Navigational support in lifelong learning: enhancing effectiveness through indirect social navigation

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Abstract

Efficient and effective lifelong learning requires that learners can make well informed choices from the vast amount of learning opportunities available. This paper suggests to help learners find their way by analysing choices made by learners facing the same navigational decisions in the past and feeding this information back as advice to present learners. The paper describes a tool developed to deploy this principle of indirect social navigation through collaborative filtering. The tool was tested in a controlled experiment with the experimental group using the tool and the control group not receiving any recommendation but choosing from a list of otherwise identical topics. Positive effects were found on effectiveness (progress and completion rates) though not on efficiency (time taken to complete) for the experimental group as compared to the control group.

Keywords: indirect social navigation, lifelong learning, Learning Networks, self-organisation, collaborative filtering

1. Indirect social navigation

Determining a path through education can prove challenging to an extend that it results in lack of progress or even drop-out [1 – 5]. In lifelong learning, where learning opportunities reach beyond institutional boundaries, traditional approaches to navigational support like pre-planned routes are inadequate. The concept of Learning Networks [6] addresses facilitation of lifelong learning. Learning Networks (LNs) are self-organised, distributed eLearning systems designed to facilitate learner controlled lifelong learning. Self-organised means that organisational structures evolve bottom up, from the actions and interactions of individuals, rather than being pre-defined. The Network contains units of learning offered by different educational providers, directed towards attainment of a certain competence level. To attain a certain level of competence different paths can be followed through these offerings. So what path best to follow through the units of learning that have to be completed in order to achieve the desired competence level? Alternatives to one-to-one advice and pre-planned routes for navigational support can be sought in several directions [7]. Social navigation, e.g. presentation of student views [5], is one of the alternatives. However, social filtering systems using explicit ratings require a large number of ratings to remain viable and users might consider it too much of a burden to rate units of learning [8]. A way to avoid this is to rely on indirect social navigation, a concept closely related to the principle of self-organisation.

For self-organisation to occur, actors have to have a high level of interactivity and access to feedback concerning the performance of similar others in the network [9]. This does not necessarily require direct interaction: traces left and modifications made by individuals in their environment can provide indirect feedback [10]. Where Rovai [4] states that “other students, staff, and faculty may not be readily accessible that can provide students with the information that they seek”, using indirect feedback might help bridge the gap: other students may be consulted as a source of information, albeit indirectly. Similar to collaborative filtering used in recommender systems [11], our approach exploits information on former user behaviour to make
a recommendation to a presently active user. In our study, learners were offered feedback regarding the best next step, based on the number of times a unit of learning had been successfully completed. A unit of learning was successfully completed when a learner passed the associated assessment. In order to feedback this information, a collective log of learner interactions is used as described in Tattersall et al. [7]. The feedback is calculated as follows: if a unit of learning ‘Y’ has been completed by 10 learners and 4 of those learners went on to successfully complete ‘X’, whereas 2 went on to successfully complete ‘Z’, the advice for the next best step to a learner who has just completed ‘Y’ as a first node, will be a random draw from the set {X, X, X, X, Z, Z}. Taking a random draw ensures that the most frequently completed unit of learning is most likely to be recommended, while leaving room for other successfully completed units of learning to be recommended as well, thereby avoiding suboptimal convergence to a single next step [9].

We expect that the navigation tool will enhance both effectiveness (i.e. producing the desired effect) and efficiency (i.e. producing the desired effect with a minimum of effort) in LNs because offering more learner centred (i.e. related to learner’s present position) planning information will facilitate planning decisions and reduce the risk of information overload. Moreover, as the feedback makes use of success rates, we expect learners to make better choices based on “tried and tested” sequences. The impact of offering this feedback on effectiveness and efficiency has been tested in a true experiment [12].

Effectiveness was considered in two respects: the amount of progress made and goal attainment [13]. Efficiency was defined as the time taken to attain the goal.

2. Method

The navigation tool was deployed in a Learning Network consisting of eleven units of learning, delivered on-line on the subject of the Internet. Participation in the LN was free for the target group of adult learners who have some experience with Internet (surfing the web and using email) and who face questions like: How safe is it to buy things on the Web? How to search for information on the Web?

Participants were randomly assigned to an experimental group that was offered feedback and a control group that proceeded through the Learning Network without any feedback. In order to encourage goal attainment completion of all eleven units within the three months experimental period was rewarded with a certificate. An e-mail newsletter was sent as a reminder of the closing date, ten days prior to the end of the experimental period.

The LN was created in Moodle [14] and modified so that an overview of the units of learning was available to all learners listing completed and to be completed units of learning separately. For learners in the experimental group the overview additionally showed an advice: “Continue with: [the best next step, based on successful choices of other learners]”. Like participants in the control group, learners in the experimental group were told they could study the units of learning in any order but were advised to follow the
recommendation. Figure 1 shows the overview for a learner in the experimental group. The order of the list of units of learning still to be completed was reshuffled each time the page was viewed so that there would be no effect in the sequencing of units of learning due to the presentation in a fixed list.

A group of 1011 people enrolled and were randomly assigned to either experimental group or control group. However, twenty percent never actually visited the website. They were excluded from the study, leaving a group of 808 learners: 398 in the control group and 410 in the experimental group.

3. Analyses

The effect of the feedback offered on the amount of progress made was measured through multivariate analysis of variance for repeated measures [15]. The average number of completed units of learning was measured four times at three weekly intervals. The effect on goal attainment was tested comparing the proportion of learners having completed all 11 units of learning at the end of the experimental period in both groups using a $\chi^2$ test. Finally, the effect on efficiency was tested using a t-test to compare the average time taken to complete 11 units in both groups. The time taken to complete was measured by counting the number of days between initial login and completion of the final unit of learning.

4. Results

The overall completed units of learning over time was denoted by a significant positive linear trend ($F(1,806)=586.91, p<.001$) and a significant positive quadratic trend ($F(1,806)=10.55, p<.001$).
But a significant effect of group on the quadratic trend was found \((F(1,806) = 4.96, p < .05)\). Simple effects analysis showed that in the experimental group progress developed along a straight line, whereas in the control group the amount of progress made accelerated towards the end. Figure 2 illustrates how the average number of completed units of learning is consistently higher in the experimental group except for the final measurement. This shift towards the end may have been influenced by the intervention of reminding learners of the course deadline ten days prior to the end of the experiment. To test whether this intervention may have had an unintended and different impact for both groups, a repeated measurement analysis was performed for the last three weeks showing that the intervention indeed only had an effect for the control group [13]. Subsequent analyses corrected for the unexpected and unequal effect of the course deadline reminder and showed a significant effect for group \((F(1,806) = 4.32, p < .05)\) on the number of units of learning completed, indicating that the amount of progress made by learners in the experimental group was significantly higher over the period up to the intervention.

Results for goal attainment immediately prior to the intervention showed a significantly higher percentage of learners completing all 11 units of learning in the experimental group (40.2%) than in the control group (33.4%) \((\chi^2 = 4.04, df = 2, p < 0.05)\).

Finally no effects were found regarding efficiency. At the point of intervention, the average number of days elapsed between enrolment for the first unit of learning and completion of the 11th unit of learning was 36.49 in the experimental group, compared to 38.96 in the control group. Although learners in the experimental group reached the goal in fewer days, a t-test comparing these means shows that this difference is not significant.

Fig. 2. Average number of completed units of learning (Y axis) at four successive moments (X axis) for experimental and control group.
5. Conclusions and discussion

Offering navigational support based on feeding back the choices of successful learners enhances effectiveness though not efficiency in lifelong learning. However the use of a rather crude measure of efficiency (elapsed time rather than actual study time) may mask significant differences in efficiency between the groups. Subsequent work would benefit from a more accurate measurement of study time.

The recommender tool was tested in a rather small and static Learning Network while in reality LNs are dynamic: courses will be added, deleted and changed. A challenge for further research will be to integrate these dynamical aspects in the system. At the moment we are developing mechanisms to support dynamical networks.

Besides research is carried out currently to investigate whether the effects found in this study can be improved by further personalisation of the approach, taking into account both characteristics of students and properties of the units of learning in the network, leading to recommendations like for instance the best next step for women or the over fifties.

References