# Introduction to Computational Intelligence


## Explainable Artificial Intelligence

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Based on Barredo Arrieta et al. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion, 58, 82-115

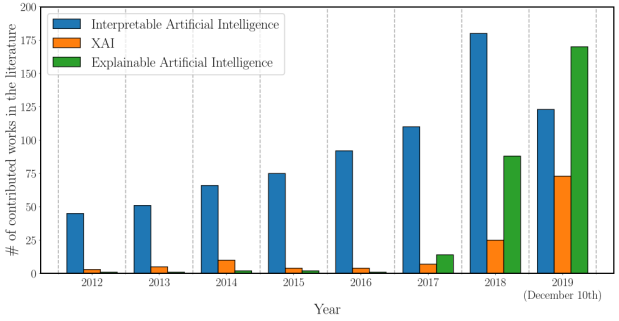
# Shapshots of AI history

- 1950s – Alan Turing, Norbert Wiener
  - small cybernetic robots (animats) ← behaviorism
  - e.g. turtles (Walter), mouse (Shannon) ← NNs, RL involved
- 1955 – Simon, Newell, Minsky, McCarthy – birth of AI (cognitivism)
  - focus on human mental tasks: math. theorem proving, problem solving, board games, later extended: e.g. medical diagnosis, legal argumentation, NLP, common sense reasoning
  - based on symbolic AI (as opposed to numeric AI = NNs), mostly transparent
- 1986 – revival of NNs (thank to backpropagation)
- 2010 – outburst of deep NN (thank to fast computers and lots of data), seen as black-boxes (with tons of parameters)



# Introduction

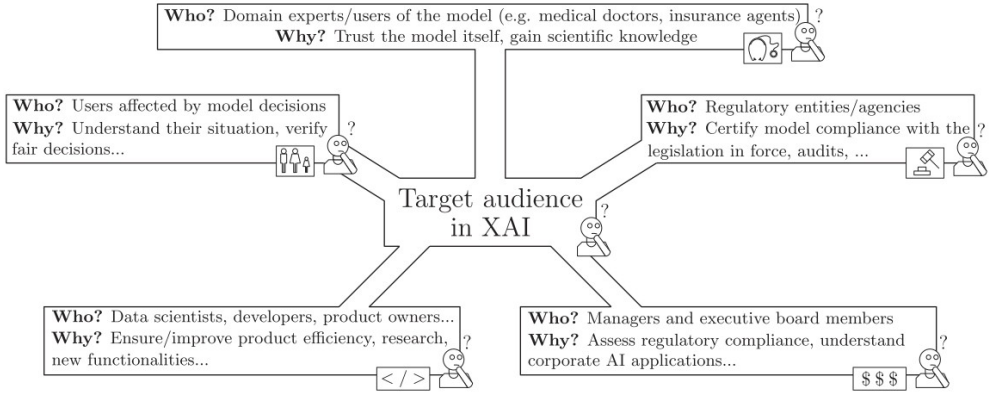
- Current hype in narrow AI thank to flourishing deep learning
  - DL started after 2006
- growing applications of DL in various practical domains
- But, neural networks as black-box models
- => need for interpretable, transparent, explainable AI (XAI)






# Different purposes of explainability in ML

Two goals dominant: need for model understanding, and regulatory compliance




(Rossi, 2019)

# Terminology

- Understandability (intelligibility) – of a model function by a human, without any need for explaining its internal structure or the algorithmic means by which the model processes data internally.
- Comprehensibility – refers to the ability of a learning algorithm to represent its learned knowledge in a human understandable fashion.
- Interpretability – the ability to provide the meaning in understandable terms to a human.
- Explainability – an interface between humans and a decision maker, i.e., at the same time, both an accurate proxy of the decision maker and comprehensible to humans.
- Transparency – Since a model can feature different degrees of understandability, transparent models fall into three categories: simulatable models, decomposable models and algorithmically transparent models.

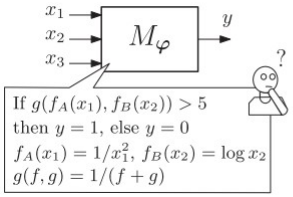


# Goals towards explainability

| Goal | Target audience |
|---|---|
| Trustworthiness | Domain experts, users of the model affected by decisions |
| Causality | Domain experts, managers and executive board members, regulatory entities/agencies |
| Transferability | Domain experts, data scientists |
| Informativeness | All |
| Confidence | Domain experts, developers, managers, regulatory entities/agencies |
| Fairness | Users affected by model decisions, regulatory entities/agencies |
| Accessibility | Product owners, managers, users affected by model decisions |
| Interactivity | Domain experts, users affected by model decisions |
| Privacy awareness | Users affected by model decisions, regulatory entities/agencies |

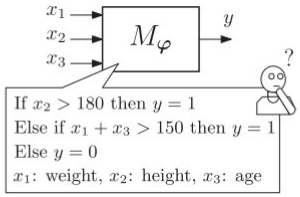


# Different levels of transparency



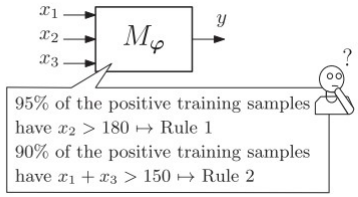

simulatability

Enable mental simulation, e.g. a simple linear model (a simple perceptron), but not a symbolic system with too many rules.




decomposability

Every input must be readily interpretable. Every part of the model must be understandable by a human without the need for additional tools.

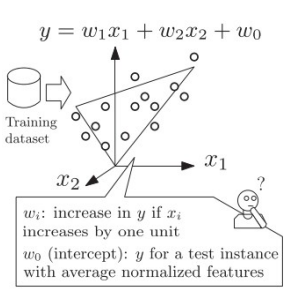



algorithmic transparency

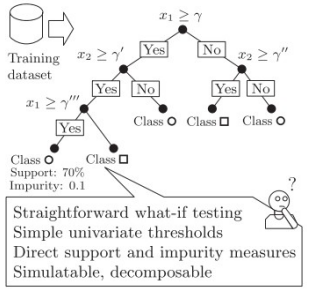
Model has to be fully explorable by means of mathematical analysis and methods (e.g. linear vs deep NN).



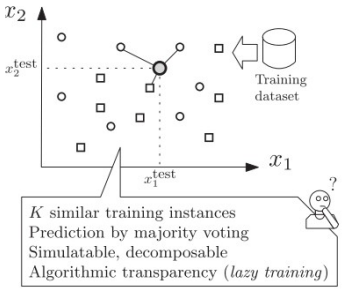
# Levels of transparency of different ML models



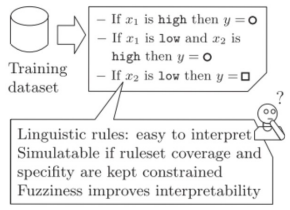

(a) Linear regression



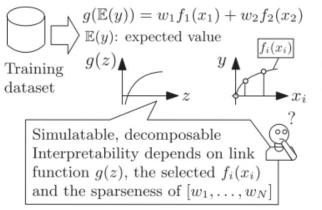

(b) Decision trees



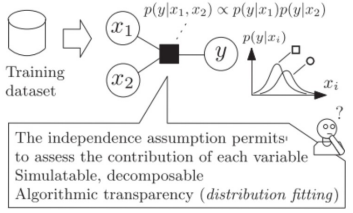

(c) K-nearest neighbors




(d) Rule-based learners

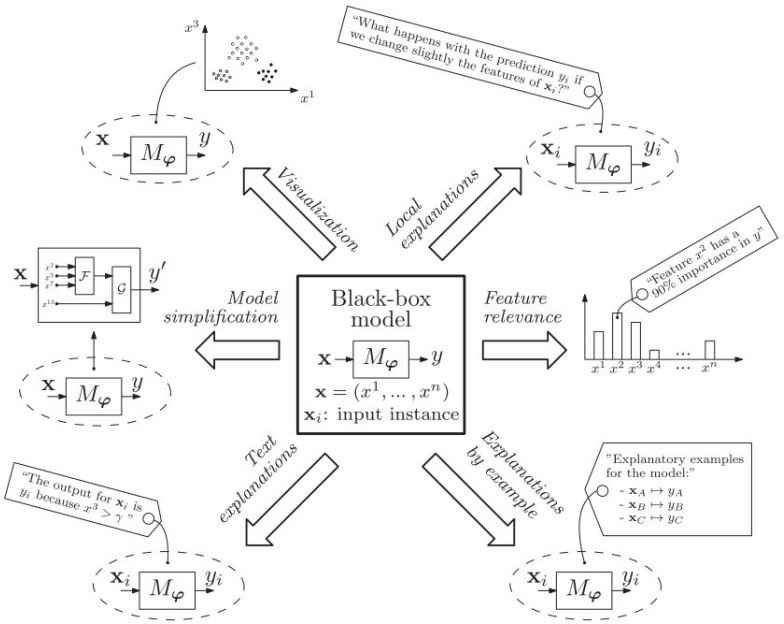



(e) Generalized additive models




(f) Bayesian models

# Post-hoc explainability approaches

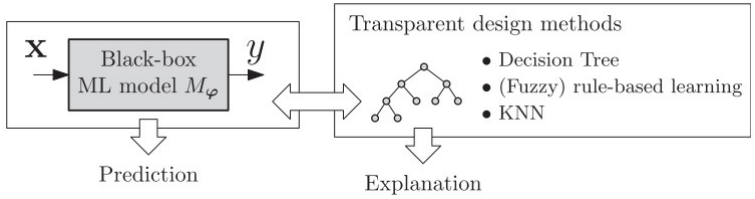





# Non-transparent approaches

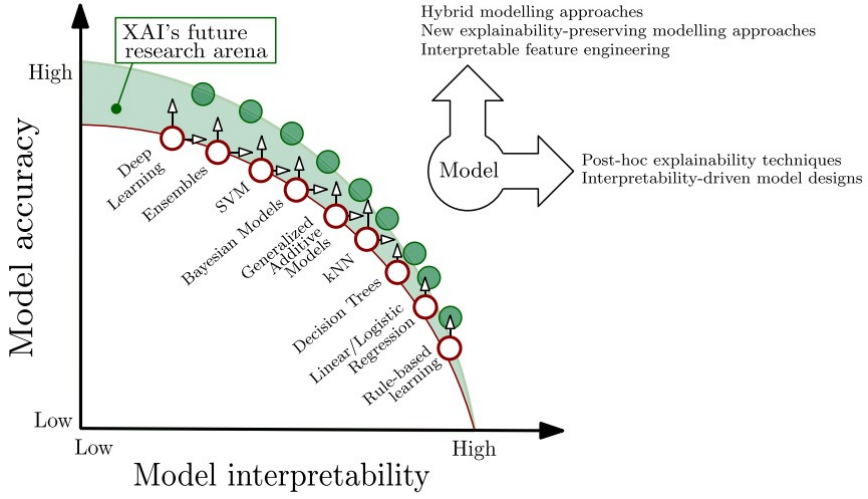
- model-agnostic host-hoc explainability, by
  - simplification, feature relevance, local, visualisation
- model-specific host-hoc explainability in
  - support vector machines, multilayer, convolutional, recurrent NN, utitilize the methods above

# Possible approach: Hybrid models






# Trade-off in AI methods






# Authors' vision