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SCHOOL OF COMPUTING & INFORMATION SYSTEMS

User modelling for people in the context of diversity

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Outline

- Adaptive hypermedia systems
- Basics on user modelling
- Typical user modelling approaches
- Research on user modelling of learning styles
- User Modelling for addressing people with special needs
- Practical session

My Research Areas

How can we make learning systems more adaptive, intelligent and personalized

- Based on a comprehensive student model that combines learner information and context information
- In different settings such as desktop-based, mobile and ubiquitous settings
- In different situations such as for formal, informal and non-formal learning
- Supporting learners as well as teachers
- Develop approaches, add-ons and mechanisms that extend existing learning systems

My Research Areas

- Students' characteristics
  - Learning styles
  - Cognitive traits
  - Context information (environmental context & device functionalities)
  - Motivational aspects
  - Affective states
- Different settings
  - Learning management systems
  - Mobile / Ubiquitous learning

Adaptive Hypermedia Systems

Adaptive Hypermedia Systems

- What is hypertext/hypermedia?
  - Hypertext: “combination of natural language text with the computer’s capability for interactive branches” (Conklin, 1987)

    → non-sequential text, connected by hyperlinks
  - Hypermedia: extends the concept of hypertext by media elements such as graphics, audio, and video, rather than text-only presentations

Adaptive Hypermedia Systems

- Adaptive Hypermedia Systems (AHS) are defined as: “hypertext and hypermedia systems which reflect some features of the user in the user model and apply this model to adapt various visible aspects of the system to the user” (Brusilovsky, 1996)
- Each AHS should:
  - Be a hypertext or hypermedia system
  - Have a user model
  - Adapt the hypertext/hypermedia using this model

Adaptive Hypermedia Systems

- Adaptation Process:
  - Building and frequently updating a model of the user
  - Use the model to provide adaptivity
- Different architectures exist for adaptive systems however, basic components are:
  - User module

    Responsible for building and updating the user model
  - Expert module

    Responsible for accessing the expert model and for the internal representation of domain knowledge

Adaptive Hypermedia Systems

- Adaptation module

  responsible for determining how the content, available from the expert model, can be presented in a proper way considering the individual needs of the user, accessed through the user model

- Interface module

  Responsible for presenting the content, as determined by the adaptation module, and controls the communication and interaction of users with the system.

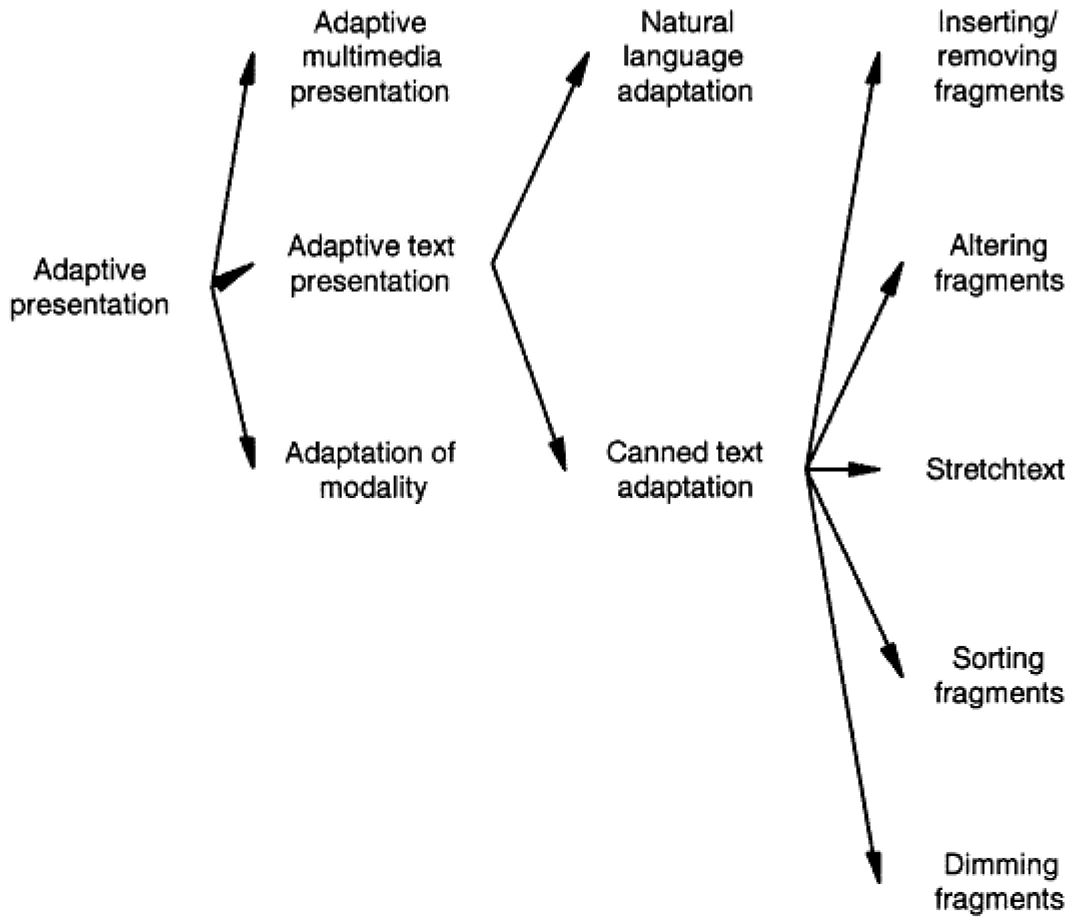
Adaptive Hypermedia Systems

- What can be adapted in a system?
  - Adaptive Presentation

    focuses on adapting the presentation of content
  - Adaptive Navigation Support

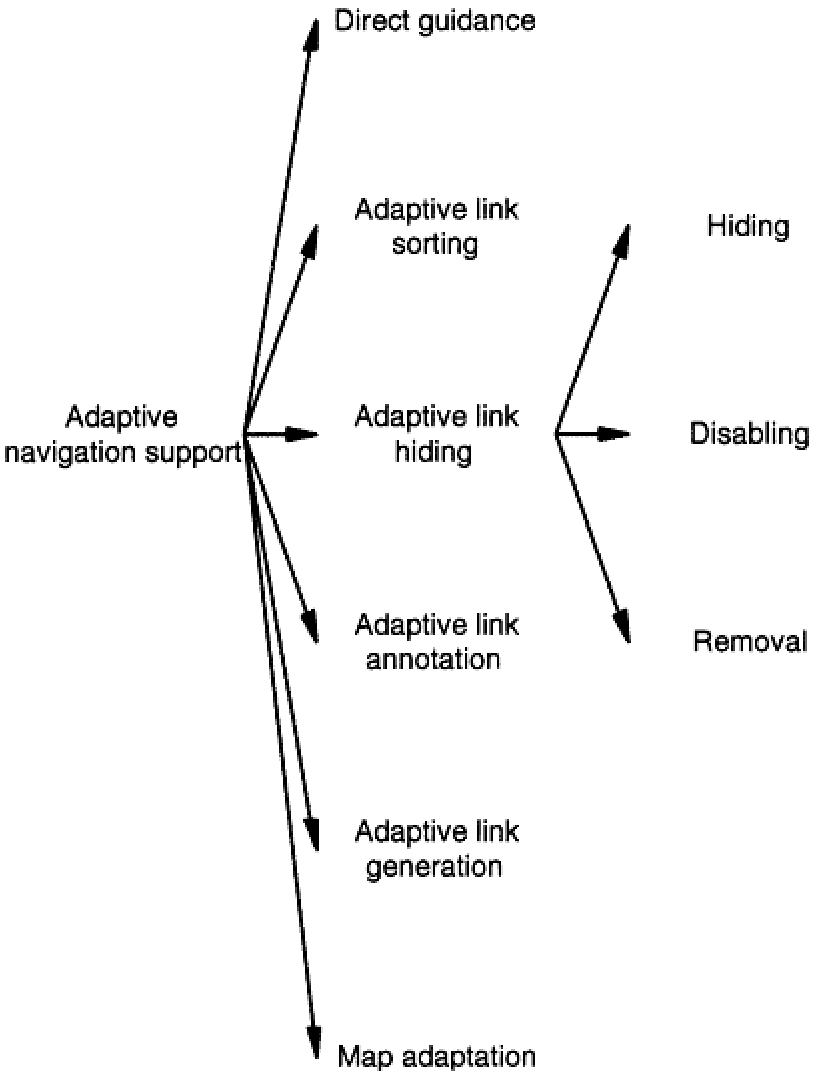
    focuses on adapting the links to content

Adaptive Presentation



(Brusilovsky, 2001)

Adaptive Navigation Support



(Brusilovsky, 2001)

Adaptive Hypermedia Systems

- What information can be used to provide adaptivity?
  - Knowledge
  - Goals
  - Cognitive Abilities
  - Learning Styles
  - Motivation
  - Location
  - Environmental Context
  - ...

Adaptive Hypermedia Systems

- What is the goal of providing adaptivity?
  - Short-term:
    Support a user and provide him/her fast with the information that is needed in a particular situation
  - Long-term:
    Help a user to improve certain skills (e.g., learning styles, meta-cognitive skills etc.)

Adaptive Hypermedia Systems

Group activity:

What are the main challenges in adaptive hypermedia systems, especially in the educational context?

-) Each person tries to come up with one most important challenge

User Modelling and User Modelling Approaches

User Modelling

- Plays a critical role in adaptive hypermedia systems
- A user model includes all information about a user that is relevant for providing adaptivity
- User modelling is the process of building and updating the user model

What data can be included in a user model?

- Knowledge
- Goals
- Motivational aspects
- Learning styles
- Cognitive abilities
- Meta-cognitive abilities
- Affective states
- Location
- Environmental context
- etc.

User modelling

Group activity

What are the three characteristics of students which are most important to consider in an adaptive educational hypermedia system?

-) Each person identifies the 3 most important characteristics

-) Discuss them in groups of 3-4 people

-) Discuss them with whole audience

User Modelling Approaches

User Modelling

Collaborative User Modelling

Automatic User Modelling

User Modelling Approaches

- Collaborative User Modelling
  - Ask user explicitly for information
  - Different approaches:
    - Using questions or questionnaires
      Challenges:
      - Reliability & validity of the instrument
      - Motivate users to fill it out reliably
      - Non-intentional influences
      - Static instrument

User Modelling Approaches

- Allow users to directly update the user model
  Challenges:
  - Reliability & validity of users' input
  - Non-intentional influences
  - Users might not update this information frequently
  - In combination with automatic modelling: user can delete the information that has been gathered through automatic modelling

User Modelling Approaches

- Automatic user modelling
  - Using automatically gathered data to identify users' situation, needs and characteristics
  - Commonly used sources for data are sensors and user interactions
  - Rather than asking a user, we use real data (e.g., What are users really doing in an online system? Where are users? etc.)
  - Advantages:
    - Users have no additional effort
    - Uses information from a time span → higher tolerance
    - Allows dynamic updating of information
  - Problem/Challenge:
    - Get enough reliable data to build a robust user model

User Modelling Approaches

User Modelling

Static User Modelling

Dynamic User Modelling

User Modelling Approaches

- Static vs. Dynamic
  - Static: user model is built once
  - Dynamic: user model is frequently updated based on new data
- Advantages of Dynamic User Modelling
  - dynamically building a user model by incrementally improving and fine-tuning the information in the user model in real-time
    → getting sooner a more accurate user model
  - dynamically updating a user model by identifying and responding to changes in users' characteristics/situations over time
    → more accuracy due to considering changes
  - consider exceptional behaviour of users
    → more accuracy due to considering exceptional behaviour

User Modelling Approaches

Group activity:

	Collaborative	Automatic
Static	?	?
Dynamic	?	?

Automatic student modelling of learning styles

How to identify learning styles?

- Collaborative student modelling
  - "Index of Learning Styles" (ILS) questionnaire
    - 44 questions (11 for each dimension)
    - Online available
  - Problems with questionnaires
    - Motivate students to fill it out
    - Non-intentional influences
    - Can be done only once

How to identify learning styles?

- Automatic student modelling
  - What are students really doing in an online course?
  - Infer their learning styles from their behaviour
  - Advantages:
    - no additional work for students
    - direct and free from the problem of inaccurate self-conceptions of students
    - analyses data from a specific time span → more accurate & allows tracking changes in learning styles
  - Problem/Challenge:
    - Get enough reliable information to build a robust student model

      → certain amount of data about the behaviour
      → use information related to learning styles as additional source

Research Question

How to automatically identify learning styles in LMS?

- General aims
  - Developing an approach for LMSs in general
  - Implementing and evaluating this approach in Moodle
  - Developing a tool which can be used by teachers in order to identify students' learning styles

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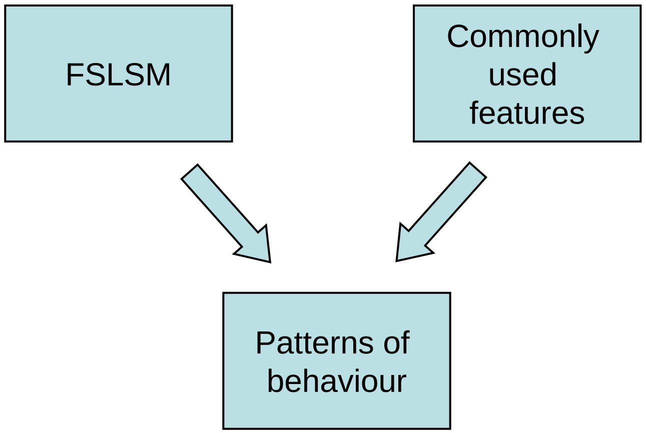
Determining Relevant Behaviour

- Felder and Silverman describe how learners with specific preferences act in learning situations
- Mapped the behaviour to online learning
- Only commonly used features are considered:
  - Content objects
  - Outlines
  - Examples
  - Self-assessment tests
  - Exercises
  - Discussion Forum



Determining Relevant Behaviour

- Content objects
  - Visits, time
- Outlines
  - Visits, time
- Examples
  - Visits, time
- Self-assessment tests
  - Visits, time on test, time on results
  - Revisions, answering a question twice wrong
  - Performance on questions about facts or concepts, details or overview, graphics or text, interpreting or developing solutions
- Exercises
  - Visits, time on exercises, time on results
  - Revisions
  - Performance on questions about interpreting and developing solutions
- Discussion Forum
  - Visits, time, postings
- Navigation
  - Skipping learning objects
  - Visits and time on course overview page

Determining Relevant Behaviour

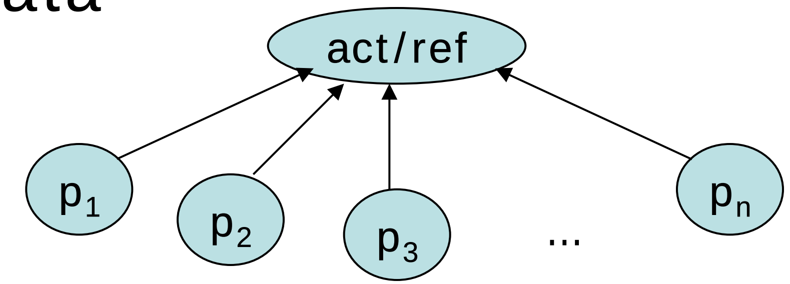
Active/Reflective	Sensing/Intuitive	Visual/Verbal	Sequential/Global
selfass_visit (+)	ques_detail (+)	forum_visit (-)	ques_detail (+)
exercise_visit (+)	ques_facts (+)	forum_stay (-)	ques_overview (-)
exercise_stay (+)	ques_concepts (-)	forum_post (-)	ques_interpret (-)
example_stay (-)	selfass_visit (+)	ques_graphics (+)	ques_develop (-)
content_visit (-)	selfass_result_duration (+)	ques_text (-)	outline_visit (-)
content_stay (-)	selfass_duration (+)	content_visit (-)	outline_stay (-)
outline_stay (-)	exercise_visit (+)		navigation_skip (-)
selfass_duration (-)	ques_rev_later (+)		overview_visit (-)
selfass_result_duration (-)	ques_develop (-)		overview_stay (-)
selfass_twice_wrong (+)	example_visit (+)		
forum_visit (-)	example_stay (+)		
forum_post (+)	content_visit (-)		
	content_stay (-)		

Building an model for inferring learning styles

- Data-driven approach
  - Using Bayesian Networks in order to build a model to identify learning styles
  - Train the model with data about behaviour and learning styles

→ can represents dependencies in the model more accurate

→ very much dependent on data



Building an model for inferring learning styles

- Literature-based approach
  - Building a model based on literature
  - Based on the idea that behaviour of learners provide hints on their learning styles
  - Using indications from data and a simple rule-based approach to identify learning styles

→ is very general since it is based on literature

→ dependencies in the model might be less accurate

Evaluation

- Study with 75 students
  - Let them fill out the ILS questionnaire
  - Tracked their behaviour in an online course
- Aim was to identify learning styles on a 3-item scale (e.g., active, balanced, reflective)
- Investigated the efficiency of the data-driven approach and the literature-based approach
- Using a measure of precision

$$\text{Precision} = \frac{\sum_{i=1}^{n} Sim(LS_{predicted}, LS_{ILS})}{n}$$

- Looking at the difference between results from ILS, data-driven approach and literature-based approach

Evaluation

Correctly detected learning styles:

	act/ref	sen/int	vis/ver	seq/glo
data-driven	62.50%	65.00%	68.75%	66.25%
literature-based	**79.33%**	**77.33%**	**76.67%**	**73.33%**

- Literature-based approach → suitable instrument for identifying learning styles

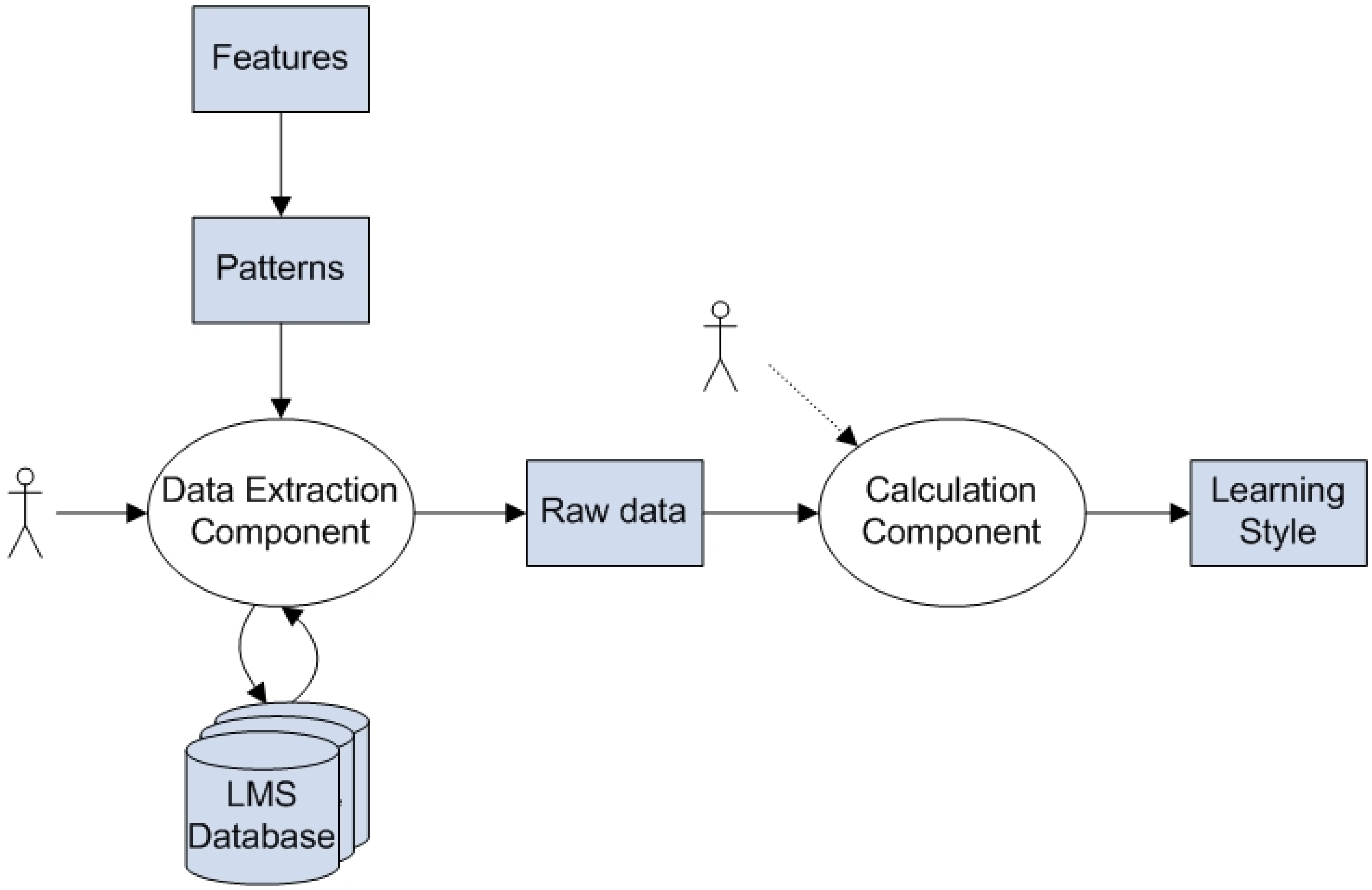
DeLeS – A tool to identify learning style in LMS

- DeLeS = **De**tecting **Le**arning **S**tyles
- Basic concept
  - Define relevant patterns of behaviour
  - Extract data about patterns from the LMS database
  - Use literature-based approach to calculate learning styles based on the gathered data
- Requirements
  - Applicable for LMS in general

    → Usable for different database schemata

    → Deal with missing data since maybe not all information can be tracked by each LMS

Tool Architecture

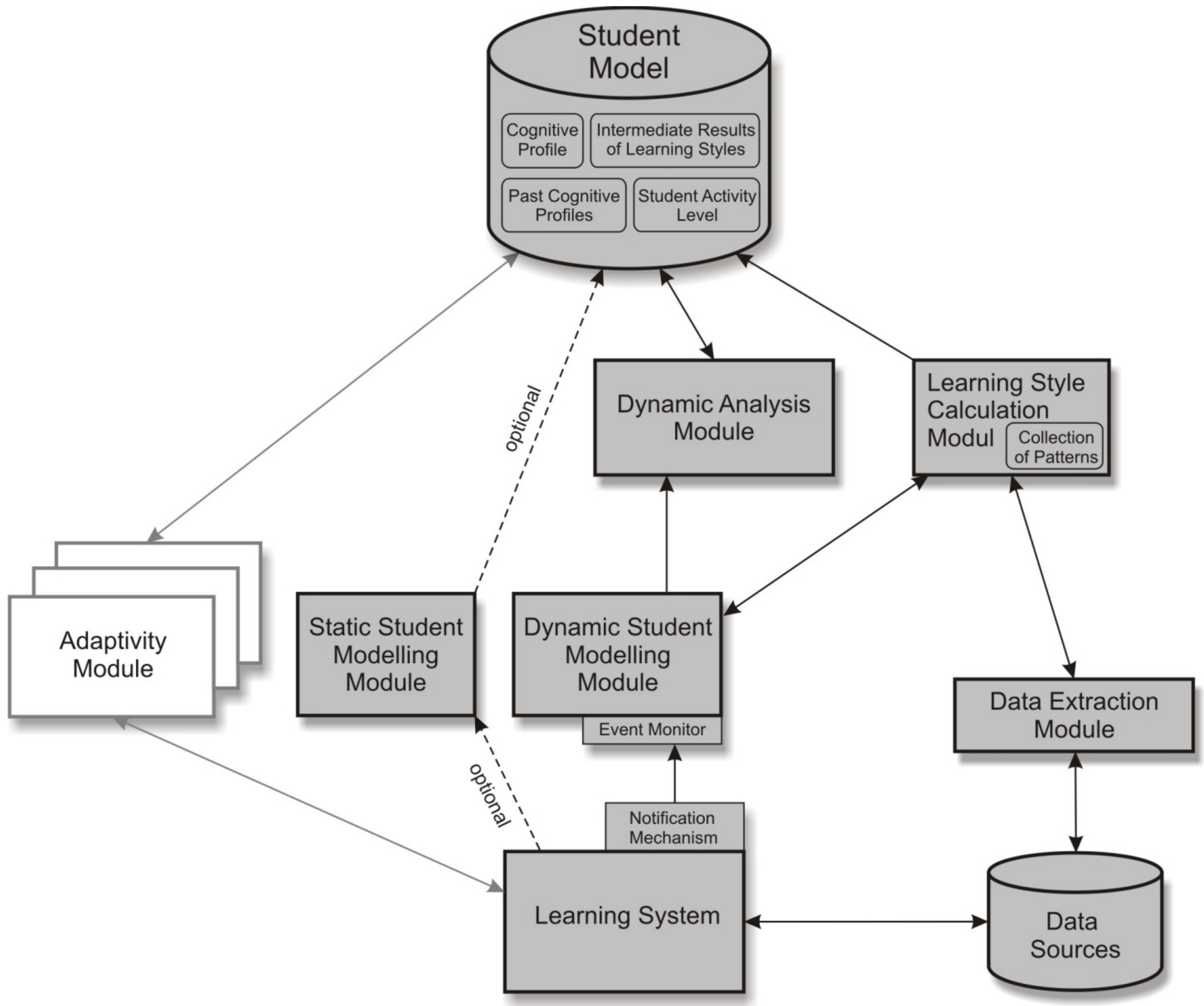


Dynamic student modelling of learning styles

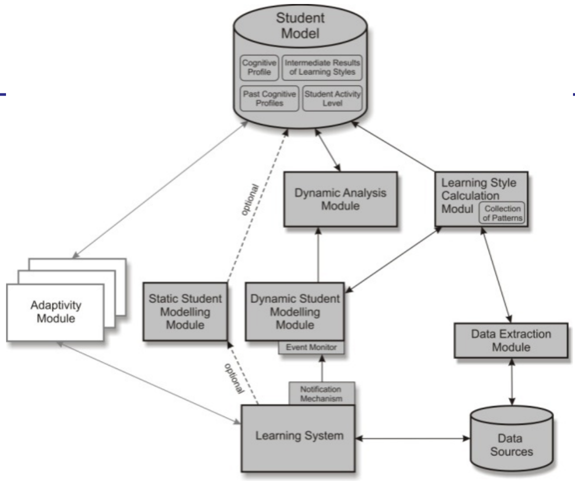
Aim of Research

- Proposes an generic architecture for automatic and dynamic student modelling of learning styles which can extend existing learning systems
- Combining collaborative and static student modelling with automatic and dynamic student modelling
- Demonstrate the architectures' application in a particular learning system
- Advantages:
  - Using collaborative/static student modelling for initializing the student model
    → getting quickly some information about students' learning styles
  - Using automatic/dynamic student modelling for refining and updating the student model
    → dynamic building of the user model through fine-tuning existing information about learning styles
    → dynamic updating of learning styles when they change over time

Architecture



Static Student Modelling Module

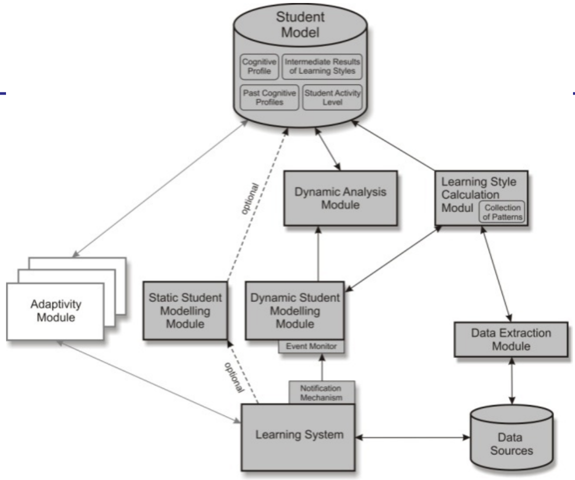


- Option for initialising the cognitive profile through a questionnaire (Index of Learning Styles by Felder & Soloman)
- Helps in quickly gather information about students' learning style

→ Adaptivity can be provided right after students filled out the questionnaire

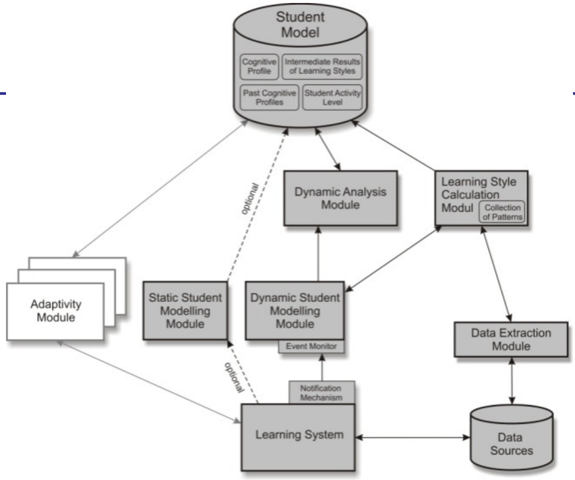
→ Use dynamic student modelling to fine-tune and revise the information in the cognitive profile of the student model

Notification Mechanism



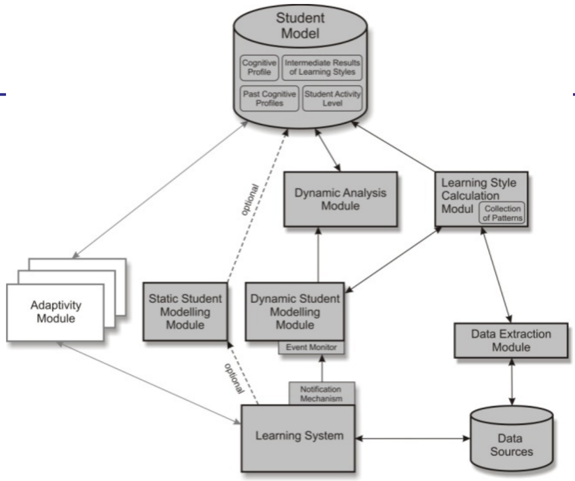
- System-dependent component
- Interface between learning system and *Dynamic Student Modelling Module*
- Responsible for notifying the *Dynamic Student Modelling Module* when a student performed an action in the learning system (e.g., visits of learning objects/activities)

Dynamic Student Modelling Module



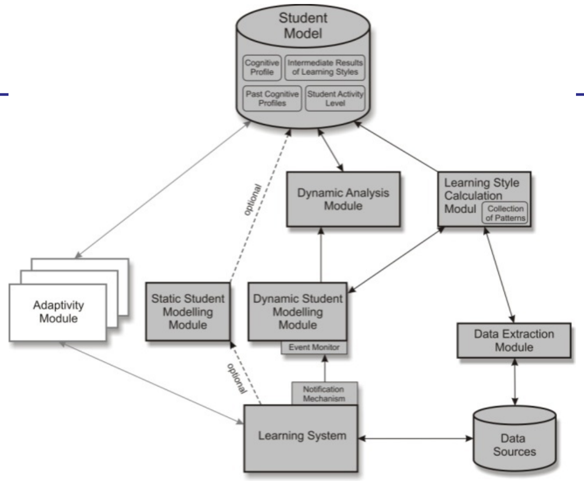
- Responsible for managing the dynamic student modelling process
  1. Monitors students' activity level based on the messages received from the notification mechanism
  2. Requests recalculation of students' learning styles based on their recent behaviour once a student performed a predefined number of actions since the last recalculation
  3. Requests checking whether the cognitive profile should be updated

Learning Style Calculation Module



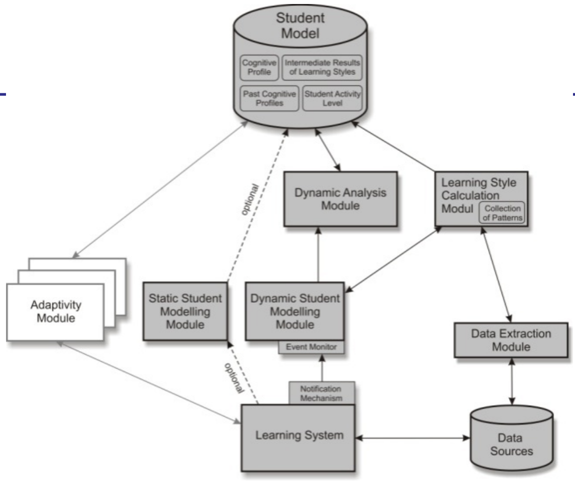
- Aims at calculating students' learning styles from their behaviour in the system
- Calculation is based on a collection of behaviour patterns
- Each pattern provides indications for identifying learning styles based on a particular dimension of the FSLSM
- Not all patterns can be included in all systems

Learning Style Calculation Module



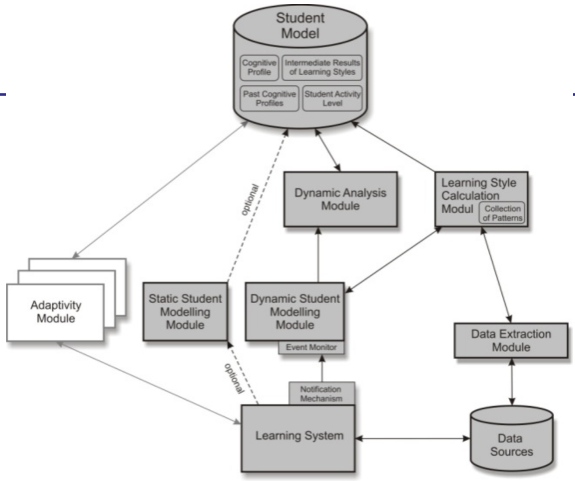
- Steps
  - Request raw data from Data Extraction Module
  - Transform raw data to ordered data based on thresholds from literature (→ high, medium, low, no information)
  - Relate ordered data to how the patterns affects the respective learning style dimension (→ strong indication, average, disagreement, no information)
  - Sum up values per dimension and divide by number of available patterns (→ measure for the respective learning style dimension)
  - Normalise to values between 0-1
- Approach has been successfully evaluated in Graf et al. (2009)

Learning Style Calculation Module



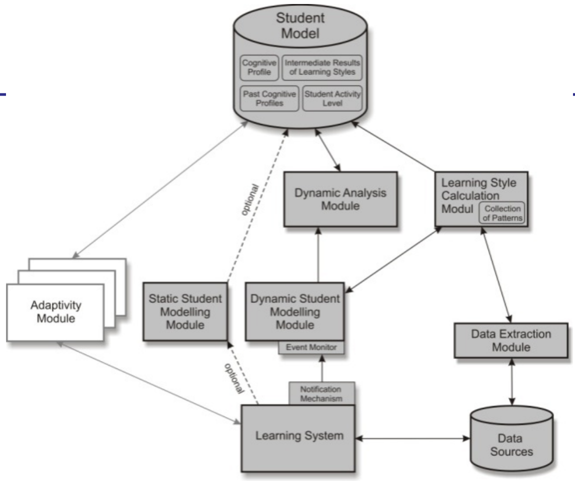
- Once learning styles are calculated
  - They are stored in the cognitive profile of the student model
  - Learning Style Calculation Module reports the completion of the calculation to the Dynamic Student Modelling Module

Data Extraction Module



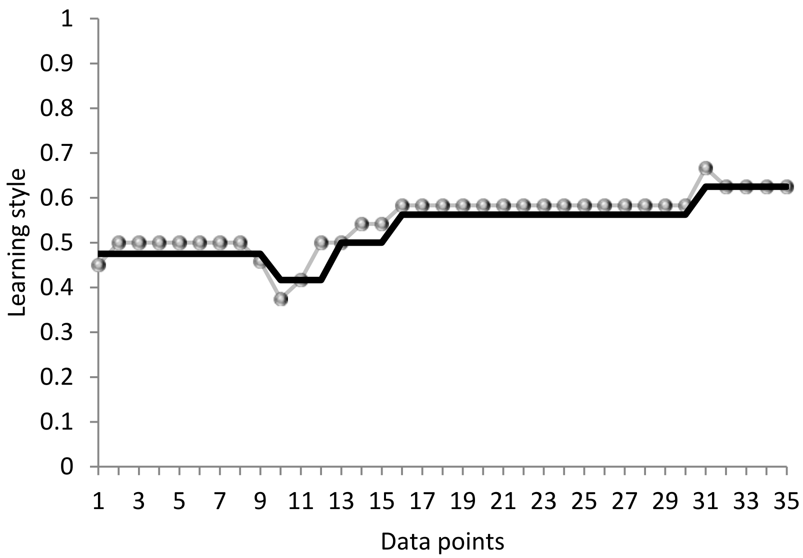
- Once the Data Extraction Module receives a request from the Learning Style Calculation Module, it
  - connects to the learning system's database (or other data sources)
  - extracts data from available patterns
  - sends the extracted data back to the Learning Style Calculation Module
- Data Extraction Module is system-dependent since data extraction depends on where data are located

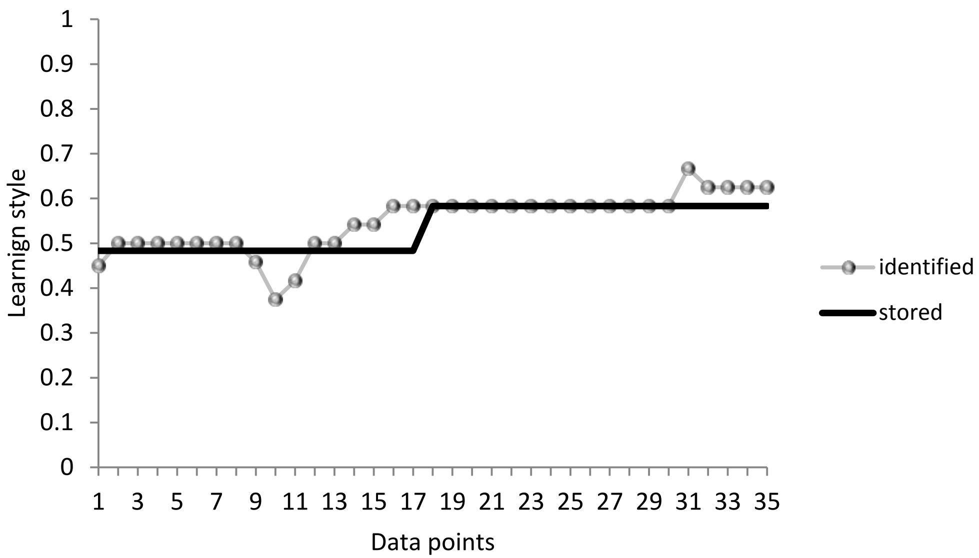
Dynamic Analysis Module



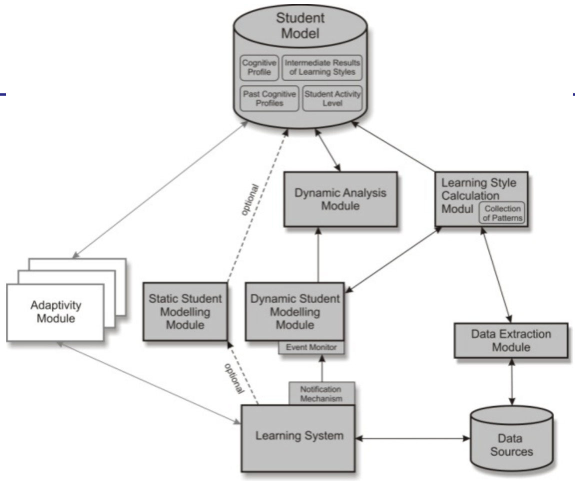
- Responsible for analysing how the learning styles change over time and whether these changes should lead to a change in the learning styles stored in the cognitive profile
- Two objectives for such a change:
  - The currently stored learning style should reflect the current learning style of students as good as possible → updating as soon as a revision can be done
  - Considering deviations of students’ behaviour and having as less as possible revisions which are then taken back shortly afterwards

More graphically …



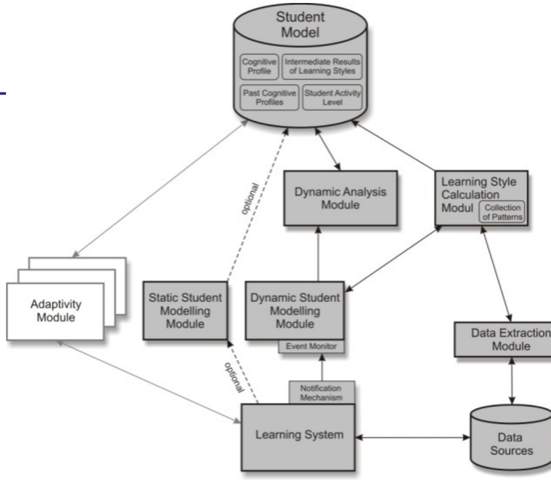


Dynamic Analysis Module



- The Dynamic Analysis Module integrates an approach that has been introduced and evaluated by Graf and Kinshuk (2009)
- Three conditions are used in order to decide whether a learning style should be updated
  - Difference between stored learning style and average learning style from current and past data
  - Difference between currently identified learning style (d_t) and previously identified learning style (d_{t-1})
  - Compare difference between previously identified learning style (d_{t-1}) and stored learning style as well as the difference between currently identified learning styles (d_t) and stored learning style
- If all three conditions point to a change in a student's learning styles (rather than an exceptional behaviour), the learning style in the cognitive profile is updated

Student Model



- Aims at storing several types of information about students
  - Cognitive profile, including 4 values of students' learning styles
    → can be accessed by adaptivity modules to provide learners with adaptive recommendations/courses
  - Students' activity level
  - Past data from the cognitive profile
  - Intermediate results from the Static Student Modelling Module including data from the questionnaire
  - Intermediate results from the Learning Style Calculation Module representing the identified learning styles over time based on students' behaviour

Application of the Architecture

- Architecture has been implemented for a learning system
  - Notification Mechanism has been integrated in the system
  - Data Extraction Module has been adjusted to the learning system's data sources and available patterns
  - Adaptivity Module has been developed that uses the information about students' learning styles

Course Structure

- Two types of courses
  - Assessment only
    - Exercises
    - Quizzes
    - Study Guide
  - Assessment & Content
    - Exercises
    - Quizzes
    - Study Guide
    - Outline
    - Learning material
    - Applied self-assessment questions
    - Theoretical self-assessment questions
    - Activity-related questions
    - Case studies

Available Patterns

Pattern name	Description of patterns	act/ref
exercise_stay	avg. time spent on solving an exercise question	ref
exercise_visits	avg. number of attempts to solve an exercise question	act
exercise_performance_increase	avg. rate of grade increase on exercise questions	ref
exercise_performance	avg. final grade on exercise questions	
exercise_stay_results	avg. amout of time spent for studying the feedback of exercise questions	ref
exercise_sequence_skip	number of time of skipping an exercise question*	
exercise_sequence_back	number of times of going back to a previous exercise question*	
quiz_sequence_revise	number of times of re-entering a quiz*	
quiz_stay	percentage of time took on avg. for submitting a quiz	
quiz_stay_results	avg. amount of time for studying the feedback of a quiz	ref
studyguide_visits	number of visits of the study guide*	
outline_visit	number of visits of outlines*	
outline_stay	avg. amount of time spent on outlines	ref
content_visit	number of visits on content pages*	ref
content_stay	avg. amount of time spent on content pages	ref
content_back	number of times of re-visiting a content page*	
content_skip	number of times for skipping content pages*	
asa_solution_visit	number of visits of solutions of applied self-assessment questions*	
asa_solution_stay	avg. amount of time spent on solutions of applied self-assessment questions	ref

Providing Adaptive Feedback

- The proposed architecture is intended to be combined with an adaptivity module that uses the information about students' learning styles to provide students with adaptivity
- Adaptivity modules have strong interdependencies with the system and are therefore system dependent
- The developed adaptivity module provides adaptive feedback within the study guide
- The feedback includes
  - Their learning styles
  - Explanation of their learning styles (pointing out typical characteristics, strengths and weaknesses of student with these particular learning styles in a general learning context)
  - Personalized learning advise including suggestions on how to learn more effectively