Women's Postgraduate College for Internet Technologies

Technische Universität Wien
Vienna University of Technology

Adaptivität in Lernplattformen – Wie können Lernstile erkannt und berücksichtigt werden?

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Outline

- What are learning styles?
- Why shall we incorporate learning styles?
- How can learning styles be identified in learning management systems
- How can cognitive abilities help in this detection process?
- How can adaptivity with respect to learning styles be presented in LMS?
- Conclusions and Future Research Directions

Learning Styles

- Complex and partially inconsistent research area
  - More than 70 different learning style models
  - Lot of research in the last 30 years
  - But still several important questions are open
    - What are learning styles?

      "a description of the attitudes and behaviours which determine an individual's preferred way of learning" (Honey & Mumford, 1992)

      "characteristic strengths and preferences in the ways they [learners] take in and process information" (Felder, 1996)

Learning Styles

- Other open issues:
  - Are learning styles stable over time?
  - How can learning styles be measured?
  - Relationships between models are not clear

- Essential questions for incorporating learning styles
  - Does students really prefer different ways of learning?
    According to educational theories & experiments → yes
  - Does matching/mismatching courses effect learning?
    According to educational theories → yes
    Experiments provide inconsistent results

Adaptive Systems

- Adaptive systems aim at providing adaptivity
  - AHA!
  - TANGOW
  - INSPIRE
  - ...
- Limitations
  - are either developed for specific content (e.g. accounting) or for specific features (e.g. adaptive quizzes)
  - content cannot be reused
  - are not often used

Learning Management Systems (LMS)

- Learning Management Systems (e.g., Moodle, Blackboard, WebCT, ...) are developed to support authors/teachers to create courses
  - provide a lot of different features
  - domain-independent
  - content can be reused in other LMS
  - are often used in e-education
  - provide only little or in most cases no adaptivity

How to incorporate learning style in LMS?

- How to incorporate learning styles in LMS?
  - How to identify learning styles automatically based on the behaviour of learners?
  - How to improve the detection process of learning styles by the use of additional sources?
  - How to provide adaptivity based on learning styles in LMS?

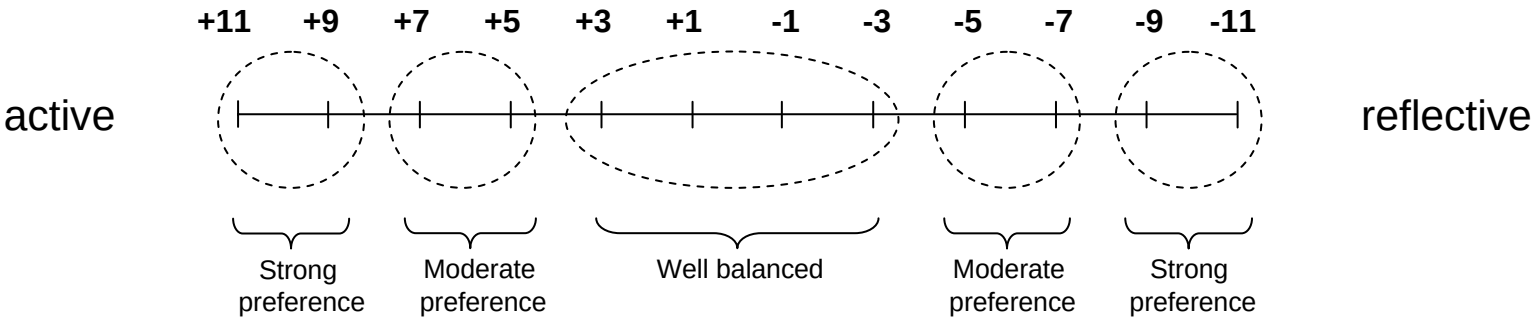
- General aims
  - Developing and evaluating a concept for LMS in general that enables the systems to incorproate learning styles
  - Teachers should have as little as possible additional effort

Felder-Silverman Learning Style Model (1/2)

- Each learner has a preference on each of the dimensions
- Dimensions:
  - Active – Reflective
    learning by doing – learning by thinking things through
    group work – work alone
  - Sensing – Intuitive
    concrete material – abstract material
    more practical – more innovative and creative
    patient / not patient with details
    standard procedures – challenges
  - Visual – Verbal
    learning from pictures – learning from words
  - Sequential – Global
    learn in linear steps – learn in large leaps
    good in using partial knowledge – need „big picture“
    serial – holistic

Felder-Silverman Learning Style Model (2/2)

- Scales of the dimensions:



→ Strong preference but no support → problems

- Differences to other learning style models:
  - Combines major learning style models (Kolb, Pask, Myers-Briggs Type Indicator)
  - New way of combining and describing learning styles
  - Describes learning style in more detail (Types <-> Scale)
  - Represents also balanced preferences
  - Describes tendencies

How to identify 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
    - Reliability & validity of the instrument
    - Motivate students to fill it out
    - Non-intentional influences
    - Can be done only once

How to identify learning styles?

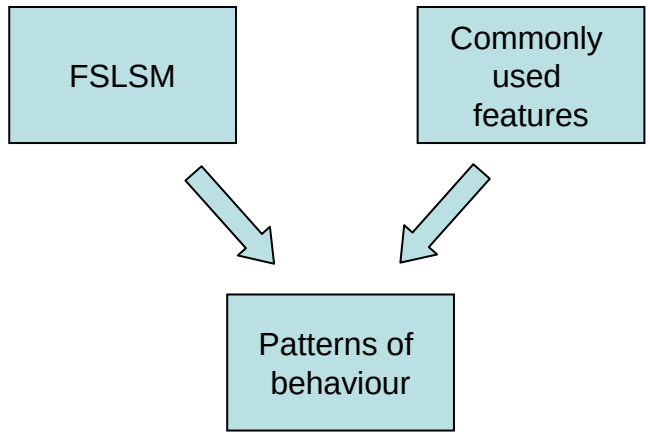
- Automatic student modelling
  - What are students really doing in an online course?
  - Infer their learning styles from their behaviour
  - Advantages:
    - Students have no additional effort
    - Can be updated frequently → higher tolerance
  - Problem/Challenge:
    - Get enough reliable information to build a robust student model
      → certain amount of data about the behaviour
      → use information related to learning styles as additional source

Automatic Student Modelling Approaches

- Determining relevant behaviour
  - Incorporated features and patterns
  - Classification of occurrence of behaviour
  - Relevant patterns for learning style dimensions
- Building a model for inferring learning styles
  - Method for building ordered data
  - Data-driven approach
  - Literature-based approach
- Evaluation

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

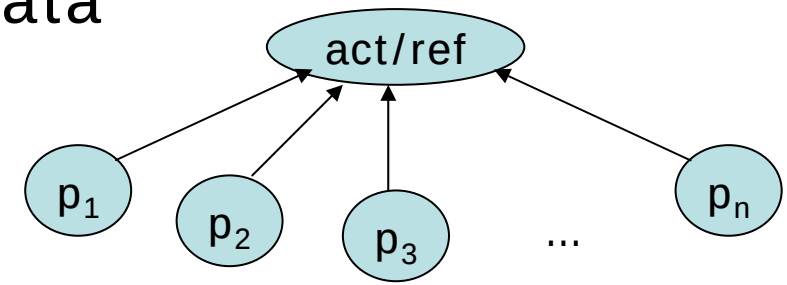
Active/Reflective	Sensing/Intuitive	Visual/Verbal	Sequential/Global
selfass_visit (+)	ques_detail (+)	forum_visit (-)	ques_detail (+)
exercise_visit (+)	ques_facts (+)	forum_stay (-)	ques_overview (-)
exercise_stay (+)	ques_concepts (-)	forum_post (-)	ques_interpret (-)
example_stay (-)	selfass_visit (+)	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 approaches such as Bayesian Networks, Decision Trees, Hidden Markov Model 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

Results

	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**

Analysis on Groups of Learning Styles

- Group questions of ILS manually based on their meaning
- Performed study with 207 participants in order to analyse the relevance of each group for each dimension

Style	Semantic group	Style	Semantic group
Active	**trying something out**	Reflective	**think about material**
	social oriented		**impersonal oriented**
Sensing	existing ways	Intuitive	**new ways**
	concrete material		abstract material
	careful with details		not carefule with details
Visual	**pictures**	Verbal	spoken words
			written words
			difficulty with visual style
Sequential	detail oriented	Global	overall picture
	sequential progress		non-sequential progress
	from parts to the whole		relations/connections

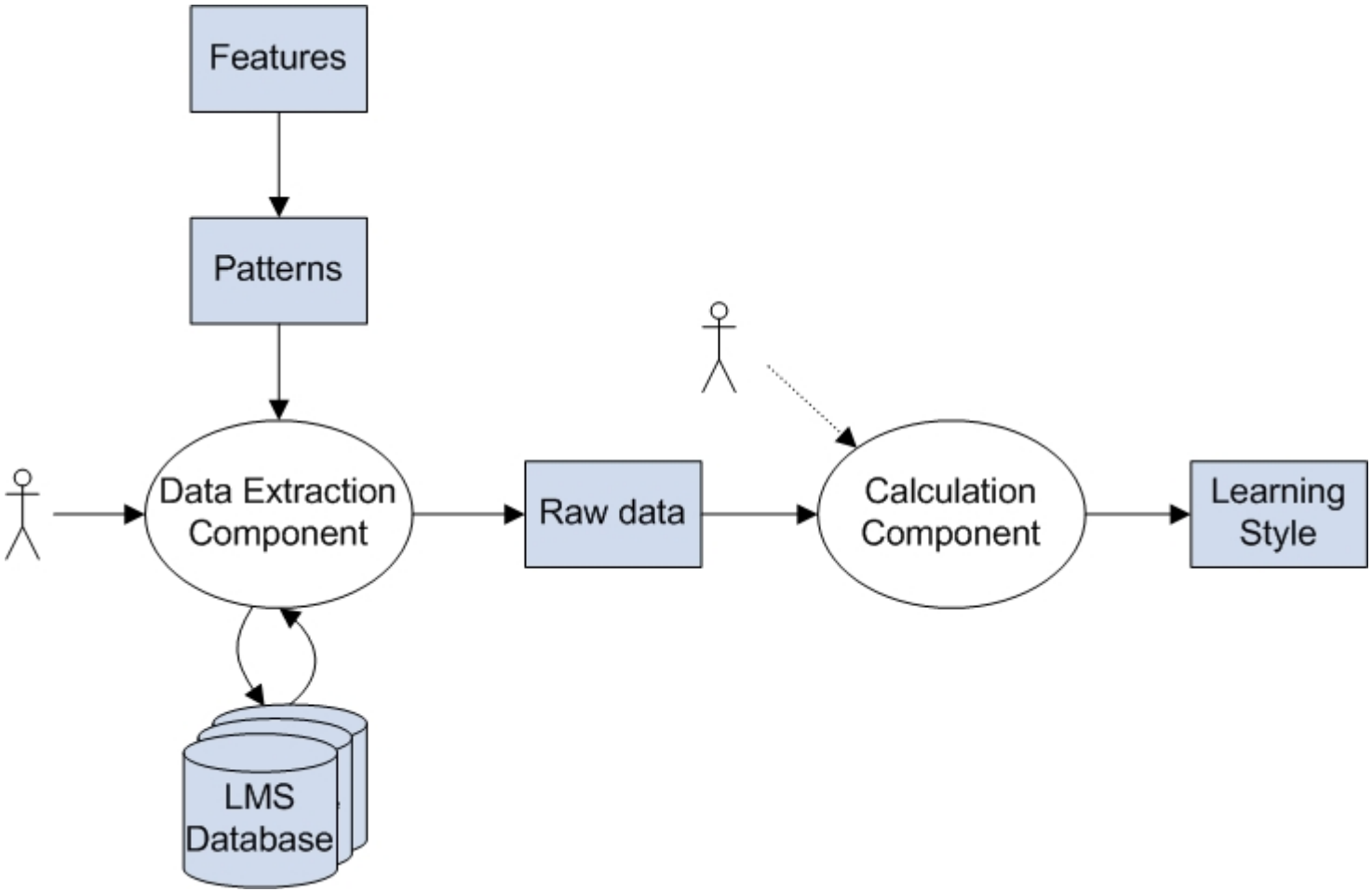
DeLeS – A tool to identify learning style in LMS

- 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



Improving the detection of learning styles by using information from cogntive traits

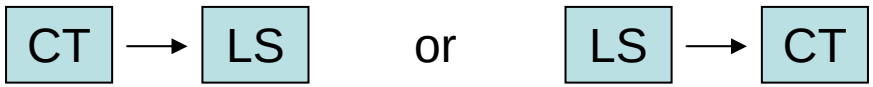
Improving the detection of learning styles

- Investigations about learning styles and cognitive abilities
  - Abilities to perform **any of the functions involved in cognition** whereby cognition can be defined as the mental process of knowing, including aspects such as awareness, perception, reasoning, and judgment.
  - Cognitive abilities are more or less stable over time
  - Important abilities for learning
    - Working memory capacity
    - Inductive reasoning ability
    - Information processing speed
    - Associative learning skills

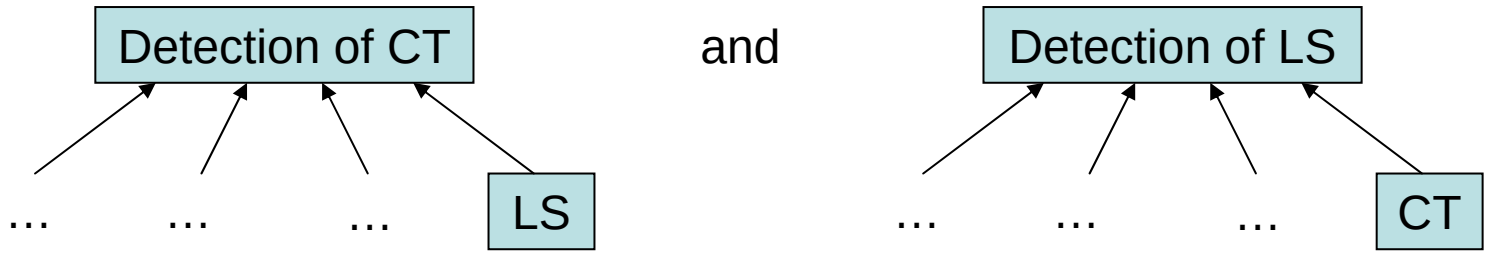
Relationship between Cognitive Traits and Learning Styles

Why shall we relate cognitive traits and learning styles?

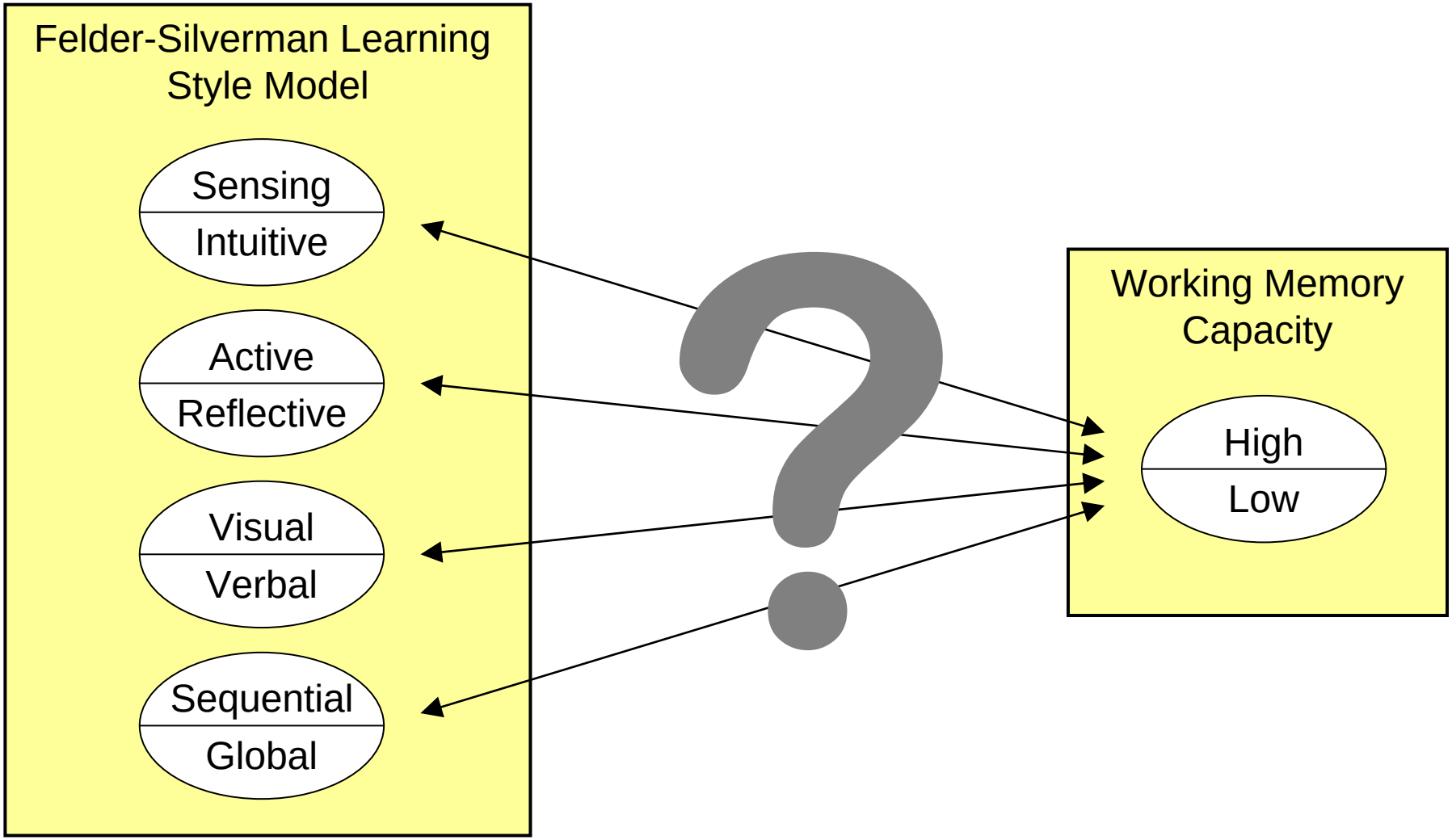
- Case 1: Only one kind of information (CT and LS) is considered
  → Get some hints about the other one



- Case 2: Both kinds of information are considered
  → The information about the one can be included in the identification process of the other and vice versa
  → The student model becomes more reliable



Relationship between FSLSM and WMC

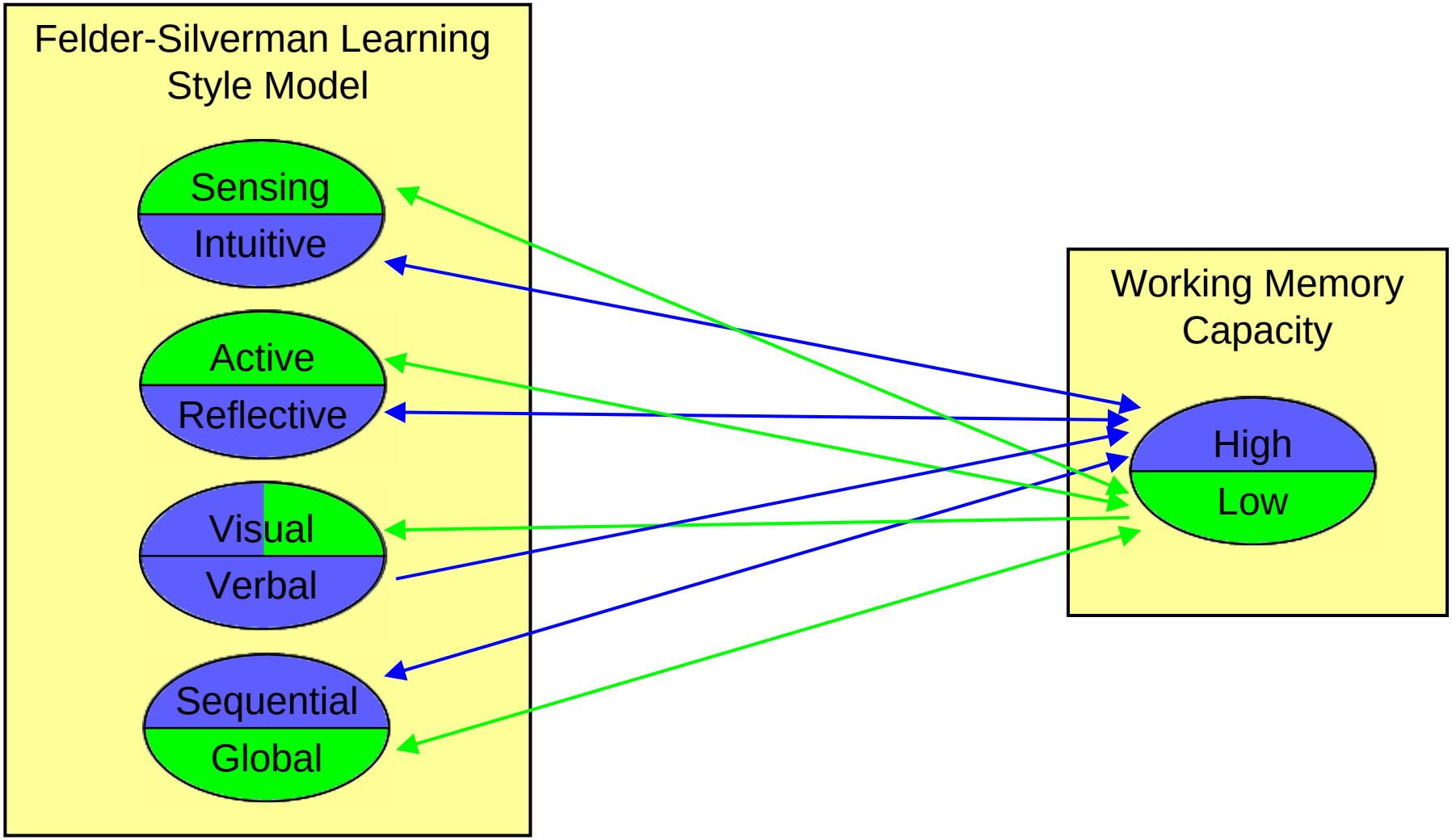


Literature Research

	High WMC	Low WMC
Felder-Silverman Learning Style Dimensions	**Reflective**	**Active**
	Beacham, Szumko, and Alty (2003) Hadwin, Kirby, and Woodhouse (1999) Kolb (1984) Summervill (1999) Witkin et al. (1977)	
	Intuitive	**Sensing**
	Bahar and Hansell (2000) Davis (1991) Ford and Chen (2000) Hudson (1966) Kinshuk and Lin (2005) Scandura (1973) Witkin et al. (1977)	
	Verbal or Visual	**Visual**
	Beacham, Szumko, and Alty (2003) Simmons and Singleton (2000) Wey and Waugh (1993)	
	Sequential	**Global**
	Beacham, Szumko, and Alty (2003) Ford and Chen (2000) Huai (2000) Liu and Reed (1994) Mortimore (2003) Witkin et al. (1977)	

	High WMC	Low WMC
Cognitive Styles	Field-independent	Field-dependent
	Al-Naeme (1991) Bahar and Hansell (2000) El-Banna (1987) Pascual-Leone (1970)	
	Divergent	Convergent
	Bahar and Hansell (2000)	
	Serial	Holistic
	Huai (2000)	

Relationship between FSLSM and WMC

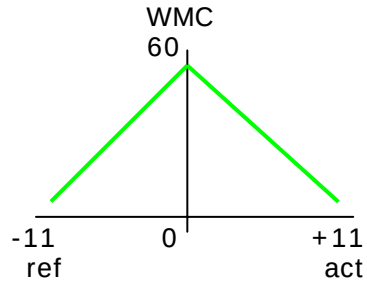


Verifying the relationship

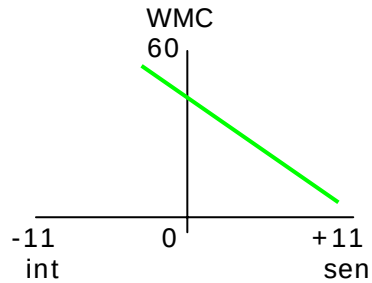
- Participants
  - 225 students from Austria
- Detecting learning style
  - ILS questionnaire
- Detecting working memory capacity
  - WebOSpan Task

Results

- Active/reflective:
  - Low WMC <-> strong active preference
  - Low WMC <-> strong reflective preference
  - High WMC <-> balanced learning preference



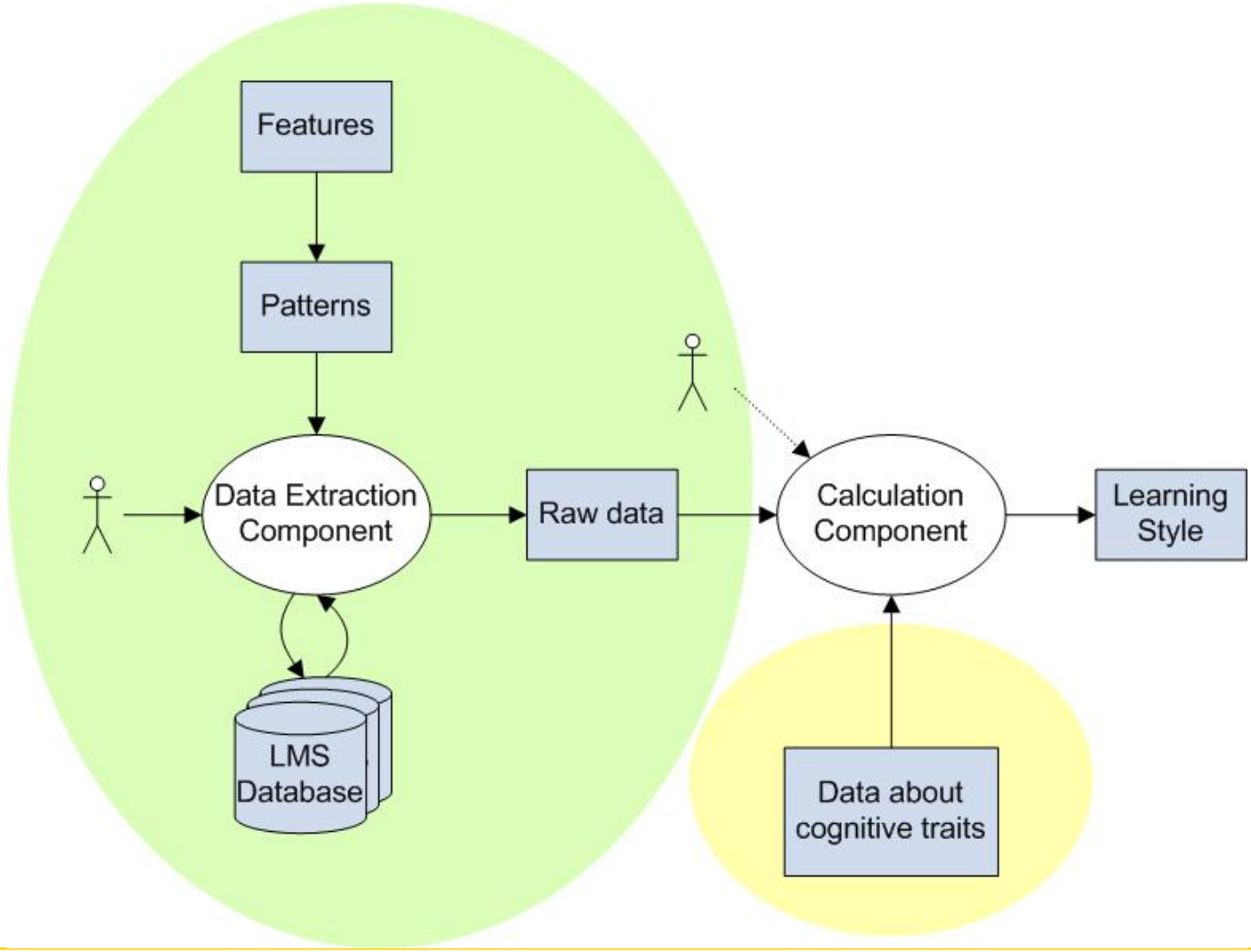
- Sensing/intuitive:
  - Low WMC <-> sensing learning preference
  - High WMC <-> balanced learning preference



- Visual/verbal:
  - Low WMC -> visual learning preference
  - Verbal learning preference -> high WMC
- Sequential/Global:
  - No relationship found

→ Identified relationships can be included in the detection process of learning styles and cognitive traits

Using the information in DeLeS



How to provide adaptivity?

How to provide adaptivity?

- Develop a concept which enables LMS to automatically generate adaptive courses
- Incorporates only common kinds of learning objects
  - Content
  - Outlines
  - Conclusions
  - Examples
  - Self-assessment tests
  - Exercises
- Requirements for teachers
  - Provide learning objects
  - Annotate learning objects (distinguish between the objects)

Structure of a course

Chapter 1:

- **Examples**
- **Self-assessment**
- **Exercises**
- **Outline**
- **Content with / without outlines between subchapters**
- **Conclusion**
- **Examples**
- **Self-assessment**
- **Exercises**
- **Conclusion**

Chapter 2:

- **...**

Adaptation features

- Number of examples
- Number of exercises
- Sequence of examples (before or after content)
- Sequence of exercises (before or after content)
- Sequence of self-assessments (before or after content)
- Sequence of outlines (only once before content or between content)
- Sequence of conclusion (after content or at the end of the chapter)

Adaptations for active/reflective learners

- Active learners
  - Self-assessments before and after content
  - High number of exercises
  - Low number of examples
  - Outline only at the begin of content
  - Conclusions at the end of the chapter
- Reflective learners
  - Outlines between content
  - Conclusion after content
  - Avoid self-assessments before content
  - Examples after content
  - Exercises after content
  - Low number of exercises

Adaptations for sensing/intuitive learners

- Sensing learners
  - High number of examples
  - Examples before content
  - Self-assessment after content
  - High number of exercises
  - Exercises after content
- Intuitive learners
  - Self-assessment before content
  - Exercises before content
  - Low number of exercises
  - Low number of examples
  - Examples after content
  - Outlines only at the begin of content

Adaptations for sequential/global learners

- Sequential learners
  - Outlines only at the begin of content
  - Examples after content
  - Self-assessment after content
  - Exercises after content
- Global learners
  - Outlines between content
  - Conclusion after content
  - High number of examples
  - Avoid self-assessment before content
  - Avoid examples before content
  - Avoid exercises before content

Ambiguous Learning Preferences

- Active/Reflective = +11 → strong active style
- Sensing/Intuitive = -11 → strong intuitive style
- Sequential/Global = -11 → strong global style
- Number of Exercises
  - Active → high number
  - Intuitive → low number
  - Global → no preference

  → Moderate number of exercises

Evaluation of the Concept (1/3)

- Implemented add-on for Moodle (Version 1.6.3)
- University course about object-oriented modelling with about 400 students
- Procedure:
  - Students filled out ILS questionnaire
  - Individual course was automatically generated according to their learning styles
  - Moodle presented the adapted course (as recommendation) to each student
  - Students were nevertheless able to access all learning objects and take a different learning path

Evaluation of the Concept (2/3)

Does adaptivity have an effect on learning?

- Research design
  - Three groups:
    - Courses that fits to the students' learning styles (matched group)
    - Courses that do not fit to the students' learning styles (mismatched group)
    - Standard course which includes all learning objects (standard group)

Incorporating learning styles in Moodle (3/3)

- Results:
  - Average score on assignments & score on final exam
    - no significant difference
  - Time spent on learning activities
    - Standard > Matched
    - Mismatched > Matched
  - Number of logins
    - Standard > Matched
  - Number of visited learning activities
    - no significant difference
  - Number of requests for additional LOs
    - Mismatched > Matched

→ Students from the matched group spent significant less time in the course but achieved in average equal grades

→ Demonstrates positive effect of adaptivity

Conclusions & Future Research Directions

Conclusions

- Proposed a method and tool for identifying learning styles
- Investigated the relationship between learning styles and working memory capacity
- Developed and evaluated a concept for providing adaptive courses in LMS

Future Research Directions

- Generalising the adaptive mechanism
- Combine Automatic Student Modelling with Providing Adaptivity
- Dynamic Automatic Student Modelling
- Supporting students in learning with their weak learning style preferences

Questions

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