Combining IGA and KG for Serendipitous Learning Contents Recommendation

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Abstract

Although there have been few attempts to propose serendipity-oriented recommender systems in the field of education, such systems appear to lack of the essential ability to support learners' agency, which is learners' feeling of ownership and control over their own learning. In this paper, we propose an Interactive Evolutionary Computation driven recommender system that enables learners to take control and responsibility of their own learning while recommending learning resources that are novel and unexpected, yet still relevant to learners' interests. The proposed system specifically employs Interactive Genetic Algorithm (IGA) and Knowledge Graphs (KG) for dynamic recommendation of learning contents related to the history of scientific discoveries. We conducted both numerical simulations that confirmed the effectiveness of the learning contents optimization algorithm and an experimental evaluation which hinted at the meaningfulness of the proposed approach towards inducing serendipity within learners.

Keywords

Recommender Systems, Serendipitous Learning, Interactive Evolutionary Computation

1. Introduction

The deployment of recommender systems in the field of technology enhanced education has attracted increased interest as a promising means to help learners navigate through suitable learning resources, given the plethora of available digital learning resources nowadays [1]. The principal and commonly used techniques to build recommender systems are collaborative filtering [2] and content-based filtering [3]. However, in an educational context, both approaches present some shortcomings: risk of overgeneralization for collaborative recommenders and risk of overspecialization as far as content-based recommenders are concerned. Such issue has been framed as the "serendipity-problem" [4], to denote that the overspecialization or overgeneralization of recommended information can impair the ability of learning support systems to provide learners with content that is interesting, novel and more importantly unexpected [5]. As a result, such approaches can lead to an overly narrow set of suggestions lacking in serendipity and inadvertently placing the learner in what is known as a "filter bubble", according to Pardos [6]. That is, proposing recommender systems that also aim at helping learners make serendipitous knowledge acquisition is necessary to tackle the filter bubble issue.

The term "Serendipitous learning" has been used to refer to learning through gaining new insights, discovering interesting aspects and recognizing new relations, which occurs by chance or as by-product of other activities [7], [8]. Serendipitous learning emphasizes the positive

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role of unexpected realization of hidden, seemingly unrelated connections or analogies for learning and research [8], [9]. Although there have been few attempts to propose serendipity-oriented recommender systems in the field of education [10], [11], [12], such systems do not necessarily support learners' agency, which is yet an essential requirement, as serendipitous encounters also owe to the open-minded attitude of the seekers, their curiosity, and their perspicacity [13].

Interactive Evolutionary Computation (IEC) is a generic term which refers to a group of optimization techniques or algorithms that uses subjective human evaluation instead of a numerical fitness function to solve optimization problems when the fitness function cannot be assumed or appropriately represented in the form of a mathematical function [14]. Given such characteristics, IEC techniques have been successfully applied in many fields, such as face identification [15], fashion design [16], music composition [17], hearing aid fitting [18]. In a typical scenario of IEC, a small number of solutions (e.g., a population of ten solutions) are shown to a human user who is supposed to assign one of a pre-specified set of ranks (e.g., 1: very bad, 2: bad, 3: average, 4: good, 5: very good) to each solution in the population.

In this paper, we propose an Interactive Evolutionary Computation (IEC) driven recommender system that enables learners to take control and responsibility of their own learning while exploring learning resources that are novel and unexpected, yet still relevant to their interests. The proposed system specifically employs Interactive Genetic Algorithm (IGA) and Knowledge Graphs (KG) for dynamic generation of learning contents.

2. Research Goal and Approach

2.1. Problem Statement and Research Goal

In the domain of technology enhanced learning, a number of recommender systems have been proposed. Yet, a closer look to the current status of their development and evaluation reveals that such efforts present some limitations. For instance, available systems seem to target learning in formal settings, do not sufficiently support learners' agency and evaluate effectiveness only from the standpoint of learners' grade. However, informal learning, which depends to a large extent on individual preferences or choices and is often self-directed [19], could be greatly enhanced by introducing in such learning environments serendipity-oriented recommender systems. As evoked in the previous section, it should also be noted that most recommender systems dedicated to learning support embed recommendation techniques that could inadvertently place learners into "filter bubbles", a type of swim-laning of learners into a particular track based on a machine learned stereotype [8]. Meanwhile, it has been suggested that serendipitous experiences are valuable to learning at a personal level [10].

Therefore, to the extent of fostering learners' engagement in informal learning settings, the goal and major contribution of this study is to propose a serendipity-oriented recommender system which fulfill the following requirements:

- Target support of learning in an informal learning environment
- Facilitate learner's agency by actively supporting self-directed learning through exploratory interaction with the learning environment
- Embed a resource recommendation algorithm that involves learners in the system recommendation refining process by actively gathering their preferences

2.2. Approach

2.2.1. Overview of proposed system

Figure 1 shows an overview of the proposed system. In the system, the learning contents are represented in the form of "learning paths" covering related concepts and presented to learners via a dedicated interface, shown in Figure

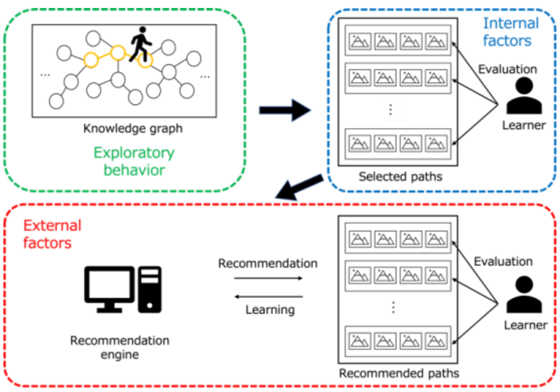

Figure 1: Schematic representation of interactions between the learner and the system

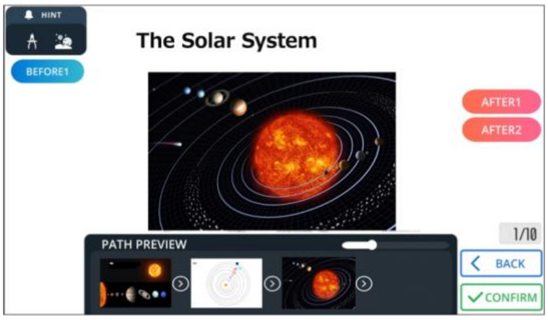

Figure 2: System Interface showing the paths navigation window

2. For instance, the knowledge database used for the study presented in this paper is a database in which learning contents (i.e., scientific discoveries and inventions) are related to each other and such relationships can be quantitatively expressed. To this extent, we built the learning contents database of the system using the contents of the book "*Science: The Definitive Visual Guide, Adam Hart-Davis (Ed.)*" [21]. It is a comprehensive book which tells the history of science and technology from the earliest times to the present day in chronological order by capturing every key moment of discovery, and showing how the concepts, the inventions, and the individuals behind them have changed our world. More interestingly, the book illustrates how one discovery is connected to another by presenting some pointers to events that preceded and followed a current discovery or invention. Such structure obviously holds the potential to make it easier for the reader to realize how scientific discoveries and inventions in a wide range of scientific fields are interrelated to each other. In the resulting knowledge graph, each piece of information (i.e., major discovery or invention) is represented by a node, and the relationship between related nodes is depicted by an edge. In other terms, each node holds the contents of each page of the book, while an edge expresses the relationship between two related pages.

Therefore, what is called "learning path" in the context of this study is a collection of nodes and edges extracted from a knowledge graph. Generation and optimization of learning path to be presented to learners at a given time of the interaction are achieved by the means of an interactive genetic algorithm (IGA), a kind of IEC algorithm.

In the proposed system, users are first asked to explore the knowledge graph and select paths of interest which they evaluate ((Phase 1). Then, the system learns the features of the paths that are interesting to the user by leveraging IGA, and generates new paths based on those features. If the generated path exists in the path database, it is presented to the user as-is, and if it does not exist, it is replaced by the most similar path in the path database and presented to the user (Phase 2). By repeating the evaluation of the proposed paths, the system attempts to learn the learners' taste and interests, and presents them with novel paths of greater interest, yet unexpected enough to achieve recommendation of learning contents that could induce serendipity.

2.2.2. Knowledge graph model

In general, a knowledge graph G= {E, R, F} is a collection of entities E, R, and facts F [22]. A fact is a triple $(h, r, t) \in$ F that denotes a link $r \in$ R between the head $h \in$E and the tail $t \in$ E of the triple. In our proposed system, the relationship between nodes and edges is also represented using the common (h, r, t) triples. Note that h and t represent two different nodes in the knowledge graph, while r represents an edge linking these nodes. In the following lines, we provide an overview of how we define these triples in the context of this study.

First of all, we expressed h as a collection of the three parameters vectors $\mathcal{H}_{\text{element}}$, $\mathcal{H}_{\text{Before}}$ and $\mathcal{H}_{\text{After}}$.

$$h = \begin{bmatrix} \mathcal{H}_{\text{element}} \\ \mathcal{H}_{\text{Before}} \\ \mathcal{H}_{\text{After}} \end{bmatrix} \tag{1}$$

$\mathcal{H}_{\text{element}}$ represents the main contents of a page, and is expressed as in equation (2), where h_{page} is the page number of the node, $h_{\text{discipline}}$ is the discipline (i.e., scientific field), and h_{era} is the era of the node contents.

$$\mathcal{H}_{\text{element}} = \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix} = \begin{bmatrix} h_{\text{page}} \\ h_{\text{discipline}} \\ h_{\text{era}} \end{bmatrix} \tag{2}$$

$\mathcal{H}_{\text{Before}}$ represents the related pages labeled as page BEFORE (=B) in the book, which refer to the related pages older than the current page. $\mathcal{H}_{\text{Before}}$ is defined as in equation (3) according to the number of older related pages N_B, and each BEFORE page b_{i}.

$$\mathcal{H}_{\text{Before}} = b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_{\text{i}} \\ \vdots \\ b_{N_B} \end{bmatrix} (1 \leq \text{i} \leq N_B) \tag{3}$$

$\mathcal{H}_{\text{After}}$ is defined similarly to $\mathcal{H}_{\text{Before}}$ and represents the related pages labeled as page AFTER (=A) in the book, as shown in (4). Note that N_A stands for the number of related pages coming after the current page a_j.

$$\mathcal{H}_{\text{After}} = a = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_j \\ \vdots \\ a_{N_A} \end{bmatrix} (1 \leq \mathrm{i} \leq N_A) \tag{4}$$

Next, t which also represents a content node similarly to h above is defined as follows. Let t_{page} denote the page number, $t_{\text{discipline}}$ denote the discipline, and t_{era} the era. t is expressed as in (5).

$$t = \begin{bmatrix} t_1 \\ t_2 \\ t_3 \end{bmatrix} = \begin{bmatrix} t_{\text{page}} \\ t_{\text{discipline}} \\ t_{\text{era}} \end{bmatrix} \tag{5}$$

Finally, r consists of the association of the following three vectors $\mathcal{X}_{\text{element}}$, $\mathcal{X}_{\text{Before}}$, and $\mathcal{X}_{\text{After}}$, as shown in equation (6).

$$r = \begin{bmatrix} \mathcal{X}_{\text{element}} \\ \mathcal{X}_{\text{Before}} \\ \mathcal{X}_{\text{After}} \end{bmatrix} \tag{6}$$

$\mathcal{X}_{\text{element}}$ expresses the relation between the main contents of node h and the main content of node t in terms of difference between discipline and era parameters, as shown in (7).

$$\mathcal{X}_{\text{element}} = \begin{bmatrix} |h_{discipline} - t_{discipline}| \\ |h_{era} - t_{era}| \end{bmatrix} \tag{7}$$

$\mathcal{X}_{\text{Before}}$ is defined as the difference between node h and t in terms of three parameters: pages number, discipline, and era, as shown in equation (8). Note that here $\mathcal{X}_{B_i} = 0$ if $t = b_i$ ($\mathrm{i} \in N_B$).

$$\mathcal{X}_{\text{Before}} = \mathcal{X}_{\text{Bi}} = \begin{bmatrix} |b_{i1} - t_1| \\ |b_{i2} - t_2| \\ |b_{i3} - t_3| \end{bmatrix} \tag{8}$$

Similarly, $\mathcal{X}_{\text{After}}$ is defined as the difference between node h and t in terms of three parameters: pages number, discipline, and, and era, as shown in equations (9). Here as well, $\mathcal{X}_{A_j}$=0 if $t = a_j$ ($\mathrm{j} \in N_A$).

$$\mathcal{X}_{\text{After}} = \mathcal{X}_{\text{Aj}} = \begin{bmatrix} |a_{j1} - t_1| \\ |a_{j2} - t_2| \\ |a_{j3} - t_3| \end{bmatrix} \tag{9}$$

Based on the proposed knowledge graph model, our key idea is to let an edge r capture differences in terms of discipline, era and page number between two given nodes, h and t. Besides, by expressing era and page number as time series parameters and adopting a similarity scale for the discipline parameter, we aim to quantitatively express the degree of relevance or divergence between two nodes (i.e., learning contents).

2.2.3. Learning path optimization algorithm

Path optimization here refers to the generation of new paths of interest to the user by the system. Let N be the number of paths generated from the knowledge graph G described in the previous section, and path_k ($k \in N$), a path arbitrarily retrieved from the path database. In this study, each path_k has a fixed length and is composed of four nodes h1, h2, h3, h4 (h1, h2, h3, h4 $\in h$) and three edges r_1, r_2, and r_3 ($r_1, r_2, r_3 \in r$).

Considering that the edges r_1, r_2, r_3 are defined as in (6), r_{path_k} which is the vector representing the whole path (i.e., $path_k$) is expressed as the sum of r_1, r_2, and r_3 as follows:

$$r_{path_k} = [r_1, \quad r_2, \quad r_3] \tag{10}$$

In the present study, the process of path optimization using IGA is based the gene information expressed by r_{path_k}. To such extent, the learner first rates some paths presented to him by the system in terms of relevance with their interests. Here, it seems important to bear in mind that learners are not prompted to evaluate each edge or node, but the whole path with a focus on the connection between starting nodes and ending nodes. The intention here, is to make the system capture how interesting the learner finds the connection between several related events across various scientific disciplines and eras. Based on the obtained evaluation values, the path is optimized by genetic algorithm processing, and the next-generation solution candidate (i.e., learning path) is presented to the learner. The path is optimized by repeating this process for a certain number of generations. Note that here, the path optimization differs from usual implementation of IGA as it requires an additional process that we call *Path retrieval*. When generating the next generation of solutions, in most cases, *Crossover* or *Mutation* will cause the generation of candidate solutions (i.e., paths) that do not exist in the path database R_{DB}. Therefore, for example, a non-existent path r_{pathA} needs to be "replaced" by an existing path r_{pathB} with the constraint that both paths are similar enough (i.e., $r_{pathA} \cong r_{pathB}$). To the extent of calculating the degree of similarity between two paths, we adopted the Dynamic Time Warping (DTW) algorithm [23], which is a well-known technique to find an optimal alignment between two given (time-dependent) sequences under certain restrictions. The DTW distance $D(path_k, path_l)$ which indicates the degree of similarity of two different paths $path_k$ and $path_l$ is recursively calculated using the following equations:

$$D(path_k, path_l) = \delta(r_{path_k}, r_{path_l}) + \min \begin{cases} D(path_k, path_{l-1}) \\ D(path_{k-1}, path_l) \\ D(path_{k-1}, path_{l-1}) \end{cases} \quad (11)$$

where $\delta(r_{path_k}, r_{path_l})$ denotes the distance between respective edges of $path_k$ and $path_l$ calculated as:

$$\delta(r_{path_k}, r_{path_l}) = |r_{path_k} - r_{path_l}| \quad (12)$$

3. Pilot Evaluation

We conducted an experimental pilot evaluation to investigate whether the proposed system could present information of interest but yet unexpected enough to the extent to induce serendipity within participants. The subjects were 3 university students majoring in science-related fields. Subjects were asked to visit and then evaluate the paths proposed by the system in terms of preference level on the scale of 0 to 5. Based on their ratings, the system generated new paths and the same operation was repeated until the ending condition (i.e., 10 generation rounds) was met. At the end of the interactions, we administrated a questionnaire survey, to collect participants' subjective opinions on the meaningfulness of their interaction with the system.

Figure 3~5 show the transition of the DTW values and evaluation scores of the most highly rated paths by each of the three participants (Subjects A~C) between the first and last generation rounds.

First, from these results, it can be noted that the proposed system was able to optimize the paths according to each user since the highest evaluation scores from participants seem to stabilize around the last generations. In other terms, the system was able to gradually present subjects with learning contents that were highly rated. The average evaluation score of the learning contents (i.e., path) presented at the last generation was relatively high (M= 3.9, SD:0.92).

Next, DTW values, which indicate similarity degrees between the generated path by the algorithm and the one retrieved from the database, tend to converge to a value near 0 around the last generation. This suggests that the proposed system was able to generate paths that are close to paths which exist in the database. This is a good indication that the proposed DTW-based path similarity calculation method performed well.

However, when analyzing the transition of DTW values for some subjects, there were cases in which DTW values rose rapidly even near the last generation or did not show a decreasing trend despite the number of generations increased, such as in the case of Subject B (Figure 4). Therefore, we cannot rule the hypothesis that using a method other than DTW distance as a method for calculating path similarity may lead to higher performance for path optimization.

From the results of the questionnaire survey, we note that the proposed system was able to present interesting and surprising learning contents to two out of three subjects. Moreover, two subjects also declared that they were able to experience serendipity through their interaction with the system. Such results seem to suggest the meaningfulness of the proposed approach.

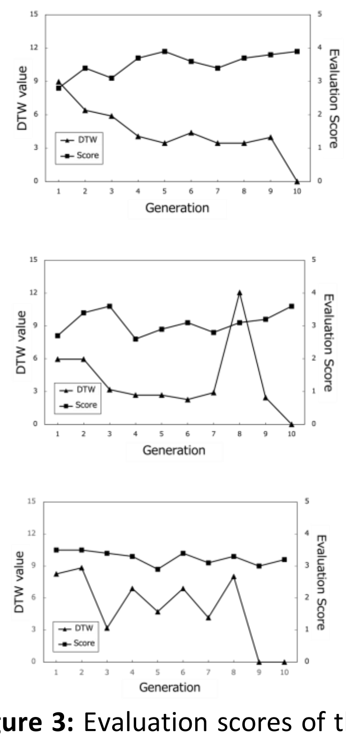

Figure 3: Evaluation scores of the best paths and corresponding DTW values (Top to Bottom Subject A, B and C).

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