

## Analysis of verbal data

Understanding the processes of collaborative learning



## **Overview**

- Theoretical background of CSCL process analyses
- Steps in analysing CSCL processes based on verbal data
  - Analysing individuals in small groups
  - Transcription
  - Unit of analysis / Segmentation of verbal data
  - Categorisation
  - Determining reliability
  - Automatic analysis of verbal data
- Examples
  - Analysis of cognitive processes based on think-aloud data
  - High level analyses on the base of process analyses

## **General research paradigm**

#### Triangle of hypotheses:

- Specific (learning) activities are positively related with a desired outcome. (b)
- An instructional support facilitates the specific (learning) activities. (a)
- The intervention fosters the desired outcome mediated by the specific (learning) activities. (c)



#### Framework on cooperative learning (O'Donnell & Dansereau, 1992)





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#### **Text-based communication**

Self-transcription of dialogues



# Joint, argumentative knowledge construction: Talking, Thinking, Learning



Example coding scheme: Weinberger & Fischer, 2006



#### **Granularity of segmentation**

Fine granularity Theoretical relation to learning?

- □ □ signs How many letters p do the learners use?
  - How many technical terms are being used?
  - speech acts
    How do learners coordinate discourse?
  - sentences How do learners structure their utterances?
  - propositionsWhich concept do learners discuss?What claims are being made?
- <sup>1</sup>/<sup>2</sup> arguments How do learners link concepts to construct arguments?
- $\vee$   $\square$  argumentations What standpoints are being defended?

Coarse granularity The granularity of the segmentation represents (different) types of knowledge in discourse (Chi, 1997)

#### Example of Different Degrees of Fine-grainedness for Segmentation

Original messages

Jim:

The teacher attributes Michael's failure in an internal variable manner. She argues that Michael is just plain lazy.

Carolyn:

I don't think so! The teacher is just making Michael feel bad.

Segmented messages

Jim:

The teacher attributes Michael's failure in an internal [manner]

[She argues that Michael is just plain lazy.]

[The teacher attributes Michael's failure in an] variable manner.

She argues that Michael is just plain lazy.

Carolyn:

I don't think so! The teacher is just making Michael feel bad.

## Categorisation

- Qualitative steps
  - (Development of) categories is related to state of the art of research
  - Generating hypotheses: Paraphrasing (Mayring), Coarse analyses (Forming clusters)



- Development of a coding scheme
  - Exhaustive: Every segment is being coded
  - Exclusive: Only one category applies per segment per dimension

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Documentation of rules, e.g., in the form of a decision tree



# Example for coding rules in form of a decision tree (Wecker, 2006)

- 1. Is there any talk in the segment at all (incl. mumbling)? yes: 2, no: 4
- 2. Is there any talk longer than 1 sec.? yes: 6, no: 3
- 3. Do the learners ask about the (i) reading progress (e.g., "Are you done?"), (ii) protest against scrolling down (e.g., "Stop!"), (iii) comment about any text (e.g., "Haha: ,chacked'!"; "What means ,focused'?") or (iv) describe the current activity (e.g., "We are reading.")?
  - 1. yes: Coding "Information intake" for the current segment and all prior segments up to that segment that has been coded as "no activity (silence)"
  - 2. no: 4

Example for a framework for analysing verbal data in CSCL environments (Weinberger & Fischer, 2006)

- Multiple dimensions:
  - Participation dimension
  - Epistemic dimension
  - Formal-argumentative dimension
  - Dimension of social modi of co-construction (incl. transactivity)



#### **Multiple Dimensions of Argumentative Knowledge Construction**

Dimensions	Question
Participation (Words and messages; Cohen, 1994) <ul> <li>Quantity</li> <li>Homogenity</li> </ul>	Do learners participate (at all) in Online-Discourse?
Epistemic Activities (κ = .90; Fischer, Bruhn, Gräsel, & Mandl, 2002) • construction of problem space • construction of conceptual space • construction of relations between conceptual and problem space	Do learners argue on task? Do learners construct arguments based on the relevant concepts?
Argumentation (κ = .78; Leitão, 2000) • construction of single arguments • construction of argumentation sequences	Do learners construct formally complete arguments and argument sequences?
Social Modes of co-construction (κ = .81; Teasley, 1997) • Externalization • Elicitation • Quick consensus-building • Integration-oriented consensus-building • Conflict-oriented consensus-building	Do learners operate on the reasoning of their learning partners? How do learners build consensus?



#### Macro-coding



## **Testing and documenting reliability**

Objectivity of coding -> interrater reliability

Two or more coders code the same segments

Similarity between codes is compared
 (-> Cohen's Kappa, Krippendorff's alpha, ICC)

Objectivity requires training



## **Standard training process**

- Explanation phase
  - Definition of dimensions and codes
- Modelling phase
  - Joint coding of example data
- Practice
  - Individual coding of example data
    - \$ if objectivity sufficient -> training successful
    - \$ if objectivity not sufficient -> modelling phase + feedback

# **Training material**

- Rule of thumb:
  - 10% of the raw data per testing/practice
- Randomly selected data
  - All experimental conditions have to be represented
  - All codes need to be coded at least several times to test objectivity



## **Feedback: Crosstables**

	S						
	1	2	3	4	88	99	Gesamt
D 1	13	7	0	0	0	1	21
2	0	6	0	1	4	1	12
3	0	1	1	2	1	0	5
4	0	1	0	4	0	0	5
88	0	0	0	0	5	0	5
99	3	3	0	1	0	5	12
Gesamt	16	18	1	8	10	7	60

		Wert	Asymptotisc her Standardfehl er <sup>a</sup>	Näherungsw eises T <sup>0</sup>	Näherungsw eise Signifikanz
Maß der Übereinstimmung	Карра	.456	.078	7.440	.000
Anzahl der gültigen Fälle		60			

## Typical consequences of low objectivity

Refinement of coding scheme, i. e. clarification of rules, additional examples

Adaption of coding scheme

combination of codes

additional codes

Beware of skewed data:

High objectivity due to code "other"



## Micro-Coding

Lombard et al Criteria	1st wave of studies 00/01	2nd wave of studies 02/03	3rd wave of studies 03/04			
size of reliability sample	ca. 500 Seg.	199 Seg.	176 Seg.			
relationship of the reliability sample to the full sample	105 participants 2821 segments	289 participants 6296 segments	243 participants 9825 segments			
N of coders	2 students	6 students	5 students			
amount of coding	50% each	ca. 17% each	ca. 17% each			
Reliabilityindices	Seg.: 87% Epi.: κ = .90 Arg.: κ = .78 Soz.: κ = .81	Seg.: 83% Epi.: κ = .72 Arg.: κ = .61 Soz.: κ = .70	Seg.: 85% Epi.: κ = .89 Arg.: κ = .91 Ø Soz.: κ = .87			
Reliability of each variable						
amount of training	ca. 500 h in each wave trained with 1000 to 1500 discourse segments					
references	Weinberger, Fischer, & Mandl, 2001; Weinberger & Fischer, 2006					

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## Automatisation of coding

Machine learning algorithms learn from already coded data

 Features of written text need to be extracted (e. g. word count, unigrams, bigrams, punctuation)

LightSIDE or TagHelper extract features and prepare them for the training of machine learning algorithms

#### Get the software "LightSIDE" (it's free):

http://ankara.lti.cs.cmu.edu/side/download.html



- Prepare your data
  - First column: text
  - Second column: code
- Save as csv-file
- Load file csv-file into LightSIDE



# Extract features

Extra	act Features Restructure Data Build Model	s Explore Results Compare Models Predict Labels
CSV Files:	Feature Extractor Plugins: Basic Features Character N-Grams Column Features Parse Features Regular Expressions Stretchy Patterns	Configure Basic Features  Unigrams Bigrams Trigrams POS Bigrams Word/POS Pairs Line Length Contains Non-Stopwords  Binary N-grams? Include Punctuation? Remove Stopwords?
Feature Table:	Rare Threshold: 5 Evaluations to Display: Target:  Basic Table Statistics Recall Target Hits Precision Total Hits Correlation F-Score Kappa	Features in Table:
Report a Bug		0,0 GB used, 4,0 GB ma

Train model

Feature Tables:	×	Learning Plugin: Naive Bayes Logistic Regression Linear Regression			Configure Support Vector Machines	
		Support Vector Machin     Decision Trees     Weka (All)     Cross-Validation     Supplied Test Set     No Evaluation	Fold Assignment:	•	Settings for Numeric Class Values: Sequential Minimal Optimization (Regression)	
Train Name: svm		Use Feature Selection?	*		14,519 sec per fold, Training fold 5/10	<b>%</b> (
	× .			r l	er Conrusion Matrix:	
Report a Bug					0.2	GB used, 4

Improving models

exclude rare features

exclude missleading features

add semantic rules



## **Automatisation: final step**

Apply model to new material

Must not be different from training material -> change of context, topic, sample may cause problems

Automatically coded data require careful supervision



### Automatisation: Does it work?

	Without extractin	ng attributes	With extracting attributes		
Segmentation layer II	Cohen's Kappa	Percent Agreement	Cohen's Kappa	Percent Agreement	
Kappa SIDE-Training Material	0.84	96.7 %	0.98	99.6 %	
Kappa SIDE-Testing Material	0.86	97.0 %	0.97	99.3 %	
Major choice	0.80	96.7 %	0.95	99.1 %	
Math	0.86	96.6 %	0.96	98.9 %	
Class reunion	0.87	97.0 %	0.97	99.3 %	
Between-culture variance	0.90	97.7 %	0.99	99.7 %	
Text-analysis	0.83	96.9 %	0.98	99.6 %	
Coding layer III					
Kappa SIDE-Training Material	0.70	75.6 %	0.77	81.3 %	
Kappa SIDE-Testing Material	0.61	67.8 %	0.81	84.5 %	
Major choice	0.63	71.2 %	0.77	82.9 %	
Math	0.67	72.3 %	0.78	82.6 %	
Class reunion	0.47	58.5 %	0.76	81.0 %	
Between-culture variance	0.53	63.1 %	0.85	87.5 %	
Text-analysis	0.68	75.0 %	0.87	89.2 % edu	

**Table 2** Comparison without and with the layer of extracting attributes to automate the content analysis

## **Checklist for argumentation analyses**

- Theoretical framework
- Research questions and methods that can address those questions in a valid manner
- Explicit and theory-based set of rules for segmentation and categorization
- Testing and documenting reliability (see Lombard et al., 2002)
- Replication



## Testing and documenting reliability: Part 1

• the size of and the method used to create the reliability sample, along with a justification of that method;

- the relationship of the reliability sample to the full sample;
- the number of reliability coders and whether or not they include the researchers;
- the amount of coding conducted by each reliability and non-reliability coder;



## Testing and documenting reliability: Part 2

- the index or indices selected to calculate reliability and a justification of these selections;
- the inter-coder reliability level for each variable, for each index selected;
- the approximate amount of training (in hours) required to reach the reliability levels reported;
- where and how the reader can obtain detailed information regarding the coding instrument,
- procedures and instructions (for example, from the authors).



#### Conclusions

 CSCL is an ideal context to investigate collaborative and individual knowledge construction processes, which can be reliably assessed with a multi-granular and multi-dimensional framework (Weinberger & Fischer, 2006).

but

- which requires major training efforts
- which captures most, but maybe not all cognitive processes of knowledge construction

## **Example 1**

 Analyses of cognitive processes of learning through think-aloud protocols in CSCL



![](_page_33_Picture_3.jpeg)

### Analysis of cognitive processes

- Think-aloud protocols
- 10-Sec segments
- coding ( $\kappa$  = .78):
  - Elaboration depth
  - Elaboration focus
    - Elaboration of content
    - Elaboration of peer contributions

![](_page_34_Picture_8.jpeg)

#### **Good learner, no script**

![](_page_35_Figure_1.jpeg)

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#### Learner with script, role of analytic

![](_page_36_Figure_1.jpeg)

#### Learner with script, role of critic

![](_page_37_Figure_1.jpeg)

## Example 2

- CSCL-assumption learners are influencing each other
- Requirement for analysis is indenpendence of observations
- Analyzing individuals, groups, or both with multi-level modeling

![](_page_38_Figure_4.jpeg)

![](_page_39_Figure_0.jpeg)

![](_page_40_Figure_0.jpeg)

## Literature

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![](_page_42_Picture_0.jpeg)