# The Alan Turing Institute

### **Explainability**

Milestone 5: Trade-offs and Interactions with other verticals in Trustworthy Al

Roseline Polle

Postgraduate, UCL

roseline.polle.19@ucl.ac.uk



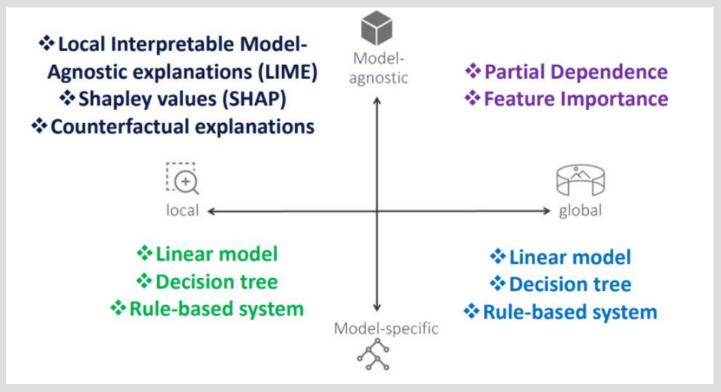
# 1. Intro on Explainability

# Interpretability/Explainability

• Interpretability: "the degree to which a human can understand the cause of a decision" [Miller, 2018]

 Explainability: the degree to which the inner mechanics of an algorithm are understood by a human

# Types of Explainability



[Koshiyama et al.,2021]

### Feature importance

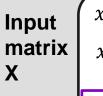
 Looks to assign a score to each feature relative to its importance in the prediction.

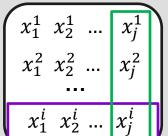
Simple example in linear regression:

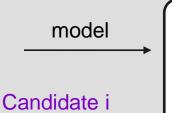
$$y = w_1 * x_1 + w_2 * x_2 + ... + w_n * x_n$$
Importance of feature 1 in outcome y

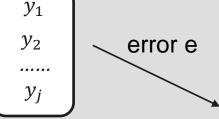
### Permutation feature importance

Feature j







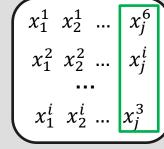


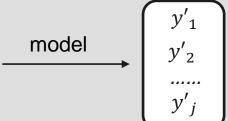
### Permute feature n

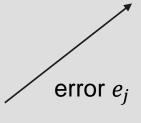






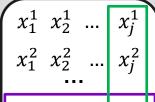






### LIME

#### Input matrix X



 $x_1^i \quad x_2^i \quad \dots \quad x_i^i$ 

Feature j

Candidate i

N(...,1)

sample 1

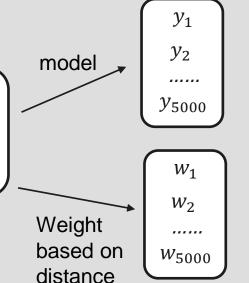
sample 2

. . . . . .

sample 5000

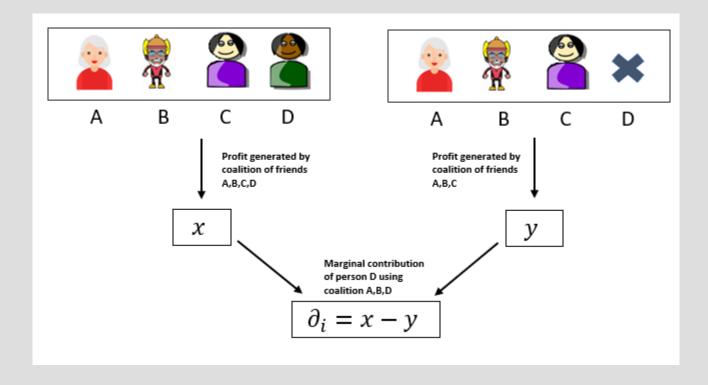
#### **Explain results for candidate i:**

- Sample 5,000 times feature vector i using a normal distribution
- Predict output
- Assign weight base on distance
- Feature selection (Lasso)

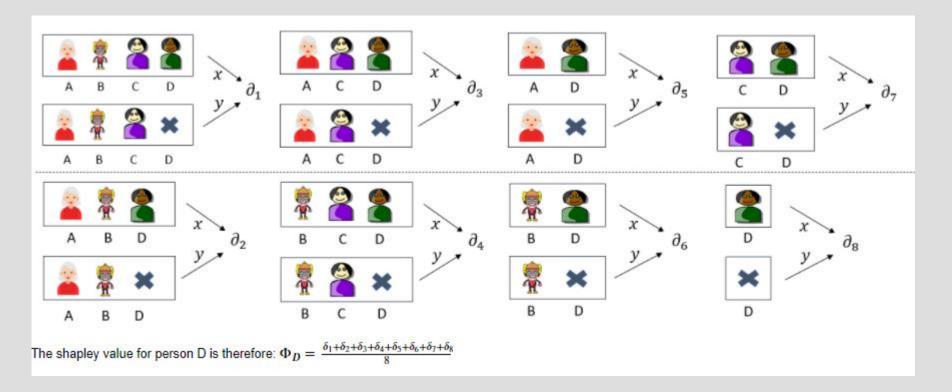


Feature importance on output

### SHAPLEY Values



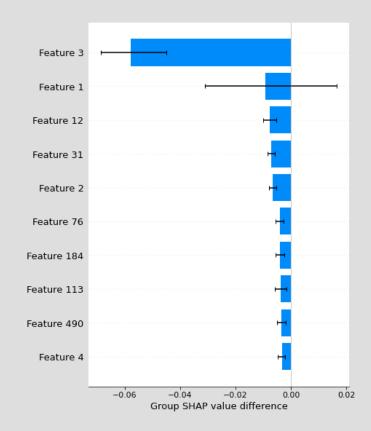
### **SHAPLEY Values**



### 2. Interactions with Fairness

### Questions one can answer

- Are the most influential factors reasonable? Are they proxy for a protected characteristics?
- Is the model relying too much on one feature?
- Are they the influential factors the same across different groups?



### Adaptation to fairness

Instead of explaining output → explain fairness metric

- Example: effect of permutation importance on Disparate Impact metric.
- Answers the question: what are the features most responsible for the observed bias (if any)?

# Further readings

 Interpretable Machine Learning. A Guide for Making Black Box Models Explainable (https://christophm.github.io/interpretable-ml-book/)