An Efficient Algorithm for Partitioning and Authenticating Problem-solutions of eLearning Contents

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ABSTRACT Content authenticity and correctness is one of the important challenges in eLearning as there can be many solutions to one specific problem in cyber space. Therefore, the authors feel it is necessary to map problems to solutions using graph partition and weighted bipartite matching. This article proposes an efficient algorithm to partition question-answer (QA) space and explores the best possible solution to a particular problem. The approach described can be efficiently applied to social eLearning space where there are one-to-many and many-to-many relationships with a level of bonding. The main advantage of this approach is that it uses QA ranking by adjusted edge weights provided by subject-matter experts or the authors' expert database.

Introduction

Any typical learning involves learning materials, instructors, questions and answers. A student may like to develop organised class notes, devise solutions to problems, create, verify and share content with peers, get access to the instructor’s resources and to an expert database, manage the self-testing environment, and have access to tutors and subject-matter experts. In this case, we have one-to-many or many-to-many relationships involving people, problems, solutions and resources. What are the relationships among those parameters? In the case of social eLearning, there is a viral effect of one another and the group as a whole. Changes can propagate easily. The coordination among the members is tight. Many ideas and much knowledge may be shared and distributed across the group, not held individually. These groups can be considered to be highly productive, creative teams with strong bonding that can deliver a good quality of work and share it with peers. Figure 1 shows a typical scenario of a problem-and-solution space (Brown & Duguid, 2000, p. 143).
The problem can be viewed as an \( n \)-dimensional dynamic cloud composed of people, contents, organisations, strategies, security issues and any number of other factors. It is important to visualise relationships and identify opportunities and trends and to obtain details regarding all cloud entities. The qualities of a solution depend on the authenticity and robustness of the solution. However, a qualitative or quantitative evaluation of the problem–solution (PS) or question–answer (QA) could help in determining the perfect or near-optimal matching between PS or QA. We will address a few of the components of the eLearning paradigm in terms of graph theory, especially using bipartite matching algorithms.

**Methodology for eLearning**

We have developed a personal e-learning system (PELS) (Dewan et al, 2011) in the context of a social network environment. The main objective of PELS is to develop individual skills on a specific subject and to share resources with peers. Our system architecture defines the organisation and management of a personal learning environment that aids in creating, verifying and sharing learning artefacts and making money at the same time. Figure 2 shows the concept and learning methodology that are involved using PELS.

![Figure 2. eLearning methodology for using PELS.](image)

To begin with, the learner plans the subject he/she would like to learn (a course or a subject). The learning planner organises the plan and advises the learner on the planning. The content organiser helps in organising the contents, notes, books, references or any kind of materials, including web resources. The problem solver helps in organising problems and solutions, guides the solving of problems in collaboration with subject-matter experts/tutors (any time and anywhere), and also shares problems and solutions with the groups in a social network (Dewan et al, 2011). The problem solver also checks any problem on the QA bank to verify the integrity of the answer. The learner takes part in the chapter review and practice test. Finally, the learner can access the report of his/her performance in terms of speed, grade, difficulty levels and ways to improve performance.
Bipartite Graph-based Model for eLearning Contents

A bipartite graph (Deo, 1987) is a graph whose vertices can be divided into two groups or partitions. The edges connect from one set to the other and there is no edge connecting to the same group of vertices. Figure 3(a) shows an example of a generic graph and 3(b) shows an example of a bipartite graph.

Figure 3(a). A typical QA graph.

Figure 3(b). A bipartite graph for QA.

eLearning content can consist of various kinds of documents that include eBooks and electronic content based on any subjects or problems. In this case, we can divide the eLearning contents by using a bipartite graph consisting of problem and solution vertices, where each problem can be mapped with a potential solution at the edges. The authenticity or correctness of the solution can be determined by the weights of the edges connecting the vertex pairs.

Bipartite Graph Matching for eLearning Questions and Answers

We have a graph $G = (V, E)$ that consists of vertices $V$ and edges $E$. Here, we would like to formulate our eLearning problems in terms of questions ($Q$) and answers ($A$). Each question is related to one set or multiple sets of answers. The problem can be viewed as a bipartite graph, and each of the $Q$ and $A$s can be matched using bipartite matching algorithms in graph theory. Here, we have two different types of vertices – one for $Q$s and another for $A$s. We would like to formulate the relationships between any of the $Q$s and $A$s, find the best match among them, and identify the best possible answer to a given problem or question.

Weighted Bipartite Graph for eLearning

A weighted bipartite graph (Secer et al, 2011) for eLearning consists of a graph $G = (V, E)$ with weights ‘$w$’ representing the degree of correctness of the answer to the question. Figure 4 shows a weighted bipartite graph that applies to eLearning contents.

In this case, the weight can be based on many factors, such as the relationship among the questions and answers, the feasibility of the answer, the degree of authenticity of the answer, and the relative weight given by experts to the answer. A weighted bipartite graph can also be useful to rank the quality of answers. This is very helpful in identifying the right answers to multiple-choice questions.
Graph Partitioning Using Weighted Bipartite Matching

We use bipartite matching and then partition vertices as in ontology (Chen & Fonseca, 2003), based on QA, social or professional affiliation and subject-matter expertise. In this section we develop the relationship for one-to-many or many-to-many based on the weights in the edges. Figure 4 shows a bipartite graph with weights. We came up with a partitioning scheme based on the criteria of the type of questions (say, concerning mathematics, physics or computer science), the answers, the academic affiliations, the teams, the subjects and the subject-matter expertise. Figure 5 shows the partitions with clusters based on our criteria and weights. The best solution or answer to any of the specific problems will be ultimately determined by the adjusted weights after partitioning, clustering and weighing, and it is given by the subject-matter experts. To partition each cluster, we use the algebraic sum of weights for a given vertex, factored by the weight given by the experts (in the case of social learning, by peer review and subject-matter experts). We also identify the least feasible solution to any specific problem and isolate it in a different cluster. These are called unsolved problems and they are open for peers and experts to solve. Once they are solved they become part of the QA database. The number of partitions will depend on NP (Non-deterministic Polynomial time) (Chapman et al., 2001) completeness of the problem. In this case, for example, we have n number of nodes divided into i and j nodes in the bipartite graph. We can partition i and j nodes into k partitions based on the weight \( w_{ij} \), such that \( w_{ij} \) is the optimum, or \( w_{ij} = w_0 \) and \( w_{\text{min}} \leq w_0 \leq w_{\text{max}} \), where \( w_{\text{min}} = 0 \) and \( w_{\text{max}} = 1.0 \).

Bipartite Matching Algorithm for eLearning Content Authentication

In this section, we present the JKnow algorithm that provides optimal matching in the bipartite graph for eLearning problem and solution contents. Here, we have a bipartite graph \( G = (V,E) \) with vertices \( V = \{i,j\} \), where i and j consist of questions and answers.

We are to find perfect or optimal matching between i and j based on weight \( w \) in edge \( E \) such for a partition \( (P) \), such that \( w \) is optimal and the solution is feasible.

Algorithm:
Input: i, j, w
Output: Q[i] ≠ A[j]

Set partition, k = 0

For partition k = 0 to n do the following:

Steps:

Create bipartite graph for G(V,E)
Partition each category of QA (i,j) based on the relationship
Create sub-cluster for the partitioned graphs based on weights
Search for feasible or optimal solution in j for the problem in i

Solve QA matching problem and authenticate:

If there are (m + 1) matches for each QA, then use Kirchhoff’s current and voltage law for the network of QA

Find new weight for each edge connecting the vertices in the cluster

If wi = wo, then colour the vertex pairs ‘GREEN’ as matched, else search for next feasible solution using the weighted graph

If no feasible solution is found, then colour the vertex(es) as RED or Empty/NULL and expose them to your social network.

If any peer provided the solution, authenticate it via the expert with new weights

If solution is feasible, then Q[i] = A[j] = ‘GREEN’
If solution is not feasible, then Q[i] ≠ A[j] = ‘RED’ or ‘NULL’

Repeat this step to find the best feasible solution through your network

Conclusion and Further Research

In this article, we elaborated the flow and learning methodology for the Personal eLearning System (PELS) and showed how graph theory can be applied in the question–answer (QA) validation process. In this context, we proposed using the bipartite matching algorithm with graph partitioning to explore the best possible matching between QAs. We also proposed using a weighted bipartite graph to find the most feasible solution where there is a possibility of multiple solutions to the same problem. We will further investigate the optimal feasible solution to a problem using the Simplex Method.

References


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