Detecting Learners' Profiles based on the Index of Learning Styles Data

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Motivation

- Learners have different needs and characteristics
- Considering the individual needs and characteristics of learners has potential to make learning easier for them
- Learning styles play an important role in education
  - Learners might have difficulties in learning when the learning style does not match with the teaching style
  - Considering learning styles makes learning easier and increases the learning progress

- Adaptive systems aim at providing adaptivity
  - AHA!
  - CS383
  - TANGOW
  - INSPIRE
  - ...
- However, for providing adaptivity, information about learners has to be identified first
- Most adaptive systems considering learning styles are using a questionnaire for identifying learning styles

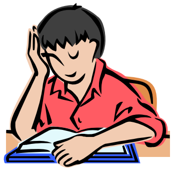
Learning Style Questionnaires

- The correct identification of learning styles is a crucial issue for providing proper adaptivity
- Some studies (e.g., Coffield et al., 2004) showed that some questionnaires lack in reliability and validity
- In a previous study, we conducted a in-depth analysis of the Index of Learning Styles Questionnaire (ILS) based on the Felder-Silverman Learning Style Model
  - Found correlations between dimensions
  - Found out that poles of dimensions might be not fully opposite of each other
  - Found the existence of latent dimensions

Aim of this study

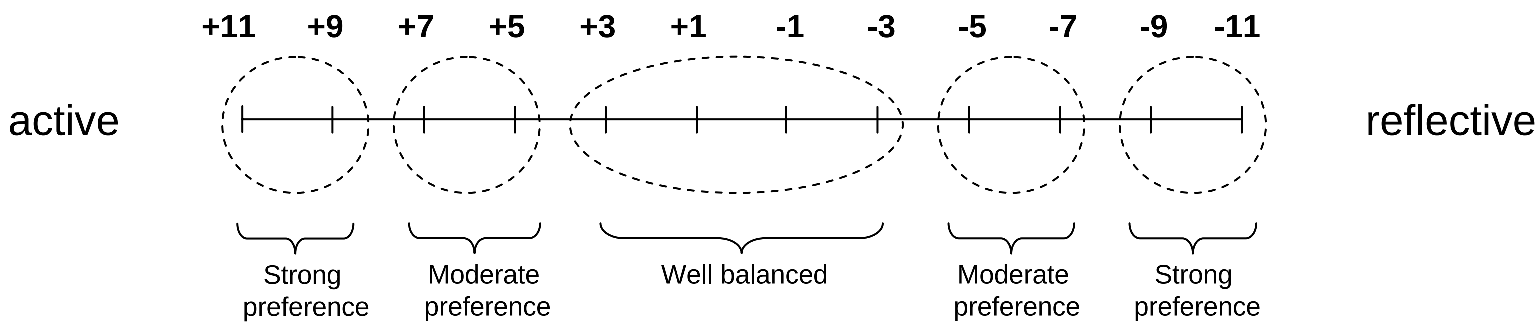
- Introduce a model for detecting learning styles that overcomes the limitations of the ILS questionnaire by incorporating dependencies and latent dimensions
- Model is based on a data-driven approach, using Multiple Correspondence Analysis
- Aims at improving authenticity of learner profiling
  - Detection of the most likely learning style of the learner
  - Detection of main characteristics of the learner profiles

- 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

- Scales of the dimensions:



→ Strong preference but no support → problems

- Differences to other learning style models:
  - describes learning style in more detail
  - represents also balanced preferences
  - describes tendencies
  - Felder-Silverman learning style model is quite often used in technology enhanced learning

Index of Learning Styles (ILS)

- Developed by Felder and Soloman (1997) to identify learning styles
- 44 questions
- 11 questions for each dimension
- Each question allows two possible answers indicating a preference for either the one or the other pole of the learning style dimension; e.g. active (+1) or reflective (-1)
- Result: a value between +11 and -11 for each dimension, with steps +/-2

Study Design

- Asked students to fill out the ILS questionnaire
- Participants: 469 students from Vienna University of Technology (Austria) and Massey University (New Zealand)
- Conducted Investigations
  - General analysis of frequencies
  - Built a model that shows characteristics of learning styles
  - Developed an approach for detecting learner profiles based on discovered characteristics of learning styles
  - Investigated characteristics of the profiles

General Analysis of Frequencies

	A	R	Sen	I	Vis	Ver	Seq	G
F	260	209	286	183	400	69	220	249
%	.55	.45	.61	.39	.85	.15	.47	.53

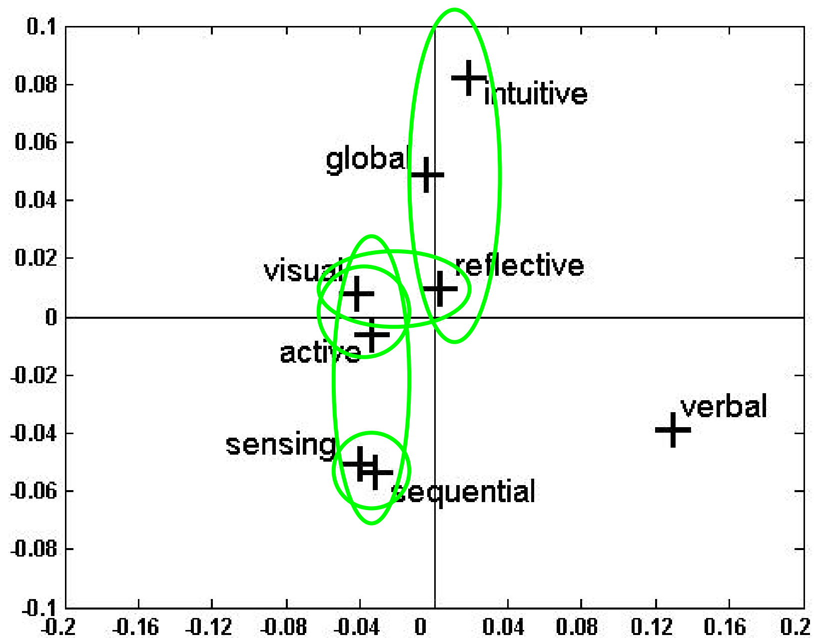
Frequencies of dimensions

ACT/REF		SEN/INT		VIS/VER		SEQ/GLO	
q29	.76	q42	.55	q35	.52	q4	.29
q1	**.77**	q22	.58	q3	**.84**	q28	**.27**
q17	**.38**	q30	.58	q7	.77	q8	.39
q25	.49	q2	.66	q11	.76	q12	**.71**
q5	.51	q26	.43	q19	.83	q16	.62
q9	.57	q6	.68	q23	.83	q40	.47
q21	.39	q10	.37	q27	.73	q24	.40
q33	.52	q18	**.75**	q31	.77	q32	.57
q41	.41	q38	.66	q39	.66	q20	.57
q37	.58	q14	.51	q15	**.41**	q44	.64
q13	.39	q34	**.36**	q43	.80	q36	.51

Frequencies of ILS questions

Building a Model showing Characteristics of Learning Styles

- Transformed data from ILS answers to frequencies and applied Multiple Correspondence Analysis (MCA) algorithm
- MCA plane shows characteristics of learning styles
- Closeness indicates shared characteristics of styles, given by shared answers



Building a Model showing Characteristics of Learning Styles

- Dependencies between styles affect the reliability for detecting learning style preference of learners
- Associations between two styles are based on many shared answers

  → difficulty in distinguish a clear preference for each of the learning styles

Learners' Profiles

- Include learners in the MCA plane
  → the closer the learner to a style the stronger the impact of this learning style on the learner
- For detecting these influences, a suitable proximity measure is necessary
- We tested different measures such as
  - Euclidean distance
  - Infinity norm distance
  - Weighted Euclidean distances
  - Cosines
- Cosines was most stable and was therefore selected
  - Positive sign of cosines → positive association
  - Negative sign of cosines → negative association
  - Absolute values indicates strength of associations

Learners' Profiles

- Calculated cosines between the points representing styles and the learners

St	A	R	Sen	I	Vis	Ver	Seq	G
c>0	346	204	299	206	365	104	286	231
I>5	212	108	261	163	364	69	180	179
%	**61.2**	**52.9**	**87.2**	**79.1**	**99.7**	**66.3**	**62.9**	**77.4**
c>.6	266	128	225	134	269	67	212	157
I>5	171	71	210	121	269	59	155	131
%	**64.3**	**55.4**	**93.3**	**90.3**	**100**	**88**	**73.1**	**83.4**
c>.8	184	71	157	82	166	40	129	104
I>5	123	43	151	77	166	36	103	88
%	**66.8**	**60.5**	**96.1**	**93.9**	**100**	**90**	**79.8**	**84.6**

Learners' Profiles

- Results show that our model can be considered as reliable for all styles except the active and reflective style

- Thresholds for cosines are a critical parameter and need to be selected carefully

Characteristics of Profiles

- Most frequent ILS answers for each learning style based on the answers of the 25 learners that are closest to each learning style according to the model

	Act	Ref	Sen	Int	Vis	Ver	Seq	Glo
1	7a	3a	6a	3a	11a	15b	19a	23a
2	43a	34b	36a	34b	31a	31b	20a	7a
3	38a	10b	44a	10b	3a	41b	12a	3a
4	29a	26b	20a	6b	7a	4b	38a	8b
5	31a	28b	12a	26b	18a	35b	6a	28b
6	19a	23a	43a	28b	19a	14b	15b	4b
7	11a	4b	19a	4b	6a	26b	18a	43a
8	23a	31a	31a	23a	1a	33b	30a	19a
9	3a	35b	38a	35b	28b	20a	36a	10b
10	6a	6b	18a	8b	4b	34b	44a	6b
11	1a	13b	2a	43b	43a	10b	16a	26b

Characteristics of Profiles

- Profiles show dependencies within learning styles
- Due to reciprocal influences between styles, profiles partially overlap each other, which makes the identification of styles more difficult

Conclusions

- We introduced an approach for profiling learners based on data from ILS questionnaire
- Since data show dependencies between styles, the approach for profiling learners aims at incorporating these dependencies
- The proposed approach showed sufficient reliable results for all styles except active and reflective learning style
- Looking at the characteristics of the profiles, it can be seen that the discovered dependencies are incorporated
- Incorporating these dependencies leads to a more accurate model of students' learning styles