TELL ME WHY

BUILDING SAFE AND ROBUST MODELS: INTRODUCTION TO EXPLAINABILITY

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WHOAMI

Bachelor in Informatics Engineering (UPC, 2016)

MSc in Innovation and Research (UPC & EPFL, 2018)

PhD in Computing (UPC)

PADS-UPC Research Group (Process Mining Data Science Group) https://www.cs.upc.edu/~pads-upc/

WHOAMI

Machine Learning for industry (Fraud Detection for Utilities)

Bundle of Datasets

Generalization about the data

Scoring

WHOAMI

User ID	Score
User 1	0.96
User 2	0.95
User ...	...
User N	0.001

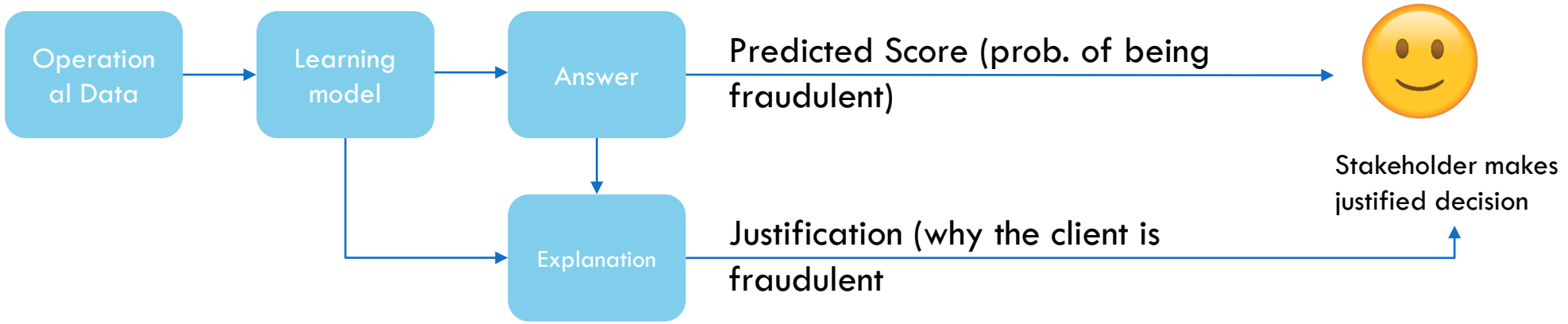
Stakeholder makes decision

Why did you that ?
When you succeed ?
When do you fail ?
When can I trust you ?
How do I correct an error ?

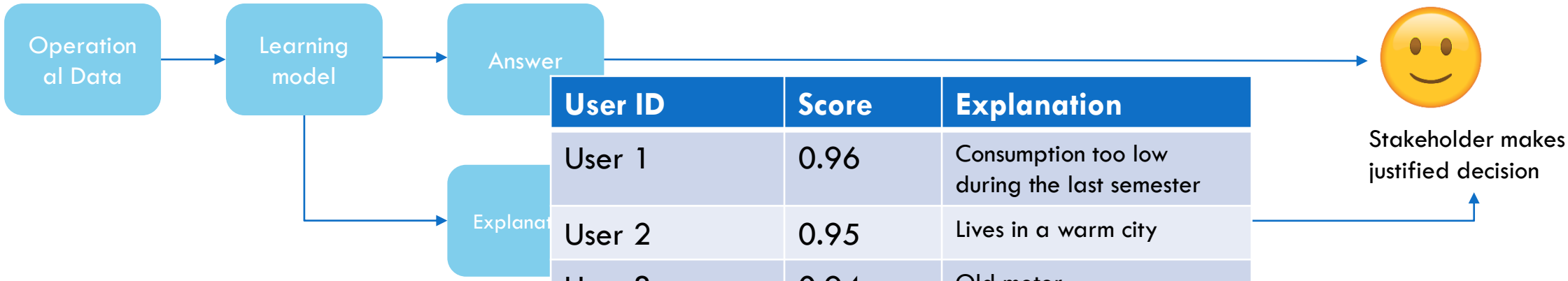
*Adapted from DARPA Slides

Problems of confidence and trust arise in sensitive models (high economic impact or lives)

WHOAMI


Operation al Data
Learning model
Answer
Explanation
Predicted Score (prob. of being fraudulent)
Justification (why the client is fraudulent
Stakeholder makes justified decision

WHOAMI



I understand why
I understand why not
I know when you fail
I know when to trust you
I know why you erred

*Adapted from DARPA Slides

FORMAL DEFINITION OF EXPLAINABILITY

· **Definition 1,** Science of comprehending what a model did, or might have done

[Leilani H. et altrum 2019]

· **Definition 2,** Ability to explain or to present understandable terms to a human

[Finale Doshi-Velez and Been Kim 2017]

· **Definition 3,** Use of machine-learning models for the extraction of relevant knowledge about domain relationships contained in data

[W. James Murdoch et altrum 2019]

EXPLAINABILITY GOALS

Explainability to confirm other important desiderata of ML systems

Fairness : protected groups are not somehow discriminated against

Privacy: means the method protects sensitive information in the data

Reliability & Robustness: ascertain whether algorithms reach certain levels of performance in the face of parameter of input variation

Causality: predicted change in output due to a perturbation will occur in the real system

Usable and trusted: information to assist users to accomplish a task

...

From : Towards A Rigorous Science of Interpretable Machine Learning Finale Doshi-Velez* and Been Kim*

AN ACTUAL DEMAND

Right to Explanation

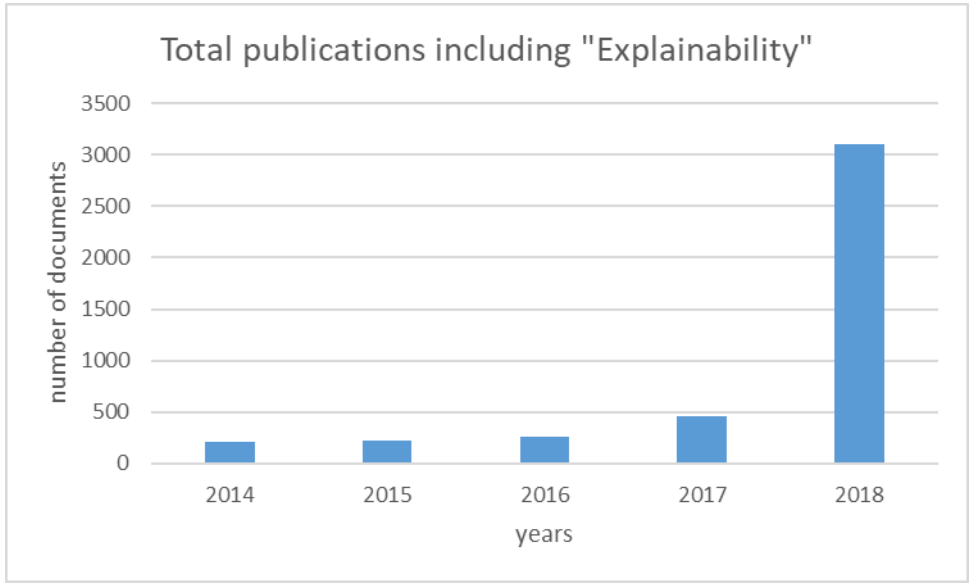
Human agency and oversight: AI systems should empower human beings, allowing them to make ***informed decisions*** *and fostering their fundamental rights.*

…

Transparency: the data, system and AI business models should be ***transparent****. Moreover, AI systems and their decisions should be* ***explained in a manner adapted to the stakeholder concerned****.*

https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai

AN ACTUAL DEMAND



Google Scholar

Explainability is included in top tier congress

- ICML (International conference on Machine Learning), B++

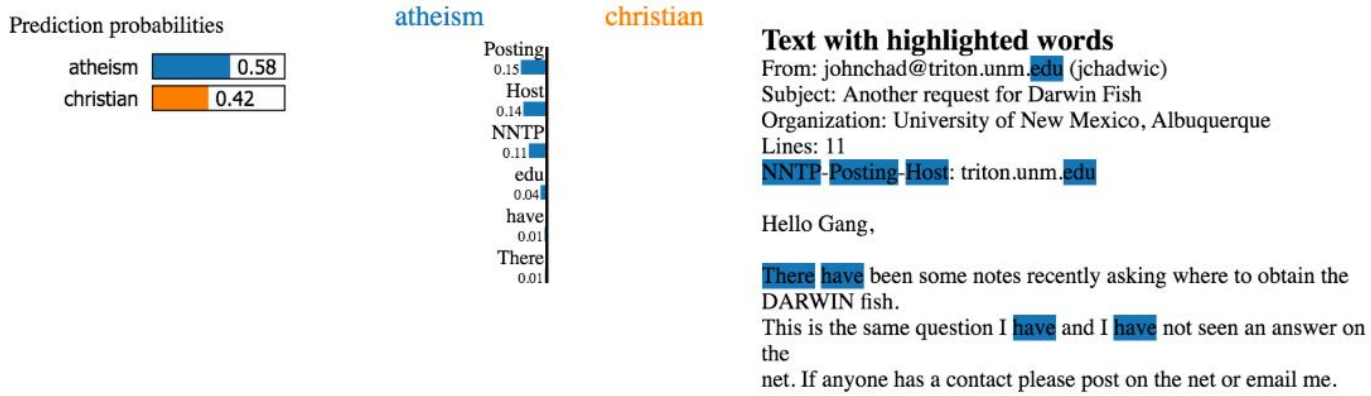
- KDD (ACM International Conference On Knowledge Discovery and Data Mining), A++

- NIPS (Neural Information Processing Systems), A++

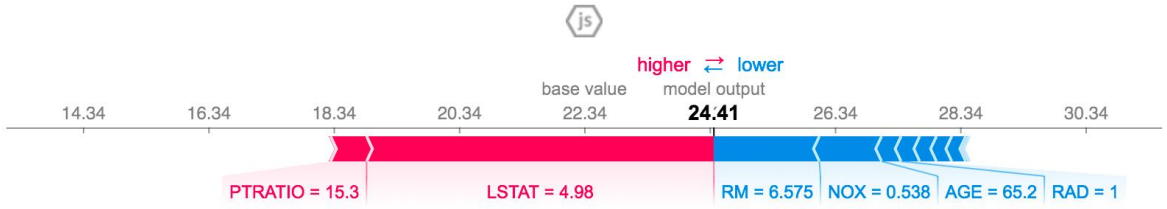
- ECAI (European Conference on Artificial Intelligence), A

EXAMPLES OF EXPLAINABILITY

Explanations in Images

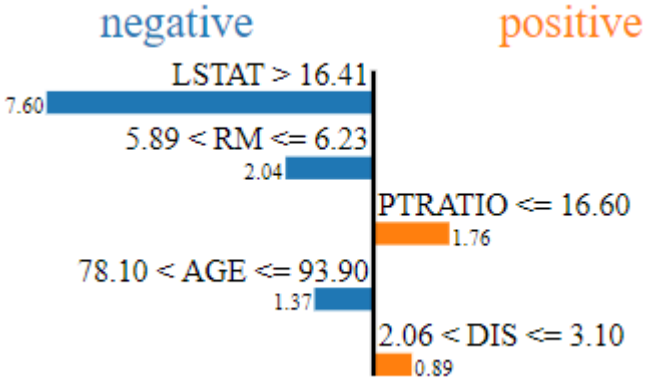


Explanations in Text

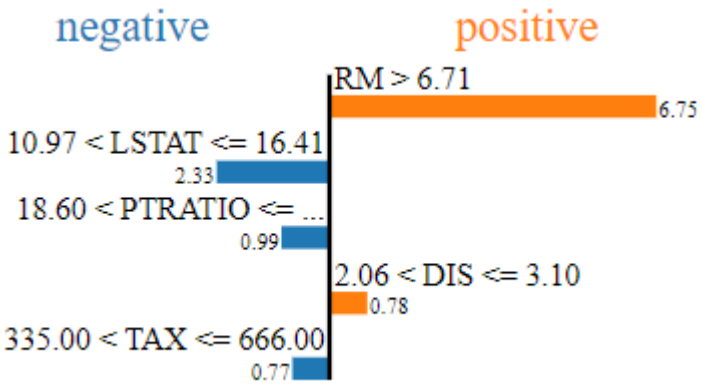


Explanations in binary classification

OPEN CHALLENGES (TOO MANY!!)



Explanation 1, predicting instance A using model ∂



Explanation 2, predicting instance A using model Ω

How to measure explainability? — Is better Explanation 1 or Explanation 2

How to represent this explanations? — Plot, Summary, Interactions between features ...

How integrate humans in the ML pipeline ? — How to Involve the human during the learning stage

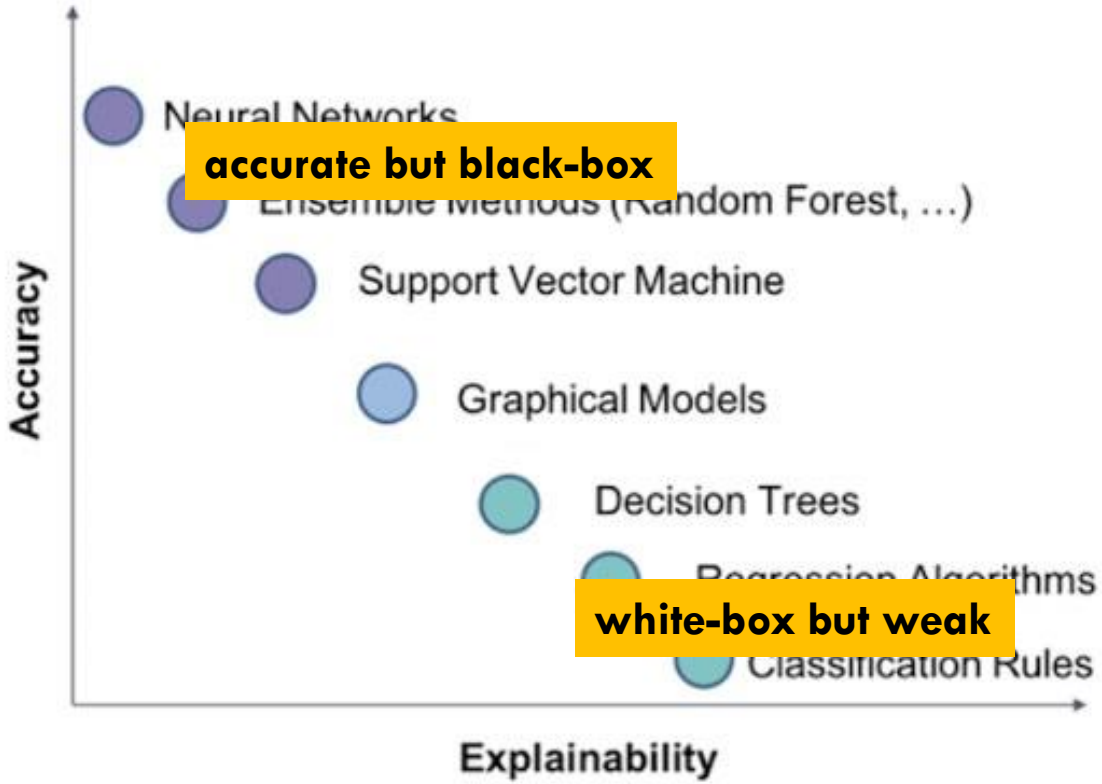
TOOLS FOR EXPLAINABILITY

Two different approaches:

- Approach 1 : Post-hoc explanations
  - Individual prediction explanations: perturbations of single points or contributions
  - Global prediction explanations: summary plots, dependence plots etc
- Approach 2 : Build Interpretable models
  - Decisions Trees, Decisions Rules, etc

TOOLS FOR EXPLAINABILITY

What model to choose ?



Accuracy – Explainability trade-off

Chapter II
Black Box Techniques
LIME and SHAP as Post-hoc tools

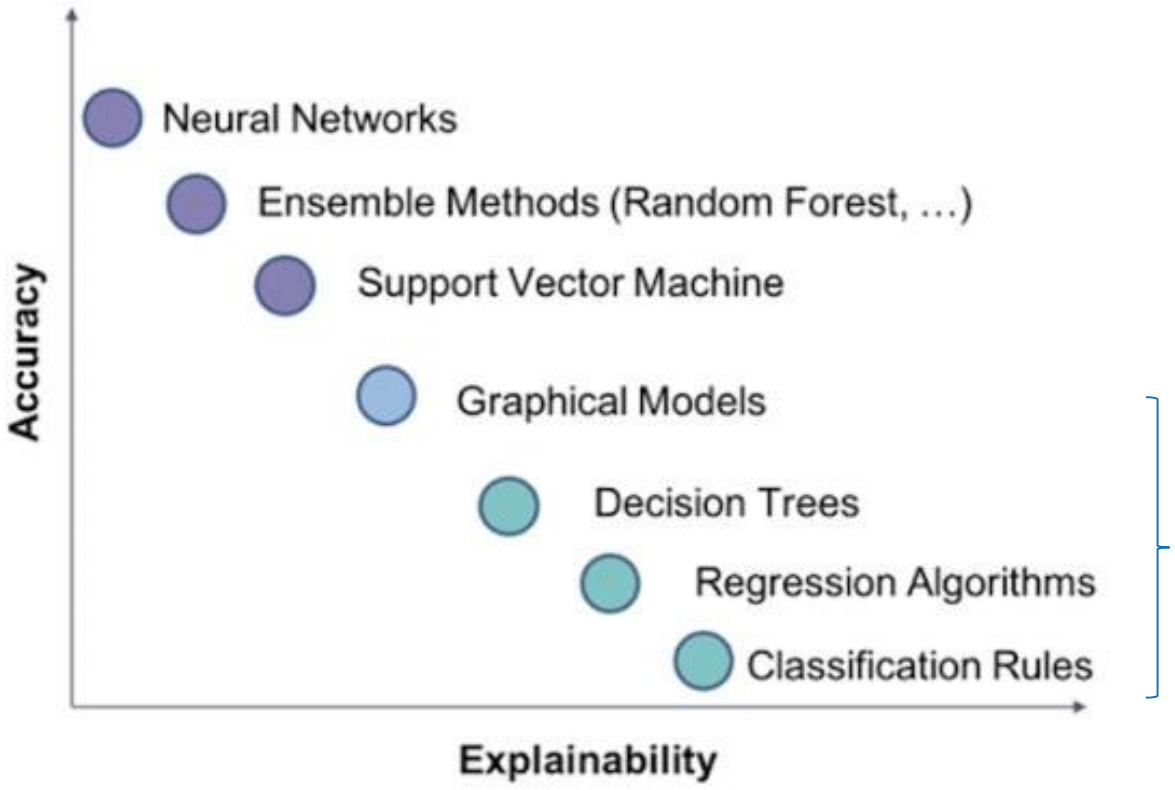
Chapter I
White Box Techniques
Classification Rules and Decision Trees

GitHub Repository:
https://github.com/albertcalv/tellmewhy

WHITE BOX MODELS

HANDS-ON I

COVER TOPICS



Hands-on I
White Box Techniques

HANDS-ON WHITE BOX TECHNIQUES

Your turn! Clone the repository: https://github.com/albertcalv/tellmewhy

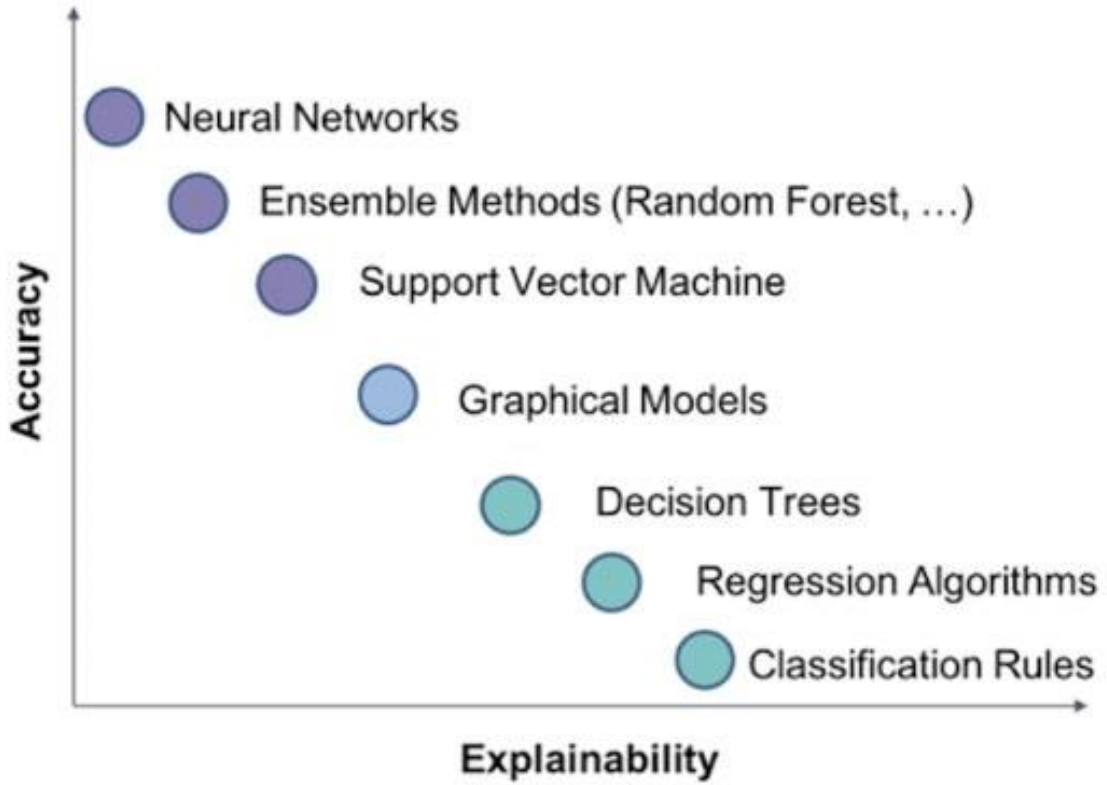
- Classification Rules
- Decision Trees

GitHub Repository:
https://github.com/albertcalv/tellmewhy

BLACK BOX MODELS

HANDS-ON II - III

COVER TOPICS



Hands-on II
Black Box Techniques

We achieve explanations using Post-Hoc Techniques

HANDS-ON BLACK BOX TECHNIQUES

Hands-on II: Black-Box Techniques

- Review of Post-Hoc techniques to explain models (Lime and SHAP)

Hands-on III: Exercise

- If time, load and train titanic dataset using a black box algorithm and apply post-hoc techniques to understand the predictions