Intelligent Instructional Design via Interactive Knowledge Graph Editing

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Abstract. The rapid emergence of knowledge graph (KG) research opens the opportunity for revolutionary educational applications. Most studies in this area use KGs as peripheral sources of educational materials rather than a primary tool for Instructional Design. Considerable effort is required to maintain the alignment between KGs and other elements of Instructional Design practice, such as syllabus, course plans, student learning objectives, and teaching outcome evaluation. To bridge such a gap, we present a novel framework named *Knowledge Graph Reciprocal Instructional Design* (KGRID), which employs KGs as an instructional design tool to organize learning units and instructional data. Viewing the two aspects as a unified ensemble achieves interactive and consistent course plan editing through manipulations of KGs. The included interactive course schedule editing tool distinguishes our framework from other timetabling approaches that only handle the initialization task. Managing instructional data in KG format is indispensable in establishing a foundation of mass instructional data collection for KG research. We envision a collaboration between the two disciplines. With these crucial functionalities and aspirations, KGRID outperforms the practice of replacing Instructional Design tables with concept maps. We present the system architecture, data flow, visualization, and algorithmic aspect of the editing tool.

Keywords: Instructional design · Knowledge graphs · Course planning.

1 Introduction

Although knowledge graphs (KGs) provides abundant and encyclopedic information, appropriate instructional design tools are necessary such that instructors can handily leverage educational KGs. Over the decades, new approaches and studies in Instructional Design have been proposed and conducted for addressing challenges brought by new educational technologies or new instructional circumstances, e.g. Digital Visual Literacy [2,24] and academic library [20]. KG technology resembles these impacts, but the research of KG for educational application is at a preliminary stage [32].

Besides the resemblance of being a challenge bring by new technology, being a representation of knowledge itself, KGs raise consistency issues in Instructional Design context. If a KG is representing a structural syllabus of a course, a course plan maps contents from the syllabus to a temporal schedule. As learning units should be "self-contained" and reusable [27], the mapping should be done in a compact way such that the schedule outlines valid learning units. As updates made on KGs might restructure the hierarchy and constituent of learning units, instructor's effort are required to restore the consistency between the syllabus and schedule (see §3.3).

We present a course plan editing tool that takes consistency management into consideration. A course plan generation process would organize and schedule course concepts from a KG into compact learning units. As the hierarchical structure of KGs has already been proven helpful in other unsupervised tasks such as learning recommendation system [19] and instructional material retrieval [26], it is plausible to apply the same strategy in the course plan generation task. Consistency between structural and temporal aspects of the course would be managed with automated consistency restoration. Such restoration process unifies different viewpoints of the design in real-time, such that interactive editing in both side is possible. Multi-view modelling approaches have been proven effective for consistency management in the field of software engineering [11]. Data visualization is also provided to support instructors design decisions.

To the best of our knowledge, there do not exist any studies that discuss course plan initialization and interactive editing through manipulating KGs. One close work from Cho et al. [10] uses concept map for collaborative Instructional Design task for a single lesson (see §2.4). As their work focuses on a scope as short as one lesson, issue such as scheduling of learning units and consistency between the schedule and the syllabus are unattended.

To provide management tools and an infrastructure for data collection as a whole, a framework, named Knowledge Graph Reciprocal Instructional Design (KGRID), is proposed. In general, we believe that a practice that integrating KGs in Instructional Design process can expedite the progress of KG technology development in a reciprocal manner.

The rest of the paper is organized as follows. The framework and the design tool would be described in §3. Brief discussion about how the proposed tool can be improved or how the instructional data collected could benefit both data science and Instructional Design discipline would be followed in §4. Backgrounds about relevant topics are given in §2.

2 Related Work

2.1 Knowledge Graphs

Graph As Data Science Techniques Data science techniques, such as graph neural networks (GNNs) and knowledge graph embedding, take graph structured input and are used for prediction tasks, question answering systems and recommendation systems [13,18]. Variants of GNNs, such as Graph Convolutional

Network, learn connectivity structure of a graph and encode and representation of entities in a graph. These techniques have various applications in such as "medical, financial, cyber security, news and education" [32].

Knowledge Graph for Education Educational applications of KGs are starting to gain more attention lately. Hierarchical relationships in KGs have been utilized for better personalized study recommendation service [19]. Ranawat et al. [26] utilized KGs for course material retrieval and course planning. Study about knowledge graph embedding models for educational application are conducted for theoretical purpose and benchmarking [31]. The main focus of educational KG research was said to be "basic relationship extraction" that more quality data might enable more profound educational applications [32].

2.2 Course Plan Generation

Research on course plan generation is to assign course concepts and timeslots considering student's maximum learning capacity. The task is an NP-complete problem that it is computationally intensive for securing an optimal solution, so heuristic approaches are often preferred [6]. Researchers have used different methods and algorithms to address this problem. For example, Betar et al. [3] use a harmony search algorithm; Lewis et al. [21] apply a grouping genetic algorithm; and Lü et al. [22] propose an adaptive tabu search algorithm. Particle swarm optimization methods is also a popular approach for the task throughout the decades [5,17,28]. The task is often formulated as a multi-objective optimization problem where instructors' or students' preferences and time budget are considered [29,30].

One recently proposed approach utilize KGs for course material retrieval [26], the sequencing however relies on minimizing the "Comprehension burden" of the course plan. Most approaches do not utilize structural information of KGs. Existing work is also decoupled with schedule editing. Interaction between user and the schedule are not handled.

2.3 Consistency Management

Consistency management enables users to edit multiple views of a design in a controlled manner [11]. These views, in the context of Model-Driven Engineering, separate different design concerns such that the complexity of the task is reduced [11].

Consistency "violation[s]" or "problems" is either "identif[ied]" through managerial activity undertaken by the designer [7] or "checked" by the design tool [7,23]. One violation check only identifies a particular form of inconsistency issue. Because of the incompleteness nature of formal systems, defining a rule-based system for achieving a fully consistent system or defining an objective function for consistency optimization is said to be "impossible" [16]. Given that consistency management is always an open problem, extensibility is then an important feature for design tools that support consistency management [23].

2.4 Instructional Design

The purpose of Instructional Design includes visualizing a systematic design process, serving as a base for project collaborations, serving as a managerial tool and providing evaluation of both Instructional Design product and theory [4,20].

Instructional Design Models and Tools To fulfill the above purposes, new Instructional Design models and tools are designed for new circumstances or challenges. Instructional Design model such as ACE (analyze, create, and evaluate), ISD (instructional system design), PAT (principles, action, and tools) [2] and the matrix model [24] were designed for Digital Visual Literacy. Systematic literature reviews are also done for academic library instruction [20]. To the best of our knowledge, research about Instructional Design models or tools for KG technology remains unexplored.

Concept maps could be conceived as a superficial resemblance of KGs without data science technology [12]. It is mostly applied as an interactive learning activity, known as collaborative concept mapping, where students' learning [12,15,25] in a flipped classroom configuration [12] is usually the focus.

Cho et al. [10] suggest to use concept map for visualizing lesson planning process to facilitate collaboration among colleagues. While concept map is perceived as a visual tool for design process, managerial and evaluative aspect of Instructional Design with such graph structure however is beyond the scope of their work. Research for tackling this multifold gap between Instructional Design and KG in terms of managerial, evaluative and technological aspect is vital.

Instructional Design and Software Engineering The idea about sharing practice between software engineering and Instructional Design has been constantly suggested. In order to improve the Instructional Design process, practices from software engineering are suggested to be integrated [1,8,14]. Software engineering and Instructional Design are said to be "sister discipline" [1].

3 Methodology

The input of KGRID is educational KGs that includes particular course entities, such as KG representing the syllabus of a course. KGRID consists of three steps as follows.

1. Preprocesses the course KG to produce an input that fits the downstream course plan generation process.
2. Labels entities of the course KG with a course plan generation process.
3. Supports interactive editing while maintaining the consistency of between course KG and course plan.

The algorithmic aspect of these steps will be described in the next three sections. The preprocessing component in step 1 is reused in step 3. The data flow of

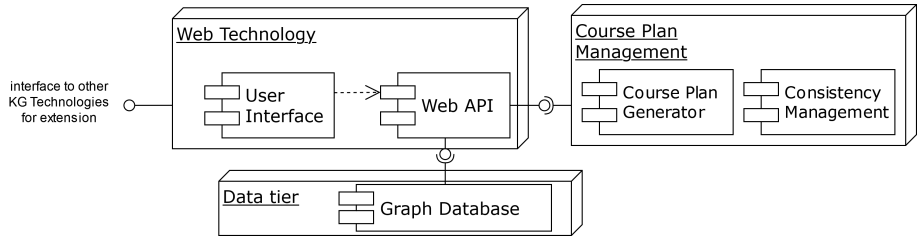

Fig. 1. Component diagram of KGRID.

KGRID is described in Fig. 2. Data for any instructional element, such as course material or student assessment results, can be stored as an entity property. Network data visualization is included in the design tool.

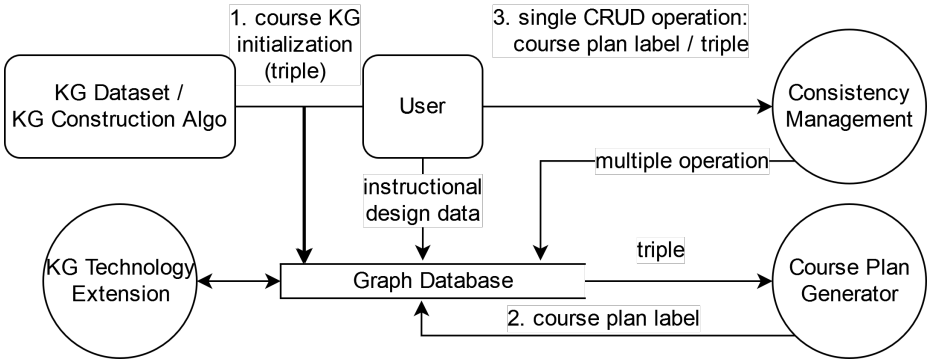

Fig. 2. Data flow diagram of the framework. Data flow are ordered. The third step can be repeated indefinitely as user interact with the course plan editor.

3.1 Knowledge Graph Preprocessing

KG is defined as a directed heterogeneous multigraph. Given a directed heterogeneous multigraph $K = (V, E, \phi, \psi)$, $\phi : V \to L_V$ and $\psi : E \to L_E$, where L_V is a set of entity type labels and L_E is a set of relation type labels. An unweighted homogeneous graph $G = (V, e)$ can be obtained by filtering edges according to their semantics; the mapping ϕ and ψ is then dropped. Edges that express the semantics of subsumption (e.g., a "*sub_topic*") in an ontology or taxonomy sense would be kept. We assumed that a vertex $r \in V$ that represents the course's entity exists. A tree structure $T = (V, e')$ is then obtained using Shortest Path Tree (SPT) construction algorithm concerning the vertex r. The preprocessing is as follows:

Procedure 1 KG preprocessing

Given:
$K = (V, E, \phi, \psi)$; r; // $r \in V$
S; // a set of relation type that has a subsumption meaning
Output:
$e \leftarrow \{x \in E \mid \phi(x) \in S\}$
$G \leftarrow (V, e)$
$T \leftarrow SPT(G, r)$ // SPT algorithm with respect to the root
return G, T

3.2 Course Plan Generation

Task Definition Given the input $T = (V, e')$ with k triplets from the preprocessing process, a course plan generation task is to split concepts to m course sections $H = \{h_1, h_2, ..., h_m\}$, where $h_1 \cap h_2 \cap ... \cap h_m = \emptyset$ and $h_1 \cup h_2 \cup ... \cup h_m = V$. Simultaneously, the grouping compartmentalizes the concept in l weeks.

Unsupervised Sequence Generation We first define the importance of each concept in the tree T. The importance W_i of a concept V_i with the edge E_i that connects it with its parent, depends on the relation type function $e : L_E \rightarrow \mathbb{R}_{\geq 0}$ and distance function from the root r as follows:

$$W_i = e(\psi(E_i)) \cdot dis(V_i, r). \tag{1}$$

In our demonstration (Fig. 4), a particular relation type function and distance are chosen such that first hop concepts with relation "*sub_topic*" have high priority. Our strategy is to perform a depth-first search for topic dependencies. Starting from the root entity, we search each subtree as profoundly as possible before returning to the next child node of the root entity. The final sequence $S = \{V_1, V_2, ..., V_n\}$ with n concepts has the ordered information that can be used for the next stage.

Lesson Section Generation The hierarchical information is utilized after sequence generation in this stage. To determine the key concepts for the course plan, we first find the candidate section concepts that concept importance is larger than threshold ϵ:

$$h_i = \{V_i | W_i > \epsilon\}. \tag{2}$$

Then, we cut the concept sequence S to m lesson sections by the weighted subtree generation method. The approach adopts recursive search as the section sequence generation that satisfies the following:

$$V_j \in \arg\max_{h_i}(h_i - V_j)^2. \tag{3}$$

Finally, We divide the section sequence H into corresponding to the weekly timestamp in a semester. We generally use the uniform distribution to classify

each concept with a weekly timestamp since there is no prior for each week's schedule.

A greedy heuristic algorithm for course plan generation is outlined in Algorithm 2. The algorithm is two stages method. Firstly, we transfer the course knowledge graph to a concept sequence S. Secondly, we cut the concept sequence S to several lesson sections, hierarchical information from the knowledge graph.

Algorithm 2 Course Plan Generation

Input: $T = (V, e')$; ϵ; l;
Output: $H = \{h_1, h_2, ..., h_m\}$;
  $S = \emptyset$, $H = \emptyset$;
  for $V_i \in T$ **do**
    $S \leftarrow S + V_i$ with $\max W_i$ based on Equation 1
    if $W_i > \epsilon$ **then**
      $H \leftarrow H + \{V_i\}$
    end if
  end for
  while $S \neq \emptyset$ **do**
    $V_j = S.pop()$
    compute V_j section h_i based on Equation 3
    $h_i \leftarrow h_i + V_j$
    $H \bigcup h_i$
  end while
  return H

3.3 Consistency Management

"Macrostructure" defined by a learning unit is said to be "self-contained " and "thematic" [27]. In KGRID, such units are represented in a nested hierarchical structure. Updates in KGs might require rescheduling of course plan to preserve such compact macrostructure.

As the course plan label is essentially an entity property, changes made in the course plan have no effect on the KG structure. The label specified by users are likely to be considered meaningful, and the interference of the rescheduling to these user-defined course plan items should be minimized. User can indicate their preference by pinning down the course plan label of specific items. When the hierarchical structure of a course KG is changed, rescheduling is done in a limited scope that includes as many items and as least pinned items as possible. Exceptionally, only descendants of a "jumping" entity would be unpinned.

A KG updated is a triple $\{V_h, E_r, V_t\}$ with a "create" or "remove" command. After a KG update, the SPT algorithm is run to determine the new hierarchical structure for the course. If the direct parent of V_t has changed after SPT, the entity is said to be "jumped". Entities are unpinned if any of their ancestors is "jumping". Jump has to be handled to main consistency. Given a set U_v =

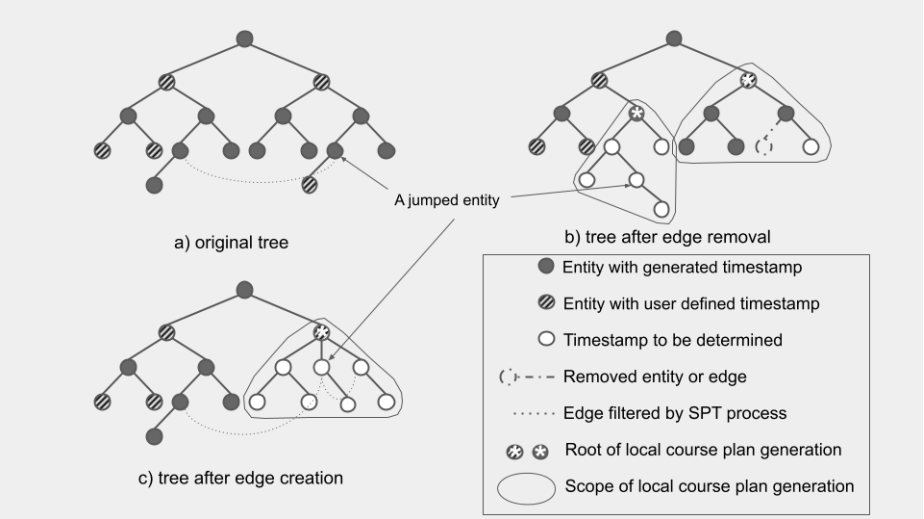

Fig. 3. Examples of consistency updates. A jumped entity with one successor is illustrated. The number of local rescheduling scope depends on whether the updated entity jumps across branches separated by pinned entity.

$\{V_h, V_t\}$ of two vertexes involved in the triple update, a set P which refers to vertexes with pinned course plan label, a set $C(x)$ which refers to the descendant of a vertex x and a function $H(x)$ which gives the course section of a vertex x, the local scope of the rescheduling is defined as follows.

$$r' = \{x \in V \mid (\exists c)[c \in C(x) \wedge c \in U_v] \wedge (\nexists c)[c \in C(x) \wedge c \in P]\}. \tag{4}$$

$$e'' = \{\{x_1, x_2\} \in e' \mid x_1, x_2 \in C(r') \cup \{r'\}\}. \tag{5}$$

$$T' = (C(r') \cup \{r'\}, e''). \tag{6}$$

.

$$H' = \{h' \in H \mid h' \in H(C(r'))\}. \tag{7}$$

Algorithm 2 is run with new input T'. The output is then mapped to H', using linear interpolation and quantization.

3.4 Instructional Data Visualization

Graph visualization might highlight patterns of structural features of the course design. Here, graph centrality metrics are visualized for brief demonstration (Fig. 4). Similar visualization can be done on other data to facilitate Instructional Design duty. For example, visualization of the number of available course materials or student's performance of different course concepts could be included.

Algorithm 3 Consistency Maintenance

Input: $T = (V, e')$; K; $\{V_h, V_t\}$; P; ϵ; l;
Output:
$T_{new} = (V, e'_{new}) \leftarrow KnowledgeGraphPreprocessing(K)$
$V_{h_{new}} \leftarrow$ an edge in T_{new} where the tail entity is V_t
procedure RESCHEDULE(x)
$e'' \leftarrow \{\{x_1, x_2\} \in e'_{new} \mid x_1, x_2 \in descendant(V_1, T_{new}) \cup \{V_1\}\}$ ▷ Equation 5
$T' \leftarrow (descendant(V_1, T_{new}) \cup \{V_1\}, e'')$ ▷ Equation 6
$LessonSectionGeneration(T', \epsilon, l)$ ▷ Algorithm 2
followed by linear interpolation and quantization
end procedure
$V_{h_{old}} \leftarrow$ an edge in T where the tail entity is V_t
if $V_{h_{old}} \neq V_{h_{new}}$ **then** ▷ check if V_t jumped
remove $descendant(V_t, T_{new})$ from P ▷ Recursive unpinning for V_t
$V_1 \leftarrow parent(V_t, T)$ ▷ Define a local scope with root V_1 descendant
while $descendant(parent(V_1, T_{new}), T_{new}) \notin P$ **do**
$V_1 \leftarrow descendant(parent(V_1, T_{new}), T_{new})$ ▷ Expand the scope
end while
$V_2 \leftarrow parent(V_t, T_{new})$ ▷ Define a local scope with root V_2
while $descendant(parent(V_2, T_{new}), T_{new}) \notin P$ **do**
$V_2 \leftarrow descendant(parent(V_2, T_{new}), T_{new})$
end while
RESCHEDULE(V_1)
if $V_1 \neq V_2$ **then** ▷ check if V_t jumped across pin-separated branches
RESCHEDULE(V_2)
end if

end if

4 Future Work

4.1 Incorporating with Knowledge Graph Technology

While utilizing KG data visualization for Instructional Design still requires instructors' effort and experience, a data-driven approach can further lighten instructors' burden. Instructional Design in the form of KG, i.e., course contents organized in a graph structure, can be used as inputs of data science techniques. With instructional data, e.g. course plan label, instructional material or students' assessment results included as node properties, prediction of teaching performance indicators of such input can be made. Supervised learning approaches could replace the heuristics used for course plan generation in KGRID. Methodologies mentioned in §2.1 outline the technical aspect of the above application.

Data-driven approaches are promising. However, data-driven often implies data-hungry. The accuracy of the prediction depends on the amount of data that has been employed to develop the algorithm [9]. In addition to closing the gap between KG technology and Instructional Design practice, KGRID also intends to close the data gap in educational KG research.

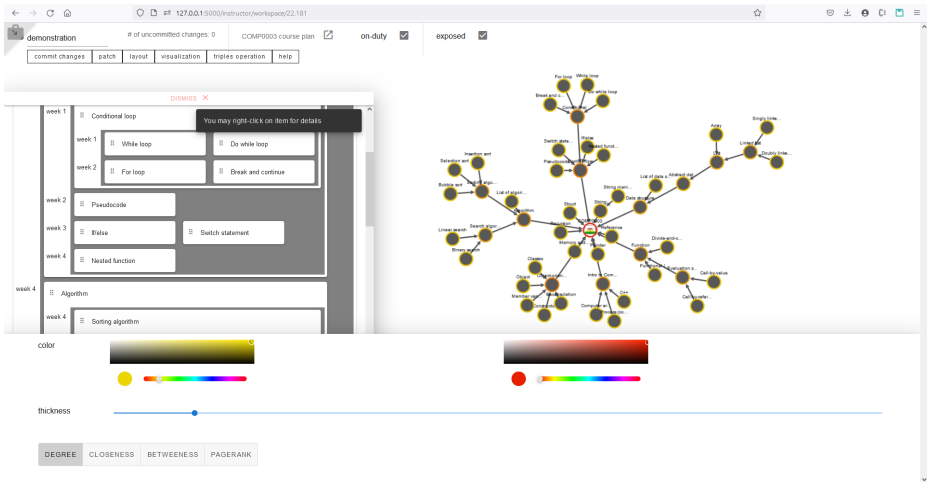

Fig. 4. Demonstration of graph visualization.

4.2 Extensibility for Consistency Management

As explained in §2.3, extensibility is a crucial aspect of consistency management tools. Currently, in KGRID, only one form of consistency between the macrostructure of learning units and the course KG is considered. Extensibility issues of KGRID are left unattended. Research for developing additional consistency checks that respond to practical needs are required.

5 Conclusions

We have proposed KGRID for integrating KG data representation in Instructional Design. An interactive course plan editor tool with automated initialization and consistent management is described. Preliminary demonstrations of prototypes with visualization have been implemented and shown. Research directions for improvement and other related applications are briefly discussed.

To expedite the application and development of educational KG research, we believe the practices of integrating KGs in the Instructional Design process are essential.

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