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Swarm-based Sequencing Recommendations in E-learning

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Abstract

Open and distance Learning (ODL) gives learners freedom of time, place and pace of study, putting learner self-direction centre-stage. However, increased responsibility should not come at the price of over-burdening or abandonment of learners as they progress along their learning journey. This paper introduces an approach to recommending the sequencing of e-learning modules for distance learners based on self-organisation theory. It describes an architecture which supports the recording, processing and presentation of collective learner behaviour designed to create a feedback loop informing learners of successful paths towards the attainment of learning goals. The article includes results from a large-scale experiment designed to validate the approach.

1 Introduction

Modular e-learning courses form the backbone of many open and distance learning (ODL) programmes, offering increased flexibility for both learning providers (by the re-use of modules in different programmes) and learners (by the picking-and-mixing of modules en route to a given learning objective). Distance Learning programmes increasingly specify an educational goal in terms of points to be attained (such as in ECTS system [1]), leaving the learner free to select and sequence modules to accumulate points.

The flipside of this flexibility is an increase in the complexity of ODL programmes which can hinder learners and even contribute to drop-out [2]. Students find it hard to gain an overview of the number of modules and the best sequence in which to study them. Yorke [3] notes that "as the unitization of curricula spreads through higher education, so there is a need for greater guidance for students to navigate their way through the schemes." We use the term educational wayfinding support [4] to refer to the tools and systems which help learners during the cognitive, decision-making process required of them as they assume responsibility for choosing and sequencing their learning events.

In this paper, we describe an approach to the provision of recommendations which draws on self-organisation theory and swarm intelligence to provide low-cost and robust educational wayfinding support.

2 Learning Networks

Our work on educational wayfinding support is being carried out within the context of a larger R&D programme, designed to help the creation of flexible learning facilities that meet the needs of learners at various levels of competence throughout their lives. We refer to these network facilities for lifelong learners as "Learning Networks" or LNs [5]. Learning Networks support seamless, ubiquitous access to learning facilities at work, at home and in schools and universities. Learning Networks consist of learning events, called Activity Nodes (ANs) in a given domain. An AN can be anything that is available to support learning, such as a course, a workshop, a conference, a lesson, an internet learning resource, etc. Providers and learners can create new ANs, can adapt existing ANs or can delete ANs. An LN typically represents a large and ever-changing set of ANs that provide learning opportunities for lifelong learners ("actors") from different providers, at different levels of expertise within the specific disciplinary domain.

Wayfinding support in LNs relies on the following concepts:

The learner's goal is a description of the level of competence a learner wants to achieve (for example, the bachelors or masters level in a particular discipline).

A route is a plan to reach a goal, described as a series of selections and/or sequences of ANs. ODL providers offer programmes with curricula (i.e routes) by which individuals can reach their goals.

A learning track is the sequence of ANs successfully completed by a Learner;

The learner's position is the set of ANs which have actually been completed (i.e. the Learning Track) together with those which can be considered as completed, perhaps as a result of exemptions arising from previous study or work experience.

Position and goal equate to "you are here" and "there's where I want to be", respectively, and wayfinding guidance concerns effective ways of getting from here to there.

3 Self-organisating wayfinding support

In offering flexible ODL programmes, providers essentially rule out the possibility of having instructional designers set fixed paths through the curriculum. Learner support services can provide personalised advice, but this comes at a price. A third avenue of wayfinding support has been pursued in the area of adaptive hypermedia systems [6], yet their heavy reliance on user modelling leaves some doubt as to their practical application.

Brookfield [7] suggests an alternative approach "successful self-directed learners … place their learning within a social setting in which the advice, information, and skill modelling provided by other learners are crucial conditions for successful learning". This observation finds echoes in the information navigation literature, where the term social navigation [8] has been coined to describe research reflecting the fact that "navigation is a social and frequently a collaborative process" [9]. Indirect social navigation exploits traces of interactions left by others [10] and can be used as the basis of a recommendation system – advice can be based on the tracks of previous learners who have followed a particular route towards a goal. This avoids pre-planning so that learning networks spontaneously acquire (sequential) structures, i.e. self-organise [11].

Bonabeau, Dorigo and Theraulaz [12] give ant foraging trails as an example of the spatiotemporal structures which emerge as a result of self-organisation. The ability of ants to find efficient (i.e. short) routes between nests and food sources suggests an approach to cost-effective, flexible and implementable wayfinding support. Paths identified by ants are not pre-planned, but emerge, spontaneously, as a result of indirect communication between members of an ant colony—a form of indirect social navigation. Dorigo and Di Caro [13] describe how ants deposit a chemical substance known as pheromone which can be sensed by other ants. When a navigational decision has to be made, such as taking a left branch or a right one, ants make a probabilistic choice based on the amount of pheromone they smell on the branches. Initially, in the absence of deposited pheromone, each of the branches is chosen with equal probability. However, if one branch leads to food faster than the other, ants on their way back will select the shorter branch due to the presence of the pheromone they deposited on the forward journey. More pheromone is deposited, leading to more ants selecting the shortest path, and so on, creating a feedback loop which leads ants along efficient paths to their destination. This process of indirect communication exploited by members of ant colonies is known as stigmergy. In their overview article Theraulaz and Bonabeau [14] state, “The basic principle of stigmergy is extremely simple: Traces left and modifications made by individuals in their environment may feed back on them…. Individuals do interact to achieve coordination, but they interact indirectly, so that each insect taken separately does not seem to be involved in coordinated, collective behavior”

Learners’ interactions with learning resources and activities are recorded automatically as they progress through a body of knowledge. The time-stamping of these interactions allows sequences to be identified which can be processed and aggregated to derive a given “pheromone strength” favouring paths along which more learners have been successful. This information can be fed back to other learners, providing a new source of navigational guidance indicating “good” ways through the body of knowledge—a self-organising, stigmergic approach to wayfinding support.

4 An architecture for swarm-based sequencing recommendations

The architecture we propose combines elements which record, collect, process and present collective learner behaviour. Andersson et al. [15] use the phrase Emergent Interaction Systems to describe systems which “consist of an environment in which a number of individual actors share some experience/phenomenon. Data originating from the actors and their behaviour is collected, transformed and fed back into the environment. The defining requirement of emergent interaction is that this feedback has some noticeable and interesting effect on the behaviour of the individuals and the collective - that something ‘emerges’ in the interactions between the individuals, the collective, and the shared phenomenon as a result of introducing the feedback mechanism.” The ‘something that emerges’ in our situation are paths through bodies of knowledge, rather like well-worn footpaths in forests.

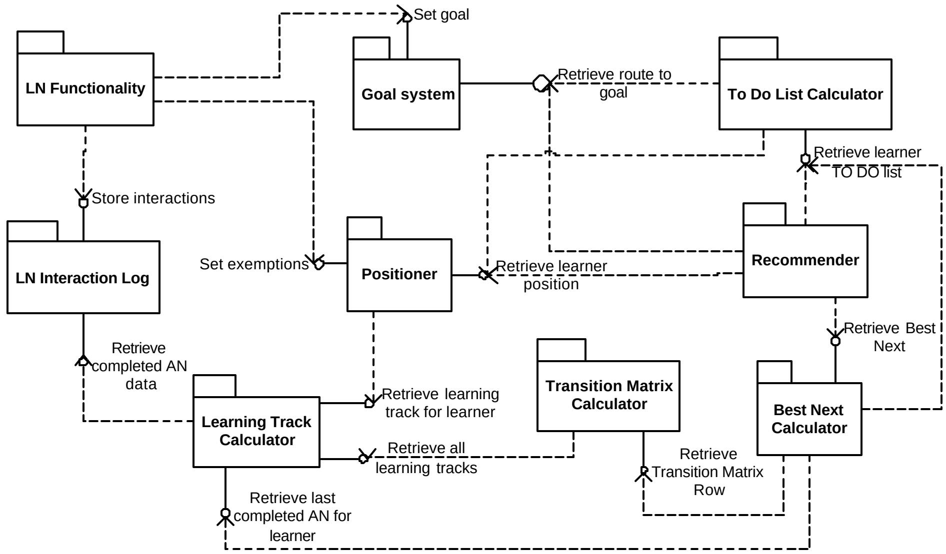

Figure 1. A software architecture for wayfinding support for learners

Fig. 1 shows the proposed architecture for self-organising wayfinding support. Learners interact with the LN Functionality available in a learning network (Koper et al., 2004). Part of the functionality available allows learners to select from a list of the learning goals in a learning network (the Goal system), and thereby also identify the route to the goal. Learner interaction is stored in an LN interaction log, including information on the learner, the AN, a timestamp and an indication of performance (for example, pass or fail). This information can be processed to create sequences of ANs successfully completed by learners (done by the Learning Track Calculator – see [16] for an examination of the techniques involved). Using information on the tracks of all learners, a transition matrix [17] can be calculated (by the Transition Matrix Calculator) over pairs of ANs, indicating, for each from node, how many learners have successfully progressed to the following to node (see table 1: learner transitions from ANs (rows) to other ANs (cols)).

The Positioner deals with the maintenance of the ANs which have been completed by learners, or can be considered as having been completed. The former is straightforward to calculate, since it is the Learning Track for a given leaner. The latter is considerably more complex, requiring techniques for the recognition of prior learning to identify ANs from which a given learner can be exempt (see [18] for an examination of approaches to this problem).

The To Do List Calculator maintains the difference between the requirements expressed in the route associated with the learner's goal, and his or her current position. Using the transition matrix and the Learner's To Do list, the Best Next Calculator selects an AN to recommend based on the progress of the swarm of other learners.

The algorithm used to select the AN from the candidates is that described by Koper [19]. Using the transition matrix shown in table I, if we imagine a learner having just completed the AN labelled 'A' and en route to a goal which requires A, B, C, D and E to be successfully completed, following, removal of those ANs already completed, a list is first drawn up of all the transitions made from A by all previous learners (i.e. 4 from A to B, 2 from A to C, 5 from A to D and 1 from A to E):[B, B, B, B, C, C, D, D, D, D, D, E]

	A	B	C	D	E
{}	1	3	2	4	5
A		4	2	5	1
B	2		2	1	3
C	3	4		1	2
D	4	2	4		5
E	1	2	5	3	

Table 1. A matrix showing learner transitions

The recommendation is identified by drawing one item randomly from this list. The result is that the most frequently followed path has a higher probability of being selected (in this case A to D), although, to prevent sub-optimal convergence to this path, there is a chance that the other paths (A to B, A to C and A to E) will be selected. The use of randomness in the procedure follows the ingredients for self-organisation described by Bonabeau et al. [12].

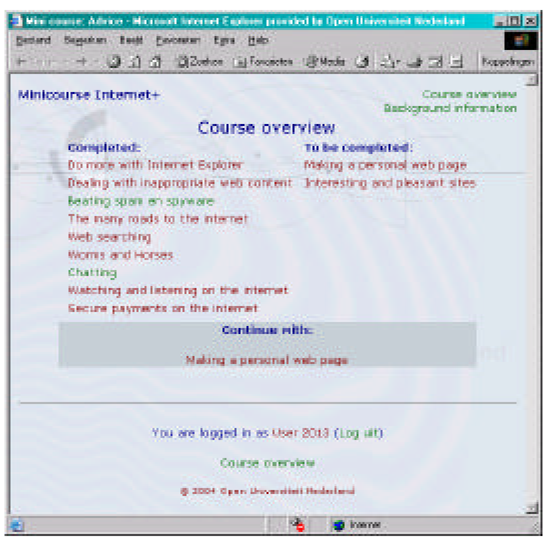

Figure 2. Overview for a learner in the experimental group

The final component in the architecture is the Recommender, which pulls together the various pieces of information to present a coherent picture to the learner, including information on the learner's goal, position, to do list and the recommendation itself. Fig. 2 shows a version of the recommender, implemented in the open source Virtual Learning environment Moodle [20].

The navigation tool is intended to enhance effectiveness and efficiency in Learning Networks; the navigational support is designed to facilitate planning decisions and reduce the risk of information overload by offering accessible and more learner centred (i.e. related to learner's present position) planning information. Moreover, as the feedback makes use of success rates, it is expected to help learners make better choices based on "tried and tested" sequences.

5 Validating the approach

The nature of distance education and lifelong learning and, more generally, discussions on definitions and calculations of output and dropout in education [21-26] suggest that in simply defining effectiveness in terms of goal attainment (rate of completion) we would be overlooking the fact that progress may have been made despite non-completion. In our study we will therefore not only look at rates of completion (the number of learners achieving a predefined goal), but also at the amount of progress made (the number of ANs that have been completed). Efficiency on the other hand will be indicated by a single variable: the time it takes to attain the goal.

To test the effects of the navigational feedback a true experiment design [27] was carried out. A course, consisting of 11 ANs, about the use of Internet was developed with an integrated recommendation tool. Each AN represents around two hours learning time and was completed with a short, five question multiple-choice quiz. If the quiz was completed successfully (a score of 60% or more), the AN is completed, added to the learning track of the learner and used in the calculations for the transition matrix. The course was offered for three months from mid-March to mid-June 2005. In total 1013 people enrolled and the learners were split into two groups, whereby one group (the experimental group) received a recommendation based on the successful progress of other learners using the transition matrix, and the other group (the control group) received no advice. In total 808 learners actually started the course, 398 in the control group and 410 in the experimental group. For all students the goal was the same: to complete 11 AN.

The following hypotheses were tested in the experiment:

- Offering feedback on the best next step, based on past choices of successful learners will result in increased effectiveness as indicated by both the amount of progress made (the number of ANs completed) and goal attainment (the proportion of learners reaching the predefined goal).
- Offering feedback on the best next step, based on past choices of successful learners, will result in increased efficiency as indicated by the time required to attain the goal.
- Offering feedback will result in greater convergence of tracks chosen by learners.

6 Results

Although at the end of the experiment, the average number of completed ANs is about the same for both groups, further analysis of the study progress demonstrates that AN completion is higher in the experimental group until 10 days prior to the end of the experiment as shown in Fig 3.

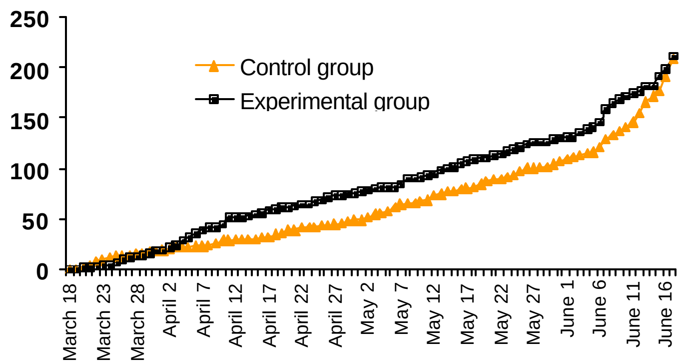

Figure3. Number of ANs completed over time

In the experimental group study progress developed along a straight line, whereas in the control group the amount of progress made accelerated towards the end. This shift towards the end may appeared to have been influenced by an intervention, carried out ten days prior to the end of the experiment, when learners where reminded of the course deadline which had an effect only for the control group [28]. Prior to the intervention the percentage of learners completing all 11 ANs was significantly higher in the experimental group (40%) than in the control group (33%) (χ^2 = 4.04, df = 2, p < 0.05). The navigational support proposed in this study did not have a significantly positive effect on efficiency, i.e. the time taken to complete 11 ANs

The hypothesis, concerning convergence of tracks, is tested by comparing the transition matrixes of both groups. Table 2 and 3 show the transitions of both the control group and the experimental group (the course modules numbered from 1 to 11).

	to										
from	1	2	3	4	5	6	7	8	9	10	11
Start	51	39	22	30	19	15	9	15	19	21	46
1		35	19	26	24	12	12	22	26	20	28
2	34		21	22	20	26	14	26	16	15	24
3	27	22		29	19	12	22	18	25	11	20
4	15	22	28		16	25	25	16	17	20	24
5	11	18	22	16		20	24	24	24	29	13
6	8	10	16	10	12		20	10	18	12	14
7	13	16	21	19	20	39		15	15	20	15
8	15	12	16	21	25	18	33		27	26	18
9	20	22	16	21	18	18	22	24		25	15
10	14	16	21	12	37	17	27	26	19		20
11	32	24	21	22	13	17	12	24	22	27	

Table 2. Transition matrix control group

Each cell contains the number of students that moved from one module to another. Convergence means in practice that learners choose the same path and can be examined by the determining how much the actual number of learners moving from course module A to B deviates from the expected number based on the standard mean of each row.

	to										
from	1	2	3	4	5	6	7	8	9	10	11
None	51	133	19	16	18	5	6	13	8	23	25
1		26	27	40	12	10	9	14	28	36	24
2	37		2	9	6	21	34	68	8	8	49
3	22	17		11	13	10	49	18	23	17	33
4	19	13	13		24	16	26	12	54	4	25
5	26	7	52	5		18	16	20	11	60	10
6	9	25	18	36	20		17	9	12	12	5
7	18	3	10	35	18	44		9	27	25	12
8	30	14	24	13	62	19	9		20	18	6
9	6	13	16	21	36	18	23	18		20	28
10	8	11	17	20	24	26	29	30	23		22
11	25	22	34	22	7	41	9	28	14	12	

Table 3. Transition matrix experimental group

	χ2 exp groep	Sig.	χ2 ctrl groep	Sig.	df
Course topic					
{ }	470	0,000	72	0,000	10
Many roads to internet	48	0,000	20	0,017	9
Get more out of IE	201	0,000	15	0,083	9
Interesting places on the web	67	0,000	15	0,087	9
Radio & TV on internet	91	0,000	9	0,409	9
Spam & Spyware	158	0,000	14	0,120	9
Creating web pages	52	0,000	11	0,303	9
Chatting	82	0,000	26	0,002	9
Inappropriate content	118	0,000	18	0,035	9
Payments on the internet	35	0,000	5	0,841	9
Virusses	27	0,002	24	0,005	9
Web searching	59	0,000	16	0,073	9

Table 4. Results Chi-square test

For each course module (row in the transition matrix) we calculated to which degree the follow up choice is spread proportionally between the options. Where this follow up choice is more concentrated (deviates more from the expected number), this demonstrates convergence. The deviations of the expected values are expressed in terms of Chi-square per row or course module. Table 4 shows the results of the Chi-square test and demonstrates that all (12) transitions in the experimental group deviate significantly from the standard mean. In the control group this amount is five.

7 Conclusions

The results of our experiment lead us to conclude that navigational support based on feeding back the choices of successful learners enhances effectiveness in lifelong learning. Converge of learning tracks is demonstrated as well as higher completion rates in the experimental group.

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