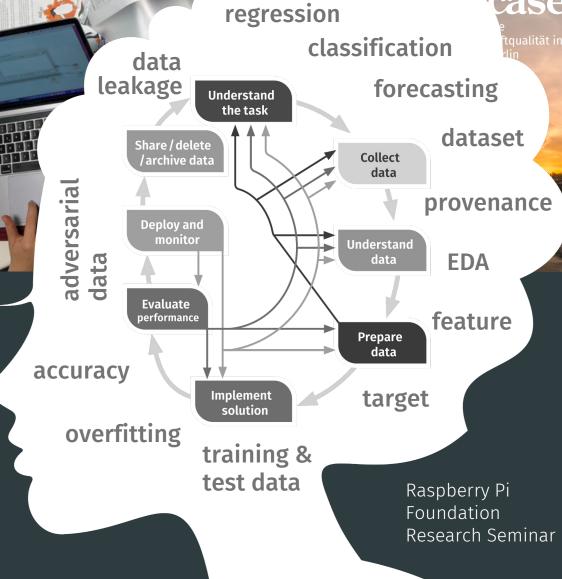




Data-related concepts and practices for AI education in K-12



Viktoriya Olari | 14.10.2025





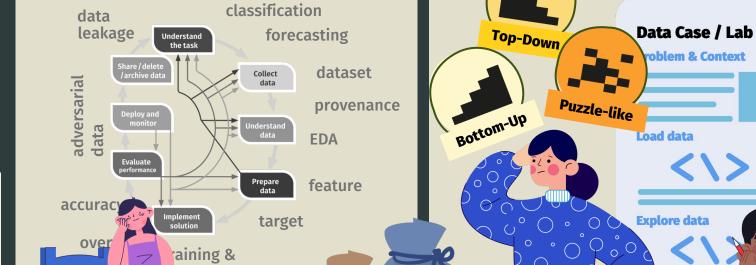
Roadmap

regression

Data concepts & practices

est data

Summary



construct features

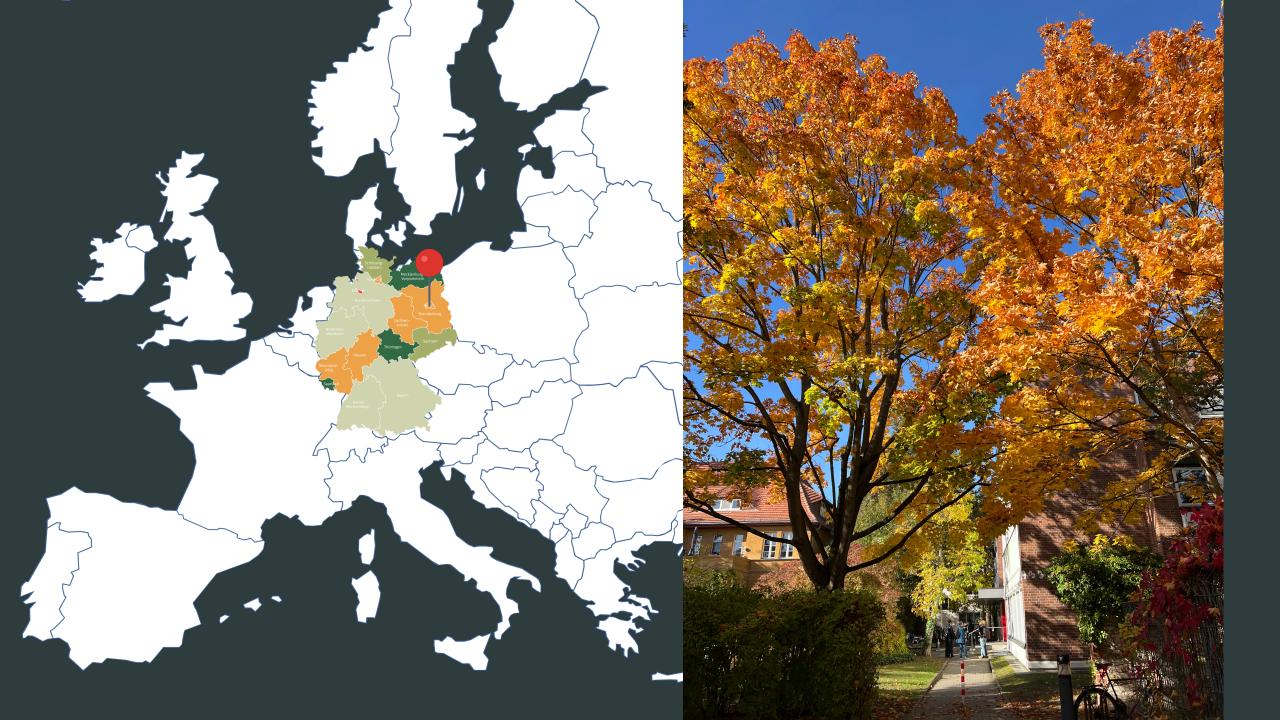


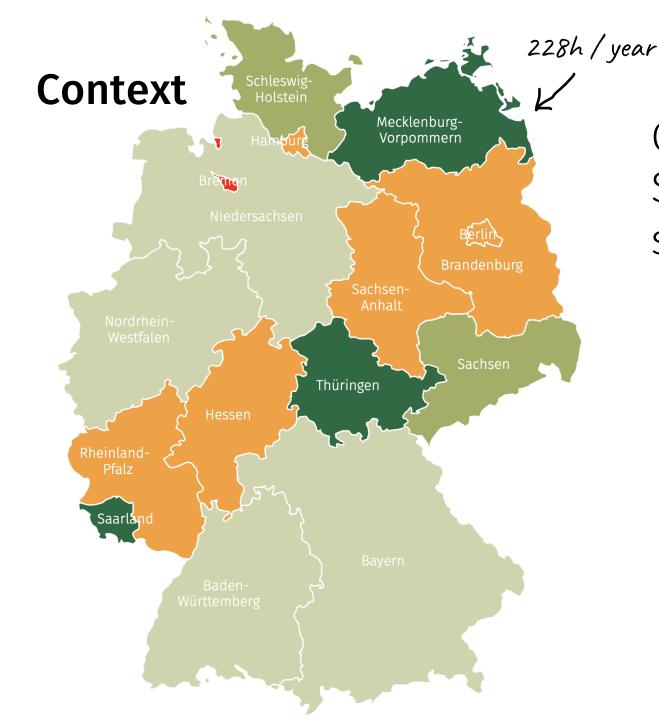
Context & Motivation



The data case study

Homew





Compulsory Computer Science Education starting in Grade 5

- At least 6 compulsory hours / week
- At least 4 compulsory hours / week
- At least **1 compulsory hour / week**
- Offered at individual school types or in individual grades
- No courses offered

https://informatik-monitor.de/2024-25

Context

Al topics are entering formal school education.

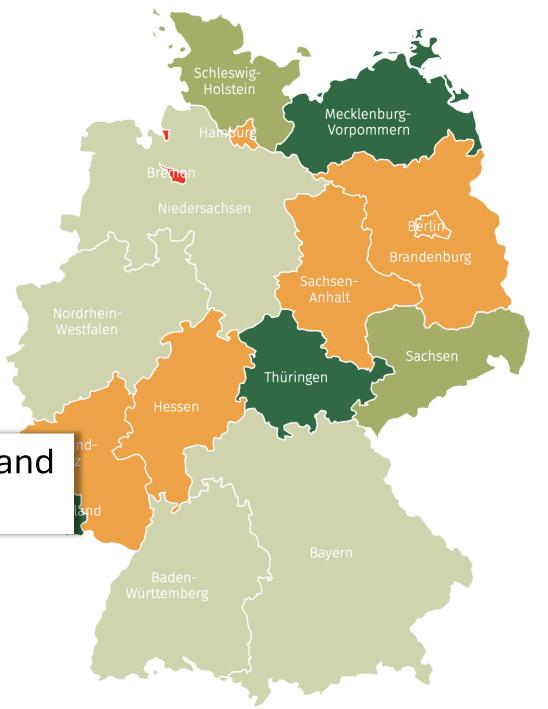


Machine Learning with decision trees and neuronal networks

des maschinellen Lernens dar (DI),

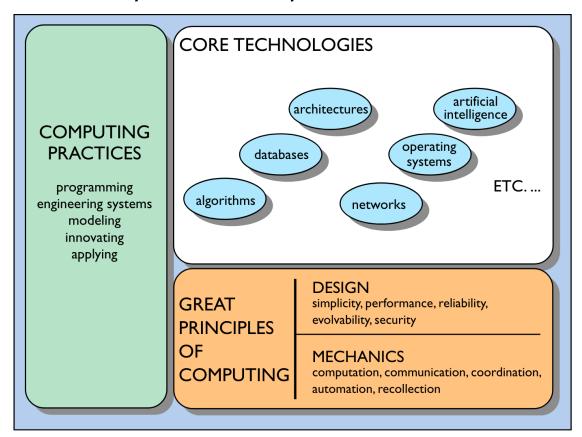
• beschreiben die grundlegende Funktionsweise künstlicher neuronaler Netze in verschiedenen Anwendungsbeispielen (KK).

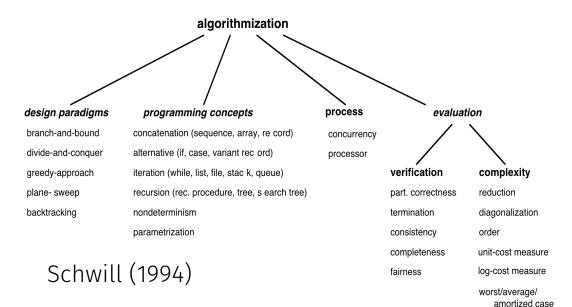
Core curriculum for secondary level I – grades 5 and 6 in North Rhine-Westphalia (2021)



Motivation

Teaching should focus on key concepts and practices of CS.

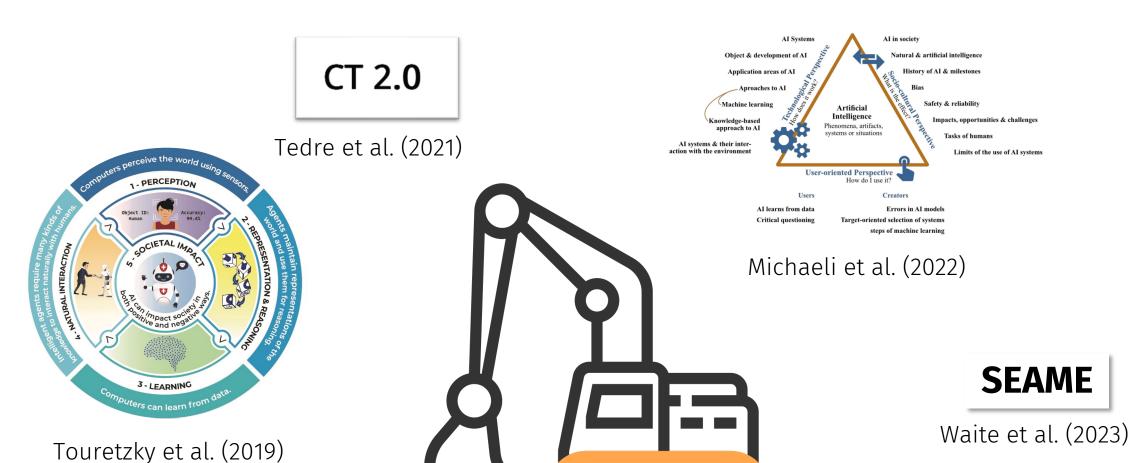






Motivation

Conceptualisation is still ongoing!



Conceptualisation is still ongoing!

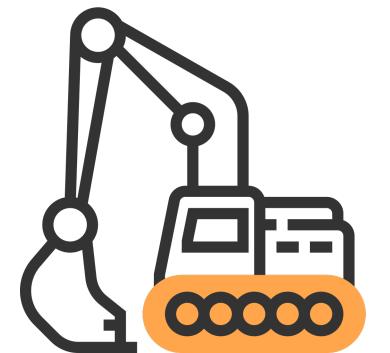
WiPSCE '21, October 18-20, 2021, Virtual Event, Germany

	Acquisition	Cleansing	Modeling	Implementation	Optimisation	Analysis	Visualisation	Evaluation	Sharing	Erasing	Archiving
[11]	-	-	✓	-	-	-	-	✓	-	-	-
[9]	✓	-	✓	-	-	✓	-	✓	-	-	✓
[1]	✓	-	-	-	-	-	-	✓	-	-	-
[14]	✓	-	-	-	-	-	-	✓	-	-	-
[3]	✓	-	-	-	-	✓	-	✓	-	-	-
[12]	✓	-	-	-	-	-	-	✓	-	-	-
[8]	-	-	-	-	-	-	-	-	-	-	-

Table 1: Coverage of the data literacy-related competencies in currently available AI educational frameworks, categorized by the stages of the data lifecycle proposed by [6].

The **role of data** is underestimated.

Olari & Romeike (2021)



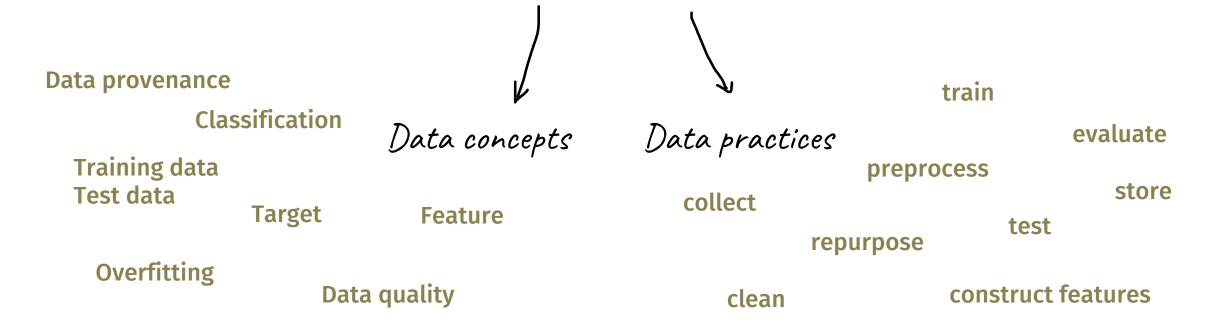
Motivation

The key role of data

Zha et al. 2023, Jakubik et al. 2024 Ali et al. 2023

In order to understand, evaluate, use responsibly, and design such systems, an understanding of data is necessary.

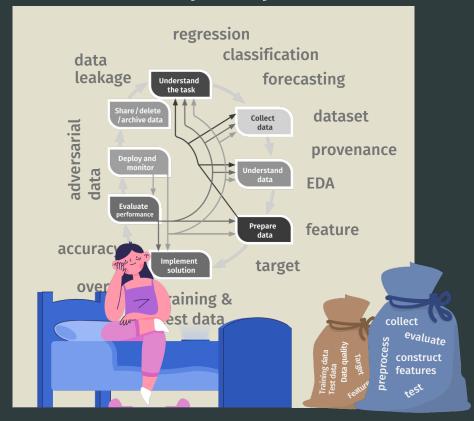
In order to understand, evaluate, use responsibly, and design such systems, an understanding of data is necessary.



Research question

What are the **key data-related concepts and practices** in context of Al that school students need to know?

Data concepts & practices



4 Steps for identification of concepts & practices

corroborate

align

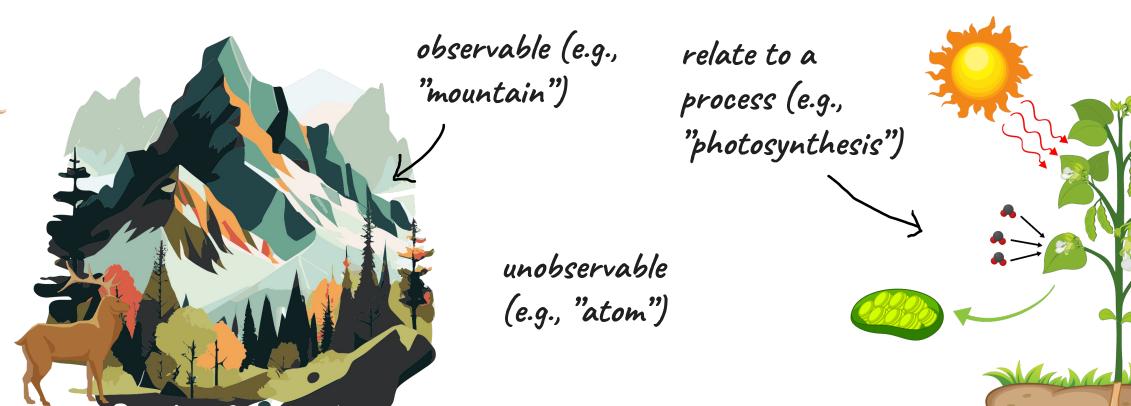
analyse

conceptualise

4 Steps for identification of concepts & practices

Concepts in sciences

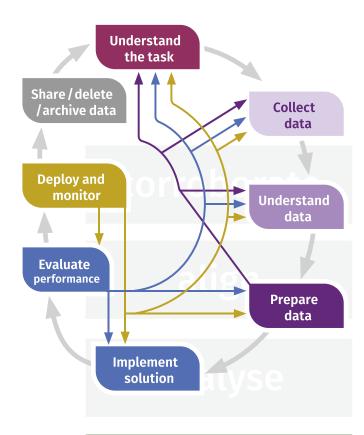
Concepts are described as systematic mental representations of the real world.



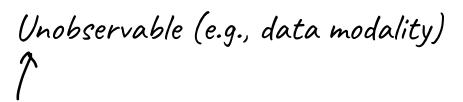
4 Steps for identification of concepts

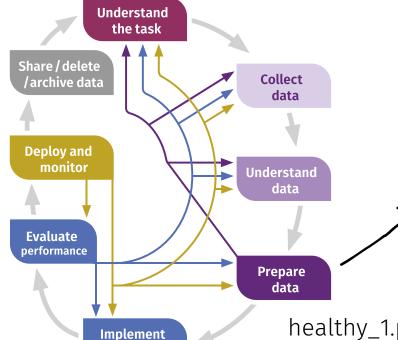
Term used to describe a specific **process**, an **observable**, or **unobservable entity related to data** in one of the stages of the data-driven lifecycle.

Olari & Romeike (2024)

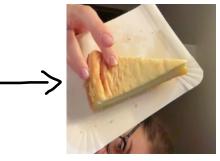


conceptualise









Relate to a process (e.g., data augmentation)

conceptualise

healthy_1.png

healthy_2.png



Observable (e.g., training data)

solution



unhealthy_1.png

Practices in sciences

Practices are actions performed by scientists to build up knowledge.

Planning and carrying out investigations.



Developing and using models.

4 Steps for identification of practices

A practice is an **action performed on data** or with data in mind in one of the stages of the data-driven lifecycle.

Olari & Romeike (2024)

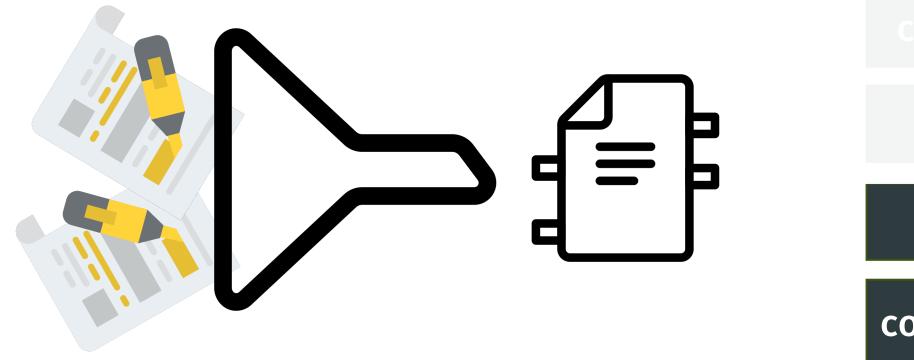
Understand the task Share / delete Collect archive data data Deploy and Understand **Evaluate** performance **Prepare** data **Implement** solution

split a dataset

train a model with the training data

conceptualise

4 Steps for identification of concepts & practices



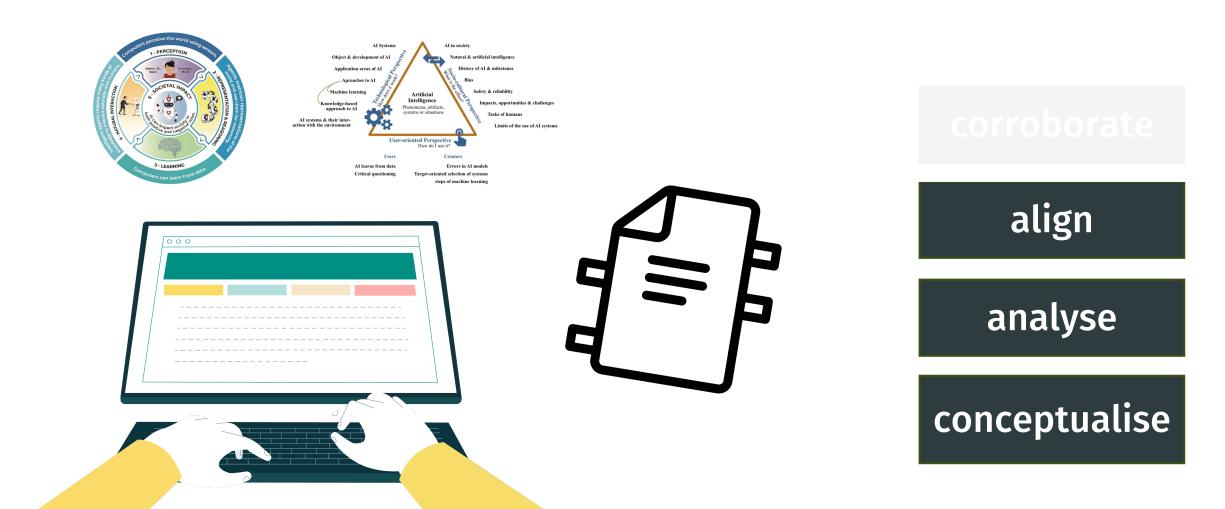
corroborate

align

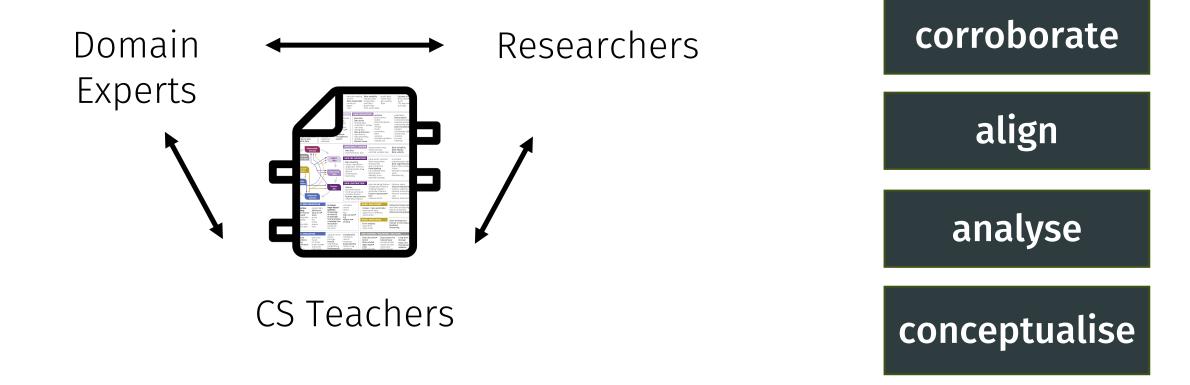
analyse

conceptualise

4 Steps for identification of concepts & practices



4 Steps for identification of concepts & practices



Results

An 8-stages process model



Collect data

Understand

Prepare data

Implement solution

Evaluate performance Deploy and monitor

Share. delete archive data

Understand the needs of stakeholders.

» Identify the needs of data producers, data agents, and data users.

Analyze the task of the project.

- » Understand which data is needed to solve the task.
- » Understand whether data is available or can be collected to solve the task.
- » Determine if AI technologies can add value to solving the problem by identifying projects that use similar data to solve similar tasks.
- » Analyze real-world constraints to collecting, managing, and storing the data.

Define success criteria.

» Formalize the task in a problem statement, taking into consideration stakeholders' needs and the data available.

Create a dataset.

» Choose a data source and collection technique

Repurpose or access a third-party dataset.

- » Check the data ownership and license.
- » Merge data from different sources.

Understands the specifics of the data modality.

» Select an appropriate strategy for data preparation.

Decide on how to store and access data.

- » Select a storage type depending on the nature of the data.
- » Establish secure access to data.

- » Find the documentation for the dataset, including the description of its collection purpose and instruments.
- » Document data provenance.

- » Conduct exploratory data analysis.
- » Understand typical data entries.
- » Explore patterns in the dataset.
- » Visualize the data.
- » Formulate a hypothesis.

- » Check data reliability, data fidelity, and data validity.
- » Check for potential biases in data
- » Detect outliers, duplicates, errors.

Clean data.

- » Correct outliers and errors.
- » Remove duplicates.

Pre-process data.

- » Lemmatize, tokenize textual data.
- » Rescale image data.

Label data.

- » Establish consensus labels.
- » Use crowdsourcing or other strategies to label data.
- » Ensure interpersonal validity between annotators.

Augment data.

- » Perform basic data manipulations
- » Create synthetic data.
- » Perform upsampling or undersampling.

Engineer features.

- » Transform features.
- » Perform feature selection.
- » Perform a reduction of samples.

Create a solution using machine learning.

- » Check the data for assumptions about the model.
- » Establish the ground truth.
- » Split data.
- » Use data to train the model.
- » Use data to test the model.

Control data and model versions.

- » Document modifications that the data is undergoing in each iteration.
- » Document which model and parameters are selected.

Prepare evaluation data.

» Generate adversarial sam-

Select an evaluation metric.

» Choose the appropriate evaluation metric based on the model and task.

Interpret the model output.

- » Compare the result to the ground truth.
- » Visualize data fit and error.
- » Visualize feature importance. » Explain what features are most important and why.
- » Interpret performance figures.
- » Accept or reject the hypoth-

Understand problems and initiate improvements.

» Understand overfitting and underfitting.

Prepare infrastructure for pro-

- » Establish a data processing pipeline.
- » Select a data processing mode.
- » Create a reporting system.

Collect unseen data entered

- » Ensure the security of storing the unseen data.
- » Preprocess the data upon collection.

Analyze the performance of the model on unseen data.

- » Analyze errors.
- » Check the unseen data on the data drift.

nitiate improvement.

- » Collect more data.
- » Select another pre-processing strategy.
- » Rebalance data.
- » Retrain the model with unseen data.

Share data.

- » Accompany the dataset with documentation.
- » Ensure that the data is transferred and treated securely.
- » Select an appropriate data license if the data is to be published.

Archive data.

- » Select an appropriate medium for long-term data storage » Accompany the data with
- documentation. » Ensure data protection if the dataset contains sensitive

information. Delete data.

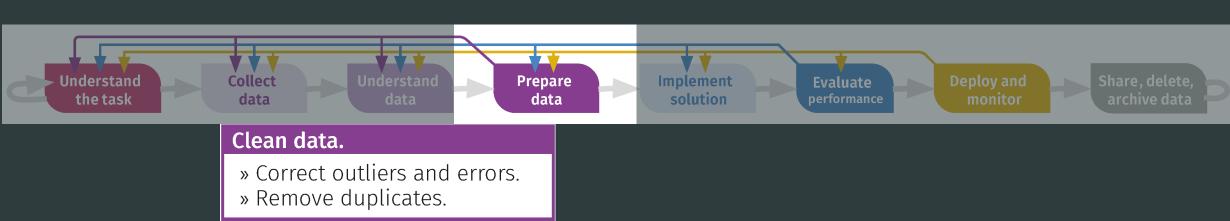
» Ensure that the data is permanently deleted

28 key data-related practices

>> 69 examples of subpractices for use in CS education

Results

An 8-stages process model



Pre-process data.

- » Lemmatize, tokenize textual data.
- » Rescale image data.

Label data.

- » Establish consensus labels.
- » Use crowdsourcing or other strategies to label data.
- » Ensure interpersonal validity between annotators.

Augment data.

» Perform basic data manipu-

key data-related practice

examples of subpractices

Results

A collection of 133 data-related concepts

TASK UNDERSTANDING

description

detection

Data-based task · localization generation regression

Understand

- association · classification (clustering)
 - ·filtering (recom- · reasoning
- answering

mendation)

information

extraction

- question ·user
- Data stakeholder · image data producer agent

· search

- ·text data ·graph data
 - ·time series data

·tabular data

- · audio data ·video data ·geo-spatial
 - ment
 - · "Do not harm" principle

Success criteria · Risk assess-

DATA COLLECTION

Primary data Secondary data Crowdsourcing Scrapping Crawling Surveys and polls Artificially generated

Sensor generated data Third-party data Historical data

DATA STORAGE

Data format structured data unstructured

data semi-structured data Data storage

· dataset relational database

- · non-relationa database · cloud data storage distributed storage sys-
 - Database management
 - system

DATA EXPLORATION

decision-making Data modality

Raw data Data noise

- · missing data redundant / dupli-
- cate data wrong data
- Data provenance data licence
- variance data ownership metadata
- Dataset com-

- position ·typical entry
- outlier · data distribution
- · mean median

data

- ·mode
- correlation skew
- · standard deviation

measurement bias

sample size

population

- Data analysis · univariate analyis
- bivariate analysis multivariate analysis
- Data visualization
- boxplot
- · distribution plot
- scatter plot
- ·line plot bar plot
- heatmap

Data bias the task representation bias Collect /archive data data Data cleaning Deploy and monito diction Tokenization data ·Stemming **Evaluate** DATA CONSTRUCTION performance

DATA QUALITY CONTROL

- ·historical bias ·omitted variable bias
- Data reliability Data fidelity Data validity

DATA PRE-PROCESSING

- values imputation
- · duplicates removal · missing values pre-

Stop words removal · Data restauration

- - Gravscaling Bias correction
 - Data labeling ·(un-)labeled data
 - ·label quality ·labeling error · labeling strategy
- Data augmentation · Basic data manipu-

interpersonal validity

annotator

- lation ·Synthetic data gener-
- Rebalancing

Feature

- · discrete feature
- · continuous feature ·complex feature
- Feature characteristic
- informative feature
- · discriminating feature ·independent feature
- · irrelevant feature
- · redundant feature
- Feature representa-
- Feature vector
- Feature space Feature engineering Feature selection
- Feature extraction
- · Feature transforma-
- Feature reduction

Data processing mode

Data processing pipeline

real-time processing

batch processing

MODEL IMPLEMENTATION

- In machine learning: Target feature Data split
- training data validation
- testing data
- array ·list

solution

- ·source data tree
- data struc-
- stack
 - · queue
- edge-based ·target data systems: Advanced Knowledge
 - elicitation Knowledge interpretation nowledge for-

In knowl-

- malization predicate
- · axiom ·query · fact
- sioning
- ·function

- constant
- Data version-
- Model ver-

MODEL DEPLOYMENT

- Unseen / real-world data
- · adversarial data ·data from a different distribution
- MODEL MONITORING
- Error analysis
- · data drift · data misfit
- Data maintanance Human-in-the-loop user feedback Retraining

MODEL EVALUATION

- Baseline Hypothesis testing
- Performance metric accuracy
- · recall ·F1-score
 - lute error ·root mean
- purity precision entropy Data fit
- · overfitting ·mean-abso- underfitting Performance
- visualization squared error confusion
 - heatmap Explainability feature im-
 - matrix
 - portance

DATA SHARING / ARCHIVING / DELETION

- tation Data-related legal regulations
 - sensitive data
- Long-term data storage Data card Permanent deletion
- Data documen-Data protection Data privacy · personal data
- · data trace Data security Data leakage

Collect data

Understand data

Prepare data

DATA EXPLORATION

Raw data Data noise

- missing data
- redundant / duplicate data
- ·wrong data

Data provenance

- · data licence
- data ownership
- metadataDataset com-

position

- typical entry
- outlier
- · data distribution
- mean
- median
- mode
- correlation
- skew
- variance
- \cdot standard deviation |
- sample size

- populationData analysis
- univariate analyis
- bivariate analysis
- multivariate analysisData visualization
- boxplot
- distribution plot
- scatter plot
- · line plot
- bar plot
- heatmap

DATA QUALITY CONTROL

Data bias

- representation bias
- measurement bias
- historical bias
- · omitted variable bias

Data reliability
Data fidelity
Data validity

How can I use it when specifying what to teach?

A collection of **133 data-related** concepts



An **8-stages process model**

... describe how to design an Al system.

OECD (2025)

Go backwards and use the collection as orientation.

... describe how to design an AI system.

OECD (2025)

What terms should my students be able to operate with?

TASK UNDERSTANDING

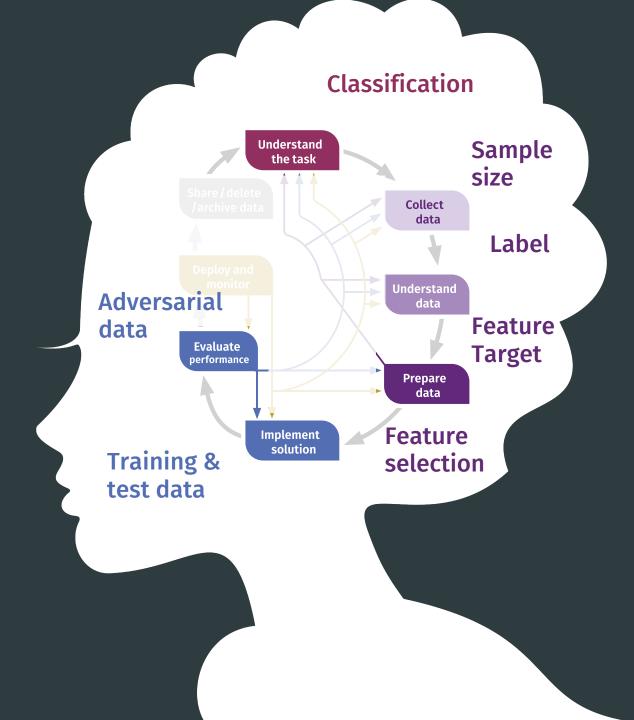
Data-based task · localization

- description
- generation
- regression
- association (clustering)
- classification detection
- filtering (recom-

Go backwards and use the collection as orientation.

... describe how to design an Al system.

OECD (2025)



Go backwards and use the model as orientation.

... describe how to design an Al system.

OECD (2025)

Which practices should my students understand?

Clean data.

- » Correct outliers and errors.
- » Remove duplicates.

Pre-process data.

- » Lemmatize, tokenize textual data.
- » Rescale image data.

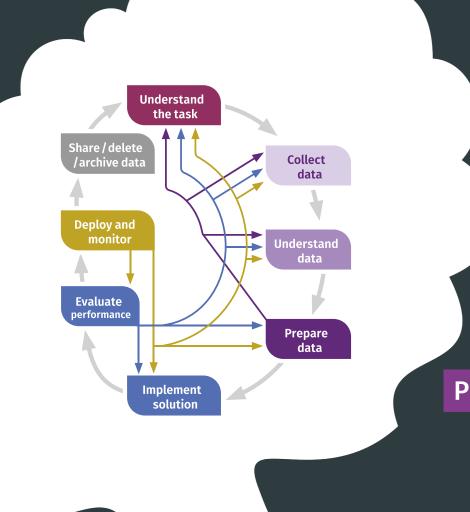
Label data.

Generate adversarial data to test robustness.

Use training data to train the model.

... describe how to design an Al system.

OECD (2025)



Create a dataset.

Verify data quality.

Label data.

Perform feature selection.

The student should be able to operate with the following vocabulary:

The student should demonstrate understanding of the following practices:

Classification

Sample size

Label

Feature selection

Feature Target

Adversarial data

Training & testing data

Create a dataset.

Verify data quality.

Label data.

Perform feature selection.

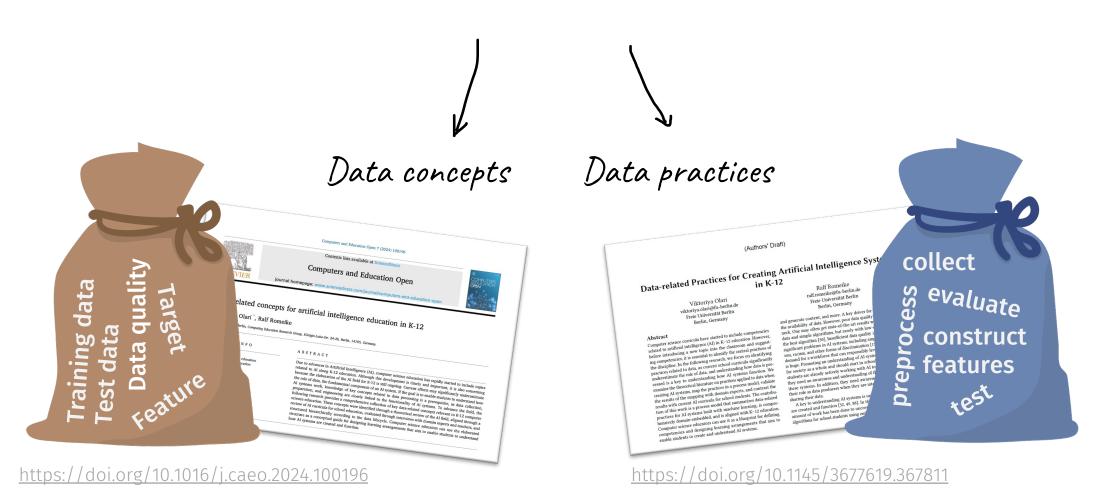
Generate adversarial data to test robustness.

Use training data to train the model.

... describe how to design an AI system.

OECD (2025)

To understand such systems, you have to understand data.



Take away so far

concepts



Can be used as a foundation for a common language when teaching about datadriven systems.

Can be used by teachers / curriculum developers as a guide when specifying competencies.

The Data Case Study

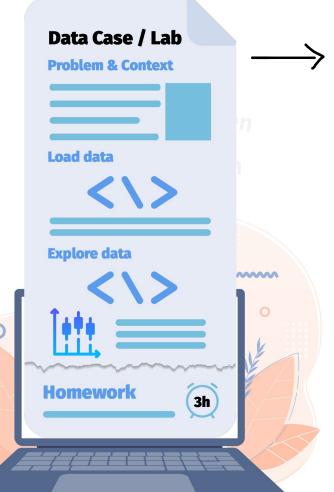
How can we support computer science teachers in addressing these **additional aspects** of data in the classroom?



The data case study

An established method in data science education

Guidance through the data-driven lifecycle using real data as an example



How will particulate matter pollution develop in Berlin over the next 10 years?

Nolan & Speed (2001) Chkoniya (2021) Wright et al. (2024)

The data case study

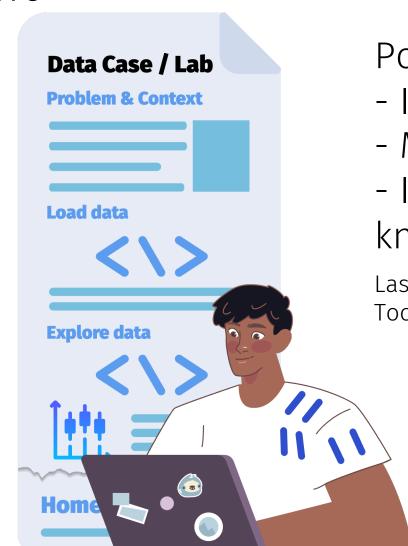
Learning theory perspective

Situated learning
Hoffer (2020)

Constructivist learning

Gill (2011), Hoffer (2020)

Active learning
Herreid (2011)



Positive effect on

- Interest
- Motivation
- Increase in knowledge and skills

Lasser (2021) Toogood (2023)

The data case study

School-specific challenges in the transfer process

Lack of programming skills

Lack of domain knowledge



The time for preparing the data cases is limited.

Research Questions

What challenges need to be considered in order to effectively use the data case study as a teaching and learning method in computer science lessons on the topic of "AI"?

Research Questions

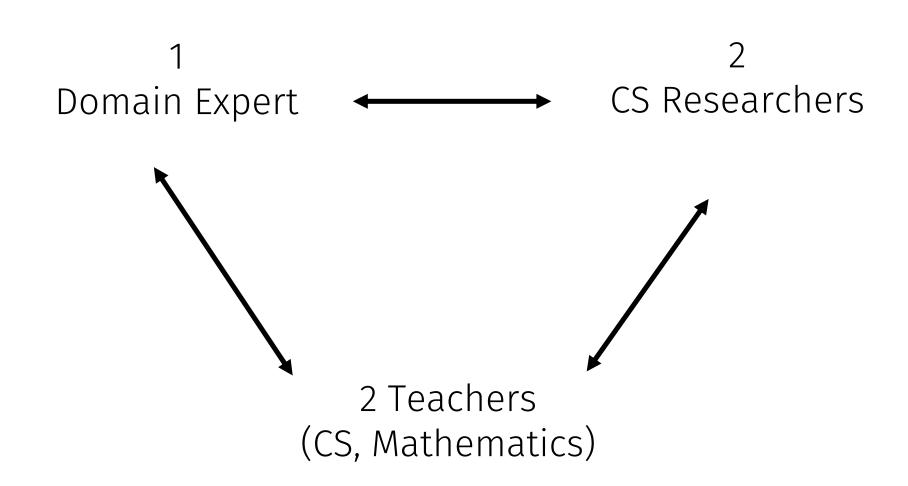
What challenges need to be considered in order to effectively use the data case study as a teaching and learning method in computer science lessons on the topic of "AI"?

How must the data case study be adapted as a teaching and learning method in order to overcome the challenges identified and meet the objectives of computer science education on the topic of "AI"?

Methodology

Methodology

Expert Team



Methodology

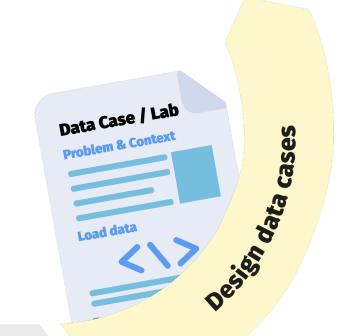
Design-based research

(Prediger 2012)



(Prediger 2012)





+ school-specific challenges and goals

+ assumptions on how to support learning

Data flow Scatter Plot Widget la.a Tree Viewer 1 ---**Feature Statistics** Tree Data Table **E** Data Datasets Select Columns Remaining Data → Data Predictions Data Sampler Data Table (1) Correlations

Flow-based

osis data cases

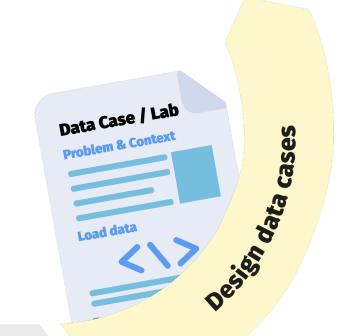
Let's also take a look to see how many monitors there are in a few cities. We can use the filter() function of the dplyr package to do so. For example, let's look at Albuquerque, New Mexico.

Text-based

We can see that there were only two monitors in the city of Albuquerque in 2006. Let's compare this with Baltimore.

(Prediger 2012)





+ school-specific challenges and goals

+ assumptions on how to support learning



(Prediger 2012)



Data Case / Lab
Problem & Context

Load data

Design

+ school-specific challenges and goals

+ assumptions on how to support learning

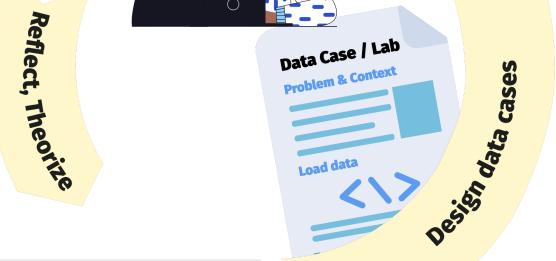




Lest data cases in school and analyze

(Prediger 2012)





+ school-specific challenges and goals

+ assumptions on how to support learning

(Prediger 2012)

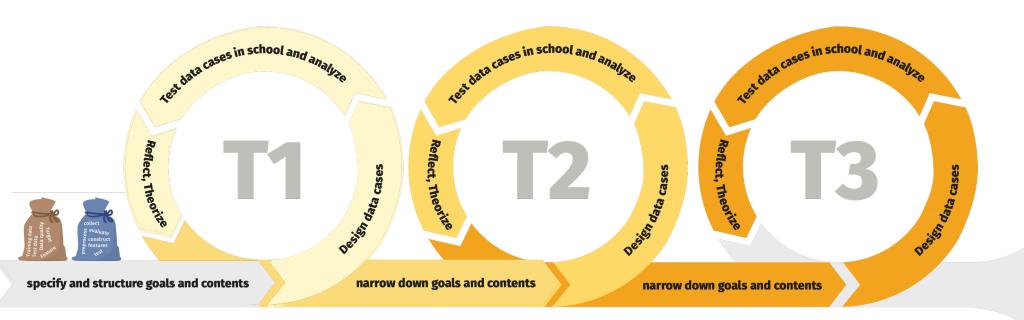


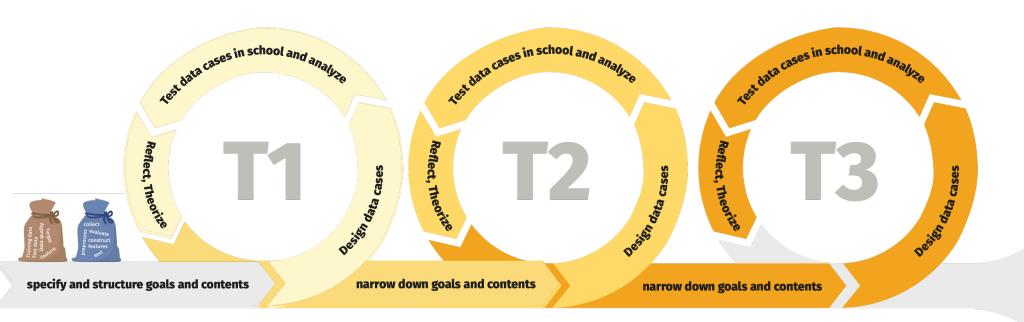
specify and structure goals and contents

collect

evaluate construct features rest

narrow down goals and contents





48h, 15 St.

48h, 13 St.

46h, 16 St.

Results



School-specific data case study in 3 architectures

The school-specific data case study

enables students using a real world data case



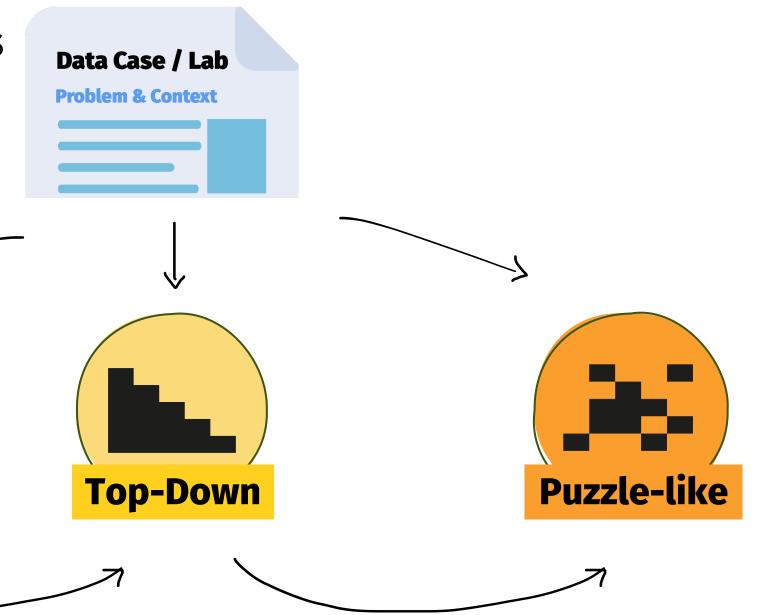
data-driven lifecycle and discover insights from each step.

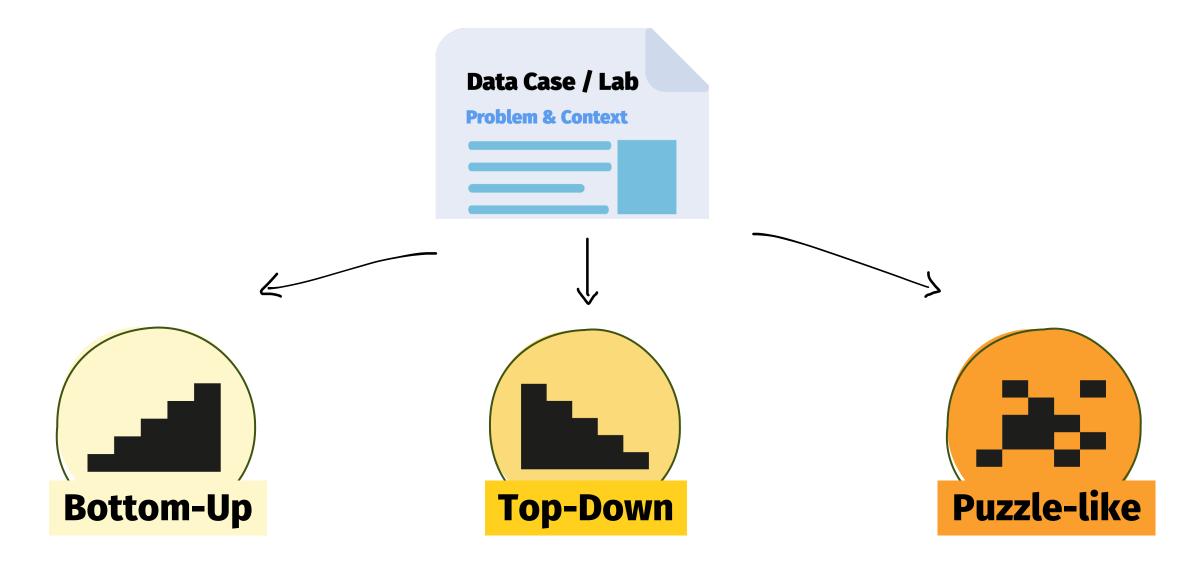


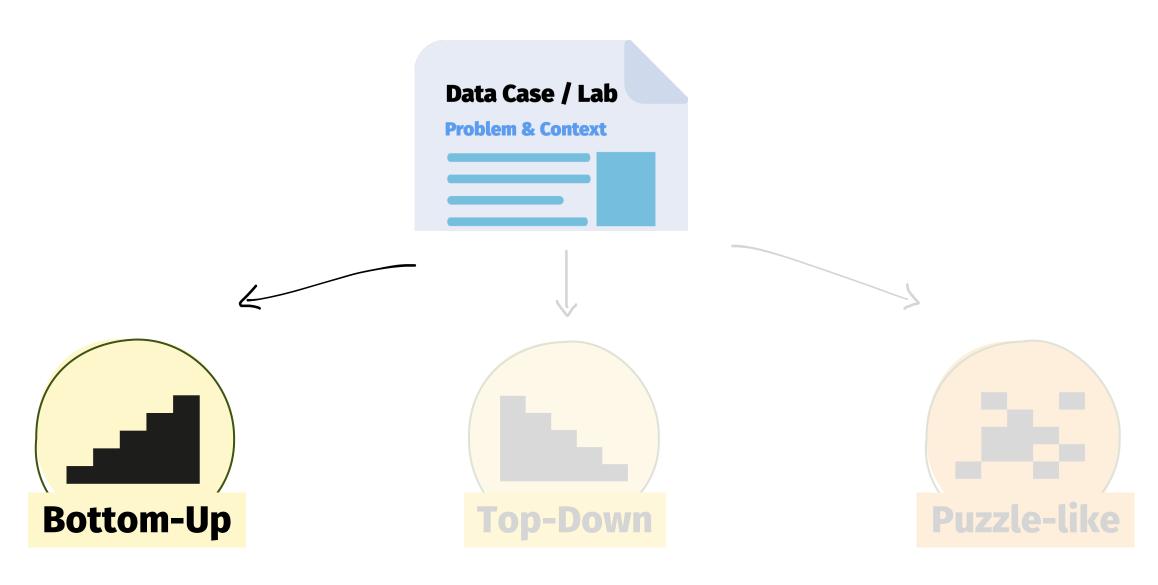




Bottom-Up







The data case study

School-specific challenges in the transfer process

Lack of programming skills

Lack of domain knowledge



The time for preparing the data cases is limited.



Get an overview of the dataset.

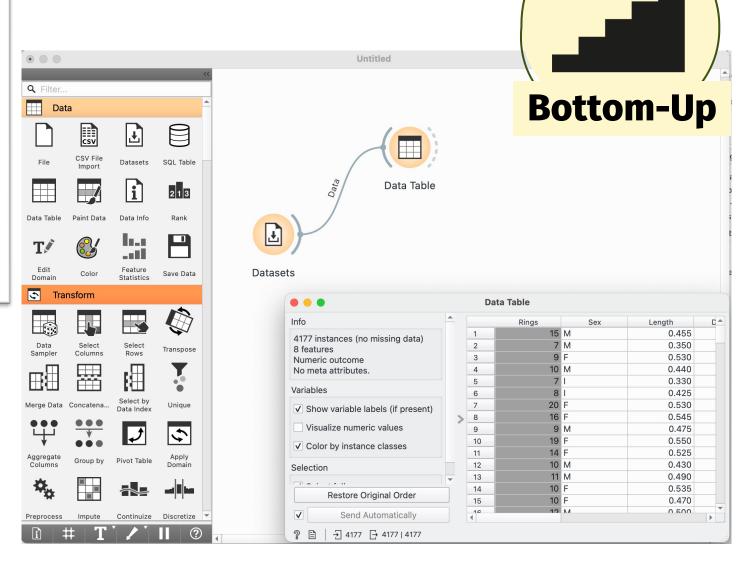
Drag Data Table onto the workspace and connect the output of Datasets to the input of Data Table.

Look at the data on abalones using OData Table and fill in the gaps.

1. ______ 2. ____

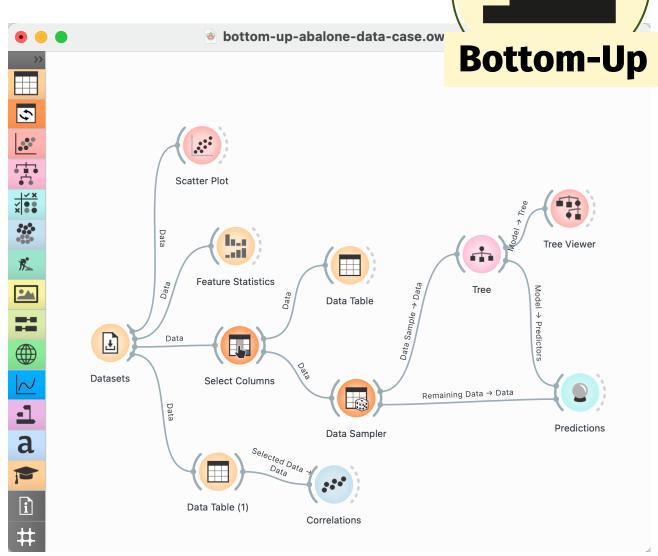
3

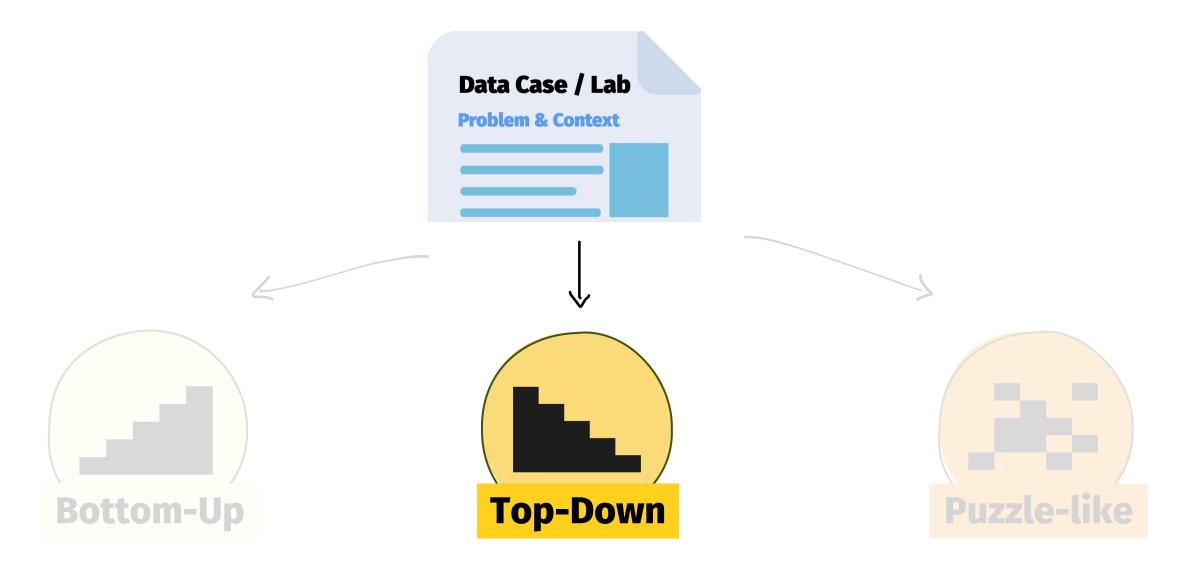




Aufgabe 3. ♀ ○ 5′	Berichte deiner Nachbarin oder deinem Nachbarn von dem Umweltproblem, über das du gelesen hast. Frage deine Nachbarin oder deinen Nachbarn nach dem Umweltproblem in ihrem oder seinem Bericht. Notiere die Gründe für das Aussterben der Abalonen.
0.72	Heißes, and eschwemmtes Wasser, Uberfishing
	Warum dürfen die Abalonen im Norden nicht gefangen werden? Einigt euch und notiert das Ergebnis.
Es gab	Keine Informationer iber eine ongenessene Größeng
Aufgabe 4. 🙉	Notiere, was über die Abalonen im Norden und im Süden bekannt ist.
() 5'	
8:34	Abalonen im Süden Abalonen im Norden
V - /	Im Sider sind die Die Abalonen erreichen
	Abalonen größer nicht die gesetzliche und schwerer. Mindestgröße (138mm).
	Und schwerer. Mindest große (138mm).
Aufgahe 5 Ω	Ihr habt einen Datensatz Abalone mit den Messungen von 4177 nörd-
5	lichen Abalonen erhalten. Ihr schlägt vor, aus diesem Datensatz eine Mindestgröße für den Fang im Norden zu bestimmen, um den Norden
8:37	für Taucher zu öffnen. Nennt vier Beteiligte, die an oder von dem Ergeb [±] nis eurer Arbeit betroffen sind.
	Einhemische, Tourister, Tosmonische Abalonen-
	Tarcher vereinigung, Abolone Verarbeiler
	Tauher
	EINZELARBEIT: Nenne zwei beschreibende Fragen, die du untersuchen
S 5'	musst, um den Norden für Abalone-Taucher zu öffnen.
8:39	Wie hat sich die Purch schnidts große Anzahl
	der Abalonen in den letzten 10 Jahren entwickel?
	Wign .
	V
Aufgabe 7. XX	Vergleiche deine Antworten zu Aufgabe ∰ mit denen deiner Nachbarin oder deines Nachbarn. Habt ihr die gleichen Schwerpunkte gesetzt?
8:41	5

Learning products are the **data flow** and the **written interpretation of findings** derived from the stages of the datadriven lifecycle.





Challenges



Overemphasis on the operating skills of Orange3

There is no reflection on the data-driven lifecycle.



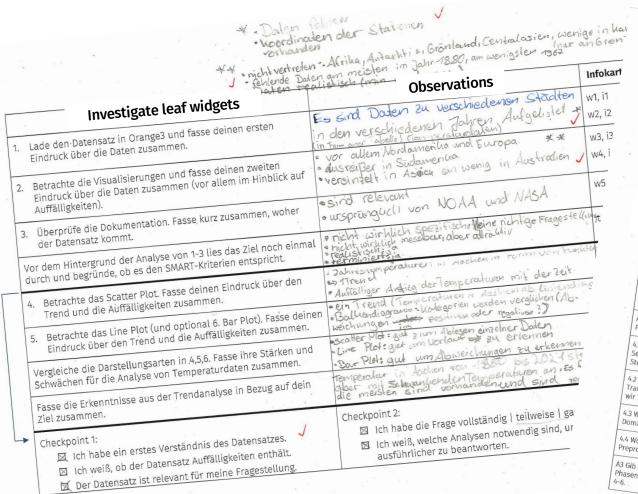




3. Examine the scatter plots. Summarize your impressions of the trend and any notable features.

A3: Give the branch a meaningful phase heading.

Interpretation of findings from the data-driven lifecycle (from the leaf nodes)



Description of the stages in the data-driven lifecycle



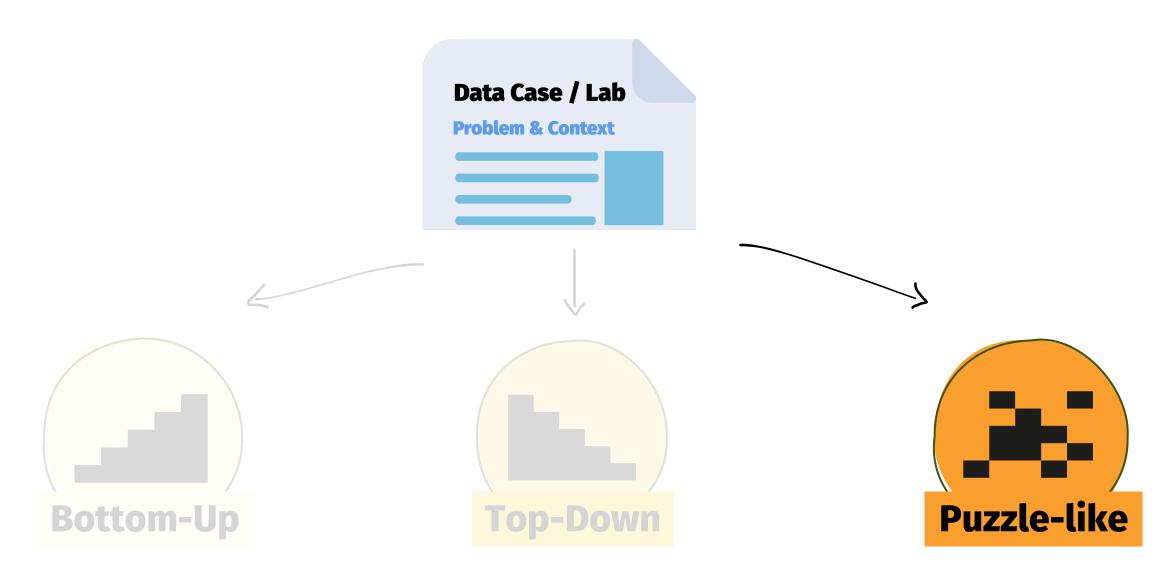
Task Sheet 2: What is the meaning of the widgets in branches for the data-driven process?

Top-Down
the branches in branches for the data-driven process?

Gehe nun durch die Widgets in den Ästen (1-7) und beantworte die Fragen hinter den roten und violetten Pfeilen. Um den Zweck der einzelnen Widgets zu verstehen, lohnt es sich, einen Blick auf den Input und Output des Widgets sowie auf die Info zu werfen.

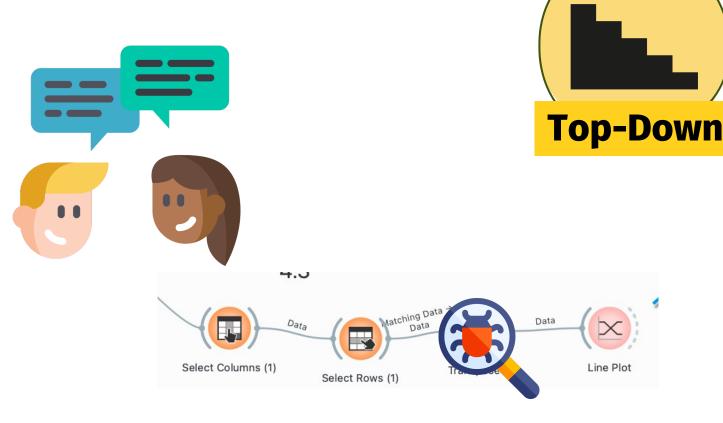


Investigate branch widgets			
1.1 Warum werden die Daten das Data Table Widget gelad	Obs	Servations	
Phasenüberschrift für den Act		pesicht und eventue netner Spallen Dalen in eine über	Ve
2.1. Wozu dient das Widget Select Rows an dieser Stelle?	Um diellouting to	mi cine When	sicht
Phasenüberschrift für den Act o	Chronold der Reihen, die Weberghing den De Karte	MallgorMelly	igesto(u
	dient zur Answahl	Marin cene opergraph	udo soller)
4.2 Wozu dient das Widget Fanspose? Warum brauchen dir Transpose an diese	dient zur Anwahlt den Blaker-Widgel da ollen Liner: alle Zo then zus fill	igedelli werden	
Wozu di	enen Daken Geng / Be	shereing de Dik	-
Wozu diona i	Role Welde Co	les on	
ib eine aus	whit werden da sale	nil den Cata	
enüberschrift für die Äste	Auswählen der Dat endliche Visualisiere	en und	



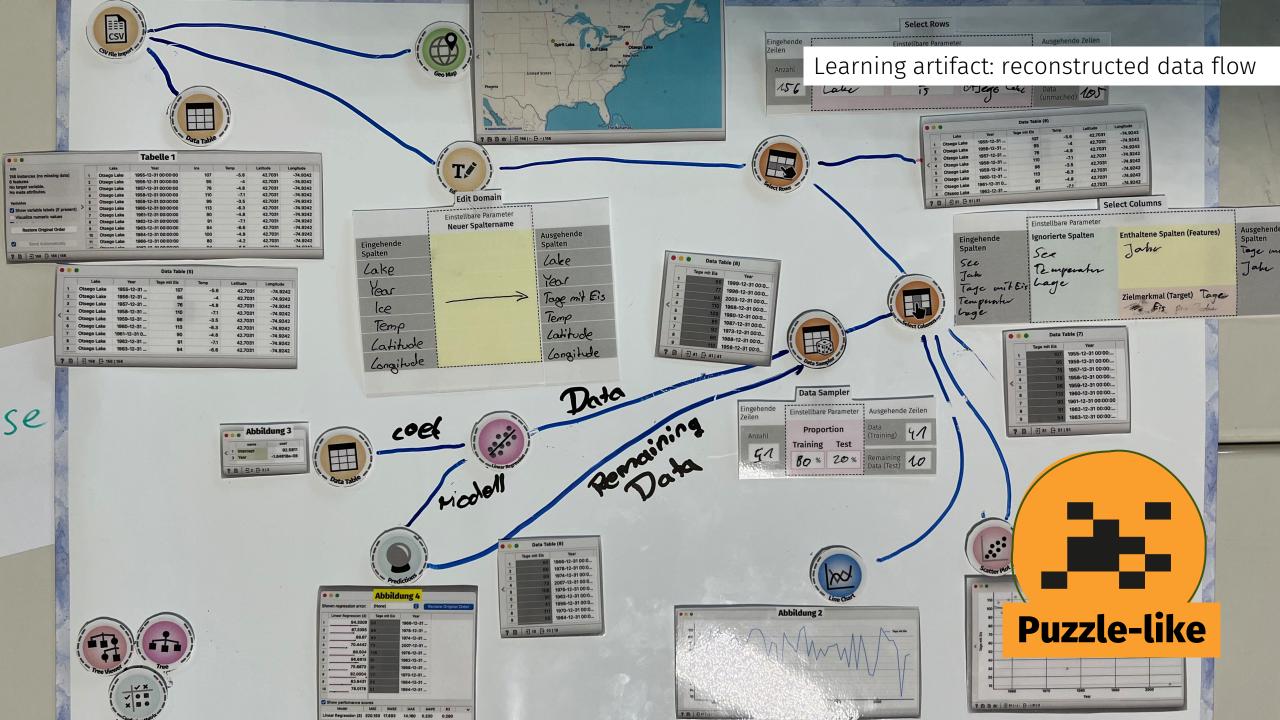
Challenges

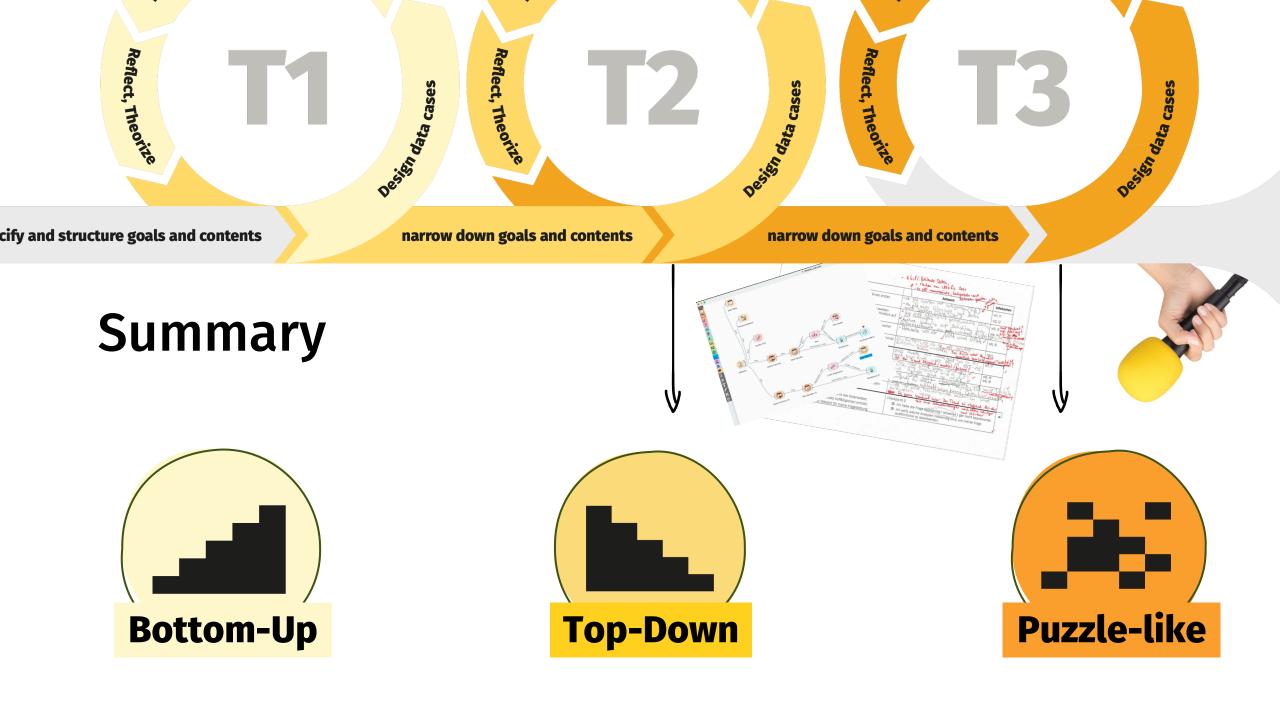
Data case studies offer few opportunities for exchange, "Where I really need to say something to someone else, where I really (...) get into a real conversation." (S1T1W3)

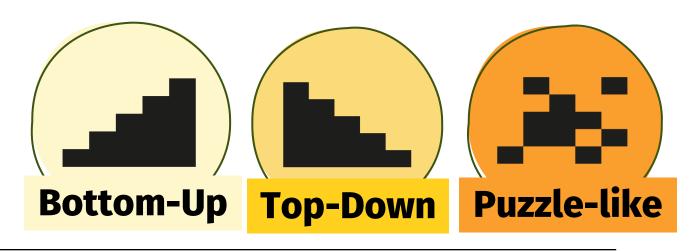


Students lack basic debugging skills.









Challenges

Lack of programming experience	Yes	Yes	Yes
Reflection on the process	No	Yes	Yes
Lack of debugging skills	No	No	Yes
•••	•••	•••	•••
Data concepts and practices	Introduction to a data practice or data concept	Phases in the data flow, reflection	Data flow, debugging flows

https://computingeducation.de



Can be used as a foundation for a common language when teaching about data-driven systems.

Can be used as a guide when specifying competencies.

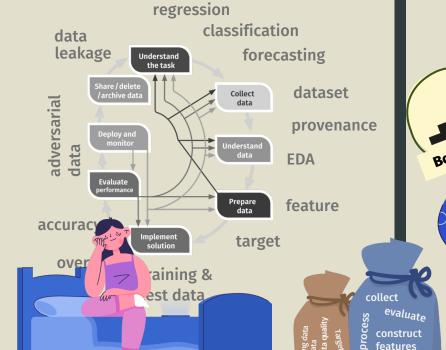
Adapting a method takes time and is challenging. Along the way, we have discovered new ways to teach about data.

Data concepts practices

Summary

Context & Motivation







The data case study

AI content is entering formal education.

Sources

Core curriculum for secondary level I – grades 5 and 6 in North Rhine-Westphalia (2021), https://lehrplannavigator.nrw.de/system/files/media/document/file/si_kl5u6_if_klp_2021_07_01.pdf.

Peter J. Denning. 2003. Great principles of computing. Commun. ACM 46, 11 (November 2003), 15-20. https://doi.org/10.1145/948383.948400

Andreas Schwill. 1994. Fundamental Ideas of Computer Science. (1994). Retrieved from http://ddi.cs.uni-potsdam.de/Forschung/Schriften/EATCS.pdf

David Touretzky, Christina Gardner-McCune, Fred Martin, and Deborah Seehorn. 2019. Envisioning AI for K-12: What Should Every Child Know about AI? In Proceedings of the AAAI Conference on Artificial Intelligence, July 17, 2019. 9795–9799. https://doi.org/10.1609/aaai.v33i01.33019795

Matti Tedre, Peter Denning, and Tapani Toivonen. 2021. CT 2.0. In Proceedings of the 21st Koli Calling International Conference on Computing Education Research (Koli Calling '21), November 2021. Association for Computing Machinery, New York, NY, USA, 1–8. https://doi.org/10.1145/3488042.3488053

Tilman Michaeli, Ralf Romeike, and Stefan Seegerer. 2022. What Students Can Learn About Artificial Intelligence – Recommendations for K-12 Computing Education. In Towards a Collaborative Society Through Creative Learning, 2022. Springer Nature Switzerland, Cham, 196–208. https://doi.org/10.1007/978-3-031-43393-1_19

Jane Waite, Ethel Tshukudu, Veronica Cucuiat, Robert Whyte, and Sue Sentance. 2023. Towards a Framework for Learning Content Analysis in K-12 AI/ML Education. In 2023 IEEE Frontiers in Education Conference (FIE), October 18, 2023. IEEE, College Station, TX, USA, 1–5. https://doi.org/10.1109/FIE58773.2023.10343368

Viktoriya Olari and Ralf Romeike. 2021. Addressing Al and Data Literacy in Teacher Education: A Review of Existing Educational Frameworks. 2021. Association for Computing Machinery, Virtual Event, Germany, Article 17. https://doi.org/10.1145/3481312.3481351

Daochen Zha, Zaid Pervaiz Bhat, Kwei-Herng Lai, Fan Yang, and Xia Hu. 2023. Data-centric Al: Perspectives and Challenges. In Proceedings of the 2023 SIAM International Conference on Data Mining (SDM), Shashi Shekhar, Zhi-Hua Zhou, Yao-Yi Chiang and Gregor Stiglic (eds.). Society for Industrial and Applied Mathematics, Philadelphia, PA, 945–948. https://doi.org/10.1137/1.9781611977653

Johannes Jakubik, Michael Vössing, Niklas Kühl, Jannis Walk, and Gerhard Satzger. 2024. Data-Centric Artificial Intelligence. Bus Inf Syst Eng (March 2024). https://doi.org/10.1007/s12599-024-00857-8

Sajid Ali, Tamer Abuhmed, Shaker El-Sappagh, Khan Muhammad, Jose M. Alonso-Moral, Roberto Confalonieri, Riccardo Guidotti, Javier Del Ser, Natalia Díaz-Rodríguez, and Francisco Herrera. 2023. Explainable Artificial Intelligence (XAI): What we know and what is left to attain Trustworthy Artificial Intelligence. Information Fusion 99, (November 2023), 101805. https://doi.org/10.1016/j.inffus.2023.101805

Kostas Kampourakis. 2018. On the Meaning of Concepts in Science Education. Sci & Educ 27, 7–8 (October 2018), 591–592. https://doi.org/10.1007/s11191-018-0004-x

Viktoriya Olari and Ralf Romeike. 2024. Data-related concepts for artificial intelligence education in K-12. Computers and Education Open 7, (December 2024), 100196. https://doi.org/10.1016/j.caeo.2024.100196

Sandro Costa and Fabiele Broietti. 2023. What are scientific practices and why are they relevant in science education? Revista Brasileira de Ensino de Ciência e Tecnologia 16, (January 2023), 1–22. https://doi.org/10.3895/rbect.v16n1.14897

Sources (continued)

Viktoriya Olari and Ralf Romeike. 2024. Data-related practices for creating Artificial Intelligence systems in K-12. Proceedings of the 19th WiPSCE Conference on Primary and Secondary Computing Education Research, Article 5. Retrieved from https://doi.org/10.1145/3677619.3678115

OECD. 2025. Empowering learners for the age of AI: An AI literacy framework for primary and secondary education (Review draft). OECD, Paris. Retrieved from https://ailiteracyframework.org

Orit Hazzan and Koby Mike. 2024. Guide to teaching data science: an interdisciplinary approach. Springer, Cham.

Yim Register and Amy J. Ko. 2020. Learning Machine Learning with Personal Data Helps Stakeholders Ground Advocacy Arguments in Model Mechanics. In Proceedings of the 2020 ACM Conference on International Computing Education Research, August 10, 2020. ACM, Virtual Event New Zealand, 67–78. https://doi.org/10.1145/3372782.3406252

Chantel Ridsdale, James Rothwell, Mike Smit, Michael Bliemel, Dean Irvine, Daniel Kelley, Stan Matwin, Brad Wuetherick, and Hossam Ali-Hassan. 2015. Strategies and Best Practices for Data Literacy Education Knowledge Synthesis Report. (2015). https://doi.org/10.13140/RG.2.1.1922.5044

Deborah Ann Nolan and Terry Speed. 2001. Stat labs: mathematical statistics through applications (Corr. 2. print ed.). Springer, New York Berlin Heidelberg.

Valentina Chkoniya. 2021. Success Factors for Using Case Method in Teaching Applied Data Science Education. European Journal of Education 4, 1 (April 2021), 77–86. https://doi.org/10.26417/236hbm84v

Carrie Wright, Qier Meng, Michael R. Breshock, Lyla Atta, Margaret A. Taub, Leah R. Jager, John Muschelli, and Stephanie C. Hicks. 2024. Open Case Studies: Statistics and Data Science Education through Real-World Applications. Journal of Statistics and Data Science Education (2024), 1–30. https://doi.org/10.1080/26939169.2024.2394541

Erin Rae Hoffer. 2020. Case-based Teaching: Using Stories for Engagement and Inclusion. 2, 2 (2020), 75–80.

T. Grandon Gill. 2011. Informing with the case method: a guide to case method research, writing, & facilitation. Informing Science Press, Santa Rosa.

Clyde Freeman Herreid. 2011. Case study teaching. New Drctns for Teach & Learn 2011, 128 (December 2011), 31-40. https://doi.org/10.1002/tl.466

Jana Lasser, Debsankha Manik, Alexander Silbersdorff, Benjamin Säfken, and Thomas Kneib. 2021. Introductory data science across disciplines, using Python, case studies, and industry consulting projects. Teaching Statistics 43, S1 (July 2021). https://doi.org/10.1111/test.12243

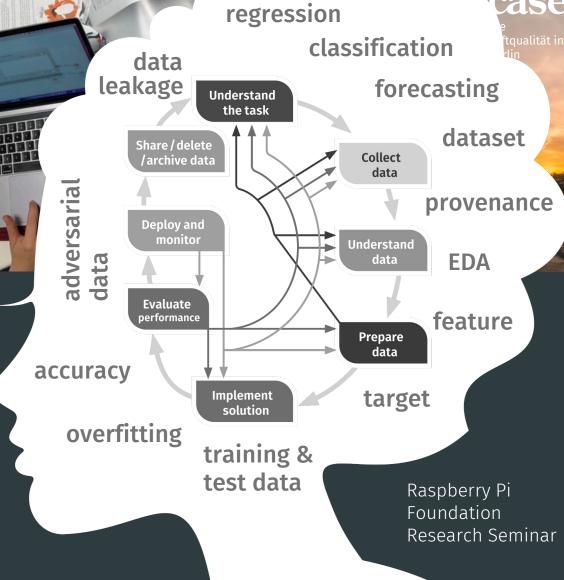
Claire Toogood. 2023. Supporting students to engage with case studies: a model of engagement principles. Educational Review (November 2023), 1–15. https://doi.org/10.1080/00131911.2023.2281227

Susanne Prediger, Michael Link, Renate Hinz, Stephan Hussmann, Bernd Ralle, and Jörg Thiele. 2012. Lehr-Lernprozesse initiieren und erforschen. Fachdidaktische Entwicklungsforschung im Dortmunder Modell. Der mathematische und naturwissenschaftliche Unterricht 65, 8 (2012), 452–457.





Data-related concepts and practices for AI education in K-12



Viktoriya Olari | 14.10.2025



