Modelling and Externalising Learners' Interaction Behaviour

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Abstract. In this paper, we propose an approach to modelling learner interaction behaviour by combining learners' interaction protocols with different variables that affect their selections, and interpret this model with the aim to characterise learners' activity. Moreover, we investigate the issue of how this information could be externalised to learners in order to support reflection and develop their awareness of style issues. An application example of the specific approach to the adaptive educational system INSPIRE is also provided.

1 Introduction

Adaptive Educational Systems (AESs) possess the ability to make intelligent decisions about the interactions that take place during learning and aim to support learners without being directive (Brusilovsky, 1996; Brusilovsky and Peylo, 2003). During the interaction an AES need to track learner usage and analyze his/her activity in order to dynamically adapt the content presentation, topic sequencing, navigation support. The type, use and focus of analysis can vary depending on what it is intended for. Moreover, an important characteristic of AESs is the sharing of control between the learner and the system, as several levels of adaptation can be distinguished depending on who takes the initiative: the learner or the system (Kay, 2001). Systems that integrate adaptive and adaptable components are based on shared decision making requiring shared knowledge between the learner and the system. Thus, if the system decides based on an analysis of learners' interaction then the learner should also be aware of this information in order to share the same knowledge and be able to decide. It would be worthwhile to investigate how an analysis of learner-system interaction could stimulate reflection on the learning process and enhance learner control opportunities.

Especially in educational systems that aim to support learners fulfil their learning goals, opportunity for reflection must be central. Several researchers have studied learner reflection using a variety of strategies to support interaction with the learner model (Bull et al., 2001; Morales et al., 2001; Dimitrova et al., 2001; Aleven and Koedinger, 2000; Zapata-Rivera and Greer, 2003). It has been argued that externalising representations of learners' understanding can raise their awareness of their knowledge, progress, difficulties and the learning process, which should in turn, lead to enhanced learning (Dimitrova et al., 2001; Bull and Nghiem, 2002; Mitrovic and Martin, 2002;). In the case of externalising learners' behaviour, as only a limited set of events from learners' interaction with an educational system is available, a challenging research goal is to investigate learner-demonstrated behaviour, relating learners' goals, selections, and navigation patterns. Furthermore, mirroring data about system usage to learners could be especially valuable allowing a direct observation of their learning strategies. Different issues that need to be addressed are how to collect, analyse and externalise data from learner interactions. Which specific measures of learners' observable behaviour are relevant indicators of learner studying preferences? Which characteristics of the resources that learners encounter during interaction, should be considered in an analysis of their navigation patterns? How can we 'describe' the context that affects learner selections and studying preferences, including tools and support offered to learners? How to interpret navigation patterns in a meaningful way to support reflection, which lead them to the accomplishment of their goals? These

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research goals may help us develop deeper knowledge of the complex interactions that are involved during a learning task between the learner and the system, and further inspire new approaches towards more learner-centred designs of adaptive educational systems.

In this paper, we attempt to model learner interaction behaviour combining learners' interaction protocols with different attributes of the instructional design of the system, and interpret this model with the aim to characterise learners' activity. Moreover, we investigate the externalisation and visualisation of this information in order to support learner reflection on their learning strategies and enhance awareness of style issues, which may lead them to improve their interaction. An application example of the specific approach to the adaptive educational system INSPIRE is also provided.

2 Investigating and externalising learners' observable behaviour

Modelling learner behaviour requires a thorough investigation of the cognitive processes at work during an interaction. Different research studies have investigated how these cognitive processes can be measured and linked with learner's social interaction or with specific characteristics of the learner such as the cognitive/learning styles. As far as AESs is concerned, in several systems learner's interaction with educational resources is used as the main source of adaptation. Lately, in a few AESs raw data from learner's interaction behaviour is externalised to learners.

Several studies have explored ways to characterise navigational path data investigating which measures of learners' observable behaviour are indicative of their learning behaviour. In a pilot study investigating if path data could be used as a basis for diagnosing differences in learning style (Andris & Stueber, 1994), different measures that were accounted were sequence of node, time at node, time per node, linearity, and reversibility. Reed et al. (2000) investigate the relationship of learners' computer experience and learning style on hypermedia navigation in terms of the linear/nonlinear steps, the percentage of nonlinear steps they performed and the time on task they spent. Ford and Chen (2000) have shown that people with different cognitive styles display different learning strategies when they are allowed to navigate in relatively non-linear learning environments. For example, there were differences in the subject categories and navigation tools selected, in the total number of navigational actions, in the numbers of levels visited and the time spent at each level, and in the sequencing of elements explored. Indicators that have been investigated for several learning/cognitive style categorizations are (Reed et al., 2000; Lu et al. 2003; Papanikolaou et al, 2003): (*i*) navigational indicators (sequence of node, linearity, reversibility); (*ii*) temporal indicators (time at node, time per node); (*iii*) performance indicators (total learner attempts on exercises, performance on tests).

Moreover, a restricted set of events from learners' interaction, such as requests on learning materials and progress as it depicted by the submission of tests, has been used in several AESs to guide adaptation during the interaction. ACE (Specht and Opperman, 1998) dynamically adapts the instructional strategy based on information coming from monitoring learner's requests on learning materials, as well as on the success of the currently used strategy; repeated occurrences of high performance in tests raise the preference value of a strategy until a threshold is reached. Also, Arthur (Gilbert and Han, 1999) dynamically adapts the instructional style according to learner's performance in the tests s/he submits. Lastly, MANIC (Stern and Woolf, 2000) uses machine learning techniques in order to identify learners' preferences by observing his/her interactions with the system. ELM-ART (Weber and Brusilovsky, 2001) and KnowledgeTree (Brusilovsky, 2004) keep data about learners' interaction with the system and externalise this information to learners in the form of statistics.

In the above studies specific aspects of learner's interaction behaviour are either used by the system as a source of adaptation or externalised to learners in a text-based form illustrating learners' performance results or final learning state. However, learners' observable behaviour during an interaction could be further exploited to provide a comprehensive view of learners' cognitive activity as it unfolds in addition to the activity outcomes, their preferences and progress in a particular context. To this end, a description of the interaction need to be developed involving the learner's actions with the educational content and system functionalities. Several research studies in the area of collaborative learning systems have explored the issue of analyzing learners' interaction in a social context and externalize these data to learners in several ways in order to enhance reflection and support collaborative interaction (Jerman et al., 2001). Moreover, as valuable resources in modeling and visualizing learners' interaction could be used research studies investigating learners' interaction with different stakeholders of the educational process such as teachers and resources (ASTILIEO, 2004).

3 Modelling learner's interaction: *guiding through mirroring*

In a learning environment learners have to make explicit decisions repeatedly during interaction. However, interaction protocols, referring to the series of events which occur during hypermedia usage with corresponding time stamps (Rouet and Passerault, 1999), are sometimes very complex including sets of heterogeneous data which must be carefully handled in order to yield meaningful information. In this process, key issues are the selection of the appropriate data, their interpretation, and the way this information is conveyed to the learner. The task of interpretation demands the construction of a model of the interaction, which is instantiated to represent the current state of interaction, and possibly the state of interaction proposed by the instructional design of the system or the state of interaction of peers. It is then up to the learner to interpret the visualization and decide what actions (if any) to take.

In particular, the process of modelling learner's interaction with the double aim of providing a mirror of the learner's actions and useful recommendations whenever a perturbation arises, contains the following phases:

- Phase 1. The data collection phase involves observing and recording the interaction. Specific *indicators* of learners' interaction with the content and functionalities of the system are logged and stored for later processing.
- Phase 2. This phase involves selecting one or more *attributes* of the instructional design of the system, which provide meaningful information about learners' actions and thus they are valuable in characterizing learner's interaction.
- Phase 3. In the final phase, *an analysis of the interaction* is provided by comparing the current state of interaction to the one proposed by the instructional design of the system and/or the one adopted by peers.

Phase 1. The study of learners' behaviour through interaction protocols demands the definition of relevant *indicators* from learners' interaction with the content and functionalities of the system, which will be further linked to specific characteristics of the learner in an analysis of the interaction. Moreover, an essential step in this study, is the definition of the appropriate *observation grain*, which relates to the precision of the events considered as units in the analysis of the interaction protocols. This relates to the events that need to be analysed, ranging from global activity patterns, which can be used to capture global features of subjects' representations or strategies (coarse grain) when studying a goal, to specific aspects of the interaction (intermediate or fine grain) (Rouet and

Passerault, 1999). The observation grain links to the study objectives and in our case a combination of different levels of grain seems appropriate.

As indicators of learners' interaction with the content and functionalities of the system that link to learners’ cognitive activity are considered specific *navigational* and *temporal* indicators such as visits on resources, sequencing of resources, time spent on the resources. Moreover, as indicators of learner’s performance are used specific *performance indicators* showing learners’ success with resources, such as total attempts on assessment questions, performance in tests, etc. In this phase, quantitative and qualitative data at different levels of observation grain, ranging from global activity to specific aspects of the interaction, should be used and shaped to the individual characteristics of the educational system and the study objectives. For example, the coarse grain approach can be used to capture global features of the learner’s state such as the different topics s/he worked with, his/her knowledge level on these topics. However, this observation grain does not permit to answer more specific questions about learner’s study preferences and strategies when working with specific topics. At the intermediate grain approach analysing the interaction protocol amounts to selecting the events of interest and making appropriate computations (e.g. frequency). This approach is useful when testing specific hypotheses about the cognitive processes at work during the interaction. For example, in case of investigating learners’ preferences of resources for a specific topic, then the frequency of learner’s selections of various educational material types - e.g. examples, exercises, theory presentations, activities - is of great importance. Lastly, at the fine grain level, all the observable actions are taken into account. In this approach the complete sequence of events included in raw interaction protocols are analysed. In this case the investigator focuses on meaningful patterns, in order to achieve an understanding of learner’s activity when working with particular tasks. Data selection or interpretation requires a careful analysis of the task and study objectives. For example, the analysis of navigation patterns to examine the way learners use assessment may result to different strategies such as using tests as a self-assessment tool during studying or using assessment questions to guide the learner’s study in particular topics.

Phase 2. An analysis of the learner’s interaction protocols, in order to provide meaningful information about learners’ cognitive activity, should take into consideration different *attributes* of the instructional design of the system. In the proposed approach, as such *attributes* could be considered (a) the type, semantic density, view of the *resources* that the learner encountered during interaction, and (b) the type and functionality of tools selected, the support (navigational aids, sequencing or presentation of content) exploited by the learner to accomplish his/her goals and tasks (*context*).

Phase 3. The system visualises all the above data providing the current state of the learner (mirroring) aside the state of interaction proposed by the instructional design of the system or the state of interaction of other peers. Moreover, the system analyses all the data collected in the previous phases and make *recommendations* to the learner about how to proceed. The analysis of learners’ actions is based on his/her interaction with the *resources* in the current *context*.

The main idea behind such a learner modelling approach is to (*i*) enable mirroring of learners’ interaction along with an interaction state derived form the instructional design of the system or adopted by other learners, with the aim to support reflection which may lead to successful behaviour, (*ii*) support the provision of meaningful recommendations to learners, (*iii*) guide system adaptive behaviour in case of an agreement between the learner and the system.

4 An application example

INSPIRE (Papanikolaou et al., 2003) is a web-based Adaptive Educational Hypermedia system designed to support web-based instruction. In INSPIRE, learners have always the option to select and study the learning goal they prefer independently of their previous selections; all the material necessary for their study is provided when a learning goal is selected. In particular, INSPIRE plans the content of instruction for the particular learning goal, i.e. selects the contents of a sequence of lessons that gradually support learners to achieve their goal. INSPIRE aims to facilitate learners during their study, providing personalized instruction (a) proposes a navigation route through the lesson contents based on learner’s knowledge level and progress, and (b) adapts the presentation of the educational material to the learners' learning style.

The educational content of INSPIRE is represented in three hierarchical levels: *learning goals, concepts and educational material* (see Figure 1). A learning goal corresponds to a topic of the domain knowledge. Each goal is associated with a subset of concepts of the domain, which formulates a conceptual structure that represents all the concepts of the goal and their relationships (outcomes, prerequisites, related). Each outcome concept of a goal is associated with several educational material pages which consist of *knowledge modules* such as theory presentations, questions introducing or assessing the concept, examples, exercises, activities. The educational material pages of each outcome are organised in three level of performance (see Figure 1): (i) Pages of the *Remember* level include knowledge modules that introduce the concept and make learners speculate on newly introduced ideas, such as theory presentations, questions (introductory or self-assessment), and examples, (ii) Pages of the *Use* level of performance include knowledge modules that support learners to apply the concept to specific case(s), such as hints of the theory, examples, exercises, activities, (iii) Pages of the *Find* level of performance include knowledge modules necessary to stimulate learners to find a new generality, principle, procedure, through specific activities. All learners receive the same knowledge modules. However, the order and mode (embedded or link) of their presentation in a page is adapted based on the learner’s learning style – the (Honey and Mumford, 1992) categorisation has been adopted which suggests four types of learner: *Activist, Pragmatist, Reflector, Theorist.*

It should be emphasised that learners working with INSPIRE have the option to select the educational material they prefer to study, in the order they prefer. In particular, INSPIRE supports several levels of adaptation from purely adaptive to purely adaptable. Learners working with INSPIRE have the options (a) to follow recommendations proposed by the system (b) to access their learner model, reflect upon its contents and change them in order to guide system’s instructional decisions (see Fig.1 - Learner Model), (c) to deactivate the dynamic lesson generation process and select the next lesson contents (see Fig.1 - Lesson tool). In the current version of the system the learner model provides information about the knowledge level of the learner on the outcome concepts of the current lesson, as well as about his/her learning style. The design approach presented below is the first step towards the extension of the learner model of INSPIRE to include information about learner’s interaction behaviour. This new version is currently under development.

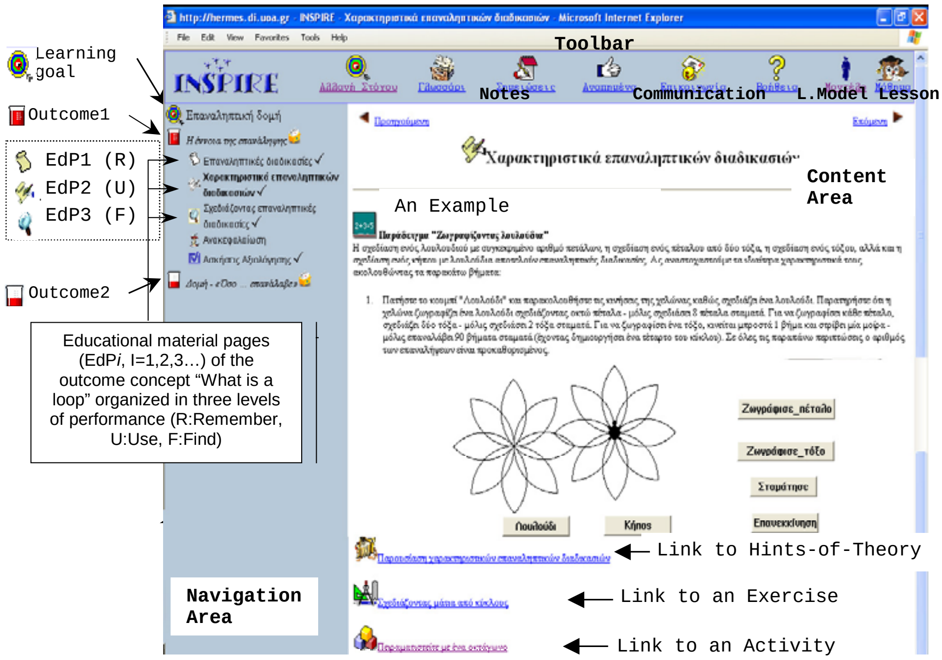

Figure 1. The main screen of INSPIRE (http://hermes.di.uoa.gr/inspire) provides learners with a complete view of the structure of the domain knowledge (Navigation Area) and direct access to learning resources (Content Area) and systems' functionalities (Toolbar). The lesson contents for the particular learner who studies a learning goal on Computer Programming, include two outcome concepts (Navigation Area): Outcome1 and Outcome2. Different icons are associated with the two outcomes, denoting variations of learner's knowledge level on the corresponding concepts: the learner has mastered Outcome1 (an almost full measuring cup appears next to Outcome1) whilst his/her knowledge level has been evaluated as {Mediocre} with regards to Outcome2 (a half empty measuring cup appears next to Outcome2). In the Navigation Area, Outcome1 has been expanded (only one outcome concept can be expanded at each time). Different icons are associated with the educational material pages (EdP*i*) of Outcome1 denoting the level of performance to which each page corresponds (R:Remember, U:Use, F:Find). At the Content Area a page of the Use level (as it appears to a Reflector) appears which includes the knowledge modules: *Example*; link to *Hints-of-Theory*; link to an *Exercise;* link to an *Activity.*

Modelling learner's observable behaviour. In this paragraph we present how the modelling approach described in Section 3 will inform the design and externalisation of the learner model of INSPIRE. The system gathers data from learner's interaction with the system and shows some visualisations of this information in order to support learners gather evidence to evaluate the efficacy of their moves. To this end the visualisations include a set of indicators that represent the state of interaction along with a set of desired values for those indicators. These values may be derived from the instructional design of the system or may reflect their peers' interaction. As will be described below, the values derived from the instructional design of the system refer to (a) the semantic density of the resources as proposed by the tutor, e.g. the time that the learner has spent on specific resources, will be presented aside the semantic density of the resources, as well as (b) the navigational advice offered based on the learner's knowledge level, e.g. the resources that the learner selects will be presented aside the system's navigational advice. In particular, through mirroring learners' interaction behaviour we aim to (a) support learners' reflection on their strategies and in cases of failure guide them towards successful behaviour; (b) enhance learners' style awareness; (c) guide system adaptive behaviour; (d) support tutors in providing personalised guidance and instruction and evaluate the educational resources.

In particular, we use navigational (number of hits, frequency of visits, sequence of first visit/revisits), temporal (time spent on different types of resources and assessment), and performance (attempts on assessment questions, performance on tests) *indicators* of learner's interaction which are recorded at three levels of grain, coarse, intermediate, fine, in order to provide a comprehensive view of learner's cognitive activity (see Table I). In a pilot study we performed to investigate learners' beliefs about the usefulness of such information, revealed that most learners believe that this type of data reflects their study preferences and that most of them would use these data to improve their interaction behaviour in case of failure. Moreover the above indicators are linked to different *attributes* of the instructional design of INSPIRE that provide useful information about learners' actions (a) semantic information of the resources such as type (theory presentations, examples, assessment, activities), view (Activist's, Reflector's, Theorist's, Pragmatist's), semantic density (study time proposed by tutor) and (b) context information including the tools (see Fig. 1 the tools: *Notes*, *Communication* that includes chat, discussion lists, e-mail, *Learner Model* through which learners may check and update their knowledge level and learning style, Lesson through which learners may deactivate the adaptive behaviour of the system) and support (navigation advice) offered. Lastly, three different levels of observation grain have been considered, following the structure of the domain knowledge (goals, concepts, educational material pages/modules), each one having a different study objective: (a) at the *coarse level*, information about the general activity of the learner during studying a specific learning goal is provided. This information provides a means to evaluate the learner's involvement in the goal through the total time s/he spent on the goal (at the current session, total study time) as well as the learner's activity such as which outcomes s/he has studied, his/her performance, etc.; (b) at the *intermediate level*, information about the learner's cognitive activity on each particular outcome concept of the goal is provided. This includes time spent on different types of resources (educational material pages, knowledge modules), time spent/frequency of visits on specific types of resources/activities, information about assessment (time spent, number of questions answered, attempts, performance), etc. The information at this grain illustrates the way the learner uses different types of resources –which is linked to learner's style preferences - and the impact on her performance. Moreover, information about the time spent on specific resources combined with the semantic density of the resources and the learners' knowledge level could provide a means to evaluate the difficulties that a learner faces with the educational material as well as the quality and adequacy of specific resources for learners with a particular knowledge level; (c) at the *fine grain* information about the learner's cognitive activity on particular tasks is provided. Learner's navigation patterns are recorded including information about the learner's actions/selections of resources and specific tools, aside with system advice. The information at this grain allows the investigation of the evolution of learner's activity over time and how this relates to his/her style preferences and knowledge level. For example, information about the resources the learner uses when working with activities or solving an exercise (e.g. the sequencing of resources s/he adopts) linked with his/her performance could illustrate his/her learning strategies as well as their success or failure. The investigation of repetitive patterns of learners' behaviour and the way these patterns link to the learner's style preferences, knowledge level and performance could provide a deeper view on the way learners use the resources and interact with the educational system.

In Figures 2 and 3 we provide two mock-ups of the visualization of learners' interaction behaviour at the coarse and intermediate observation grains, as these will appear in the learner model. Figure 2 represents data about learner's interaction at the coarse observation grain, i.e. during studying a learning goal, whilst Figure 3 at the intermediate observation grain, i.e. during studying a specific outcome concept of the learning goal. For a detailed description of the interaction behavior data visualized in both Figures 2, 3 see Table I. In both Figures the black lines denote the current state of the learner's interaction whilst the double ones, the state proposed by the instructional design of the system.

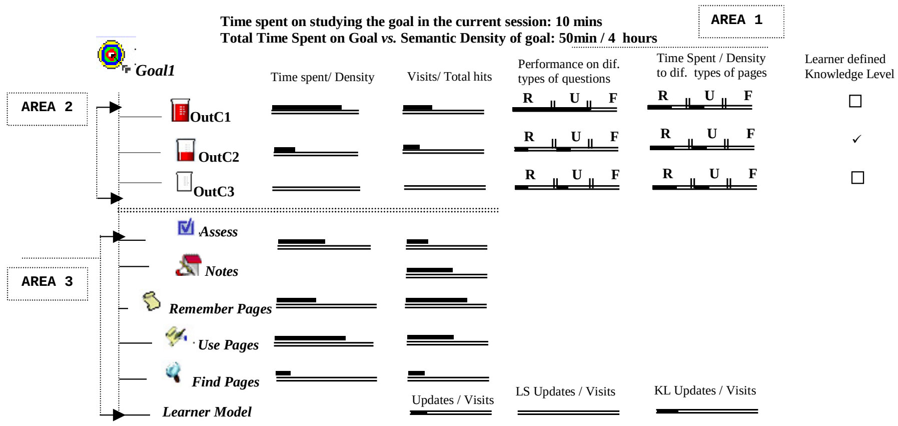

Figure 2. A mock-up of the visualization of learners' interaction with the resources and system functionalities at the coarse observation grain. Note that the different icons that accompany the educational material pages and the outcome concepts reflect the type of resources and the knowledge level of the learner (see also Figure 1). Note that: (a) the outcomes that the learner has to study are OutC*i*: outcome concept *i*=1,2,3; (b) the different levels of performance on which the educational material pages of the outcomes correspond are: R:Remember, U:Use, F:Find; (c) the different functionalities the learner used are *Assess*: submission of assessment tests, *Notes*: answering on questions, exercises, activities using the Notes tool from the toolbar, *Learner Model*: visits/updates on the learner model which presents the learners' Knowledge level (KL) and Learning Style (LS). For a detailed description of the interaction behavior data visualized in this figure see Table I – *Coarse grain*.

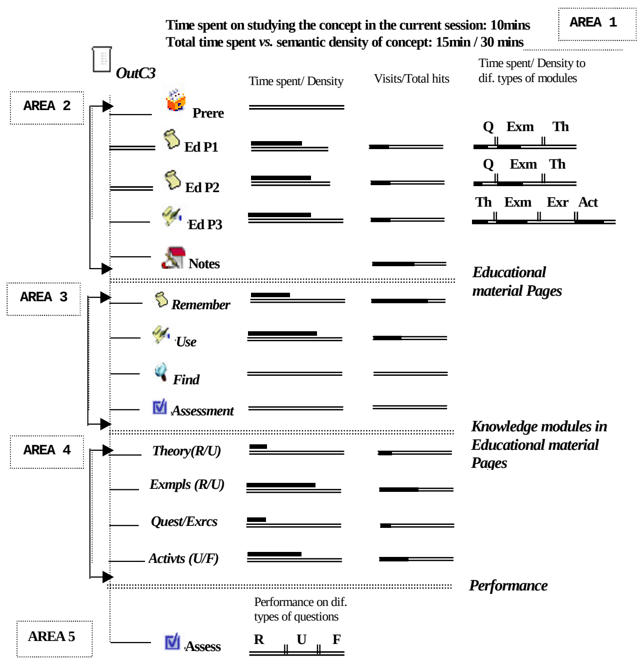

Figure 3. A mock-up of the visualization of learners' interaction with the resources of the outcome concept "OutC3" of the learning goal (intermediate observation grain). Note that: (a) the educational material pages are: Prere which present the prerequisite concepts of the outcome, Ed P*i*: educational material pages of the OutC3; (b) the different knowledge modules included in the educational material pages are Q: Question, Exm: Example, Th: Theory, Exr: Exercise, Act: Activity; (c) the different levels of performance on which the educational material pages correspond are: R: Remember, U: Use, F: Find. For a detailed description of the interaction behavior data visualized in this figure see Table I - *Intermediate grain*.

Table I. Data describing learner's interaction behaviour at three observation grains: coarse, intermediate, fine.

Coarse grain (Goal level) Data visualized in AREA 1 of Figure 2 - Time spent on studying the goal in the current session (see Figure 2 – the goal is *Goal1*) - Total time spent on studying the goal *vs.* semantic density of goal resources Data visualized in AREA 2 of Figure 2 The following information is provided for each outcome concept of the goal (see Figure 2 – OutCi): - Time spent on studying a concept of the goal *vs.* semantic density of the concept resources - Frequency of visits: Visits on the resources of a concept of the goal *vs.* total hits on concept resources - The learner's correct answers on the assessment test of a concept of the goal analyzed in her performance on different types of questions *vs.* total number of different types of questions (R: Remember, U: Use, F: Find)

- Time spent on studying the educational material pages of the (Remember, Use, Find) level of a concept of the goal *vs.* semantic density of the particular resources
- Information about how the learner's Knowledge Level (KL) was estimated: through tests or defined by the learner

Data visualized in AREA 3 of Figure 2

- Time spent on assessment *vs.* semantic density of the assessment tests
- Frequency of visits: Visits on the assessment tests of a goal *vs.* total hits on goal resources
- Frequency of visits: Visits on the Notes tool (where learners submit their answers to questions, exercises, activities) *vs.* total hits on questions, exercises, activities of the goal
- Time spent on studying the educational material pages of the (Remember, Use, Find) level of performance *vs.* semantic density of the particular resources of the goal
- Frequency of visits: Visits on the educational material pages of the (Remember, Use, Find) level *vs.* total hits on the educational material pages of the goal
- Updates of the learner model *vs.* visits on the learner model plus updates of Learning Style (LS) information *vs.* total visits on the model plus updates of Knowledge Level (KL) information *vs.* total visits on the model

Intermediate grain (Concept level)

Data visualized in AREA 1 of Figure 3

- Time spent on studying the concept in the current session (see Figure 3 – the concept is *OutC3*)
- Time spent on studying the concept *vs.* semantic density of concept resources

Data visualized in AREA 2 of Figure 3

- Time spent on studying prerequisite concepts of the outcome *vs.* semantic density of the particular resources
- Time spent on studying the educational material pages of the (Remember, Use, Find) level of the concept *vs.* semantic density of the particular resources
- Frequency of visits: Visits on the educational material pages of the (Remember, Use, Find) level of the concept *vs.* total hits of the learner on the educational material pages of the concept
- Time spent on studying the knowledge modules (Question, Example, Exercise, Theory, Activity, Hints of Theory) included in educational material pages of the (Remember, Use, Find) levels of the concept *vs.* semantic density of the particular resources
- Frequency of visits: Visits on the Notes tool to submit their answers to questions, exercises, activities *vs.* total hits on questions, exercises, activities of the concept

Data visualized in AREA 3 of Figure 3

- Time spent on studying the educational material pages of the (Remember, Use, Find) level of performance and the assessment test page *vs.* semantic density of the particular resources
- Frequency of visits: Visits on the educational material pages of the (Remember, Use, Find) level and the assessment test page *vs.* total hits on the concept resources

Data visualized in AREA 4 of Figure 3

- Time spent on studying the knowledge modules (Question, Example, Exercise, Theory, Activity, Hints of Theory) included in educational material pages of the (Remember, Use, Find) levels of a concept *vs.* semantic density of particular resources
- Frequency of visits: Visits on the knowledge modules (Theory at the Remember (R) and Use (U) levels, Examples at the R/U levels, Questions/Exercises, Activities at the Remember and Find levels) included in pages of the (Remember, Use, Find) levels of a concept *vs.* total hits on the knowledge modules of the concept

Data visualized in AREA 5 of Figure 3

- The learner's correct answers on the assessment test of the concept analyzed in her performance on different types of questions *vs.* total number of different types of questions (R: Remember, U: Use, F: Find)

Fine grain (Educational material level)

- Learner's navigation pattern on the knowledge modules included in educational material pages of the (Remember, Use, Find) levels and assessment pages at a goal level (first time visit)
- Learner's navigation pattern on the knowledge modules included in educational material pages of the (Remember, Use, Find) levels and assessment pages at each specific outcome concept of a goal
- History of learners' selections of pages (including information about the concept, the level of page, time spent, system proposals/advice), visits/updates on the Learner Model (including model view, options changed), assessment (total attempts and performance), visits/actions with the Lesson, Notes, Communication tools.

5 Conclusions and Future Plans

In this paper we propose an approach to model learner interaction based on learner-system interaction protocols. Interaction protocols provide direct access to learners' activity rather its outcomes and thus they can be used as dependent measures to understand the nature of the learning process. In the proposed approach learners' interaction behaviour is modelled based on a combination of analysis of learner's actions with quantitative indicators such as time spent on resources, frequency of re-visits on specific resources, etc. We also investigated the externalisation of this information to the learner through the learner model in a meaningful way with the aim to support reflection and awareness of style issues, which may lead to improve their interaction and accomplish their goals.

Currently the new version of INSPIRE is under development. The proposed approach of modelling and externalising learners' interaction through the learner model will be further evaluated. Based on these results as well as on data about learners' interaction with their model we aim to design a negotiated model that will allow the learner and the system to jointly discuss the contents of the model. Moreover, in the near future we intend to further investigate (a) the visualisation of learner's navigation patterns at the fine observation grain, (b) the recommendations provided by the system, and (c) the selection and visualisation of data about peers' interaction behaviour augmented with comments about successful and unsuccessful interactions.

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