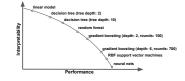
Interpretable Machine Learning

Introduction, Motivation, and History

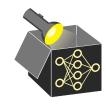


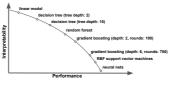
Learning goals

- Why interpretability?
- Developments until now?
- Use cases for interpretability



Interpretable Machine Learning Introduction, Motivation, and History





Learning goals

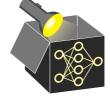
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WHY INTERPRETABILITY?

- ML: huge potential to aid decision-making process due to its predictive performance
- ML models are black boxes, e.g., XGBoost, RBF SVM or DNNs

 → too complex to be understood by humans
- Some applications are "learn to understand"







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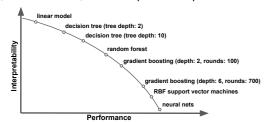




Interpretable Machine Learning - 1/4

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 - hurts trust
 - 2 creates barriers
- Many disciplines with required trust rely on traditional models, e.g., linear models, with less predictive performance













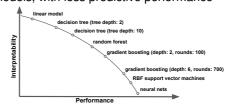
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Interpretable Machine Learning - 1/4 - 1/4

INTERPRETABILITY IN HIGH-STAKES DECISIONS

 Credit scoring and insurance applications ➤ Society of Actuaries

> Reasons for not granting a loan Fraud detection in insurance claims













Examples of critical areas where decisions based on ML models can affect human life



INTERPRETABILITY IN HIGH-STAKES DECISIONS

Examples of critical areas where decisions based on ML models can affect human life

- Credit scoring and insurance applications Click for source
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Interpretable Machine Learning - 2/4 - 2/4

INTERPRETABILITY IN HIGH-STAKES DECISIONS

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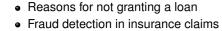


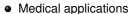




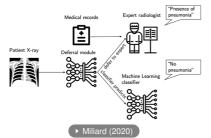








- Identification of diseases
- Recommendations of treatments
- ...



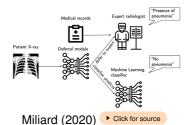


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Interpretable Machine Learning - 2/4 - 2/4

NEED FOR INTERPRETABILITY

Need for interpretability becoming increasingly important from a legal perspective

- General Data Protection Regulation (GDPR) requires for some applications that models have to be explainable
 Goodman & Flaxman (2017)
 - → EU Regulations on Algorithmic Decision-Making and a "Right to Explanation"
- Ethics guidelines for trustworthy AI European Commission (2019)





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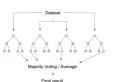
Interpretable Machine Learning - 3 / 4

BRIEF HISTORY OF INTERPRETABILITY

- 18th and 19th century: Linear regression models (Gauss, Legendre, Quetelet)
- 1940s: Emergence of sensitivity analysis (SA)
- Middle of 20th century: Rule-based ML, incl. decision rules and decision trees
- **2001**: Built-in feature importance measure of random forests
- >2010: Explainable AI (XAI) for deep learning
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Interpretable Machine Learning - 4/4 - 4/4