Dependency Matrix and Duration in Time Based Composition of Learning Paths

Ayman Moghnieh, Fabien Girardin, Joseph Blat

Department of Technologies, Universitat Pompeu Fabra
Passeig de Circumval·lació, 8, 08003, Barcelona, Spain
E-mail: {Ayman.Moghnieh, Fabien.Girardin, Josep.Blat} @upf.edu

Abstract: Users of online infrastructures for life long learning face the task of developing long-term plans for their learning objectives. They plan by choosing among the pool of available Competence Development Programs (CDPs) those relevant to their learning ambition, divide them into learning steps, and arrange them sequentially in time. This task becomes progressively difficult as it stretches further with long term learning goals. In this paper, we provide a foundation for developing interactive information visualization tools that help the learner design a learning path based on personal preferences.

Keywords: Lifelong Learning, Semantic distance, representative dependency matrix, learning path description

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Biographical notes: Ayman Moghnieh is a PhD student at the information technology and communications department of Universitat Pompeu Fabra, Barcelona, Spain. His work focuses on investigating ways for augmenting access to information spaces and developing personal information management systems. His research areas of interests include eLearning, information visualization, interface and interaction design techniques, semantic analysis, and semantic web.

1 Introduction

A learning path is an ordered set of CDPs that represents a viable plan for achieving a desired learning goal. The learning path determines when to start learning each CDP without violating the competence dependency relations among them. These relations are implicitly expressed in the competences associated with each CDP, whether being required or awarded. Given a set of CDPs related to a certain learning goal, we focus on finding possible learning paths and model the space created by this set.

Learners generally plan their paths in order to acquire the competences associated with their learning goals before engaging in learning activities. Moreover, they usually revise or update their paths based on their performances as they progress along their envisioned plans. In eLearning infrastructures such as TENCompetence (Koper, R. and Specht, M., 2007), learners might face the task of composing learning paths from large collections of CDPs upon defining their learning goals. This is generally true when planning long-term learning activities or far-set goals. Learners also seek to decompose these learning processes into steps or stages such as semesters in a masters degree in order to organize their learning paths.

Our aim hence becomes to develop methods for representing a set of CDPs whose borderlines are defined by the learner's own competences from one side, and the competences offered by the learning goal from the other. These methods compute the dependency relations among the CDPs in the set and identify potential learning paths. Furthermore, we explore ways to decompose the learning path into several steps based on the learner's available time and dedication. We also measure the path's length based in the time requirements of each involved CDP.

2 Previous works

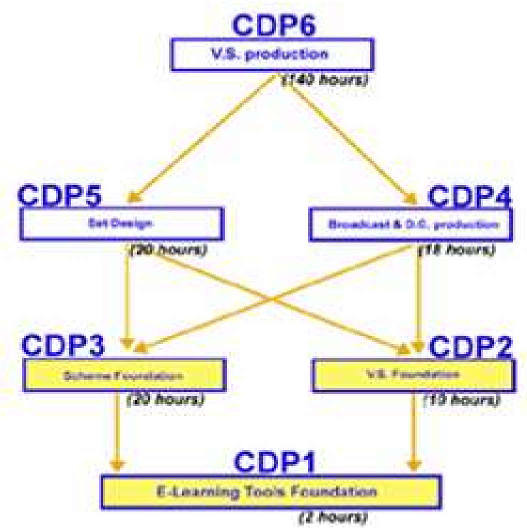
In general, matrices are handy whenever the relationships among a large set of elements needs to be analysed. Dependency matrices are frequently used in different scientific domains to represent constraint relations among elements of a set. A Dependency Structure Matrix or DSM is a matrix representation to model complex systems for design and engineering (Austin S., 2000). The DSM is also used for planning and/or managing projects where its analysis provides insight on activity flows and the effects induced by potential changes (Sangal, N., E. Jordan, et al., 2005). Dependency matrices are also used in semantic analysis to measure semantic distance between elements. Semantic proximity matrices enable vector representations of semantic spaces (Kandola, J. et al., 2003).

In the context of lifelong learning, flexibility and personalization are required in the process of designing learning paths composed from large sets of shared CDPs produced by different sources (Janssen, J et al., 2007). Both requirements are related with the prolonged learning process that stretch over years in circumstances that differ for each individual learner. Such need provides the direct motivation for developing a semantic infrastructure upon which learner support in terms of planning and visualization services can be provided.

3 Basic Scenario

In order to illustrate our proposal, we present a basic scenario based on the domain of digital cinema where 6 CDPs are made available for a degree on virtual sets production[1]. The structure of the curriculum composed from these CDPs is shown in figure 1. This figure exposes the dependency relations among the CDPs as well as the time required to achieve each of them. Given a cinema professional planning to acquaint herself with virtual sets production technologies, the task at hand becomes to arrange these CDPs in a learning path according to her personal preferences. The time that the learner can dedicate to the learning activities is considered to be around six hours weekly.

[1] The IP-Racine project website http://www.ipracine.org/objectives/objectives.html



	Competences					
	C1	**C2**	**C3**	**C4**	**C5**	**C6**
CDP6	-1	-1	-1	-1	-1	1
CDP5	-1	-1	-1	0	1	0
CDP4	-1	-1	-1	1	0	0
CDP3	-1	0	1	0	0	0
CDP2	-1	1	0	0	0	0
CDP1	1	0	0	0	0	0

Figure 1: Virtual Sets curriculum (left) and the RDM of CDPs and Cs involved (right)

4 Representative Dependency Matrix (RDM)

The CDPs pool compiled in relevance to a learning goal G encompasses a competence set that generally contains intermediate and additional competences besides those inherent in G. Each CDP can hence be represented as a vector of the competence set where for each competence an associated value of **1** signifies that it is offered by this CDP, and a value of **–1** when it is a prerequisite of the CDP. A value of **0** signifies that the competence is unrelated or irrelevant to the CDP. We can now build a RDM where each row becomes the representative vector of a CDP. Note that prerequisite competences define a transitive relation where if CDP1 requires a competence C1 and CDP2 provides C1 but requires C2, then CDP1 requires C2 also. Figure 1 (right) shows an example of a RDM based on the scenario defined above.

The CDPs in figure 2 are sorted by dependency, meaning that the CDPs with larger prerequisite competence sets are found higher in the matrix. Notice that CDP1 does not have any prerequisite competence and can be considered the start of the learning path. The learning goal can also be represented in the matrix by a raw of (**-1**)s and (**0**)s and it can be placed on the top of the CDPs hierarchy. Such RDM poses a direct question on the existence of a learning path that joins any possible starting point with the goal sought. This problem is formally defined as Path Existence.

5 Path Existence

Let RCDP be the set of CDPs retrieved for a learning goal G with a set of involved competences C. Let A0 be the set of CDPs $\subset$ RCPD / for each $c \in C$, $A0(c) \geq 0$. A0 is hence the set of CDPs that do not have prerequisite competences and offer a set of competences $C0 \subset C$ / $\forall$ c $\in$ C0, A0(c) = 1.

Let A1 = step(A0) be the set of CDPs $\subset$ RCPD / for each c $\in$ C0, A1(c) $\leq$ 0. A1 represents the set of CDPs accessible from A0. We say that Path(A0, A1) = true if and only if CR1 $\neq \emptyset$, CR1 being the set of competences {$\forall$ c $\in$ C0 / A1(c) = -1}.

Path is a transitive relationship as previously explained. If Path(A,B) = true and Path(B,C) = true, then Path(A,C) = true. Hence we say that a goal G is attainable by RCDP if and only if $\exists$ A0 $\neq \emptyset$ / Path(A0, G) = true.

Given that the precedence relationships among the CDPs are respected, multiple paths are often possible to reach the goal. To tackle that, we developed an algorithm that find the first possible path, stores it and deletes it from the matrix, then searches for another one until all paths are found. Identifying multiple paths helps visualizing them for the learner to pick among them. However, such solution is not practical if the choices are numerous, especially in large-scale programs where hundreds of CDPs might be involved. For such cases, new methods should be developed.

6 Path steps and segmentation

Another problem that requires formal definition is that of automatically segmenting the learning path into phases or steps based on the dependency relationships that govern its inherent CDPs. A path in RCDP can be hence expressed by Path(A0, G) = true where the unitary steps in this relation define unitary competence-driven dependency steps.

$$A0 \rightarrow A1 \rightarrow A2 \ \ldots\ldots\ An \rightarrow G$$

Any segmentation of Path(A0, G) is a composition of these unitary steps that can be normalized by the factor of CDP duration. In this logic, the segments proposed for a learning path are more or less homogeneous in time after respecting dependency relations among the inherent CDPs.

7 Path length

The path length represents the effort or work required to reach a desirable learning goal. We measure such length by aggregating the hours a learner needs to spend on the activities inherent in the adopted path. If a path can be segmented into its unitary steps as previously argued, than the length covered by the path is the summation of the unitary steps' widths.

$$LENGTH(\text{ Path}(\boldsymbol{A0}, \boldsymbol{G})\ ) = \sum LENGTH(\text{ Path}(\boldsymbol{Ai}, \boldsymbol{Aj})\ ) = \sum TIME(\boldsymbol{Ai})$$

Based on our scenario, the learner can spend up to *6 hours* a week studying for the virtual set diploma. She can either finish CDP after CDP or commit to several at the same time. As shown in figure 1, the CDPs have different lengths in time and those represented with the same color can be taken simultaneously.

The following figure shows three combinations of the first three CDPs composed without breaking any precedence relationship. If plan A is followed, the learner will finish a CDP before starting a new one. Two CDPs are taken at the same time in plan B, and plan C attempts to distribute time on all of the three courses.

In our scenario we assume that the learner is trying to plan as efficiently as possible by assigning all 6 hours of each week and avoiding having unassigned hours or gaps in time. Based on that, the learner plans the second phase of her LPD that covers CDP4 and CDP5, knowing that the first phase ends in on the sixth week with 4 hours to spare. Figure 2 shows two possible plans for the second phase, one asks to complete a CDP before starting another, while the other suggests taking both CDPs concurrently. Finally, CDP6 requires 140 hours to complete, and can only be taken after finishing CDP4&5.

Plan A ***weeks 1-6***

CDP1: E-Learning foundation	**2**					
CDP2: V.S. foundation	**4**	**6**				
CDP3: Scheme foundation			**6**	**6**	**6**	**2**

Plan A ***weeks 7-13***

CDP4: D.C. Production	**4**	**6**	**6**	**2**			
CDP5: Set design				**4**	**6**	**6**	**4**

Plan B ***weeks 1-6***

CDP1: E-Learning foundation	**2**					
CDP2: V.S. foundation	**4**	**2**	**2**	**2**		
CDP3: Scheme foundation		**4**	**4**	**4**	**6**	**2**

Plan B ***weeks 7-13***

CDP4: D.C. Production	**2**	**3**	**3**	**3**	**3**	**3**	**1**
CDP5: Set design	**2**	**3**	**3**	**3**	**3**	**3**	**3**

two different plans for CDP4&5

three different plans for CDP1,2,&3

Plan C ***weeks 1-6***

CDP1: E-Learning foundation	**2**					
CDP2: V.S. foundation	**2**	**2**	**2**	**2**	**2**	
CDP3: Scheme foundation	**2**	**4**	**4**	**4**	**4**	**2**

Figure 2: LPD planning

8 Conclusion and discussion

The methods and processes presented in this short paper form a foundation for developing information visualization tools that help learners plan their learning paths. We have been investigating relevant approaches such as Self Organizing Maps (H. Ritter and T. Kohonen, 1989) and map-based metaphors and evaluating their usability in the context of planning learning paths. Based on our current approach, the CDPs can be graphically represented by delegating the vertical axis of a graph to time duration and the horizontal axis to the spectrum of involved competences.

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