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Citation for published version (APA):

Van den Berg, B., Van Es, R., Tattersall, C., Janssen, J., Manderveld, J., Brouns, F., Kurvers, H., & Koper, R. (2005). Swarm-based Sequencing Recommendations in E-learning. In *Proceedings. 5th International Conference on Intelligent Systems Design and Applications* (pp. 488-493) https://doi.org/10.1109/ISDA.2005.88

DOI:
10.1109/ISDA.2005.88

Document status and date:
Published: 30/05/2005

Document Version:
Peer reviewed version

Please check the document version of this publication:

• A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
• The final author version and the galley proof are versions of the publication after peer review.
• The final published version features the final layout of the paper including the volume, issue and page numbers.

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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 initial 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 in 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. Although learner support services can provide personalised advice, 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.

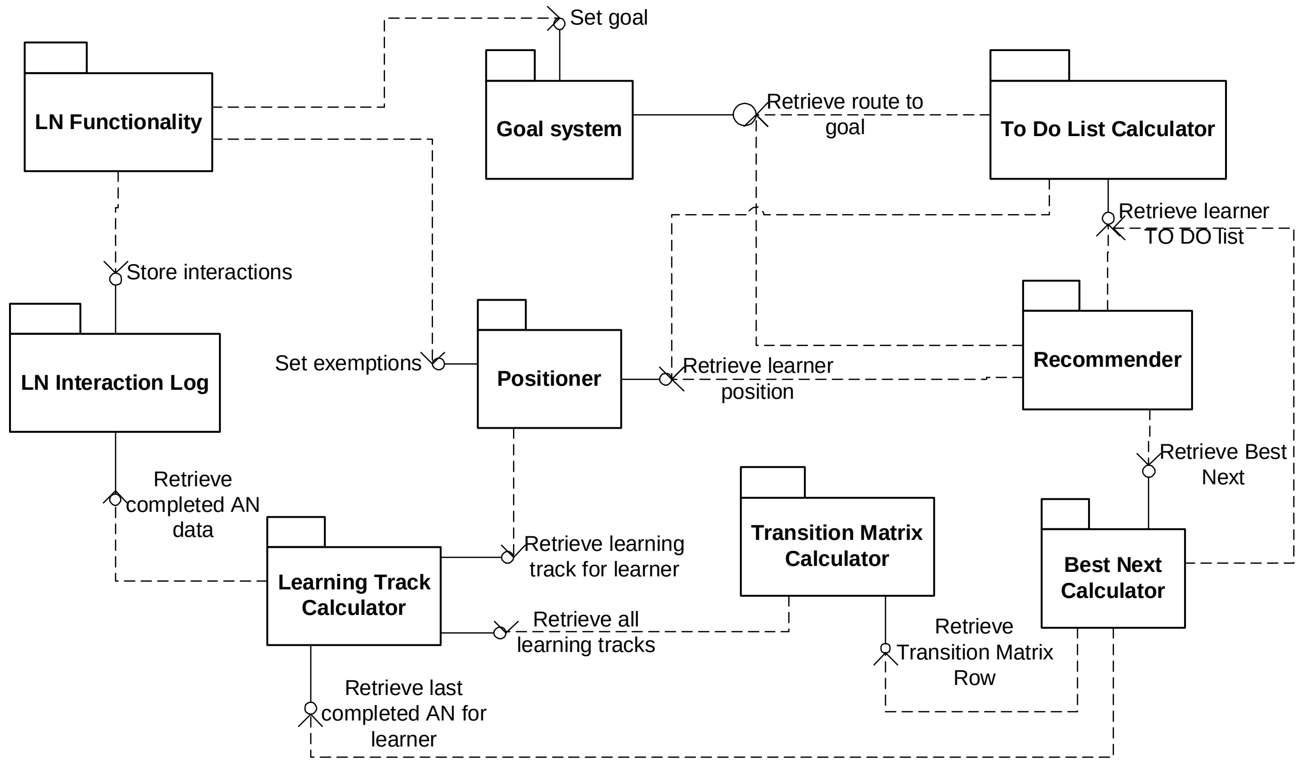

Figure 1. A software architecture for wayfinding support for learners.

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 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 Figure 2).

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).

	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	

Figure 2. A matrix showing learner transitions from ANs (rows) to other ANs (cols).

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 Figure 2, 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, 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]

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].

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. Figure 3 shows a version of the recommender, implemented in the open source Virtual Learning environment Moodle (Dougiamas, 2004).

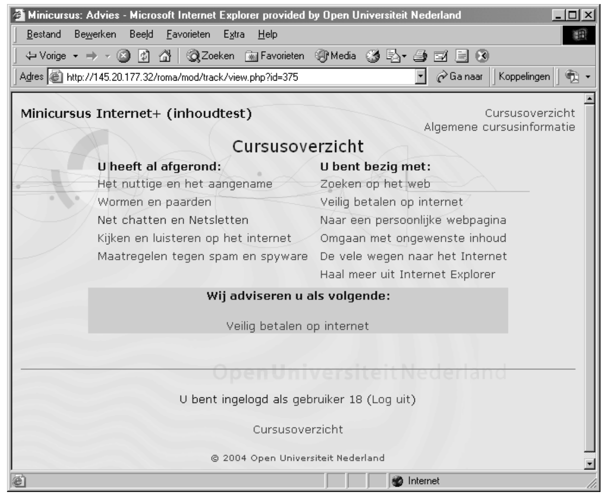

Figure 3. The Moodle-based prototype.

5. Validating the approach

We are currently carrying out an experiment to test two hypotheses related to the architecture and focusing on improvements in educational efficiency. We define educational efficiency as the ratio of the number of learners starting to follow a route vs those who complete the route.

- Hypothesis 1: Offering feedback to learners will lead to significantly higher output rates given the same input.
- Hypothesis 2: Offering feedback will result in greater convergence of tracks chosen by learners.

In order to test the hypotheses, we enrolled 1,013 people interested in learning more about the Internet in an e-learning course consisting of 11 ANs. The course was offered for three months from mid-March to mid-June 2005

Each AN represents around two hours learning time and is completed with a short, 5 question multiple-choice quiz. If the quiz is 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 learners were split into two groups (505 and 508), 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.

Hypothesis 1 will be tested both by counting the number of learners who successfully complete all 11 modules (i.e. reach the goal), as well as computing the average number of modules completed by the group.

The second hypothesis will be testing using sequential data mining techniques [16]. A learning track is seen as a sequence, that is, an ordered list of elements (AN's). The length of a sequence is given by the number of elements of the sequence and a k-sequence is a sequence that contains k elements. A learner supports a sequence s if s is contained in the learning track for this learner. The support for a sequence s is the fraction of total learners who support this sequence. Sequences with a certain user-defined minimum support are called frequent sequences.

Sequential data mining techniques will be used to compute the number of frequent sequences for both groups at various levels of minimum support. Furthermore the length of the frequent sequences at various levels of minimum support for both groups will be examined.

6. Initial results and discussion

Since the experiment is still running at the time of writing,, we are not in a position to show the final results. However, the Table 1 shows the state-of-play with respect to the first hypothesis with three weeks of the experimental period remaining.

Table 1: Numbers of completed ANs in the two groups

# completed ANs	Control group	Experimental group	Total
0	245	211	456
1	39	49	88
2	21	26	47
3	21	17	38
4	16	15	31
5	8	12	20
6	17	11	28
7	14	12	26
8	9	13	22
9	7	9	16
10	8	9	17
11	100	124	224
Total	505	508	1013

The data shows an efficiency of 24.4% (124/508) for the experimental group and 19.8% (100/505) for the control group.

Turning to the frequent sequence mining techniques as a measure of the convergence of learning tracks resulting from stigmergy, table 2 shows sequences found at various levels of support for those learners having successfully reached the goal, using the Prudsys Basket Analyzer tool [20]. Note that the sequences are what Mobasher et al. [21] term Sequential Patterns (SPs) rather than Contiguous Sequential Patterns (CSP) – "CSPs are a special form of sequential patterns in which the items appearing in the sequence must be adjacent with respect to the underlying ordering. In contrast, items appearing in SP's, while preserving the underlying ordering, need not be adjacent, and thus represent more general navigational patterns".

Table 2: The results of sequence mining

		Control group	Experimental group
15%	1-seq	11	11
	2-seq	109	110
	3-seq	526	481
	4-seq	118	120
	5-seq	0	5
10%	1-seq	11	11
	2-seq	110	110
	3-seq	775	745
	4-seq	602	532
	5-seq	4	32
5%	1-seq	11	11
	2-seq	110	110
	3-seq	965	954
	4-seq	2869	2173
	5-seq	777	596
	6-seq	4	46
	7-seq	0	1
3%	1-seq	11	11
	2-seq	110	110
	3-seq	985	984
	4-seq	4996	4530
	5-seq	4648	3285
	6-seq	579	569
	7-seq	7	52
	8-seq	0	2

Table 2 shows that for a given support value, longer frequent sequences are found and so both tables show support for the hypotheses at this stage of the experiment. Further articles will report and analyse the final data in more detail following completion of the experiment.

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