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Detecting Differences in "Meaningful Learning" Behaviours and their Evolution: A Data Driven Approach

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Abstract: *In this paper we investigate two different ways in which learners construct personal semantic maps, expressed by navigational behaviours. The first of them concerns the usage of hypermedia structures non-sequentially, i.e. without following a strict order within two nodes; the second one concerns the usage of glossaries and concepts maps. A data driven approach, described in the paper, is used. The dataset is made by 254 sessions realized by learners interacting with the WINDS Advanced Learning Environment. The results show that the differences in two behaviours are statistically significant ;that the usage of maps and glossaries is less frequent than the usage of hypertextual structure; that the usage of maps and glossaries is clustered above all around a single course; that when different from zero, the two behaviours have statistically significant opposite trends. We can conclude that the presence of two different behaviours of non sequential navigation in Electronic Learning Environments is likely, and that the corresponding strategies are likely to be learned. The results and the implications are analysed and discussed.*

Keywords: *Data mining, Individual differences detection, User modelling, Time series analysis, Sequential and non sequential patterns*

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1. Introduction

The introduction of technology inside learning contexts has deeply changed the traditional ways in which media present information to be learned. Hypermedia allows learners to have much more freedom in interacting with the materials. One of the main open problems in technology mediated learning concerns the different behaviours in interacting with the materials. The Literature refers to the preference for learning paths structured sequentially or non sequentially also as "linear" or "non-linear" preferences, that would result in different behaviours of learners. In most of the traditional learning media information is presented sequentially from the beginning to the end, while more personalized, flexible and self-directed approaches are considered the added value provided by hypermedia to learning.

The behaviours of learners during interaction can also be sequential or non sequential.
Sequential or non sequential behaviours can be affected by a number of different factors, and different studies show that they can affect the quality of the experience of interaction, as well as the overall quality and effectiveness of learning.

In hypermedia environments more and more importance is acquired by ways of learning stimulating learners' autonomy and self-regulated learning; the potential of technology emphasizes the aspects coherent with constructivist and active approaches to learning: one of these is the so-called "meaningful learning" approach (see eg [2]).
Thanks to the improvements in technologies, a huge amount of data concerning the learners is currently

available. Hence, a data driven approach [18] for detection and profiling of learner behaviours could greatly improve the quality of interaction, allowing to detect the behavior of the learner, to monitor its evolution and to adapt dynamically to the interaction to the user.

This study aims at investigating the different navigational paths according to which learners construct personal semantic maps by a data driven approach. From a semantic viewpoint, hypermedia can be seen as a knowledge structure, and the non sequential patterns of interaction with the materials can be trails of such knowledge structure.
The paper is organized as follows. In section 2 we will give the motivations for the work. In section 3 we will survey some of the related works concerning individual differences in interaction with hypermedia and data driven approaches to detect them. In section 4 we will present the materials and the methods used in this study. In sections 5 and 6 the results drawn from a preliminary association analysis are shown and the subsequent selection of patterns is addressed. In section 7 we will present the results concerning the individual differences detection and their analysis along time, that will lead to identify and explore trends, when any. Section 8 will conclude the work.

2. Motivations and background

We will survey some constructivist approaches to technology mediated learning (subsection 2.1) and their relationship with the "learning to learn" domain (subsection 2.2).

2.1 "Meaningful learning" approaches to learning and hypermedia

Hypermedia allows learners to interact with a variety of different materials and tools, involving different channels, different information processing strategies, as well as the accomplishment of different activities (e.g. technology mediated collaborative activities). The possibility to follow non sequential paths within the learning materials is one of the main differences between hypermedia and traditional learning tools [29] and several advantages over traditional learning tools have been pointed out [9, 29]. Nonlinear, collaborative and active elements of hypermedia environments could influence deeply the meaningfulness of the learning process, affecting cognitive and metacognitive characteristics of the process itself, as the literature has underlined [28].

"Meaningful learning" approaches started with Bruner's and Ausubel's works on cognition and learning. Meaningful learning can be defined as a process in which new information is related with previous knowledge within the cognitive structure of the learner.

Inside the meaningful learning approaches the creation of knowledge is seen as an "assimilation" of the new knowledge to the former one made by the learner; meaningfulness of knowledge is conceptualized in terms of subjective connections between concepts.

Bruner's works (see eg [8]) stressed the role of active and constructivist dimensions inside the learning process; in particular, he underlined the importance of finding effective sequences in presenting materials for the effectiveness of learning.
Ausubel's works (see eg [3, 4]) focused on cognitive structures and tools implied in learning large amounts of information in traditional educational settings (in particular "advance organizers").

Ausubel's ideas have been developed by Novak [38, 39] who proposed to use cognitive maps in order to enhance meaningfulness of learning.
Novak [41] argues that learning by doing personal connections between materials gives raise to a better quality of learning, and calls this approach "meaningful learning" distinguishing it from mnemonic learning, in which no meaningful connections are made by the learner between the contents he/she learns. He proposes to use concepts maps as tools for organizing materials according to semantic connections.
More recently, Jonassen [27] argued that since learning is the process of actively constructing knowledge by integrating new experiences into the learners' existing schemata, learning environments should support this process by providing multiple perspectives or interpretations of reality. Based on this assumption Jonassen defines "mindtools" as computer based tools and learning environments aimed at supporting the learner in developing higher-order skills.

Novak's ideas had a great impact in the technology-mediated learning field due to the potential of technologies coherent with meaningful learning assumptions (e.g. [19]). Concepts maps are today more and more incorporated into Electronic Learning Environments. However, concept maps have been then shifted from being mental subjective representations (Bruner) to being tools (Ausubel, Novak).
In fact, Novak [39, 40] focuses on the importance of cognitive maps as "*tools* for organizing and representing knowledge", giving to maps some physical and perceptive characteristics that overcome the notion of "mental representations".
The lack of consensus and the ambiguity in defining maps affects technologies-mediated learning field. As an example, while it could be reasonably hypothesized that hypermedia support the construction of semantic maps in terms of subjective "mental representations", cognitive maps intended as tools can help in meaningful learning, but they are in

most cases standardized and not personal; moreover, different design procedures of cognitive maps could led to different outcomes.

In learning environments, maps are designed to allow learners to personalize their interaction in a non sequential fashion according to semantic criteria. Looking in depth into technologies potential, it can be seen that hypertexts and hypermedia themselves could be viewed as recipients of a great number of semantic maps created by every learner. In learning Environments *navigation could be considered a track of the semantic maps construction during learning*: it is in fact possible to associate Learning Objects (LOs) with semantic areas suggested by the main topics of the objects themselves and navigational paths with certain preferences of learners.
Moreover, the basic assumption is that in hypermedia environments learners *can*, but not *must*, follow the paths provided by the environment, and thus they can make a choice that express itself in different individual behaviours. To the purpose, hypermedia environment provides different options to arrange personal connections between the materials.
In particular, the nonlinear interaction could reveal a subjective association of concepts made by the learner according to a personal assimilation that is semantic-based; the collaborative dimension could be stated in terms of connections between different (subjective) semantic maps; the active one could be stated in terms of connections between thinking and experience. All these assumption are referred to the so-called "meaningful learning" pedagogical frameworks to learning.

For this reason, in learning environments, the ways of interacting with the environment can also be expressive of the *strategies* carried out by learners during the learning process. Hence, they could reveal interesting characteristics of the learner and/or of the learning process, if properly and coherently interpreted.

Within the Literature on "meanigful learning", it is underlined that the learning process can be meangiful if and only if an active *choice* of learning meanigfully is made by the learner [41]. It is also underlined that meaningful learning strategies are based on the assimilation of concepts made by the learners. Assimilation is the creation of personal concepts between materials according to subjective criteria.
For all these reasons, it can be also hypothesized that:
1) Meaningful learning can be considered strictly related to the "learning to learn" domain;
2) It is likely that these strategies show a certain evolution during time, due to different internal and external factors. Thus, the patterns of interaction would be the observable trails of this underlying learning process.

2.2 Relationships of strategies to the "learning to learn" domain

The "learning to learn" domain is here intended as described by Gregory Bateson in terms of any change in behaviour that can be considered adaptive with respect to the environment in which the learner enacts.
We would recall briefly that Gregory Bateson describes learning phenomena in terms of "levels of learning". In [5] he indicates four levels of learning, numbered from zero to three, according to the different degree of generality of the changes implied in both the process of learning and in what has to be learned.

Inside Bateson's framework, levels zero and one refer, broadly speaking, to the learning of contents, while levels two and three refer to the "learning to learn" level. In particular, learning two is characterized in terms of "learning to learn", that is the ability to learning *how* to learn, and level three is characterized in terms of learning to change the strategies acquired in the "learning two" step. According to Bateson's framework, it can be supposed that the strategies in technology mediated pedagogical settings reveal traits belonging to "learning two" and/or "learning three" levels.

The Literature has hypothesized connections between "meaningful learning" approaches and the so called "learning to learn" domain [31, 38, 40] since its origins.

In his works, Bruner advocates the link between learning outcomes and the search for the "best" sequences of contents to be learned [8].
The so-called "Zone of Proximal Development", defined by Vygotsky [47] focuses on one side on the social dimension of learning, but on the other on the optimal choice of the subset of arguments people could learn easier in sequence.

Moreover, the wider freedom in learning allowed by hypermedia, with respect to traditional media, requires to learners higher, more refined and more granular skills for fully profit from the interaction of the environment [21,30,34]. These skills are generally referred as belonging to the "learning to learn" domain. But these skills are also the ones claimed by "meaningful learning" as essential characteristics of a "meanigful learning" process, because express the engagement and self-direction of the learner [28].

To the purposes of our work, we are interested in investigating the evolution of learners' behaviours.

The discovery of such an evolution would help in testing the hypothesis that these strategies are *learned*. In fact, the learning of these strategies will result in a change of the behaviours of learners during time. Such an evolution would ultimately result in confirming a relationship between these strategies and the "learning to learn" domain.

3. Related works

In this section, we will survey some studies concerning how individual differences can affect the interaction with hypermedia (subsection 3.1). Subsequently, we will survey some data driven approaches to nonlinear navigation patterns detection, especially focusing on web environment (subsection 3.2).

3.1 Individual differences and hypermedia interaction

The Literature has investigated both the factors impacting on the different behaviours, and the impact of these behaviours on the quality and the effectiveness of the learning experience (e. g. [6]).
The Literature also suggests that some cognitive characteristics of the learners could advantage them in the interaction with hypermedia for learning [22, 23].

Within the studies aimed at investigating the factors impacting on the different sequential and non sequential behaviours, one can remember, as examples, the explicitness of the semantics of links [37]; the prior knowledge regarding the domain and the system [10, 17]; the cognitive styles or traits of the learners [15, 16, 24]; other factors such as age and gender [11].
However, the ability to navigate non-sequentially within hypermedia could also depend on many external factors, that have been scarcely investigated.

We can assume that navigational behaviours should be intended as *tendencies*, that is, as preferences that are neither necessary nor deterministic. Consequently, one should assume that they are not necessarily persistent or mutually exclusive. The presence of different behaviours in the same individual has to be considered likely, and has to be foreseen when approaches for building profiles are devised and developed.
In particular, since many factors affecting the behaviour are subject to develop them in time, it is to take into account that these preferences could vary during time.

3.2 Data Mining Approaches to Individual Differences Detection

In Web-based Environments, the problem of finding linear and non-linear navigation behaviours could be stated as the problem of finding sequential and non sequential patterns inside learners' sessions, once defined an order between objects.
A sequential pattern can be generally defined as the co-occurrence in succession of two or more items with respect to a given order. The loss of compliance with respect to the given order characterize in general a non sequential pattern, that can have more than one definition.
The problem of finding sequential and non sequential patterns has been defined by the Literature in terms of association analysis and sequential pattern mining [44].
The problem has been firstly explicitly addressed in terms of Frequent Itemsets Mining by Agrawal and Srikant [1]. Subsequently, other approaches, such as the one developed in [33], have been developed.
When applied to WWW data, sequential and non sequential patterns have been defined accordingly to different characteristics, such as the topology of the websites to which they apply the structure of the sessions, and the purposes of the analysis [32].
Examples of applications to the WWW data are given in [7], in [12], in [13], in [14], in [35], in [36] and in [42].

4. Materials and Methods

In this study, we used a set of 254 sessions realized by 53 European students attending eight different courses offered by the WINDS Advanced Learning Environment (ALE).
The WINDS ALE provides different kinds of Learning Objects (Los) devised and indexed according to the pedagogical criteria inspiring the ALE; these objects vary from traditional objects, such as written texts and images (units, paragraphs) to interactive ones, such as objects stimulating active (cases, exercises) and collaborative (annotations, discussions) learning. Moreover, objects devoted to meaningful learning engagement of learners, such as glossaries (concepts) and concept maps, are provided.
In the ALE LOs are grouped in Units and then in Courses, and a sequence of navigation between contents, recorder by the ALE database, is suggested to learners, although learners could freely access all other contents in two ways: using the hierarchical menu for navigating and using the glossaries (concepts) associated with each paragraph.

During preprocessing steps data was cleaned from redundant and uninformative contents; each session was associated to a unique learner; the sessions greater than ten item were selected after cleaning.
For appreciating the changes of the distribution of these patterns during the different stages of the navigation of each learner, we focused at two levels of granularity: the profile level, in which the average learner profile is investigated; the sessions level, in which the evolution in the first six sessions is considered, as explained below.
Because sequential and non sequential patterns are defined in terms of co-occurrences of objects with respect to a given order, it follows that the partial order of subsequent items, rather than the absolute one, is important. To explain that, consider the following. We are interested in finding each occurrence of one object directly followed by its

neighbor irrespective for the position within the whole session in which the pattern occurs. The same happens when we are interested in finding non sequential patterns. We are interested in finding the order of the local arrangement of the objects. In both cases, the absolute order within the session is not relevant.
This problem can be stated in terms of events discovery within sequences [33]. These algorithms allow the comparison of heterogeneous sequence objects using sliding windows of the same length over them. The algorithm is also intended for dealing with heterogeneousness of data, resulting in the different lenght and number of sessions belonging to each learner.

More formally, given a set *E* of event types, an event is defined as a pair (*X, k*) where $X \in E$ and $k \in \square$ is the step of occurrence.
An event sequence *s* of length *n* is a triple (s, K_s, K_e) where

$$s = \{(s_1, k_1); \ldots (s_n, k_n)\}$$

is an ordered sequence of events all belonging to *E*, that is $s_i \in E$ for all s and $k_i \leq k_{i+1}$ for all *i=1,...,n-1*; K_s and K_e are called respectively starting point and ending point, $K_s, K_e \in \square$, $K_s \leq k_i \leq K_e$ for all i=1,…,n-1, $n = |K_e - K_s|$.
Every session is considered an event sequence *s* in which *E={units, ..., maps}* according to the objects labels, and every event type $s \in E$ is a random variable assuming one of all discrete values in *E* with unknown Probability Distribution Function (PDF).
Episodes, indicated by greek letters, are defined to be partially ordered collections of events occurring with a given order, and modeled as directed acyclic graphs whose random vertices are the items of sequences.
In particular, in this works serial episodes are searched. Serial episodes are defined as the ones for which partial order is not trivial.
In serial episodes detection the focus is put on the empirical frequency of subsequent occurrence of object e_i at step *k* together with object e_j at step *k+1*

$$f(s_i = e_i, k = i; s_{i+1} = e_j, k = i+1)$$
$$\text{for all } k, k \leq n$$

irrespective of the absolute value of *k*, that is, for the absolute position of the item inside the sequence.

For episodes detection a sliding window $W(s, win)$ of size *win*, starting at step *s*, is used; at every next step, $W_{i+1}(s = i+1, win)$ the starting point *s* shifts by one position on the right, while *win* does not vary, until $s_k, \{k \mid s_k + |win| = n\}$, that is, the end of the sequence, is reached.
In this study the threshold was set as the average frequency for each pattern to be searched calculated over the whole sample, that is $W_S = W(S, win)$, $S = \{s_1, \ldots, s_{254}\}$.

Frequency of episodes in learner profiles is defined as the fraction of windows belonging to the sessions made by the learner in which an episode occurs:

$$f_p(\alpha, s, win) = \frac{|w \in W(s, win) \mid \alpha \in w, s \in p|}{|W(s, win)|}$$

where $p_j \in P$, $P = \{p_1, \ldots, p_{53}\}$ indicates the profile of the *j*th student.
An episode in a profile is defined frequent with respect to the whole sample frequency of the same episode, that is, when

$$f_p(\alpha, s, win) > f(\alpha, S, win).$$

5. Preliminary Analysis

At this step, the frequencies of paths going from one kind of object to another are investigated. According to objects classification, four general usage patterns category were found:
a) sequential patterns, to which belong linear navigation between traditional objects in which there is a strict sequence of steps between objects;
b) non sequential patterns, to which belong non linear navigation in which there is no strict sequence of steps between objects;
c) collaborative patterns, to which belong all patterns that contain a collaborative object;
d) active patterns, to which belong all patterns that contain an active object.
The size of the episodes is always 2; *win* is set to 3, 5 and 10. All possible combinations have been taken into account.

While sequential patterns have an average occurrence of order 10^{-1}, non sequential patterns occur with an average of order 10^{-2} (when concepts are considered) or 10^{-3} (when maps are considered).
Collaborative patterns occur with average frequency of order 10^{-3} or less. Active patterns occur with average frequency of order 10^{-2} or 10^{-3}.
These differences are due to the difference in absolute frequencies of each kind of object, but could also reveal the persistence and transfer of traditional cognitive strategies in the usage of electronic environments.
The complete results of the preliminary analysis are reported in [46]. According to the results, some patterns have been selected and investigated in depth.
While the sequences of objects proposed by the ALE are well determined and correspond to sequential patterns, an analysis of the topology of the WINDS ALE (Figure 1) indicates that two ways of construction of non sequential patterns are available: the first one using the tree menu that allow to jump from one material to another; the second one using concepts and maps.

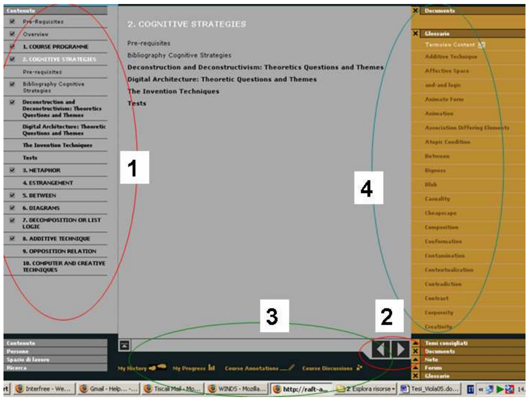


Figure 1. The WINDS ALE. 1. Tree menu. 2. Next/previous buttons. 3. Collaborative objects. 4. Concepts

This leads to hypothesize that two ways of semantic maps construction, different from cognitive and metacognitive viewpoints, have been made available by the WINDS ALE.
For this reason episodes of larger size, able to detect these non sequential patterns, were investigated.

6. Patterns selection

In this new step of analysis episodes of size 3 are considered.
Here are investigated the differences in navigating using:
a) concept and maps associated with each paragraph;
b) the hierarchical menu for navigating between contents

Inside the whole set of episodes considered in the preliminary study four non sequential patterns were selected according to the frequency of occurrence inside sessions.
Selected episodes are:
α) $(s_1 = par, s_2 = unit, s_3 = par)$;
β) $(s_1 = unit, s_2 = concept, s_3 = map)$;
γ) $(s_1 = par, s_2 = concept, s_3 = map)$;
δ) $(s_1 = concept, s_2 = map, s_3 = par)$.
The first of them is related with a way of constructing semantic maps using hypermedia structures (hierarchical menu for navigating from content to another); all the others involve the usage of linked concept maps and glossaries.
Win was set to 3, in order to avoid biases given by the position of the episode in the sequence, as happens if greater windows are used.
In particular, relationships, in terms of frequencies, between episode α and episodes β, γ and δ are investigated.

7. Results

This section is articulated as follows: first, we will give and discuss the results of the analysis of the different patterns (subsection 7.1); subsequently we will discuss the results regarding the behaviour of these patterns over time (subsection 7.2).

7.1 Individual differences detection[1]

The comparison of the sample means of each episode with the ones of learners profiles (Table 1) shows that while the frequency of episode α increases with respect to the episode of size 2 "par + unit" (20/53 students > mean, 33/53 students < mean on win=3), all the others decrease with respect to correspondent 2 sized episodes.
Moreover, the number of learners profiles that use episodes involving concepts in order to navigate from a paragraph to another one is very small (3/53) and for this reason is not considered here.

Table 1. Learners' profiles

episodes	α	β	γ	δ
mean	.097	.0015	.0022	.0031
p > mean	23	7	8	11
p < mean	30	46	45	42
max	.363	.0132	.0385	.0279
min	0	0	0	0

Learners' profiles that show a preference for the usage of maps and concepts (episodes β, γ, δ) are clustered above all around a single course, while learner profiles that show a preference for episode α are sparser.
Furthermore, the preference for episode α seems to be in general mutually exclusive with the preference for one or more episodes β, γ or δ (only in four cases all the means of profiles are greater than the sample mean).
According to the results, one can suppose the existence of two separate ways of creating personalized semantic maps: the first one of them, based on the usage of hypertexts, seems also to be more intuitive and easy for a greater number of students. Moreover, results show that concepts and maps are not widely used.
The hypothesis that episode α includes objects provided by a more understandable semantics seems also to be likely. In particular, episode α is similar to the action of leafing through a book, in which the navigation menu enacts as an index.
From a metacognitive viewpoint, the massive usage of learning objects similarly to the traditional objects could reveal the transfer of cognitive strategies derived from traditional learning settings inside the technology-mediated context. While in facts traditional objects are more used since they contain learning contents, the usage of interactive objects seems to be too small and scarcely diffused. One can suppose a metacognitive difficulty of learners, since many of them seem not to be able to integrate the usage of these objects into their existing strategies of

[1] These results have been initially published in [45].

learning. Furthermore, the easiness and the effectiveness of complex objects such as cognitive maps seem to be a problematic point in E-Learning.

Above all, it seems that a latent variable, that is, teacher style enacts on learners profiles as clusters show. In particular it seems that the usage of complex objects, such as concepts maps, has to be learned and that teacher's influence is determinant.

While teacher's influence could not be investigated since no data about teachers is at this moment available, the statistical significance of the differences in learners profiles has been tested.

According to previous results, two set, one of them containing students that show profiles higher than the mean in episode α, the other containing students that show profiles higher than the mean in at least two of episodes between β, γ and δ have been selected, in both cases irrespective for the distance from the mean. The first group – thereinafter *G1*- contains 19 students, the second one – thereinafter *G2* – contains 7 students. Students that shows a mean profile higher in all episodes (4/53) have not been considered. The whole cardinality is 26. The assumption concerning independence of samples needs a deeper investigation that is not discussed here.

The analysis of the significance has been performed using chi-square test and *p* values at the level of significance .05.

Results show that the difference is significant. In particular *p* value is near to 0 (less than 10^{-4}) and chi-square value is 36.116 on 3 d.o.f., 2 groups, 26 individuals.

Such relevant values confirm the hypothesis of the existence of two different strategies; moreover, the latent variable related with teacher's influence seems to be determinant for the strategy chosen by students.

We can conclude that:

a) the differences in usage of the two kind of non sequential patterns are statistically significant;

b) the usage of maps and concepts is less frequent than the usage of hypertextual structure;

c) the usage of maps and concepts is clustered above all around a single course.

Hence, we can conclude that two different non sequential navigation strategies are detected.

These results could be motivated by the fact that different characteristics enacts in the two strategies; that maps seem to be more difficult to use, due to a different underlying semantics; that the clustering of maps users around a unique course suggests the importance of the interaction with teacher in order to learn how to use maps.

7.2 Analysis of individual differences along time and trend detection

For the analysis of the behaviour of the patterns within the two above mentioned groups – namely G1 and G2 – sessions have been grouped according to the step in which they have been realized.

All the first sessions (irrespective with the time in which have been realized) have been grouped together; all the second have been grouped and so on.

The frequency of the α β γ and δ episodes during the first six steps have been considered. The first six steps reach about 65% of the total number of sessions.

The following figures (Figures 2 and 3) show, for all considered episodes, the mean at each of the six steps considered here.

It can be seen that while a trend appear in Figure 2, Figure 3 show rather a fluctuation of the values, whose meaning is quite uncertain and needs further investigations.

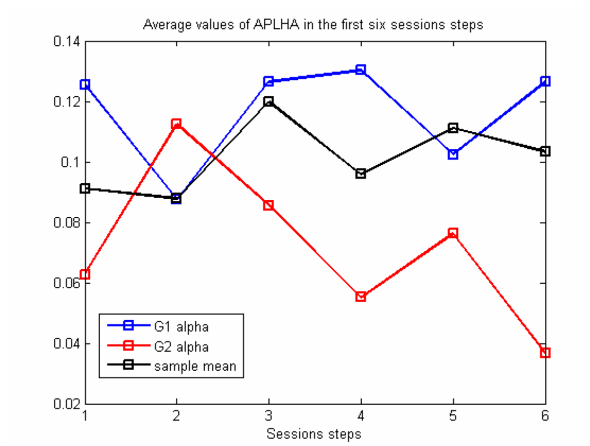


Figure 2. The average values for G1 α (blue), G2 α (red) and the sample mean (black) in the first 6 sessions.

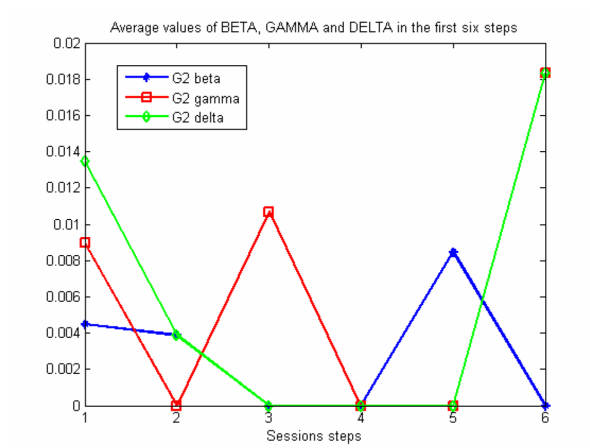


Figure 3. The average values for G2 β (blue), G2 γ (red), G2 δ (green) inthe first 6 sessions.

Regarding Figure 2, one can observe that:

a) When all the patterns are nonzero, the two patterns belonging to G1 and G2 behave in opposite ways during time;

b) Episode α in G1 shows a slow increase, although not monotonically; all the other G1 episodes are equale to zero.

c) Episode α in G2 shows a slow decrease, although not monotonically; all the other G2 episodes are nonzero.

All the other episodes do not show a clear trend (Figure 3).

These results become clearer if compared with the whole sample mean (black line in Figure 2). While in fact α episode fluctuates for what concerns the whole sample, G1 is slowly increasing, while G2 is slowly decreasing, although not monotonically in both cases. Both G1 and G2 series can be easily distinguished from the sample mean.

To detect if there is a trend in the series, the Mann-Kendall test has been used. The Mann-Kendall test is a nonparametric test for detecting increasing or decreasing trends in time series made by at least 4 observations, and for testing for their significance (e.g. [20]).
The Mann-Kendall statistics, referred as *S*, is calculated by comparing sequentially every observation in the serie to all the subsequent observations.
More formally, given a serie $\langle x_1,...x_n \rangle$ of lenght *n*, S is calculated as

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} s(x_i, x_j)$$

where $s(x_i, x_j)$ is the following step function

$$s(x_i, x_j) = +1 \text{ iff } x_i < x_j ,$$
$$s(x_i, x_j) = 0 \text{ iff } x_i = x_j ,$$
$$s(x_i, x_j) = \text{-}1 \text{ iff } x_i > x_j$$

In general, an increasing trend is given by a positive *S*, while a decreasing trend is given by a negative *S*. The significance of *S* is tested against an absolute critical value $|S|$ corresponding to a given α coefficient. The literature suggest to consider an α greater than .20 significant [20]. With respect to a serie made by 6 observation, the critical value is $|6|$ with α=.20.
For α episode in G1, a value *S=+7* is obtained; for α episode in G2, a value *S=-7* is obtained.
These results show that the two series exhibit a trend and that this trend is opposite in the two cases. Moreover, being the critical value $|6|$, the results can be considered significant in both cases.
For all the other episodes the test gives values below the significance critical value. It can be then concluded that, for non null β, γ and δ episodes (G2) the test indicates only a tendency that has no statistical significance.

In order to achieve a clearer picture of the trends of the episodes crosscorrelation analysis has been used.
The opposite trends are confirmed again looking at cross-correlation values (Table 2) calculated at 0 lags.

Table 2. Crosscorrelation values at 0 Lags

Crosscorrelation 0 Lags				
	G2 α	G2 β	G2 γ	G2 δ
G1 α	-.77	-.62	.56	.28
G2 α		.35	-.56	-.56
G2 β			-.50	-.17
G2 γ				.75

The confidence bounds have been set equal to 2 standard deviations, with a confidence interval 95%, and are equal to +/- .8165.
G1 α and G2 α episodes show a negative crosscorrelation achieving an absolute value (.77) that is high, although not significant with respect to the critical value - .8165.
Regarding episodes β, γ and δ, it can be seen that G2 α show a negative crosscorrelation coefficient with respect to G2 γ and G2 δ episodes. However, these values are less than the critical value, and then not significant.
This would indicate also that an increase in usage of concepts and maps is in many cases synchronous to a decrease in the usage of hypermedia structures (episode α). However, these values are far from significance and just confirm the tendency shown by the Mann-Kendall test.

All these results confirm the previous ones given by chi-square analysis.
Moreover, from these results it seems likely the hypothesis that such strategies are learned in time and belong to the “learning to learn” domain.
Learners tend in fact to follow their initial behaviour for what concerns α episodes (hypermedia, α episodes), when they are not encouraged to use concepts and maps (others episodes always equal to zero). When they are engaged to use glossaries and maps (probably thanks to the teacher), the more the learner acquires expertise in maps and glossaries usage (episodes β, γ and δ in G2), the more he/she discards to use hypermedia structures (G2 α).
For what concerns the episodes β, γ and δ in G2, although their usage tends to increase, the consistent fluctuations confirm that maps and glossaries are in general more difficult to use.
Again, likely explanations could be provided by easiness of use and the semantics of links: it seems in fact that hypermedia structures have a clearer and more understandable semantics that helps learners in navigation, especially when they are non expert.
G1 shows to follow and develop its initial strategy. G2 shows a more complex behaviour. In particular, G2 shows clearly to discard the strategy based on hypermedia. Nevertheless, there is no clear evidence that any new strategy replaces the existing one. Again, a difficulty in replacing and modifying existing strategies is likely.

A comparison with the Literature is quite difficul, because of the different results reported.

In [10] it is argued that novice learners could benefit from the introduction of "restrictive technologies" aimed at hiding links; on the contrary, expert learners could benefit from the introduction of "rich linking technology". From the results we achieved, we found an increase in non sequential behaviours as the expertise increases.

In [17] it is argued that novice learners behave differently from expert learners, and require additional support tools. Maps are indicated as effective tools for novice learners, thanks to the structured knowledge they provide. From the results we achieved, we can see that maps are scarcely used during the initial steps, and seem not easy to use for novice learners. As the expertise increase, it is not clear when maps provide a meaningful structure of the knowledge to be learned.

In [43] the efficay of maps in hypermedia environment is investigated. The Authors conclude that the greater use of maps led to less relevant searching behaviour and less effective search. The results achieved here suggest that learners prefer to follow their own semantic maps rather that standardized ones, and that a free exploration of relationships could be more engagaing and understandable from a semantic viewpoint for non expert learners.

As an overall conclusion, it can be concluded that the way of constructing semantic maps using hypermedia structures is more intuitive for non expert learners and that without any external influence, in particular due to the teacher, learners show to prefer hypermedia structures.

From a "meaningful learning" approaches viewpoint, hypermedia seem to constitute an effective environment for semantic maps construction. This could also be explained by the theoretic assumption of constructivism according to which knowledge construction is a subjective activity, that seems to be disconfirmed when standard maps are employed. In fact, while it could be reasonable to hypothesize that hypermedia support the construction of semantic maps in terms of "subjective mental representations" (Bruner, [8]), cognitive maps provided by e-learning environments have to be intended as tools (Novak, [38, 39]) and could help in meaningful learning, but they are not personal; moreover, different design procedures of cognitive maps could lead to different outcomes.

Furthermore connections between personal semantic maps construction and learning to learn domain - intended as the process of development of strategies aimed at adapting to a given environment – can be argued from these results as well.

8. Conclusions and Future Work

In this work two different non sequential navigational behaviours within an hypermedia learning environment are investigated. These behaviours, corresponding to different strategies and expressed by different patterns, are investigated and monitored during time.

The first concerns non sequential navigational behaviours involving the usage of glossaries and concepts maps; the other concerns non sequential navigational behaviours involving the usage of hypermedia structures.

The results are twofold. First, the two behaviours of non sequential navigation in Electronic Learning Environments are in almost every case mutually exclusive and significantly different. Secondly, these behaviours show to evolve during time according to given trends, and thus the corresponding strategies are likely to belong to the "learning to learn" [5] domain.

From the results we can draw two kinds of conclusions. First, that these behaviours can be considered two different strategies in learning hypermedia. Secondly, that these behaviours evolve during time. It can be also assumed that they are affected not only by internal factors, but also by situational factors.

From a methodological viewpoint, data driven approaches show to be effective in learning process patterns characterization, useful in knowledge management and monitoring systems in e-learning, and promising for the usage in real-life systems.

Future work will deal with the in-depth analysis of the semantics involved in these patterns, from one side; from the other, with the devising and development of effective approaches for profiling.

References

[1] Agrawal, R., Srikant, R. (1995). "Mining sequential patterns". *Proc. of Eleventh Int. Conf. on Data Engineering*, , IEEE Computer Society Press, Los Alamitos, CA, p. 3-11.

[2] Abrams, R., Kothe, D., Iuli, R. (2006). "Meaningful Learning. A Collaborative Literature Review of concept mapping". http://www2.ucsc.edu/mlrg/clr-conceptmapping.html (visited on April 19, 2007).

[3] Ausubel, D. P. (1963). *The psychology of meaningful verbal learning*. New York.

[4] Ausubel, D. P., Novak, J., Hanesian, H. (1978). *Educational Psychology: a Cognitive View*. New York.

[5] Bateson, G. (1972). *Steps toward an ecology of mind*. Chandler.

[6] Baylor, A. (2001). "Perceived Disorientation and Incidental Learning in a Web-based Environment: Internal and External Factors", *J. of Educational Multimedia and Hypermedia*, 10(3):227-251, 2001.

[7] Borges, J., and Levene, M. (1998). "Mining association rules in Hypertext Databases." *Knowledge Discovery and Data Mining*, pp. 149-153.

[8] Bruner, J. (1966). *Toward a Theory of Instruction*. Cambridge MA, 1966.

[9] Brusilovsky, P., and Peylo, C. (2003). "Adaptive and Intelligent Web-based Educational Systems." *Int. J. of Artificial Intelligence in Education*, 13, 156-169.

[10] Brusilovsky, P. (2003). "Adaptive navigation support in educational hypermedia: The role of student knowledge level and the case for meta-adaptation." *British Journal of Educational Technology*, 34(4), 487-497.

[11] Cagiltay, N. E., Yildirim S., Aksu M. (2006). "Students' Preference on Web-Based Instruction: linear or non-linear". *Educational Technology and Society*, 9(3):122-136.

[12] Carmel, E., Crawford, S. Chen, H. (1992). "Browsing in hypertext: a Cognitive Study". *IEEE Tr. on Systems, Man and Cybernetics* 22(5):865-884.

[13] Catledge, L. D., Pitkow, J. E. (1995). "Characterizing Browsing Strategies in the World Wide Web". *Computer Networks and ISDN Systems*, 27(6):1065-1073.

[14] Chen, M-S.(1998). "Efficient data mining for Path Traversal Patterns." *Knowledge and Data Engineering*, 10(2), 209-221.

[15] Chen, S. Y and Mecredie, R. D. (2002). "Cognitive Styles and Hypermedia Navigation: Development of a Learning Model." *Journal of the American Society for Information Science and Technology*, 53(1), 3-15.

[16] Chen, S. Y. (2002). "A cognitive model for non-linear learning in hypermedia programmes." *British Journal of Educational Technology*, 33(4), 453-464.

[17] Chen, S. Y., Fan, J-P., and Mecredie R. D. (2006). "Navigation in Hypermedia Learning Systems: Experts vs. Novices." *Computers in Human Behaviour*, 22(2), 251-266.

[18] Cherkassly, V., Mulier, F. (1998). *Learning from data*. Wiley, New York.

[19] Cicognani, A. (2000). "Concept Mapping as a Collaborative Tool for Enhanced Online Learning". *Educational Technology and Society*, 3(3): 150-158.

[20] Conover, W. J. (1971). *Practical Nonparametric Statistics*. New York.

[21] Dede, C. (2005). "Planning for neomillenial styles." *Educause Quaterly*, 28(1):7-12.

[22] Ford, N. and Chen, S. Y. (2000). "Individual differences, Hypermedia Navigation and Learning: An Empirical Study". *Journal of Educational Multimedia and Hypermedia*, 9(4), 281-311.

[23] Gauss, B. and Urbas, L. (2003). "Individual differences in navigation between sharable content objects – an evaluation study of a learning prototype" *British Journal of Educational Technology*, 34(4), 499-509.

[24] Graf, S., Lin, T., and Kinshuk (in press). "The relationship between learning styles and cognitive traits getting additional information for improving student modeling." To appear in *Computers in Human Behavior.*

[25] Hacker, D. J.: "Metacognition: definitions and empirical foundations". http://www.psyc.memphis.edu/trg/meta.htm (visited on April 17, 2007)

[26] Hogo, M., Snoek, M., Lingras, P. (2003): "Temporal web usage mining". *Proceeding of Int IEEE/WIC Conference 2003*. pp. 450-453.

[27] Jonassen, D. H. (2000). *Computers as mindtools for Schools: Engaging Critical thinking*. Prentice Hall.

[28] Jones, B., Valdez, G., Nowakowski, J., & Rasmussen, C. (1994). "Designing Learning and Technology for Educational Reform." Oak Brook, IL: North Central Regional Educational Laboratory. Online at http://eric.ed.gov/ERICDocs/data/ericdocs2/content_storage_01/0000000b/80/24/eb/44.pdf, (visited April 18, 2007).

[29] Khalifa, M. and Lam, R. (2002). "Web-based learning: effects on learning process and outcomes.". *IEEE Transactions on Education*, 45, pp. 350-356.

[30] Lawness, K. A. and Brown, S. W. (1997). "Multimedia Learning Environments: issues of learner control and navigation." *Instructional Science* 25, 117-131

[31] Lee M., Baylor A. M. (2006): "Designing metacognitive maps for Web-Based learning". *Educational Technology and Society*, 9(1):344-348.

[32] Levene, M., and Poulovassilis, A. (2001). "Web dynamics". *Software Focus*, 2, 60-67.

[33] Mannila, H., Toivonen, H. Verkamo, A. I. (1997): "Discovery of Frequent Episodes in Event Sequences". *Data Mining and Knowledge Discovery*, 1:259-289.

[34] Marchiorini, G. (1988). "Hypermedia and learning: freedom and chaos". *Educational Technology* 28(11):8-12.

[35] Messaglia, F.., Teisseire, H., Poncelet, P. (2001). "Real Time Web Usage Mining with a distributed Navigation Analysis". *Proc. of 2nd Int. Conf. on Web Information Systems Engineering.* vol. 1, pp. 288-297, 2001.

[36] Mobasher, B., Dai H., Luo T., Nakagawa M. (2002). "Using sequential and non sequential patterns in predictive web usage mining tasks". *Proceedings Of IEEE ICDM 2002*. pp. 669-672.

[37] Mobrand, K. A, Spyridakis, J. H. (2007). "Explixitness of Local Navigational Links: Comprehension, Perceptions of Use, and Browsing Behaviour". *J. of Information Sciences*. 33(1):41-61.

[38] Novak, J. D., Gowin, D. B. (1984). *Learning How to Learn*, Cambridge MA.

[39] Novak, D. J. "The theory Underlying Concepts Maps and How to Construct them". Technical Report, http://cmap.ihmc.us/Publications/ResearchPapers

/TheoryCmaps/TheoryUnderlyingConceptMaps.htm (visited on April 17, 2007).

[40] Novak, J. D. (1991). "Concepts maps and vee diagrams: Two metacognitive tools to facilitate meaningful learning". *Instructional Science*. 19. pp. 1-25.

[41] Novak, D. J. (1998): *Learning, creating and using knowledge*. New Jersey.

[42] Spylopolou, M.,and Faulstich, L. C.(1999). "WUM: A Tool for Web Utilization Analysis." *Lecture Notes in Computer Science*. N. 1590/1999 p. 184-203. Springer.

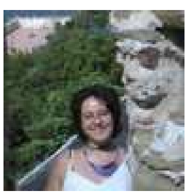
[43] Stanton, N., Correia, A. P., Dias, P. (2000). "Efficacy of a map on search, orientation and access behaviour in a hypermedia systems". *Computers and Education*, 35:263-279.

[44] Tan, P. N., Steinbach, M. and Kumar, V. (2005). *Introduction to Data Mining*. Addison Wesley, NY, USA.

[45] Viola, S. R., Giretti, A., Leo, T. (2006) "Differences in "meaningful learning" strategies of navigation: an empirical model". *Proc. of ICALT 2006 Conference*, Los Alamitos, CA, pp.441-445.

[46] Viola, S. R. (2006). "Learning Process Patterns Extraction and Characterization using mathematical and statistical methods". Ph D. thesis, online at http://www.del.univpm.it:8080/del/Members/silvia/tesiViola.PDF (visited April 26, 2007).

[47] Vygotsky, L. S. (1978). *Mind and Society: the Development of Higher Mental Processes*. Cambridge M.A., Harward U. P.



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