



Instructional approaches and professional learning: Inputs from Germany (ProDaBi Project)

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Paderborn University, Germany

A Workshop on International Practices in K-12 Mathematics Education:
The Role of Computational Thinking, Data Science, and AI
Washington, D.C., February 23-24, 2026

NATIONAL ACADEMIES *Sciences
Engineering
Medicine*

General curricular situation in Germany

National standards, 16 state curricula



Mathematics education

- Probability and statistics (called stochastics) in all curricula
 - Part for data analysis limited and varying
- Computational thinking is not a central concept
- Many local and regional initiatives for using AI for teaching and learning
- Less initiatives for learning to understand AI

Computer science education

- Computer science education is becoming obligatory in a growing number of curricula
- Understanding AI is becoming part of most curricula, not data science

Opportunities experimental for innovation

- Elective compulsory courses in grade 9/10 and 12/13

Key Initiatives in Germany



Active community of data science and stochastics educators

- Growing interest in data science and AI literacy
- New working group with representatives from 14 associations of didactics of school subjects

Innovative projects in data science and AI education K-13

- ProDaBi, CAMMP–Project (Sarah Schönbrodt), KI macht Schule! (Steffen Schneider)

Project QuaMath (all topics and levels in mathematics education K-13)

(<https://www.leibniz-ipn.de/en/research/projects/quamath>)

Focusing on better teaching, not new content

QuaMath Modules in probability and statistics include

- Data analysis with CODAP
- Bayesian inference in real-world contexts (e.g., health diagnostics)
- Understanding sampling variability and confidence interval

QuaMath in Numbers (January 2026)



15



Federal States

With 18 State Directors, 21 State Coordinators in Primary Education, and 24 in Secondary Education.

2,312



Schools – 1st & 2nd Cohort

The target was 2,000 schools by the 2025/26 school year.

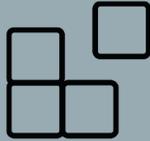
8,253



Teachers

Participating in professional development training as school teams within school networks.

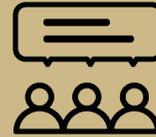
27



Modules

Basic, Advanced, and Content Modules for professional development with 23 professors in the network.

515



Multipliers

The target was 400 multipliers.

524



Participants at the 4th Conference

Multipliers, State Coordinators, State Directors, DZLM-Network, IPN staff at the QuaMath Federal Conference.

12



DZLM University Locations & IPN

Are responsible for the content in the QuaMath Program.

QuaMath

Developing quality in mathematics classrooms and teacher professional development

Prediger, S., & Selter, C. (2024). Establish shared visions and support productive adaptations on all levels: Aims, strategies, and architecture of a nationwide implementation program. *Implementation and Replication Studies in Mathematics Education*, 4(1), 15–49. <https://doi.org/10.1163/26670127-bja10020>

Prediger, S., Götze, D., & Kortenkamp, U. (2025, online first). Robust and high-quality materials for supporting facilitators: Design research for scaled-up professional development programs. *Mathematical Thinking and Learning*. <https://doi.org/10.1080/10986065.2025.2579008>



Project Data Science and Big Data at School (www.prodabi.de/en)



Initiated und sponsored by
Deutsche Telekom Stiftung



Cooperation at Paderborn University

Rolf Biehler	Didactics of Mathematics
Carsten Schulte	Didactics of Computer Science
Karin Binder	Didactics of Mathematics

Team:

Yannik Fleischer	Didactics of Mathematics
Sven Hüsing	Didactics of Computer Science
Luca Jotzo	Didactics of Mathematics
Patrick Schüren	Didactics of Computer Science

Former team members

Lukas Höper	Didactics of Computer Science
Susanne Podworny	Didactics of Mathematics

ProDaBi I : 2018 - 2020
ProDaBi II: 2020 – 2023
ProDaBi III: 2023 – 2026
ProDaBi III: 2026 – 2029 (?)





- Engage students in authentic data practices
- Connect data, modeling, and algorithmic systems conceptually
- Support generalizing transfer to other contexts
- Make ethical and political dimensions an explicit part of instruction



Teaching units, mainly for **elective compulsory courses**

Some are available in English:

<https://www.prodabi.de/en/prodabi-ressources-in-english/>

Challenges for mathematics and computer science teachers – ProDaBi view



- Triple content expansion (MathEd + CSE + domain knowledge)
- Deeper content knowledge needed for transfer and generalization
- Tensions with traditional curricula and teachers' mindsets
- New pedagogical content knowledge, particularly TPACK
- Moderation of ethical/political discourse, teacher positioning



Professional development courses
Collaboration with regional schools and administrations

Core Learning Domains (building-blocks) in ProDaBi



Data Exploration

- Working with real datasets in CODAP

Modeling & Machine Learning

- (Re-)constructing and understanding predictive systems

Socio-Scientific Reasoning

- Connecting data analysis to societal and scientific issues

Critical Data Awareness

- Reflecting on personal and societal algorithmic data use

Epistemic Programming

- Gaining knowledge through programming / coding

Data Exploration

Working with real datasets in CODAP



Instructional Decisions: Tool choice

- Need for tool with low entrance:
 - CODAP, maybe iNZight

Instructional Decisions: Choice of data

- Tidy data to begin with
- Multivariate
- Starting with „near“ data, later „far“ data
- Creating students' interest
- Potential for exploring many questions

Podworny, S., Fleischer, Y., Stroop, D., & Biehler, R. (2022). *An example of rich, real and multivariate survey data for use in school* Twelfth Congress of the European Society for Research in Mathematics Education (CERME12), Feb 2022, Bozen-Bolzano, Italy, <https://hal.archives-ouvertes.fr/hal-03751842>

Frischemeier, D., Biehler, R., Podworny, S., & Budde, L. (2021). A first introduction to data science education in secondary schools: Teaching and learning about data exploration with CODAP using survey data. *Teaching Statistics*, 43(S1), S182–S189. <https://doi.org/https://doi.org/10.1111/test.12283>

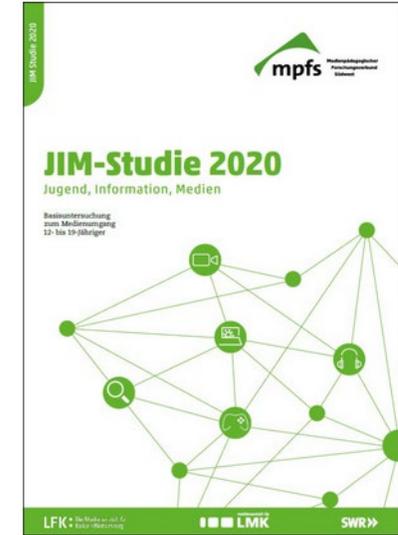
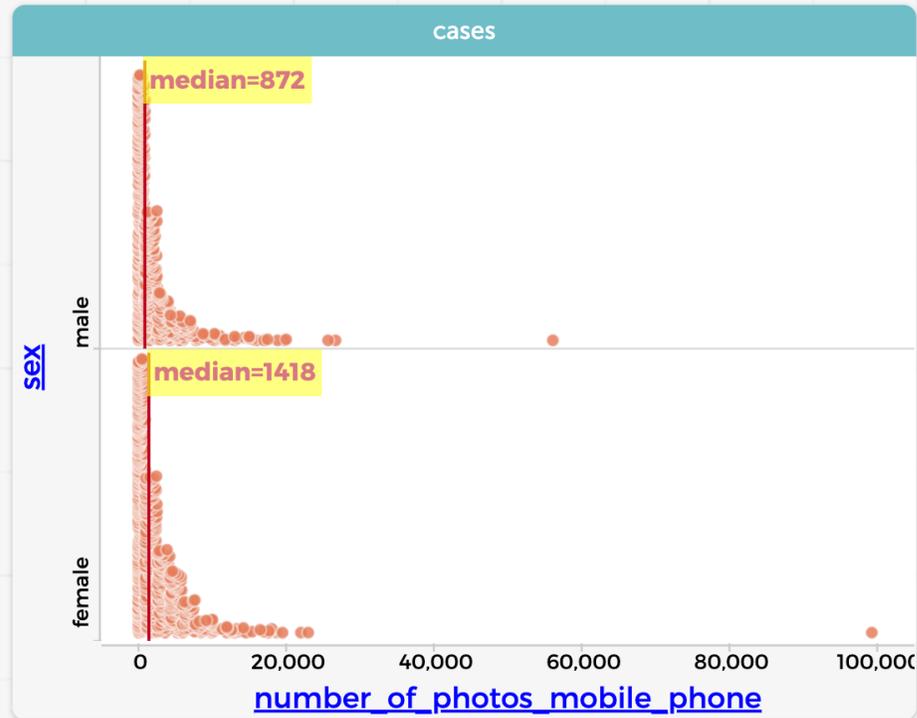
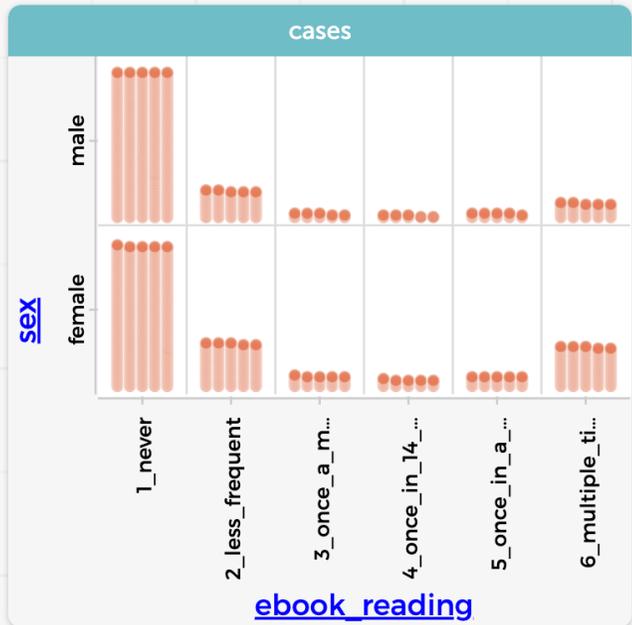
Data in English/ CODAP <https://tinyurl.com/you-pb-160en>

YOU-PB data

- Based on an official representative German survey
- Report shows aggregated data
- 161 Questions about media use
- We collected own micro data of ~1200 teenagers
- **Variables**
 - Grade, Age, Gender
 - Owning digital devices
 - Computer, GameConsole, Tablet, ...
 - Use of online platforms, social media
 - Instagram, Facebook, TikTok, Youtube, ...
 - Use of classical media
 - Gaming
 - ...



YOU_PB_160en											
cases (1278 cases, 9 set aside)											
friends	do sports	community of faith	play music	visit party	go out with family	attend sports event	library	cinema	ebook reading	printed newspapers reading	online newspapers reading
	2_less_f...	1_never	1_never	1_never	2_less_fre...	1_never	2_less_f...	3_once_...	6_multi...	1_never	1_never
e_in_1...	2_less_f...	1_never	7_daily	1_never	1_never	2_less_frequ...	1_never	2_less_f...	1_never	1_never	1_never
e_in_a...	7_daily	1_never	3_once_a...	1_never	3_once_a_...	1_never	5_once...	2_less_f...	2_less_f...	1_never	1_never
e_in_a...	2_less_f...	1_never	1_never	4_once_i...	5_once_in...	1_never	1_never	2_less_f...	1_never	1_never	1_never
e_in_1...	6_multi...	4_once_in...	7_daily	1_never	1_never	1_never	1_never	1_never	5_once...	2_less_frequ...	1_never
	7_daily	1_never	1_never	1_never	5_once_in...	1_never	1_never	2_less_f...	6_multi...	1_never	2_less_frec
frequ...	5_once...	1_never	1_never	1_never	3_once_a_...	1_never	1_never	2_less_f...	1_never	1_never	1_never



Rathgeb, T., & Schmid, T. (2020). *JIM-Studie 2020 - Jugend, Information, (Multi-)Media, Basisstudie zum Medienumgang 12- bis 19-jähriger in Deutschland*. Medienpädagogischer Forschungsverbund Südwest.



Modeling & Machine Learning: Decision Trees. Instructional choices



Methods

- *Decision trees, maybe k nearest neighbors*

Tool progression

- Unplugged data cards
- CODAP with Arbor plug-in
- Menu-based Jupyter Notebooks (JNB) with elementarized libraries
- Python with minimal coding

Data sets and problems: entrance

- Food items: recommendable or not
- YOU-PB media use: predicting age from media use

Data sets and problems: advanced (also with artificial neural nets)

- Predict parking space occupancy in Paderborn
- Recognize sign language live
- Receive outfit suggestions

Modeling & Machine Learning: Decision Trees



Unplugged material for hands-on construction

Apple



Nutrition Facts (typical value per 100g)	
Calories	52 kcal
Fat	0,2 g
of which saturated	0,0 g
Carbohydrates	13,8 g
of which Sugars	11,0 g
Protein	0,3 g
Salt	0,0 g

ProDaBi

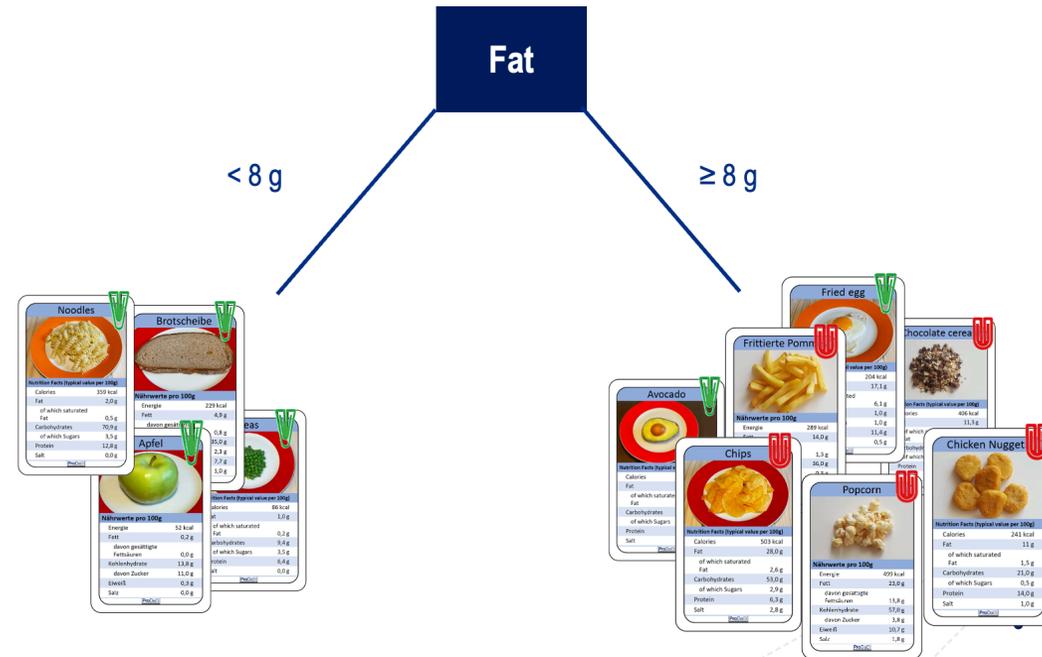
Popcorn



Nährwerte pro 100g	
Energie	499 kcal
Fett	23,0 g
davon gesättigte Fettsäuren	13,8 g
Kohlenhydrate	57,0 g
davon Zucker	3,8 g
Eiweiß	10,7 g
Salz	1,8 g

ProDaBi

Classifying food: recommendable or not



- 55 data cards about food items
 - nutrition facts (typical value per 100g)
- green and red paper clips to label the cards
- worksheets and slides



Modeling & Machine Learning: Decision Trees



Tool support for construction. CODAP and Arbor plug-in

„Predicting“ age from media behavior

JIM_PB_MatheWelt

Fälle (1287 Fälle)

In- dex	Playing ...linegames	Age	Own Computer	Own GameConsole	Own E Reader	Use Instagram	Use Twitter	Use TikTok	Use Twitch	Read Online Newspaper
1	frequently	under13	No	Yes	No	rarely	rarely	rarely	rarely	rarely
2	rarely	13_and_above	No	Yes	Yes	frequently	rarely	frequen...	frequen...	rarely
3	rarely	13_and_above	No	Yes	Yes	rarely	rarely	frequen...	rarely	rarely
4	frequently	under13	No	Yes	Yes	rarely	rarely	frequen...	rarely	rarely
5	rarely	13_and_above	Yes	Yes	No	frequently	frequen...	frequen...	rarely	rarely
6	frequently	13_and_above	No	Yes	Yes	frequently	frequen...	rarely	frequen...	frequently
7	rarely	13_and_above	No	Yes	Yes	rarely	rarely	rarely	rarely	frequently
8	frequently	under13	No	Yes	No	rarely	rarely	rarely	rarely	rarely
9	frequently	13_and_above	Yes	Yes	Yes	frequently	frequen...	frequen...	rarely	rarely
10	frequently	13_and_above	Yes	Yes	No	frequently	rarely	frequen...	rarely	frequently
11	rarely	13_and_above	No	No	No	frequently	rarely	frequen...	rarely	rarely
12	rarely	13_and_above	No	Yes	No	frequently	rarely	frequen...	rarely	frequently
13	frequently	13_and_above	Yes	Yes	No	frequently	rarely	rarely	rarely	frequently
14	rarely	13_and_above	No	No	No	rarely	rarely	frequen...	rarely	rarely
15	rarely	13_and_above	No	Yes	No	frequently	rarely	rarely	rarely	rarely
16	frequently	13_and_above	No	No	No	frequently	frequen...	rarely	frequen...	rarely
17	frequently	13_and_above	No	Yes	Yes	frequently	rarely	rarely	frequen...	rarely
18	rarely	13_and_above	No	No	Yes	rarely	rarely	rarely	rarely	rarely
19	frequently	under13	Yes	Yes	No	frequently	rarely	frequen...	frequen...	rarely
20	rarely	13_and_above	No	Yes	Yes	frequently	rarely	frequen...	rarely	rarely
21	rarely	under13	No	No	No	rarely	rarely	rarely	rarely	rarely
22	frequently	13_and_above	No	Yes	No	frequently	frequen...	frequen...	rarely	rarely

2025e classification (decision) tree

tree table mosaic doubletree settings help!

TP = 205 TN = 844 FP = 118 FN = 120

► in order to export...

► in case of emergency...

Classification Tree Records

classTrees (1 Fälle)

In- dex	predict	Focus- Node	MCR	sens	TP	FN	FP	TN
1	Age is u...	Age	0,185	0,631	205	120	118	844



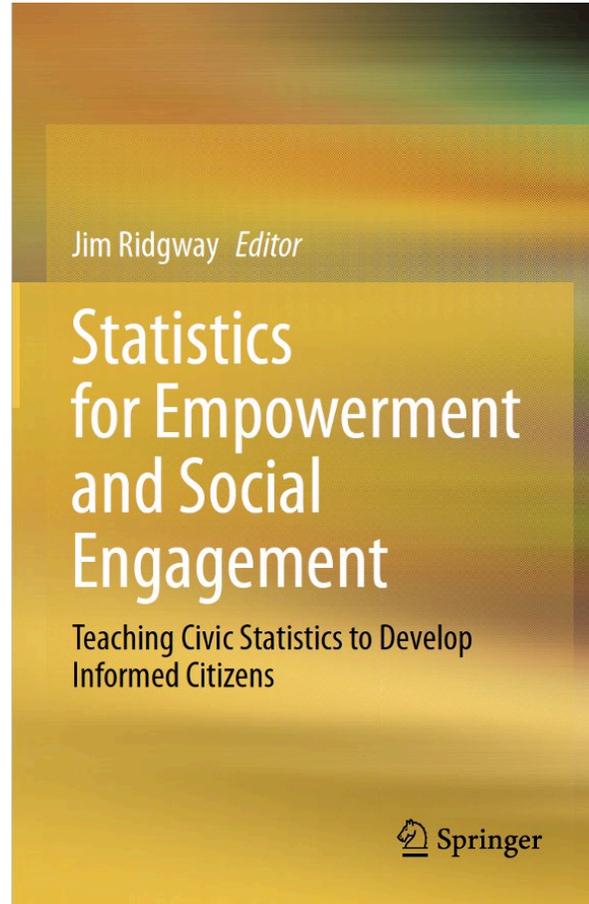
Research and development papers: Machine learning in ProDaBi



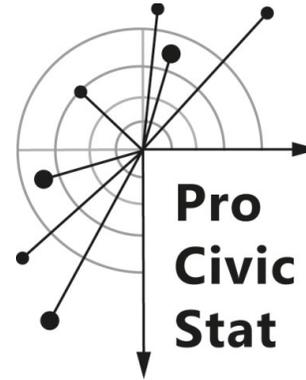
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- Fleischer, Y., Podworny, S., & Biehler, R. (2024). Datenbasiertes Entscheiden - Wie TikTok dein wahres Alter herausfinden kann. *mathematik lehren. MatheWelt(244)*.
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- Fleischer, Y., & Biehler, R. (2024). Intuitiver Zugang zu datenbasierten Entscheidungsbäumen. In P. Ebers, F. Rösken, B. Barzel, A. Büchter, F. Schacht, & P. Scherer (Eds.), *Beiträge zum Mathematikunterricht 2024. 57. Jahrestagung der Gesellschaft für Didaktik der Mathematik* (pp. 167-170). WTM.
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- Podworny, S., & Fleischer, Y. (2022). An approach to teaching data science in middle school. In *Proceedings of the 15th international conference on technology in mathematics teaching (ICTMT 15)* (pp. 308-315). Danish School of Education, Aarhus University.
- Fleischer, Y., Hüsing, S., Biehler, R., Podworny, S., & Schulte, C. (2022). Jupyter Notebooks for Teaching, Learning, and Doing Data Science. In S. A. Peters, L. Zapata-Cardona, F. Bonafini, & A. Fan (Eds.), *Bridging the Gap: Empowering and Educating Today's Learners in Statistics. Proceedings of the Eleventh International Conference on Teaching Statistics*. <https://doi.org/10.52041/iase.icots11.T10E3>
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- Podworny, S., Fleischer, Y., Hüsing, S., Biehler, R., Frischemeier, D., Höper, L., & Schulte, C. (2021). Using data cards for teaching data based decision trees in middle school. In *21st Koli Calling International Conference on Computing Education Research (Koli Calling '21), November 18-21, 2021, Joensuu, Finland*. ACM. <https://doi.org/10.1145/3488042.3489966>
- Biehler, R., & Fleischer, Y. (2021). Introducing students to machine learning with decision trees using CODAP and Jupyter Notebooks. *Teaching Statistics, 43(S1)*, S133-S142. <https://doi.org/10.1111/test.12279>

Socio-Scientific Reasoning

Connecting data analysis to societal and scientific issues



2022



<https://iase-web.org/procivicstat>

Chapter 11 Exploring Climate Change Data with R

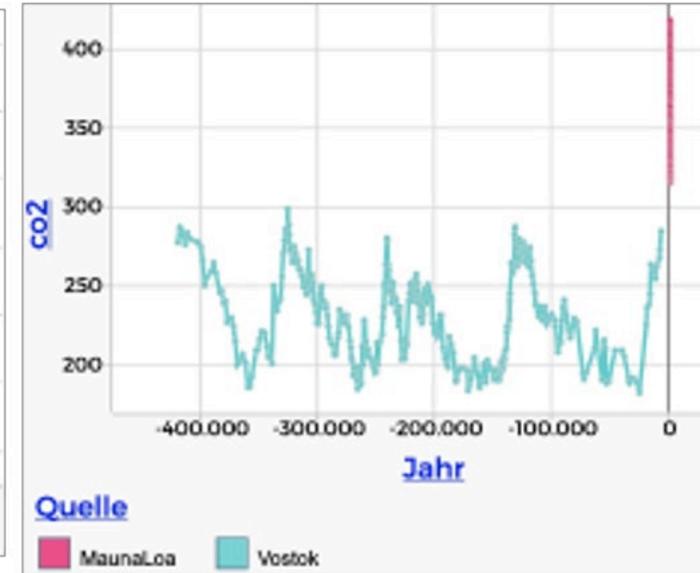
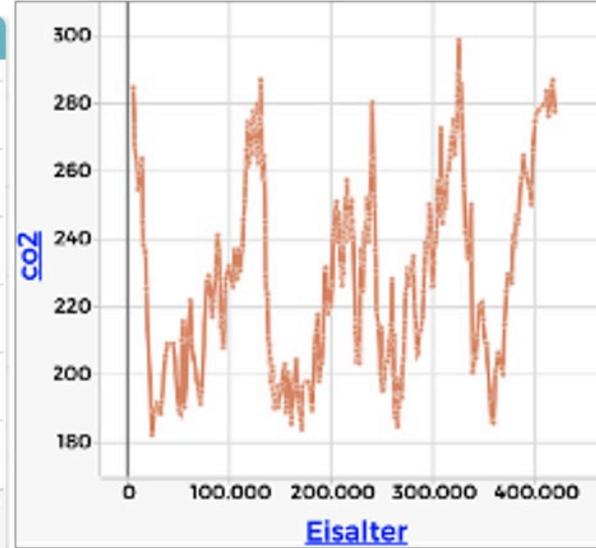
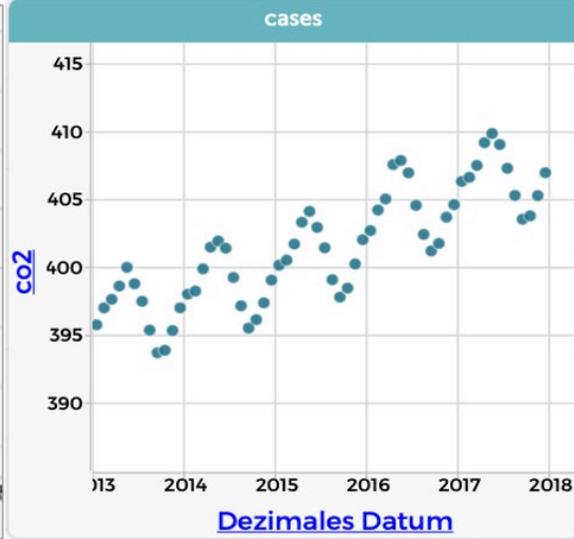
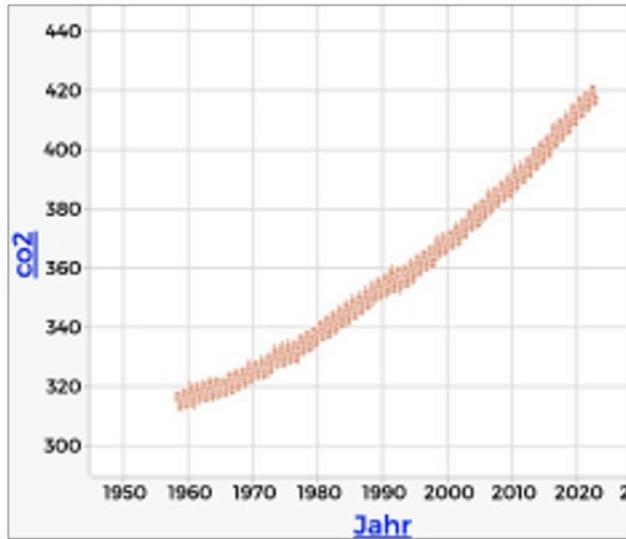


Nuno Guimarães , Kimmo Vehkalahti, Pedro Campos, and Joachim Engel

ProDaBi: Exploring climate change data with CODAP



Two of the „Five most important data sets for climate change“



Monthly average of CO₂ concentration in ppm in Earth's atmosphere (CO₂), measured at Mauna Loa, Hawaii, from 1958 to 2023.

Global CO₂ concentration in ppm in reconstructed from icecore measurements in Vostok, Antarctica, inverse time axis

Combined data set

<https://tamino.wordpress.com/2018/11/01/the-5-most-important-data-sets-of-climate-science/>



Instructional decisions and challenges for climate change unit



ProDaBi unit: Grade 10 Interdisciplinary Elective

Two coordinated strands (2 hours per week each):

- Biology – domain knowledge and scientific context
- Data Science – data analysis, modeling, and critical reflection

Innovation challenge for biology teacher

- Working with large-scale external datasets instead of only self-generated experimental data

Innovation challenge for data science teacher

- Engaging with the complexity of socio-scientific evidence and public discourse

Biehler, R., Engel, J., Frischemeier, D., & Podworny, S. (2025). Civic Statistical Literacy: Konzept und praxisnahe Umsetzung am Beispiel des Klimawandels. *mathematica didactica*, 48.

Podworny, S. (submitted to ZDM) Integrating data literacy and climate science: A multidisciplinary teaching unit for grade 10 students on human-induced climate change



Working with Authentic Climate Data

- Students analyze publicly available datasets and critically reflect on their origin, validity, and interpretation

Core activities

- Identifying and evaluating the **reliability of data sources**
- Importing, cleaning, and manipulating datasets in **CODAP**
- Formulating and discussing **critical questions about data and evidence**

Some critical questions

- Why can data from **Mauna Loa** or **Vostok ice cores** be used as indicators of *global* CO₂ concentration?
- How can atmospheric CO₂ levels from the distant past be reconstructed or “measured”?
- What assumptions and uncertainties are involved?



Context

- Exploration of authentic mobile phone location data
- Data set, made public by Malte Spitz (German Green Party politician)
- to demonstrate the scope and risks of personal data collection (and analysis)

Student Inquiry

- Reconstructing daily routines from movement patterns
- Developing and testing hypotheses about personal habits
- Example student inference: "He seems to have a girlfriend!"

Instructional Focus: Working as data detectives

- Understanding how seemingly neutral data reveal sensitive personal information
- Reflecting on primary and secondary data use purposes

Web application

Filter the location data and explore them on the map

Locations in the time range:
 from:
 to:

Locations on the weekday:
 Tagwahi:

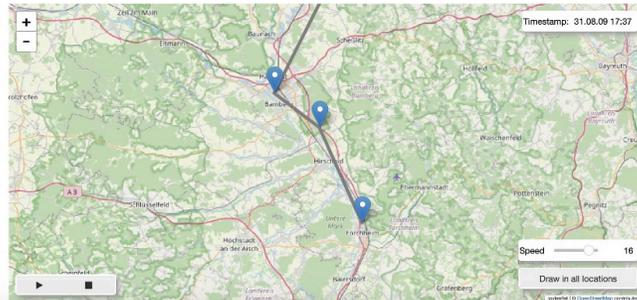
Locations in the month:
 Month cho...:

Reset or apply the filters:

The following data are loaded:

	Begin	End	Service	In/outgoing	Longitude	Latitude
0	31.08.09 07:57	31.08.09 08:09	GPRS	ausgehend	13.396111	52.529444
1	31.08.09 08:09	31.08.09 08:09	GPRS	ausgehend	13.383611	52.530000
2	31.08.09 08:09	31.08.09 08:15	GPRS	ausgehend	13.374722	52.530278
...
21503	13.02.10 10:00	13.02.10 10:10	GPRS	ausgehend	13.404444	52.531667
21504	13.02.10 10:10	13.02.10 10:10	GPRS	ausgehend	13.404444	52.531667
21505	13.02.10 10:10	13.02.10 10:13	GPRS	ausgehend	13.404444	52.531667

21506 rows x 6 columns



Timestamp: 31.08.09 17:37
 Speed: 16

Höper, L., & Schulte, C. (2024). The data awareness framework as part of data literacies in K-12 education. *Information and Learning Sciences*, 125(7/8), 491–512. <https://doi.org/10.1108/ILS-06-2023-0075>

Höper, L., Schulte, C., & Mühlhng, A. (2024). Learning an Explanatory Model of Data-Driven Technologies can Lead to Empowered Behavior: A Mixed-Methods Study in K-12 Computing Education. In *Proceedings of the 2024 ACM Conference on International Computing Education Research (Vol.1)* (pp. 326–342). <https://doi.org/10.1145/3632620.3671118>



Critical Data Awareness: Unit 2



Unit 2 Recommender systems

Students work with a prepared **Jupyter Notebook** that serves as an interactive learning environment.

Exploration:

- Students interact with a functioning recommender system embedded in the notebook.

Personal Experience:

- Students rate movies and receive individualized recommendations.

Looking “Under the Hood”:

- Students inspect how the system processes ratings and generates suggestions.

Model Reconstruction:

- Students reconstruct the underlying data model based on the **k-nearest neighbours (kNN)** method.

Conceptual Focus

- From user experience to algorithmic understanding
- From black-box interaction to transparent modeling
- Understanding similarity, distance, and prediction in data models

Generalization to other digital artefacts

- Distinguishing primary and secondary purposes of data collection
- Generalization in form of a **explanatory model** for analyzing other data-driven systems



Results of data exploration: Computational Essays

- Computational essays serve as a medium for **epistemic programming**.
- Integrating **text, code, and visualizations** to construct knowledge
- Making assumptions, models, and analytical decisions **explicit and inspectable**
- Enabling **transparent and reproducible** reasoning processes
- Using code to explore, test, and refine explanations

Learning Support

- **Worked examples** scaffold epistemic practices

Technical Implementation

- Implemented in **Jupyter Notebooks**

Hüsing, S., Schulte, C., Sparmann, S., & Bolte, M. (2024). Using Worked Examples for Engaging in Epistemic Programming Projects. *SIGCSE 24*, 443–449.
<https://doi.org/10.1145/3626252.3630961>

Hüsing, S., Schulte, C., & Winkelkemper, F. (2023). Epistemic Programming. In S. Sentance, E. Barendsen, N. R. Howard, & C. Schulte (Eds.), *Computer Science Education: Perspectives on Teaching and Learning in School* (2nd ed., pp. 291–304). Bloomsbury Academic; Bloomsbury Collections.
<http://dx.doi.org/10.5040/9781350296947.ch-022>



Why should students program in data science education?

- Makes data processes explicit
- Opens the black box of algorithms
- Supports reproducibility
- Authentic image of AI practices

Challenges (ProDaBi experience)

- Coding is an obstacle for many students (and teachers)
- Works well in grade 12/13 - with selected and interested students
- Integration in grade 9/10: First positive experience, code snippets embedded in Jupyter Notebooks

Thank you for your attention.