Comprehension, Correction and Competence: Combining XAI and ITS for Human and Machine Teaching

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Machine Teaching for Explainable AI

Workshop

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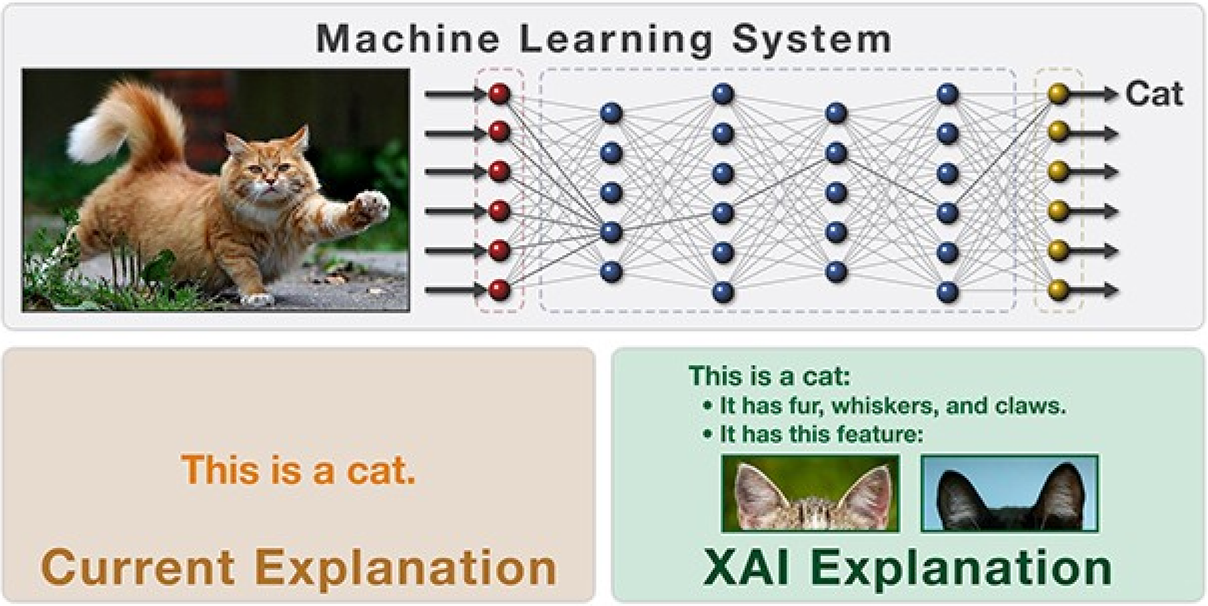
XAI is for comprehending ML models



http://www.darpa.mil/program/explainable-artificial-intelligence

David Gunning, IJCAI 2016

ITS is for comprehending a knowledge domain

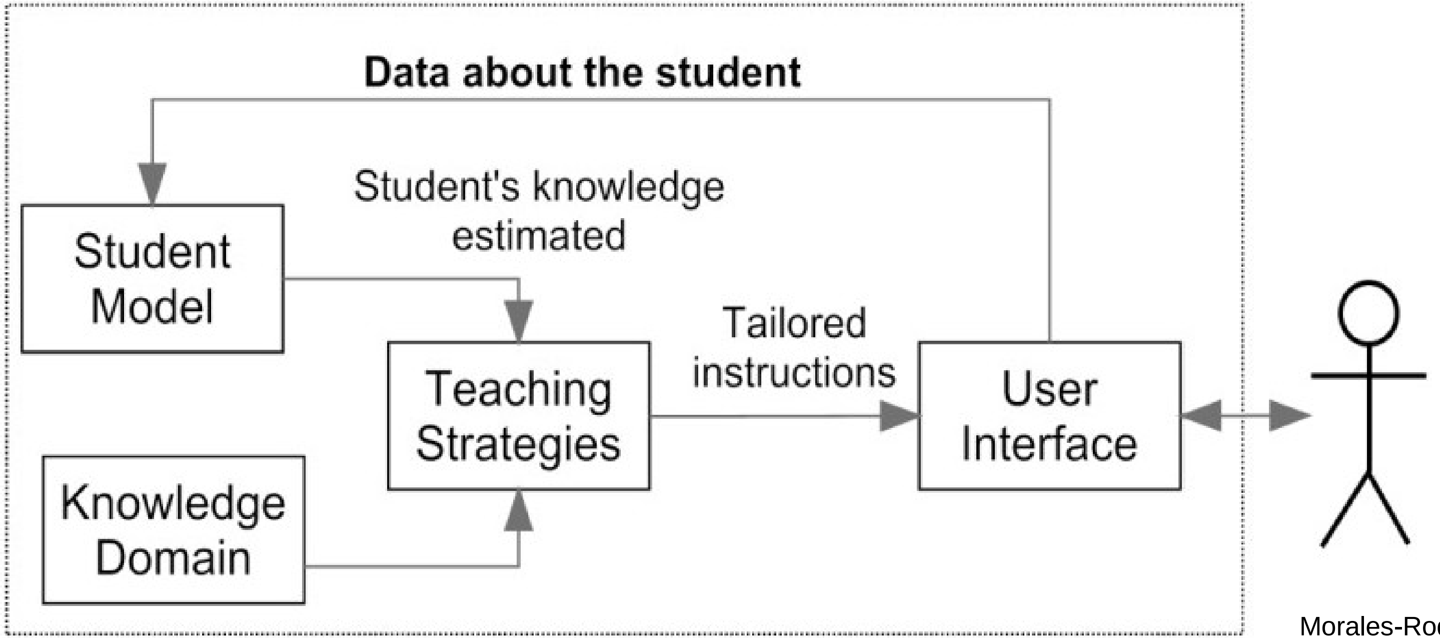


Fig. 1. Basic architecture of an ITS [7].

Morales-Rodríguez, M.L., Ramírez-Saldivar, A., Hernández-Ramírez, A., Sánchez-Solís, J.P., & Flores, J.A. (2012). Architecture for an Intelligent Tutoring System that Considers Learning Styles. Res. Comput. Sci., 47, 37-47.

How can XAI and ITS be interleaved?

- XAI offers an ever growing set of explanation methods
- ITS provides methods to model the knowledge states (and maybe other psychological aspects) of humans
- XAI can profit for tailoring explanations to fit the specific information need of humans
- ITS can profit by extending the set of didactic interventions

Explanation Methods in XAI

What a good explanation is, is context-dependent:

- what is explained

a current output or the model (local vs. global), a classification, a detected anomaly, a generated text ... (type of model output)

- to whom

an ML expert, a domain expert, a end-user

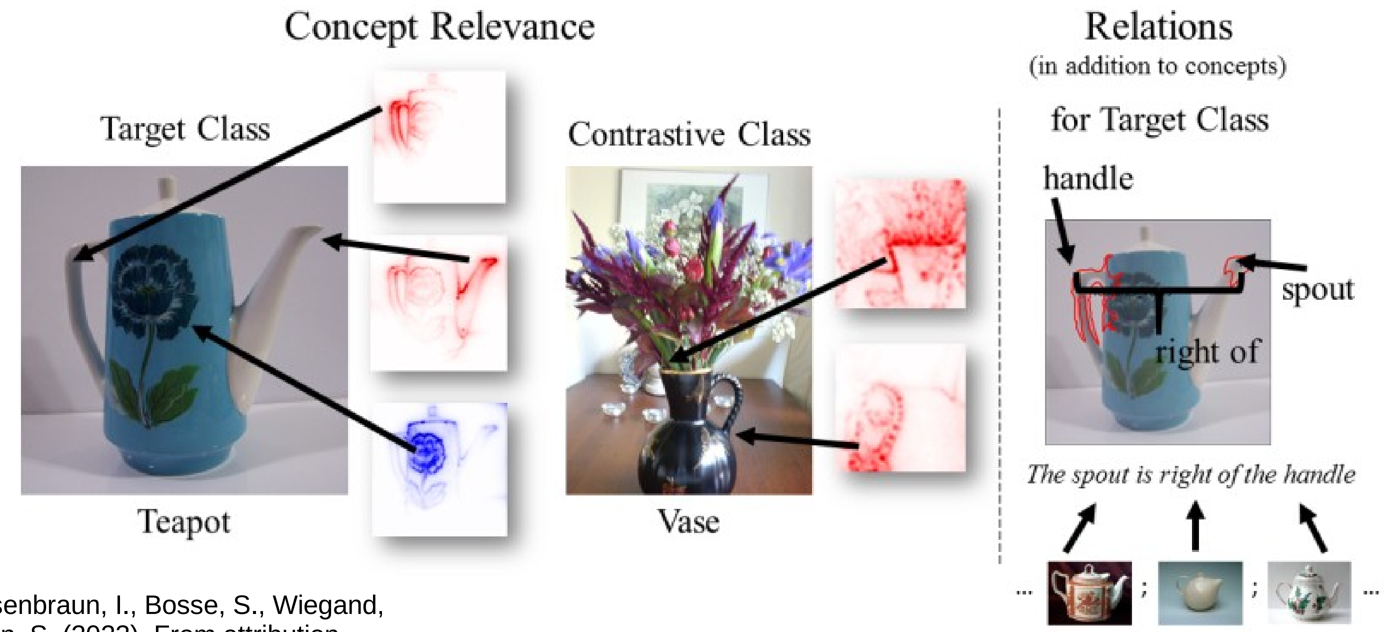
- in what way (how)

highlighting, symbolic/verbal, example, prototype, counterfactual, contrastive

- for what reason (why)

Understand reason for possible wrong output, decision boundaries, understand to correct (XIML)

Explaining with concepts and relations



See esp.:

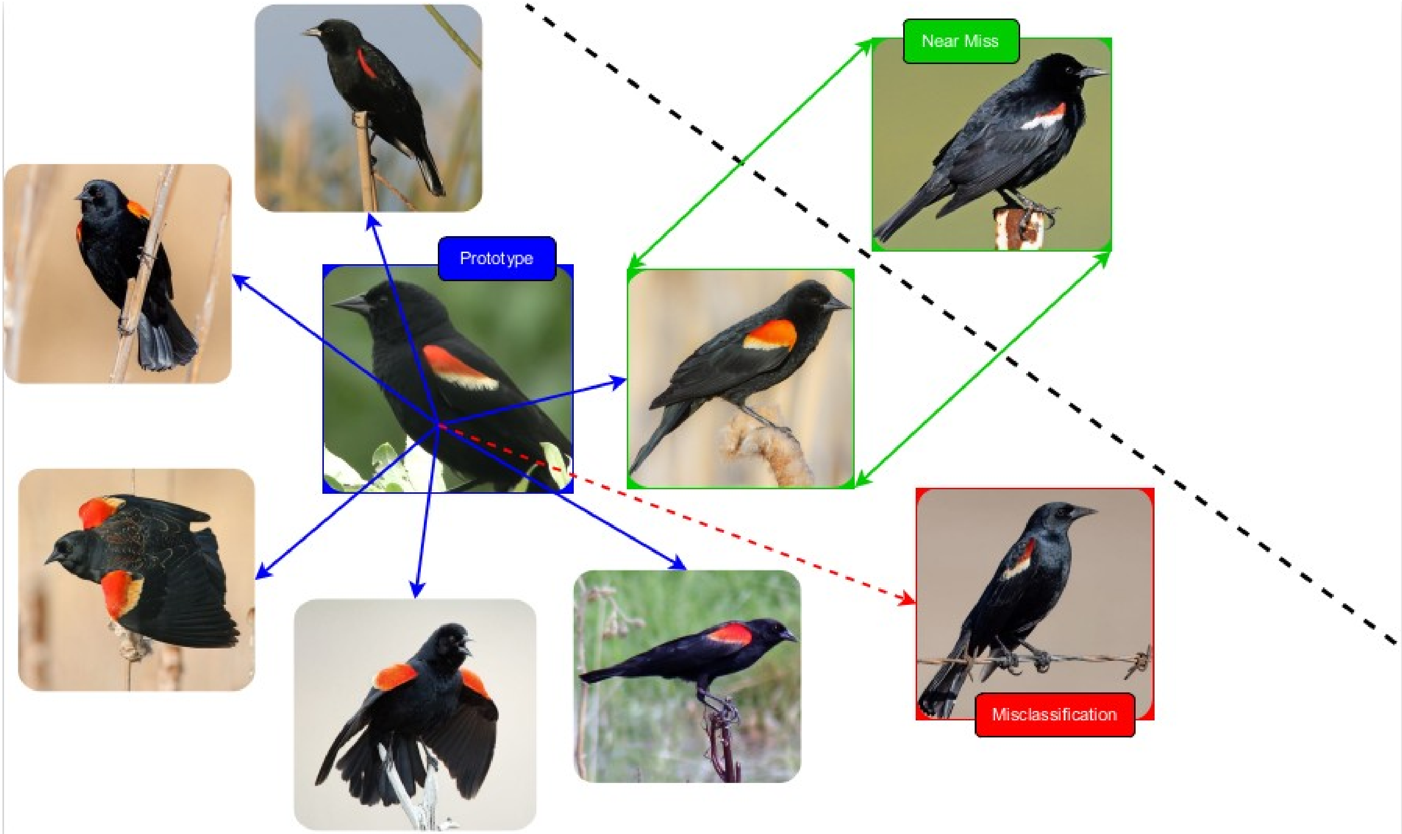
Achtibat, R., Dreyer, M., Eisenbraun, I., Bosse, S., Wiegand, T., Samek, W., & Lapuschkin, S. (2023). From attribution maps to human-understandable explanations through Concept Relevance Propagation. Nature Machine Intelligence, 5(9), 1006-1019.

Explanation by Near Misses and Prototypes

See also:

Herchenbach, M., Müller, D., Scheele, S., & Schmid, U. (2022, May). Explaining Image Classifications with Near Misses, Near Hits and Prototypes: Supporting Domain Experts in Understanding Decision Boundaries. In International Conference on Pattern Recognition and Artificial Intelligence (pp. 419-430). Cham: Springer International Publishing.

Rabold, J., Siebers, M., & Schmid, U. (2022). Generating contrastive explanations for inductive logic programming based on a near miss approach. Machine Learning, 111(5), 1799-1820.



Near Miss Explanations for Effective Teaching

Table A1. *High- and low-similarity word pairs used in Experiments 1 and 2*

Similar pairs		Dissimilar pairs	
Light bulb	Candle	VCR	Lounge chair
Kitten	Cat	Hammock	Horse track
Magazine	Newspaper	Bed	Hockey
Bowl	Mug	Football	Boutique
Phone book	Dictionary	Kite	Painting
Microphone	Stereo speaker	Sculpture	Navy
Piano	Organ	Army	Abacus
Air conditioner	Furnace	Calculator	Escalator
Freezer	Refrigerator	Stairs	Stool
Hammer	Mallet	Broom	Sailboat
Bicycle	Tricycle	Yacht	Missile
Dumpster	Garbage can	Chair	Banana split
Lake	Ocean	Ice cream sundae	Clock
Telephone	CB radio	McDonald's	Couch
Diamond	Ruby	Police car	Burger King
Sponge	Towel	Rocket	Motel
Computer	Typewriter	Hotel	Tape deck
Staple	Paper clip	Watch	Ambulance
Shoe	Sandal	Casino	Mop
Chemistry	Biology	Stove	Hang glider
VCR	Tape deck	Light bulb	Cat
Hammock	Lounge chair	Kitten	Newspaper

Gentner & Markman. Structural alignment in comparison: No difference without similarity. Psychological Science, 5(3):152–158, 1994.

Contrastive Explanations and Causality

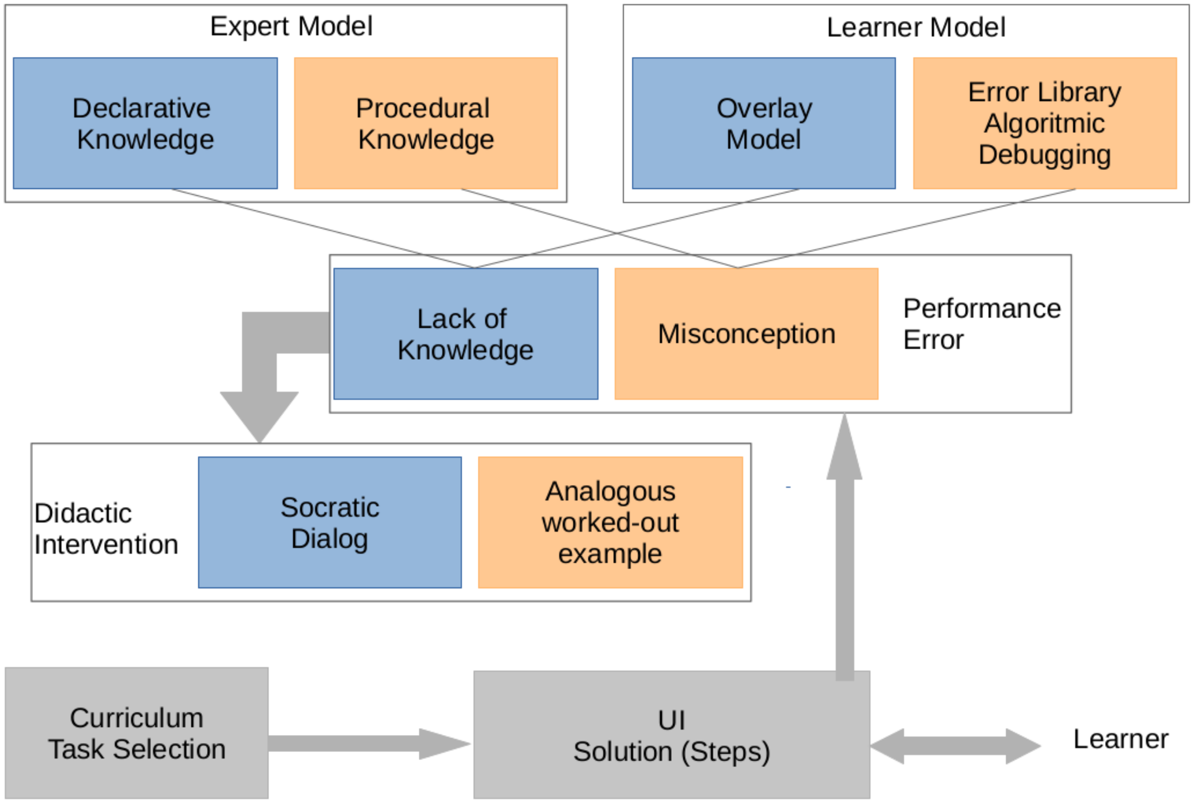
Causal explanations are contrastive (Tim Miller, 2019, refering to P. Lipton, Contrastive explanation, Royal Institute of Philosophy Supplement 27, 1990)

- To be a beetle, an arthropod must have six legs, but this does not cause an arthropod to be a beetle – other causes are necessary.
- But, to answer the question: “Why is image J labelled as a Beetle instead of a Spider?” it is sufficient to cite the fact that the arthropod in the image has six legs.
- We do not need information about eyes, wings, or stingers to answer this, whereas to explain why image J is a spider in a non-contrastive way, we must cite all causes.

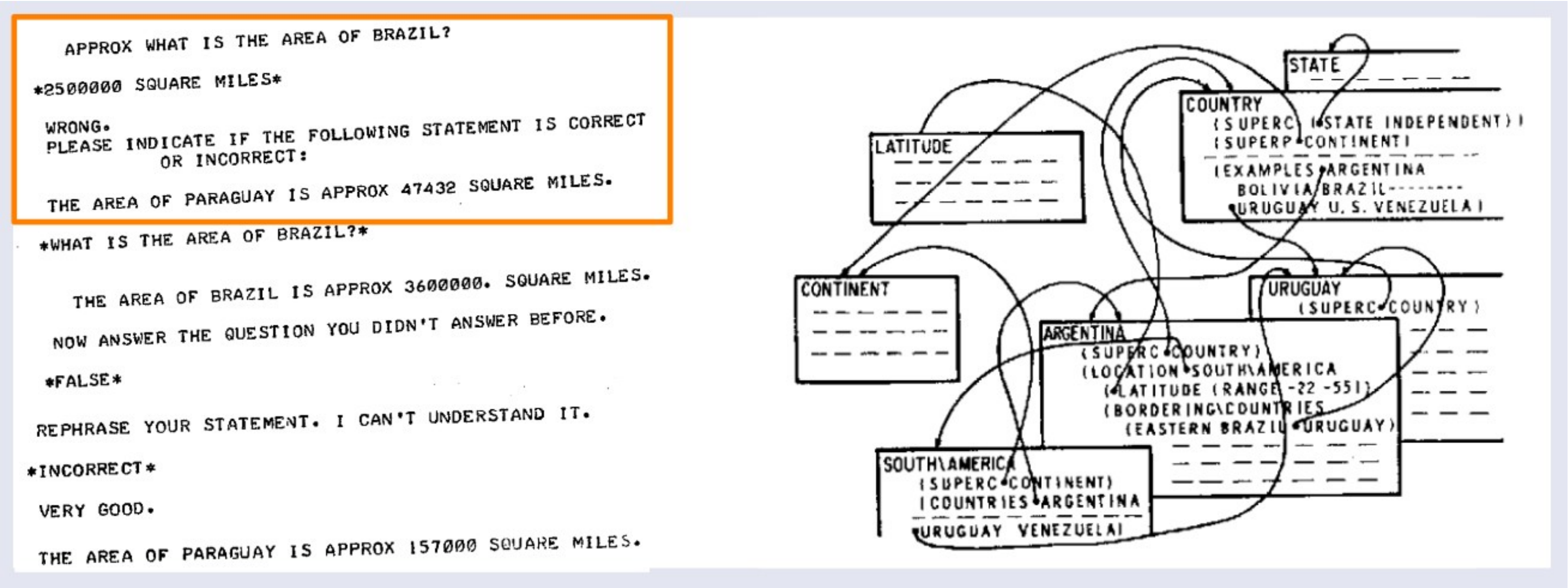
Type	No. Legs	Stinger	No. Eyes	Compound Eyes	Wings
Spider	8	✘	8	✘	0
Beetle	6	✘	2	✔	2
Bee	6	✔	5	✔	4
Fly	6	✘	5	✔	2

Tim Miller, Explanation in artificial intelligence: Insights from the social sciences. AIJ 2019

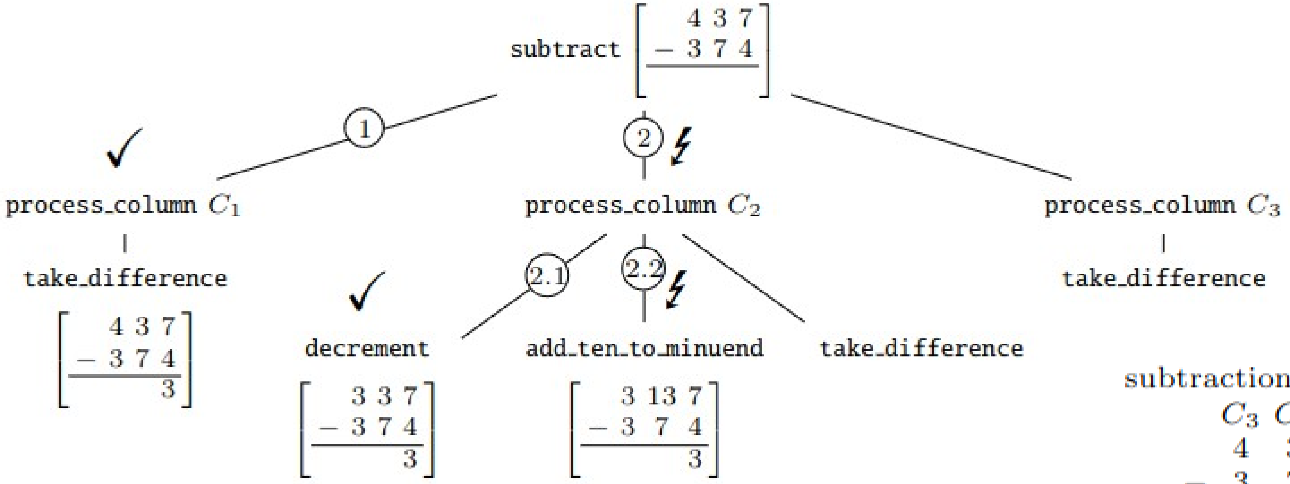
Modeling knowledge states



Example: Overlay Model in Scholar (Carbonell, 1970)



Identifying misconceptions with Algorithmic Debugging



subtraction problem

	C_3	C_2	C_1
	4	3	7
−	3	7	4

typical student solution

	m_{-1}	m^{+10}	m
	3	3	7
−	3	7	4
	0	4	3

analogous problem

	C_3	C_2	C_1
	4	1	0
−	1	8	0

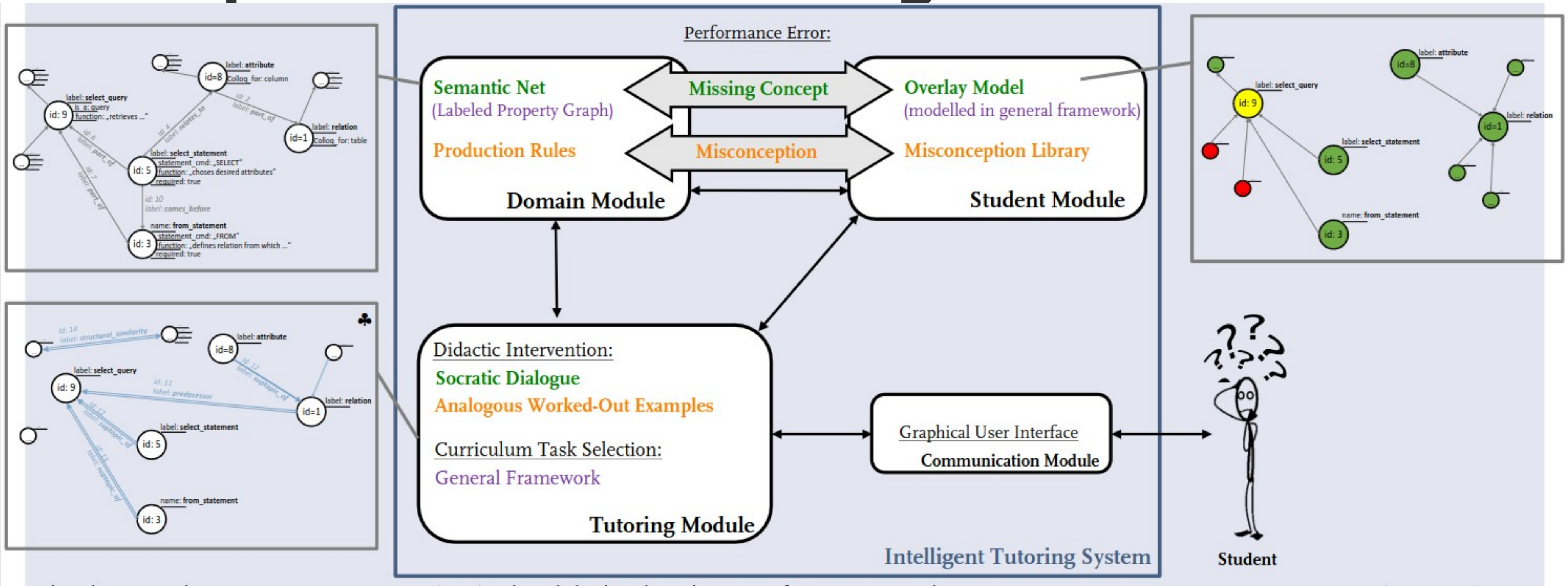
analogous problem solution

	m_{-1}	m^{+10}	m
	3	11	0
−	1	8	0
	2	3	0

And giving feedback
with an analog worked-out example

Zeller, C., & Schmid, U. (2016). Automatic generation of analogous problems to help resolving misconceptions in an intelligent tutor system for written subtraction.

General Structure to ITS with declarative and procedural knowledge



Thaler, A. M., Mitrovic, A., Schmid U. (2022). Worked Examples as Application of Analogical Reasoning in Intelligent Tutoring and their Effects on SQL Competencies. Biannual Conference of the German Cognitive Science Society. (KogWis, 2022, Freiburg, Germany)

An ITS for Primary School Education

Learn to look closely and be aware of relevant feature values to discriminate local trees

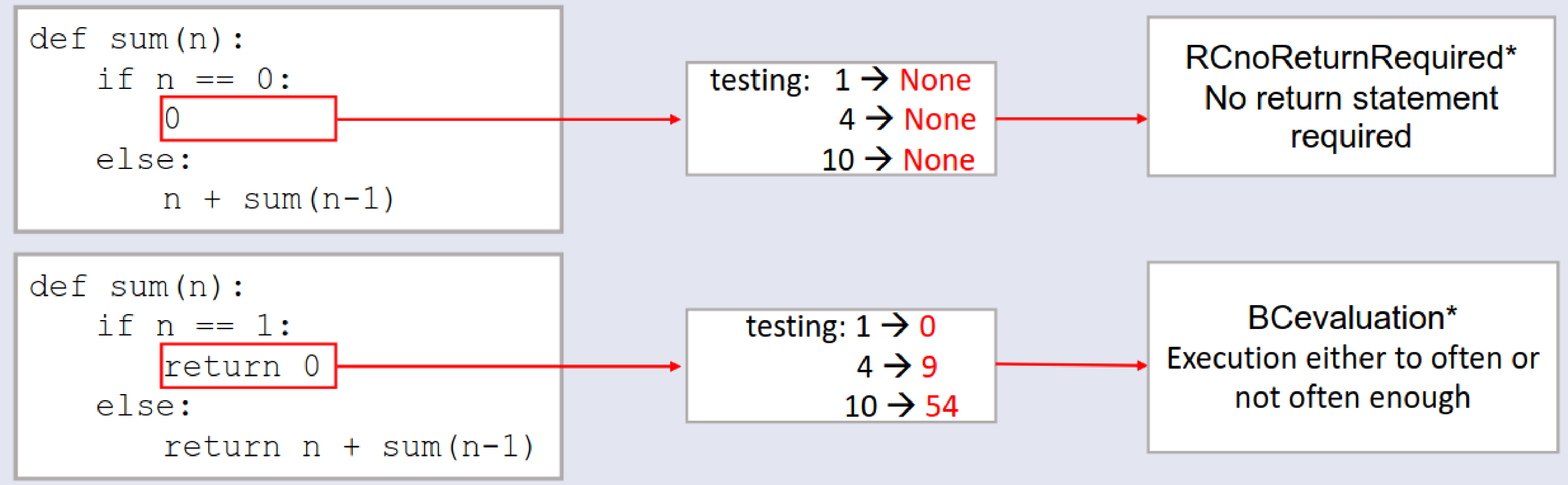
- Shape: tripartite, lobed, elliptic
- Margin: even, wavy toothed, saw toothed

https://en.wikipedia.org/wiki/Leaf

Near miss on feature value:
show a leaf which indeed is saw toothed
and one which is wavy toothed
(but from another category)

Schmid, U. (2020). AI goes to school: learning about and learning with artificial intelligence. In Proceedings of the 15th Workshop on Primary and Secondary Computing Education.

ITS for Recursive Programming – Identifying misconceptions by testing

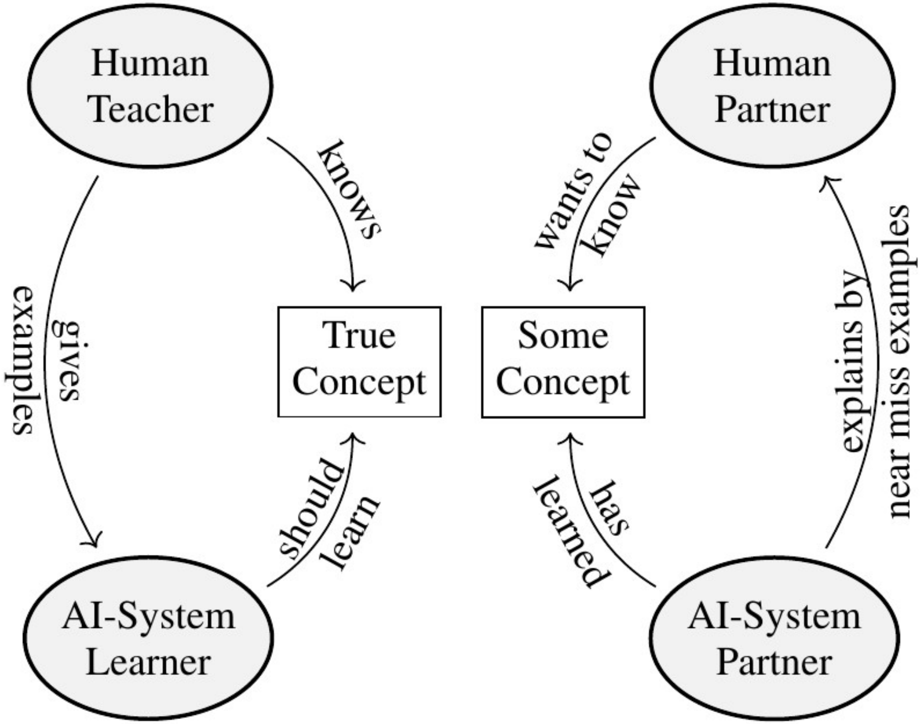


*Sally Hamouda, Stephen H. Edwards, et al., (2017) A basic recursion concept inventory, Computer Science Education, 27:2, 121-148

See esp.

Nguyen, M. H., Tschiatschek, S., & Singla, A. (2023). Large Language Models for In-Context Student Modeling: Synthesizing Student's Behavior in Visual Programming from One-Shot Observation. arXiv preprint arXiv:2310.10690.

Near Miss Explanations for Effective Learning and Effective Teaching



(a) Learning (b) Explaining

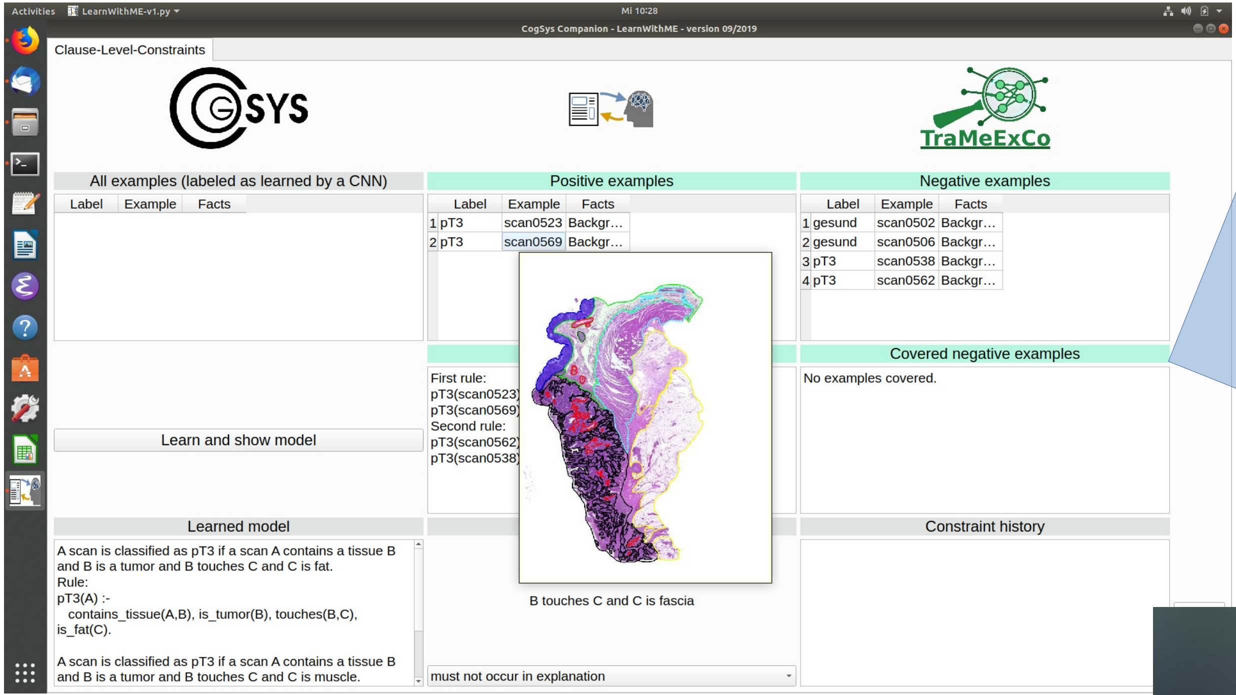
Patrick Winston, Learning structural descriptions from examples.
MIT/LCS/TR-76, 1970.

Principles of efficient teaching

Shafto, Goodman, & Griffiths, A rational account of pedagogical reasoning: Teaching by, and learning from, examples. Cognitive Psychology, 71, 55-89, 2014

Telle, J. A., Hernández-Orallo, J., & Ferri, C. (2019). The teaching size: computable teachers and learners for universal languages. Machine Learning, 108(8), 1653-1675.

Decision Making in Medicine



Explanation as foundation for Interactive ML

Schmid, U., & Finzel, B. (2020). Mutual explanations for cooperative decision making in medicine. KI-Künstliche Intelligenz, 34(2), 227-233.

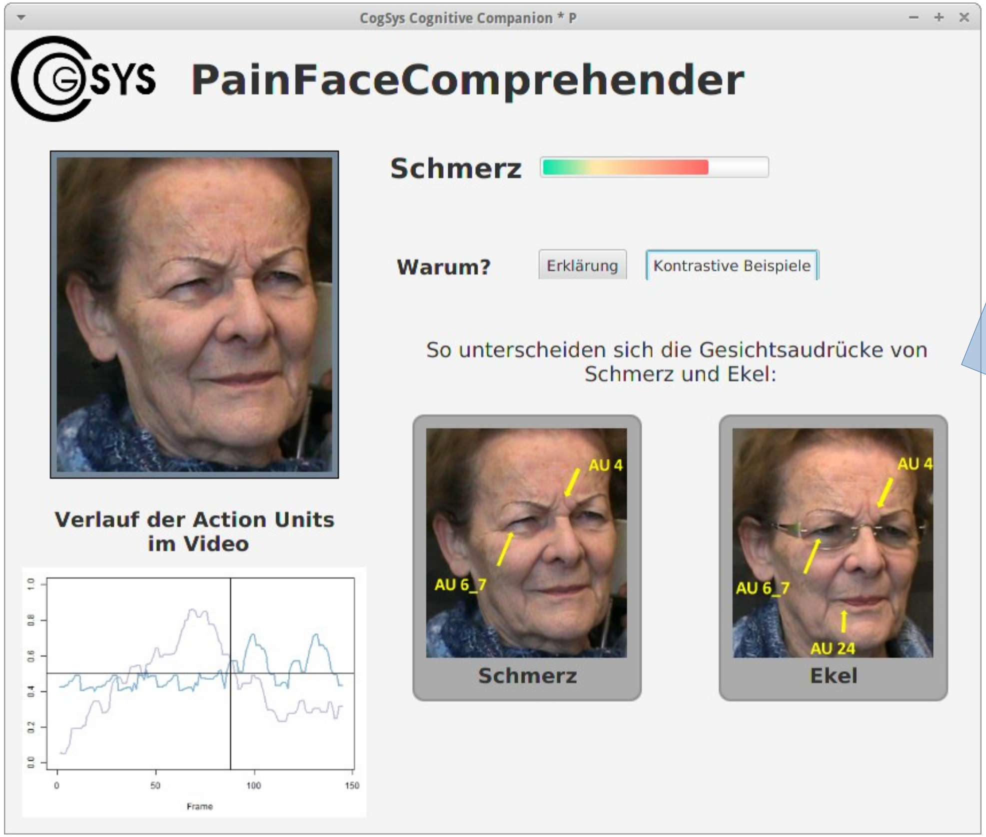
Near-miss Explanations for interactive ML and ITS

- Near-miss explanations can be used for interactive explanatory ML (e.g., CAIPI by Teso & Kersing)
  taking the human as teacher for an AI system
- Near-miss explanations can also be used for intelligent tutoring systems
  taking the AI system as teacher (ultra-strong ML)

TESO, Stefano; KERSTING, Kristian. Explanatory interactive machine learning. In: Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society. 2019. S. 239-245.

Educating Nurses

Deutsche Forschungsgemeinschaft



Learned model + explanation
as input to educate nurses
= ultra-strong ML

Hassan, T., Seuß, D., Wollenberg, J., Weitz, K., Kunz, M., Lautenbacher, S., ... & Schmid, U. (2019). Automatic detection of pain from facial expressions: a survey. IEEE Transactions on Pattern Analysis and Machine Intelligence, 43(6), 1815-1831.

Ultra-Strong Machine Learning

Donald Michie (1988):

- **Weak ML:** machine learner produces improved predictive performance with increasing amounts of data
- **Strong ML:** additionally requires the learning system to provide its hypotheses in symbolic form (interpretable machine learning, e.g. Rudin, Nature ML, 2019)
- **Ultra-strong ML:** extends the strong criterion by requiring the learner to teach the hypothesis to a human, whose performance is consequently increased to a level beyond that of the human studying the training data alone

Human to Machine Teaching

Machine to Human Teaching

Explanatory Dialog

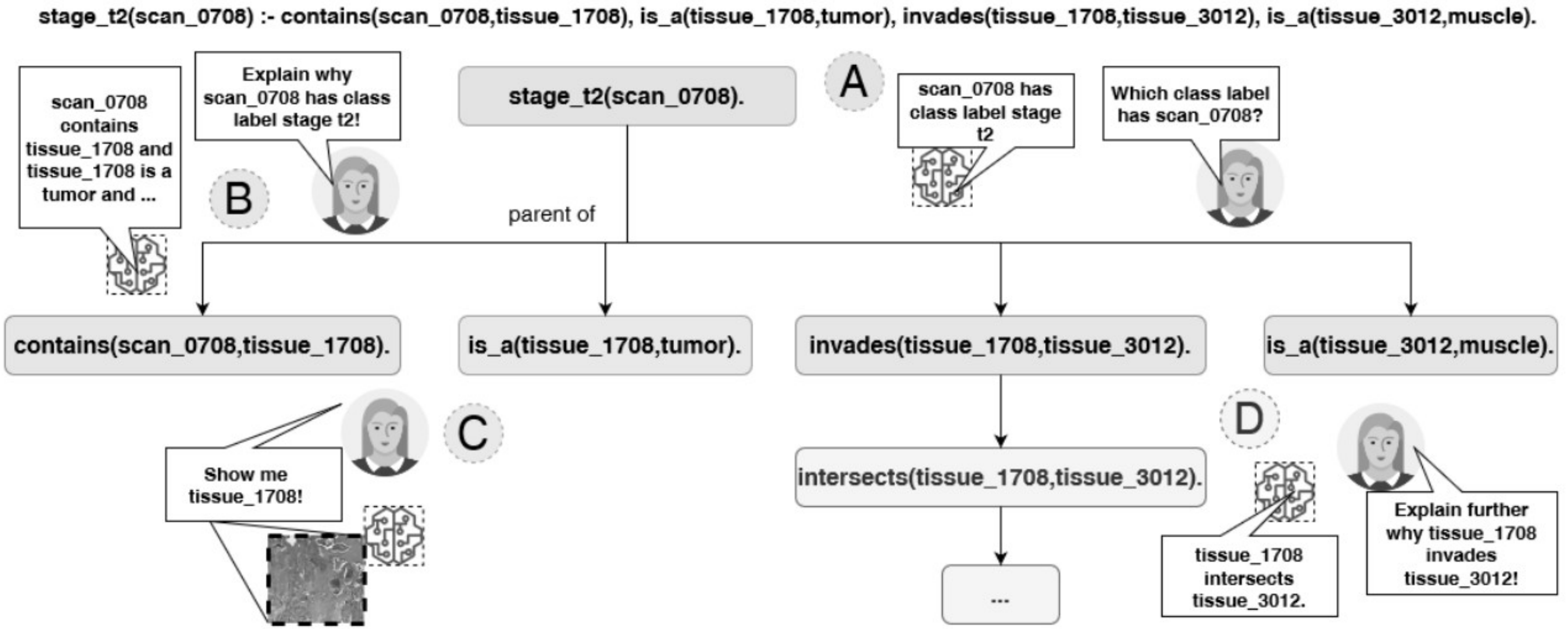


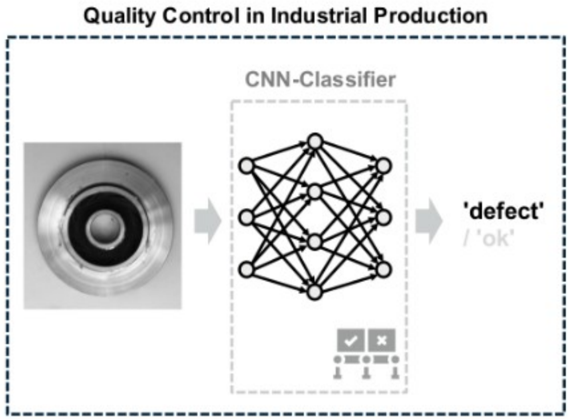
Figure 2: An explanatory tree for *stage_t2(scan_0708)*, that can be queried by the user to get a local explanation why scan_0708 is labeled as T2 (steps A and B). A dialogue is realized by further requests, either to get more visual explanations in terms of prototypes (step C) or to get more verbal explanations in a drill-down manner (step D).

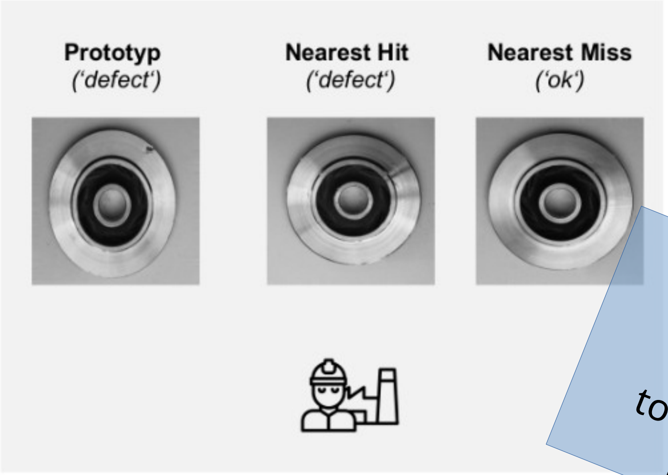
Finzel, Tafler, Thaler, & Schmid, 2021 AAAI Fall Symposium Human.AI

Wrapping Up

- XAI offers a growing set of approaches to explain ML models but for beneficiary human-AI partnerships, it is important to take into account the specific information need of the human in a given context, here methods from ITS may be helpful
- Human-AI partnerships can be realized in two ways
  - Human as provider of information for model adaptation (XIML)
  - Learned model as provider of new insights (ultrastrong ML)
- Interleaving XAI and ITS might be a way to address both perspectives

Example-based Explainable AI (XAI) Demonstrator





Help the quality engineer
to understand classification
bounderies of the model
to provide helpful examples
for model adaptation

Re-implementation of Kim, Khanna, Koyejo: Examples are not Enough – Learn to Criticize! Criticism for Interpretability, NeurIPS 2016

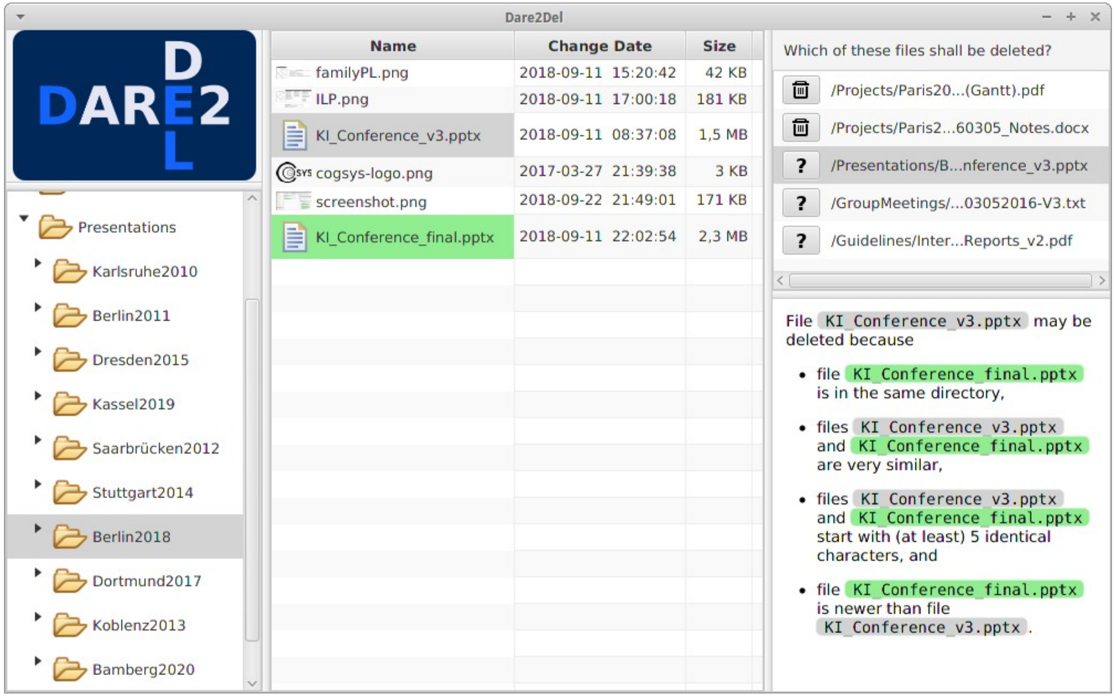
$$\mathrm{MMD}^2(X, Y) := \frac{1}{|X|^2} \sum_{x_1, x_2 \in X} k(x_1, x_2) + \frac{1}{|Y|^2} \sum_{y_1, y_2 \in Y} k(y_1, y_2) - \frac{2}{|X| \cdot |Y|} \sum_{x \in X, y \in Y} k(x, y)$$

Maximum Mean Discrepancy, similarity measure on distributions

Extended to Near Miss Explanations

Herchenbach, Müller, Scheele, & Schmid, Explaining image classifications with near misses, near hits and prototypes. ICPRAI 2022.

Deleting Irrelevant Files/Data



Deutsche Forschungsgemeinschaft

What must be minimally changed that this file is not classified as Irrelevant?

Schmid, U. (2021). Interactive learning with mutual explanations in relational domains. In: S. Muggleton and N. Chater, Human-like Machine Intelligence,(chap.~17). 338-354, OUP.