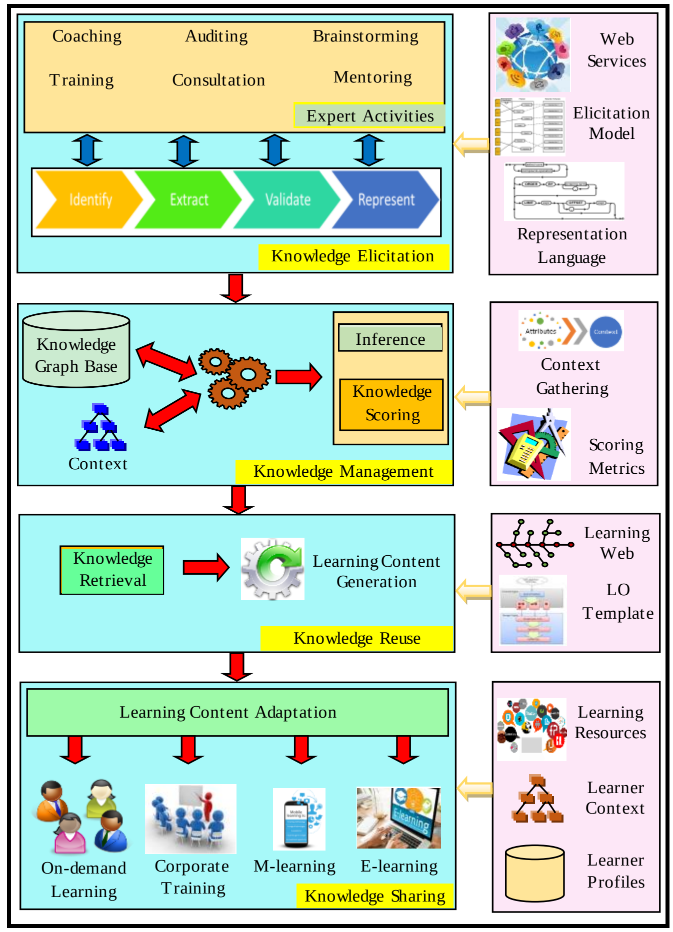

Fig. 1. Knowledge Management Architecture.

C. Knowledge Reuse

This step provides the necessary modules for retrieving knowledge and generating the learning material. Reusing knowledge for learning relies on two components: the Learning Web (LW) and the Learning Object Template. LW is the main learning structure which organizes the learning material. LW is generated by the Learning Content Generation module. It is similar to a tree of nodes where the root is the first learning object and the other nodes represent LOs available for the learner to visit to complete the learning requirements. LOs are learning units including a set of resources that are organized into specific templates. Algorithm ConstructLW in Fig. 2 takes three parameters Le, KG and LW. Le is an input list of ordered concepts in the knowledge graph base selected by an instructor to deliver a particular e-course. This list should be ordered according to the pre-requisite teaching precedence. KG is the input knowledge graph base as described in Section 2; it is defined as {E, R, F}. LW is the learning web which is initially set to an empty list and which will include a list of ordered concepts in relation with the concepts in Le. ConstructLW retrieves all direct concepts e’ in relation with concepts e in Le and adds them to LW. It is noted that the union set operation (Line 9) prevents the duplication of concepts already in LW. The complexity of ConstructLW is in $O(n^2)$ where n is the maximum number of concepts e’ that can be in relation with a concept e in LW.

```
ConstructLW (Le, KG, LW)
input: Le                      is a list of concepts in the
                               knowledge graph KG
input: KG = {E, R, F}          is a knowledge graph;
output: LW = ∅                 is the Learning Web
   for each e ∈ Le do
   {
    LW = LW ∪ {e}              add e to LW
    for each e' such that (e, r, e') ∈ KG do
                               e' is a concept in relation with e
          LW = LW ∪ {e'}       add e' to LW
    Le = Le – {e}   remove e from Le
   }
return LW
```

Fig. 2. Learning Web Generator Algorithm.

D. Knowledge Sharing

In this phase learning generated is adapted to fit different learners according to their context and profiles. Sharing knowledge is vital for organizations. It should be a daily integral part of a learning organization which must develop clear strategies for diffusing knowledge and define the appropriate use of the transmitted knowledge. In order to be able to share and adapt knowledge this phase uses three components namely learning resources, learners' profile and context which allow content adaptation to different types of learners.

V. Case Study

The Inspection Report case study presented in this section illustrates the knowledge management architecture (Fig. 1) and shows how expertise is elicited and reused. A petroleum and gas company has many natural gas processing plants which includes satellite stations that treat Liquefied Natural Gas (LNG). These stations have specialized maintenance engineers who monitor the station's devices (such as piping systems, storage tanks, vaporizers, control devices, pressure regulating valves, etc.) in order to conduct risk assessment, predict deficiencies and propose corrective maintenance actions. The objective is to improve operational efficiency, guaranty safety and protect the environment. Engineers perform regular on-site visits and write reports about the station devices. In case there is a deficiency they propose the repairing to be done and the devices to replace. Reports have a specific template which include an identification section, a description of the problem (if any), reference to previous reports about the same device (or problem), corrective actions proposed and possible maintenance (replacement, reparation, …) to be done on the device along with the execution schedule. While on-site engineers can access all the reports stored in the database to check the maintenance history and evaluate the progress of previous defects. They can also communicate with each other seeking advice or corroboration of their diagnostics. Reports are recorded using a mobile tablet through a template allowing the engineer to write text, take pictures and record audios and videos. Also communication with peers is recorded and added to the report.

A. Eliciting Knowledge Reports

Reports represent a valuable source of expertise that is consulted by managers, experts, maintenance engineers. Also trainees and new recruits can learn and practice their knowledge from inspector reports. When inspectors do their inspection task a knowledge graph is created based on the report attributes such as the inspector ID, the task name, and the component inspected. Fig. 3 shows part of the knowledge graph including two types of concepts: domain knowledge concepts about Refrigeration Piping (green colored circles), and task related knowledge (blue colored circles) which captures the inspection tasks done by inspectors to check pressure of a specific Refrigeration Piping. The figure shows a superposition of concepts for *Inspection Report* and *Inspector* exhibiting the fact that multiple reports have been done by many inspectors for the same task that is to check pressure of component Piping GNL 225-R3674. Knowledge elicitation is done in a transparent manner without intervention of inspectors. While performing their tasks, the task related knowledge is acquired whenever an inspector creates an inspection report to inspect a component. The report is then added automatically as a subgraph in the knowledge graph base as a task related knowledge.

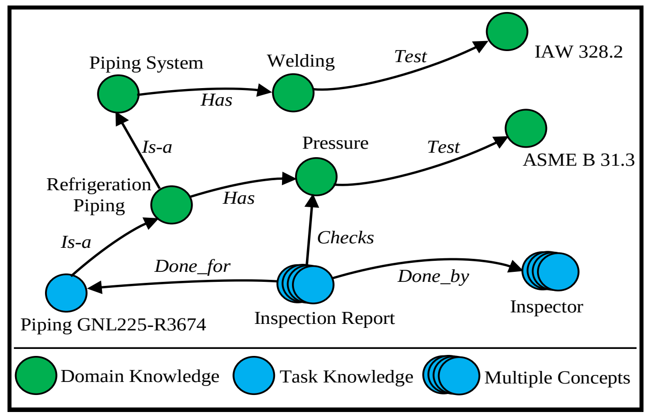

Fig. 3. Piping System's Knowledge Graph.

B. e-Learning Content Generation

Inspection reports expertise represented as knowledge graphs is used by experts, inspectors, and engineers to plan on-site inspections and to follow up on maintenance. It is also exploited by the training and development unit to provide learning content for trainees and new recruits. Training material is generated, as e-learning courses, by querying the knowledge graph base for both inspection trainees and new recruits for the plant. These two types of learners have different backgrounds and different learning objectives and hence require different learning material. Inspection trainees are company employees who need to be trained on inspecting the site, they are knowledgeable about the plant processes. They need to be trained on testing the refrigeration piping system by using the test specification ASME B 31.3. New recruits are engineers who need to acquire knowledge about the plant processes and get some practice on the unit piping system. In order to cover the learning needs of these two types of learners, two different learning webs are generated as shown in Fig. 4.

1) Learning web generation: The learning web is a learning structure organized as a tree of units including the building blocks of learning called Learning Objects (LO) [3]. LW represents the e-course that is traditionally designed by instructors. In our case LW is automatically generated from the knowledge graph base which is queried to retrieve the knowledge subgraph containing the necessary knowledge concepts to fulfill the requirement of learning for a specific learner [17], [18]. These concepts are then ordered to form a tree of concepts. Each concept is materialized by a LO (or set of LOs) that includes the necessary learning resources to be exposed to the learner [9].

Both LWs in Fig. 4 are generated by *ConstructLW* algorithm (Fig. 2). They include mandatory and elective LOs. Mandatory LOs represent the required knowledge that is essential in any learning course. They correspond to domain knowledge concepts in the knowledge graph (Fig. 2). Elective LOs are supporting learning units which are not essential to achieve the learning outcomes but they can support learners to understand, practice or have examples about the core concepts. Elective LOs correspond to task knowledge concepts in the knowledge graph.

Trainees' LW (TLW) is focused on a specific task that is to check and maintain the refrigeration piping system. They need to learn about this system and also be able to elaborate a report using the test specification ASME B 31.3. The input list of concepts Le for generating TLW is Le = {Refrigeration Piping, Pressure}. Algorithm ConstructLW generates LW by including the following: i) mandatory LOs: Refrigeration Piping, Pressure, and ASM B 31.1 representing the necessary domain knowledge and ii) elective LOs: Piping GNL225-R3674 and all reports that have been done for this particular component of the refrigeration piping. The new recruits' LW (RLW) is generated to acquire knowledge about the piping system and get some practice about the regular system maintenance. The input list of concepts Le is Le = {Piping System, Welding, Refrigeration Piping, Pressure}. In this case, ConstructLW generates RLW including the following: i) mandatory LOs: all domain knowledge concepts to allow engineers to learn about the piping system and ii) elective LOs: Piping GNL225-R3674 and the inspection and maintenance reports to allow engineers to have practical sessions on the piping system.

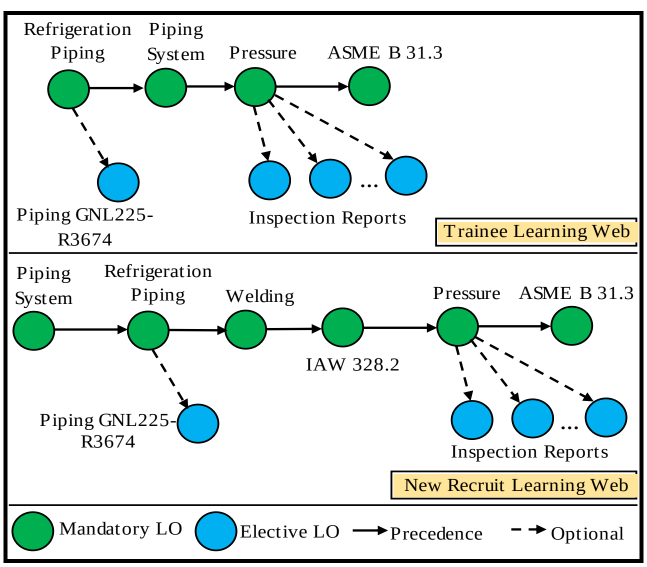

Fig. 4. Generated Learning Webs for Inspector Trainee and New Recruit.

2) Learning objects generation: Once the LW is built learning object are generated for each concept. During the elicitation phase resources are gathered and stored. These resources are then retrieved and packaged as LOs using specific templates. An example of a domain concept, the *Piping System LO*, is illustrated in Fig. 5. The generated LO includes a text description about the concept *Piping System*. It includes also a video, an image and a list of topics organized the same way as the LW, i.e. a sequence of domain concepts and task concepts supporting domain concepts.

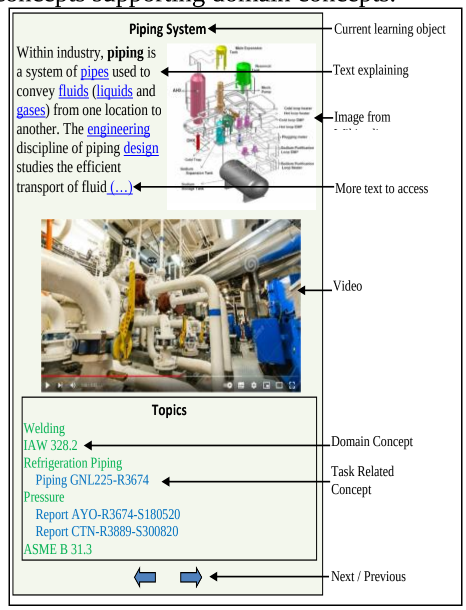

Fig. 5. Piping System Learning Object.

Navigation in the LW can be done in two ways. The first possible navigation is to use *Next* and *Previous* arrows at the bottom of the LO. This allows a sequential navigation in the LW moving forward (or backward) to the next (or previous) domain concept triggering the generation of the corresponding LO. The second possibility is to navigate freely in the LW by clicking on any LO listed in the *Topics* area. This gives more freedom to the user to focus on the concepts he is more interested in and do not waste his time with concepts already known.

VI. Discussion

The framework presented in this paper is designed to safeguard expertise and promotes a smooth transition from expertise represented as knowledge graphs to e-learning courses adapted to different learner types. Usually experts (such as doctors, consultants and auditors) in organizations perform their daily duties using computer programs or applications to facilitate their tasks. While these activities are generally recorded in databases (such as the inspection reports) rarely this expertise is shared and reused within or outside the organization. The framework contributes to not only gather expertise during experts' activities but explicitly turns expertise recorded into e-learning material for sharing by learners in the organization. The representation of expertise using knowledge graphs offers a clear flexibility to the web learning generation algorithm which allows to extract a subgraph on-demand. The proposed algorithm extracts the target concepts and their related concepts to generate the learning web used for e-learning. Although the algorithm in its actual version is restricted to the first level related concepts, it can be easily updated to consider additional levels offering more learning depth and more adaptation to learners.

VII. Conclusion

Reusing expertise is e-learning opens many opportunities for organizations to exploit and share efficiently their know-how and skill set. The framework presented in this paper supports such fluent transition from expertise elicitation till its reuse for learning and training. Expertise is represented as knowledge graphs which provides two advantages: i) concepts are semantically organized which allows an inherent mapping in e-learning where concepts are prerequisite of other concepts, ii) accessing concepts over the web is facilitated by available technologies that allow querying remotely knowledge graphs which opens the possibility to reuse all knowledge graphs on the web. The transition from knowledge graph representation to a learning web is made possible by the learning web constructor algorithm which maps concept graphs into a tree-like structure of learning objects composing a e-course. This gives the possibility to adapt knowledge to different learner types based on their needs and context. The case study presented illustrates the framework's feature while the same knowledge graph has been queried for Inspection Trainee and New Recruit to generate learning material to both learners taking into account their context and learning needs. Future research plans are to develop the scoring function which scores learning resources according to diverse criteria such as author profile, resource creation time, resource popularity (such as number of likes, number of views). This will promote the use of the most interesting resources to fulfill effectively the learning requirements.

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