



Automated Analysis of Physics Lesson Plans

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Introduction: lesson plans as learning outcomes of pre-service physics teachers

Session Title:

„Challenges in measuring learning outcomes in STEM fields“

Computer-based
classification of
lesson phases



Lesson
planning



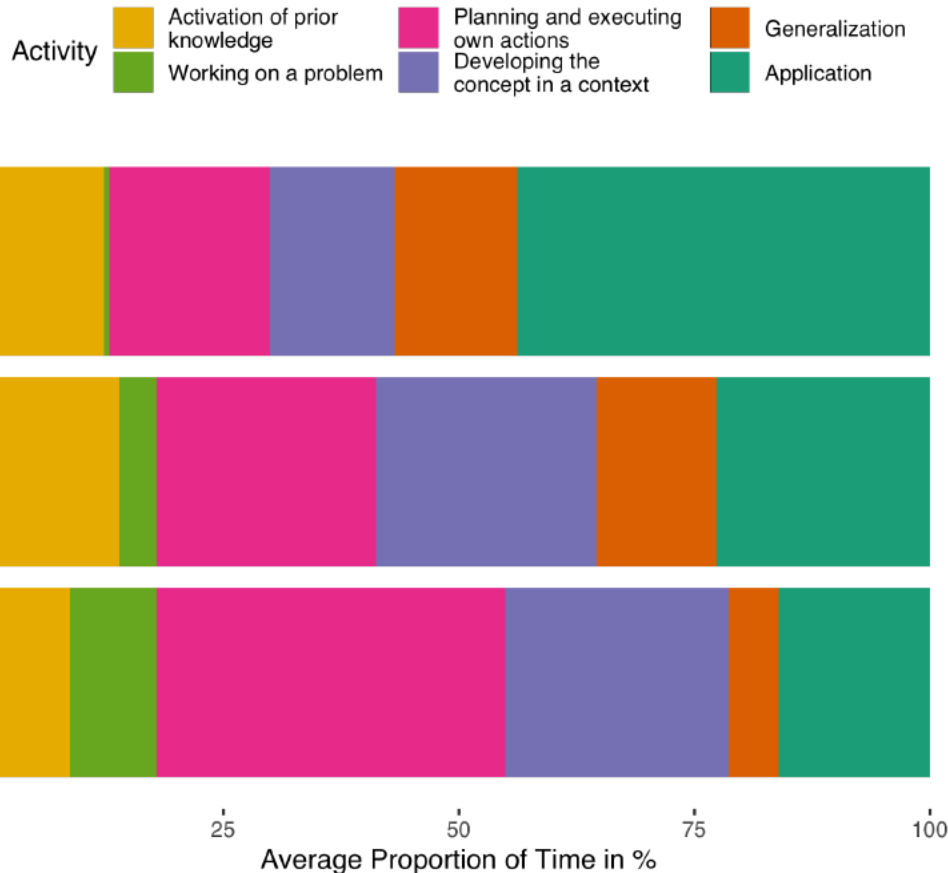
Pre-service
physics teachers



Can machines hypothesize about learning processes?

- » Why automation of classification of phases is beneficial from a practical perspective
 - Problem: Lesson planning in physics
 - Basis models: A theory to solve the problem
 - Machine Learning models as a basis to support automated feedback
- » Study: A first step towards feedback
- » A perspective for future research

Teachers in Germany tend to use experience to build theory

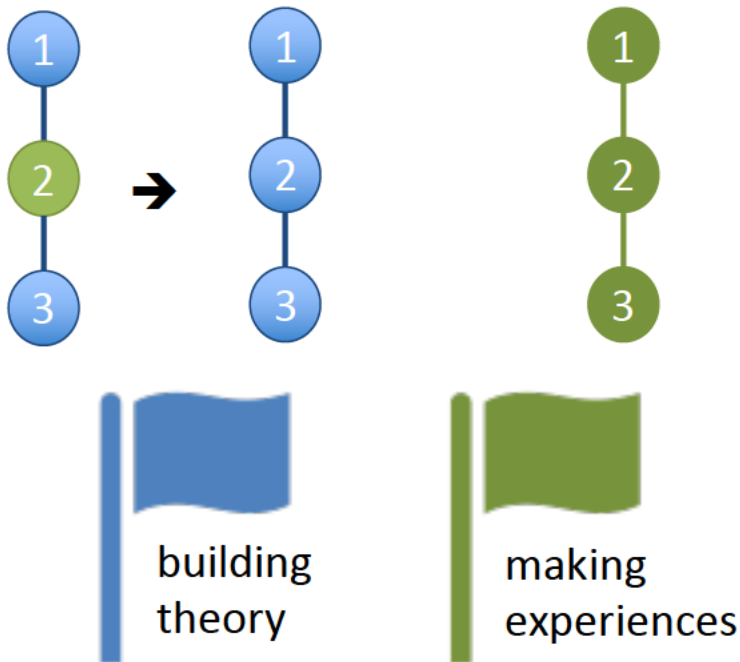


- » German teachers provide a mix of both learning by experience and building theory
- » German students show less learning gains than Finnish students
- » Students can't directly infer a new concept from their experience (Muckenfuß, 1996)

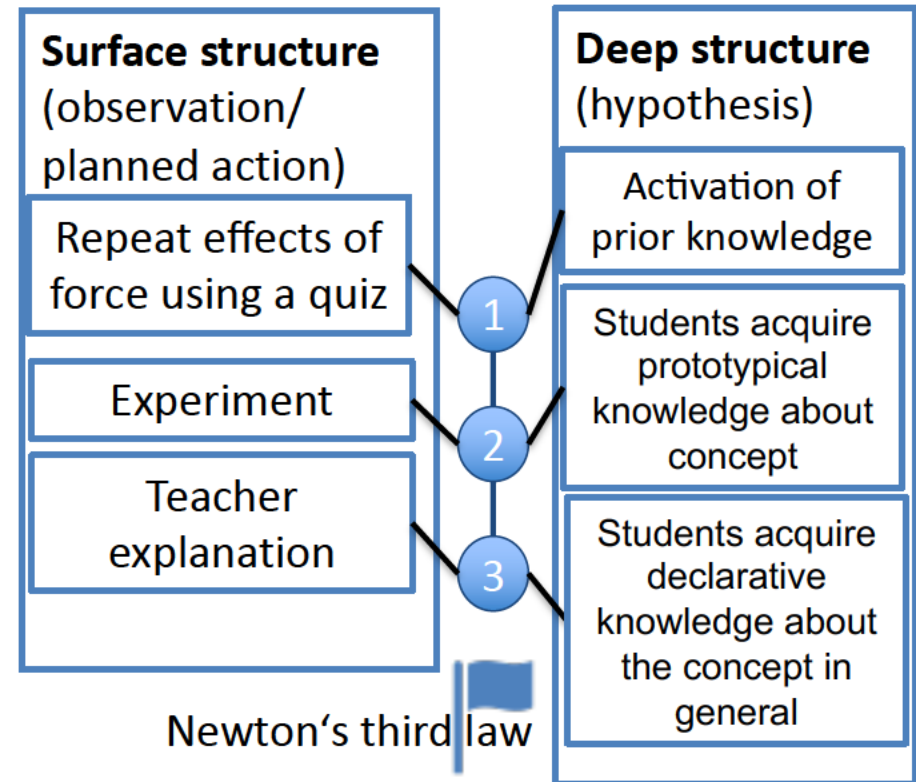
(Geller, 2015, p. 111; graph replotted and translated; values extracted from graph; for exact values see original)

Planning lessons means hypothesizing about learning

Basis Models of Teaching and Learning (e.g. Oser & Baeriswyl, 2001): Different chains of actions (phases) for different teaching goals



+ 12 other basis models



Planning lessons means **hypothesizing about learning**

Providing more feedback would be useful but challenging

- » Problem seems insensitive to instruction followed by experience for pre-service physics teachers (Mutschler et al., 2021)
- » More frequent feedback would be beneficial (Hattie & Timperley, 2007, Lee et al., 2021) & more research is needed in this field (Mutschler et al., 2021; Geller, 2015)
- » Coding related to **deep structures** is resource intensive
 - **Experts need extensive experience**
 - **Low interrater-agreement**
 - Kappa: 0.39-0.50 (Geller, 2015, p. 85)
 - Kappa: 0.4 median (Reyer, 2004, p. 200)
 - Consensus-validation (Gerber, 2007)
 - Others failed finding agreement and switched research question (Borowski, personal communication)

A machine learning model would enable us to store the expertise

- » **For science education/assessment (Zhai, Shi, & Nehm, 2021; Zhai, Yin et al., 2020) many examples for students:**
 - Extracting student ideas of generality of explanations (Rosenberg & Christ, 2020) unsupervised
 - Computer Assisted Scoring, Biology, Subject Matter Knowledge: ($Kappa > 0.8$) (Nehm & Härtig, 2012; Nehm, Ha, & Mayfield, 2012)
 - Learning progressions on the concept of flux $Kappa > 0.6$ (Jescovitch et al., 2021)
- » **Less for teacher performance**
 - Teacher Reflection (e.g. Wulff et al., 2020)
 - Araya et al. (2011): Teacher activities and mathematical content (agreement mostly high but scatters by characteristic) from lesson transcripts.
- » **Can we also classify deep structural characteristics?**
 - High complexity and high diversity (Zhai, Haudek, et al. 2020; Haudek & Zhai, 2021) and many ways how the same deep structure can be expressed (Zhai, Shi, & Nehm, 2021) makes classification challenging
 - Unclear if even worth trying?
- » **The study: Just a step in that direction**
 - Can we classify the steps of concept building automatically via machine learning in very restricted lesson planning scenario?

Task: Machine



Activation



Prototype



Concept



Application/
Transfer



Outside of
Basis Model

Order	Description of Classroom Action	HKS
1	Teacher greets the students	Outside
2	Students observe a Text experiment	Activation
3	...	

Classifier (logistic regression, decision tree, ...)



Data (Schröder et al., 2020):

- » Paper and pencil-test
- » 126 Lesson plans (1231 segments) of pre-service physics teachers

Task: Plan a lesson on Newton’s third law of motion

Goal: Students should be able to explain the law after the lesson

Human Analysis

- » Paraphrasing
- » Segmentation
- » Digitalization
- » Assignment of chain of phases →

order	Description	Phase (label)
1	Start by explaining the general rule of Newton’s third law	Concept
2

Machine learning

- Pre-Processing
- Machine learning: model selection & evaluation (cross-validation, hyperparameter tuning, 30% test data)

A first step: Shallow Learning to assign chains of lesson phases

Multinomial Logistic Regression

	precision	recall	f1-score	N
Activation	0.74	0.68	0.71	72
Prototype	0.68	0.82	0.75	142
Concept	0.96	0.61	0.75	44
Application / transfer	0.70	0.75	0.72	64
Outside of the basis model	0.67	0.13	0.22	15
accuracy				0.72
macro avg	0.75	0.60	0.63	337
weighted avg	0.73	0.72	0.71	337

- Cohen's Kappa = 0.60 (acceptable, Caspar & Wirtz, 2002 p. 49; Geller, 2015, p. 85)
- This would allow group-feedback for this planning situation
 - Are "all" steps of concept building in the lesson plan?
 - Is there enough application?

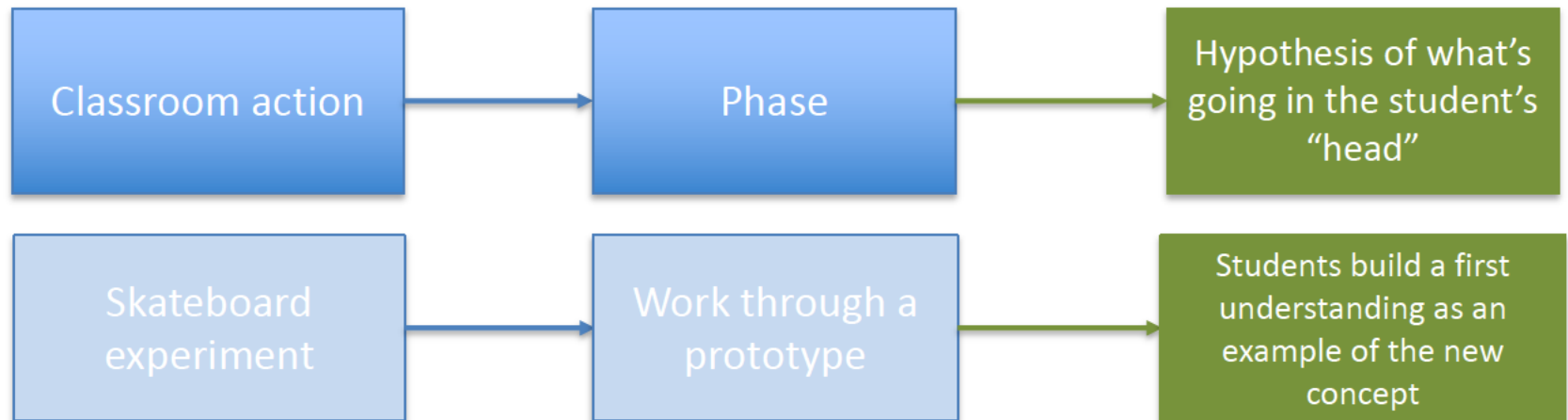
The algorithm is interpretable

Higher regression coefficient ↑

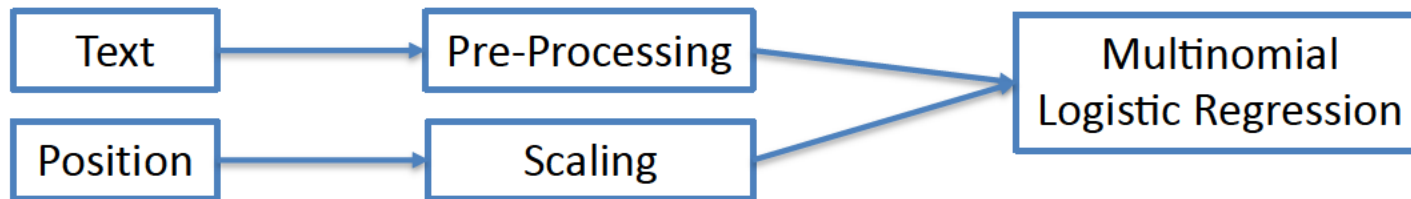
Concept		
Feature	English (Example word in German)	
merksatz	mnemonic sentence (Merksatz)	Generic term
tafelbild	blackboard image (Tafelbild)	
na	short for Newton's Law (Newtonsches Axiom)	Content specific term
order	-	Position in the lesson
tafel	blackboard (Tafel)	

In principle we build a machine which makes hypothesis on learning process

- » Does this machine make hypotheses about (intended) learning processes?



But how should it think? Limitations and possible extensions



- Account for context of the classroom action to be classified (Gerber, 2007)

Demonstration of an experiment with skateboards and explaining, why the active person will also be accelerated

Is this a prototype or an application?

- Other basis models

What do we learn for future research?

Common Question: „Will Artificial Intelligence Replace Teachers in the Future?“ (AnalyticsInside, 2021)

What are the possibilities?

- Science Education and STEM Education have to provide answers related to categories most important to us
 - » Science Assessment (Zhai, Shi, & Nehm, 2021; Zhai, Yin et al., 2020)
 - » For teaching performance: Deep structure characteristics (Fischer et al., 2003) → less evidence
- This study provides first evidence that this might be possible
- Challenges
 - Cohen’s kappa of 0.6 in a very restricted scenario shows that it will be challenging to provide such a classifier in general
 - Also content specific terms (Newton’s third law) are used for prediction
 - Logistic regression seems to be a good classifier: accuracy vs. substantial validity of the reasoning process

What do we learn for future research?

“[...] planning of instructional action according to hypothesized learning processes is usually primarily intuitive.”
(Gerber, 2008, p. 35 translated)

A machine would add to the teacher



We should try it



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Thank you!

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