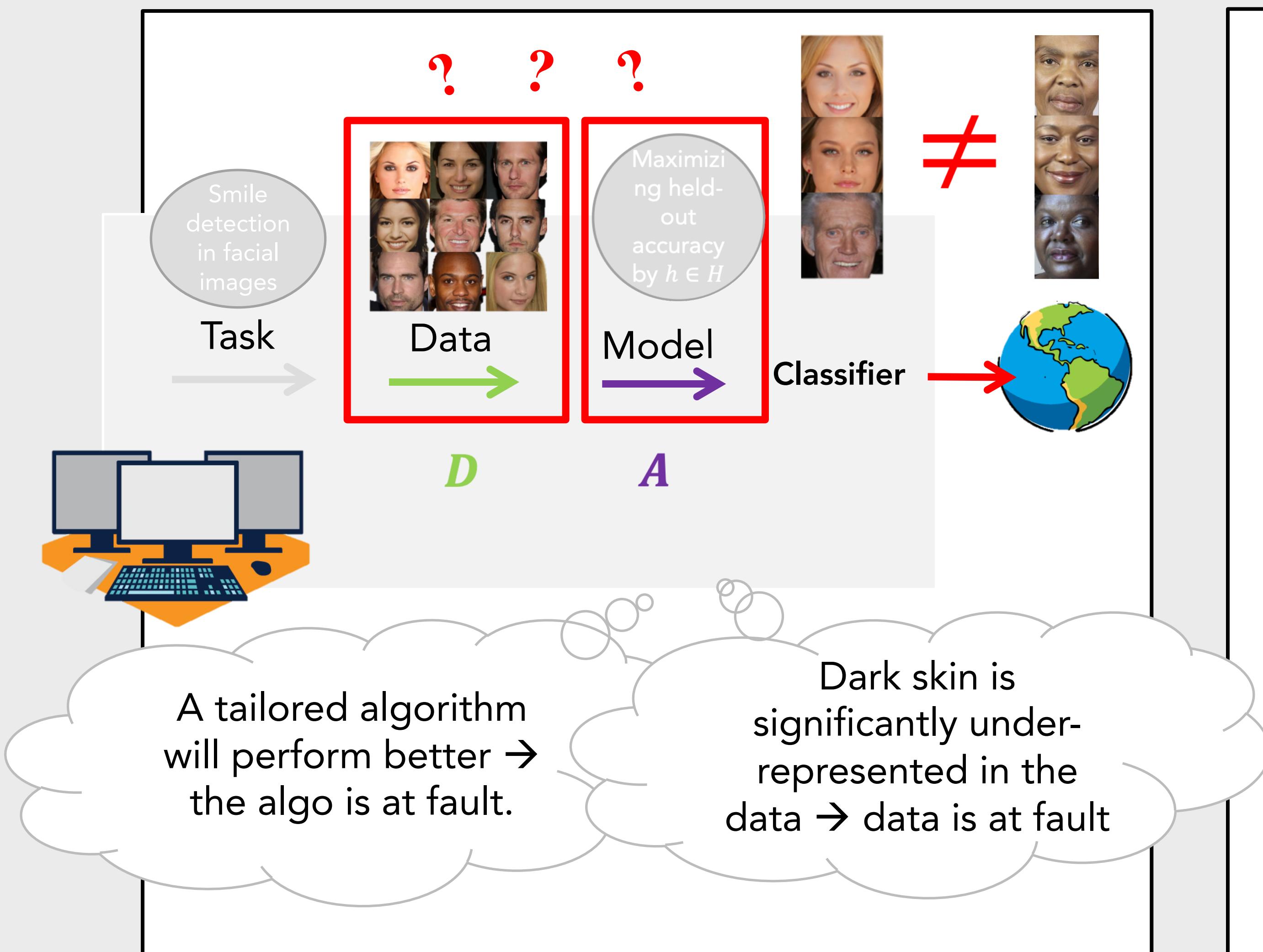


Who's Responsible? Jointly Quantifying the Contribution of the Learning Algorithm and Data

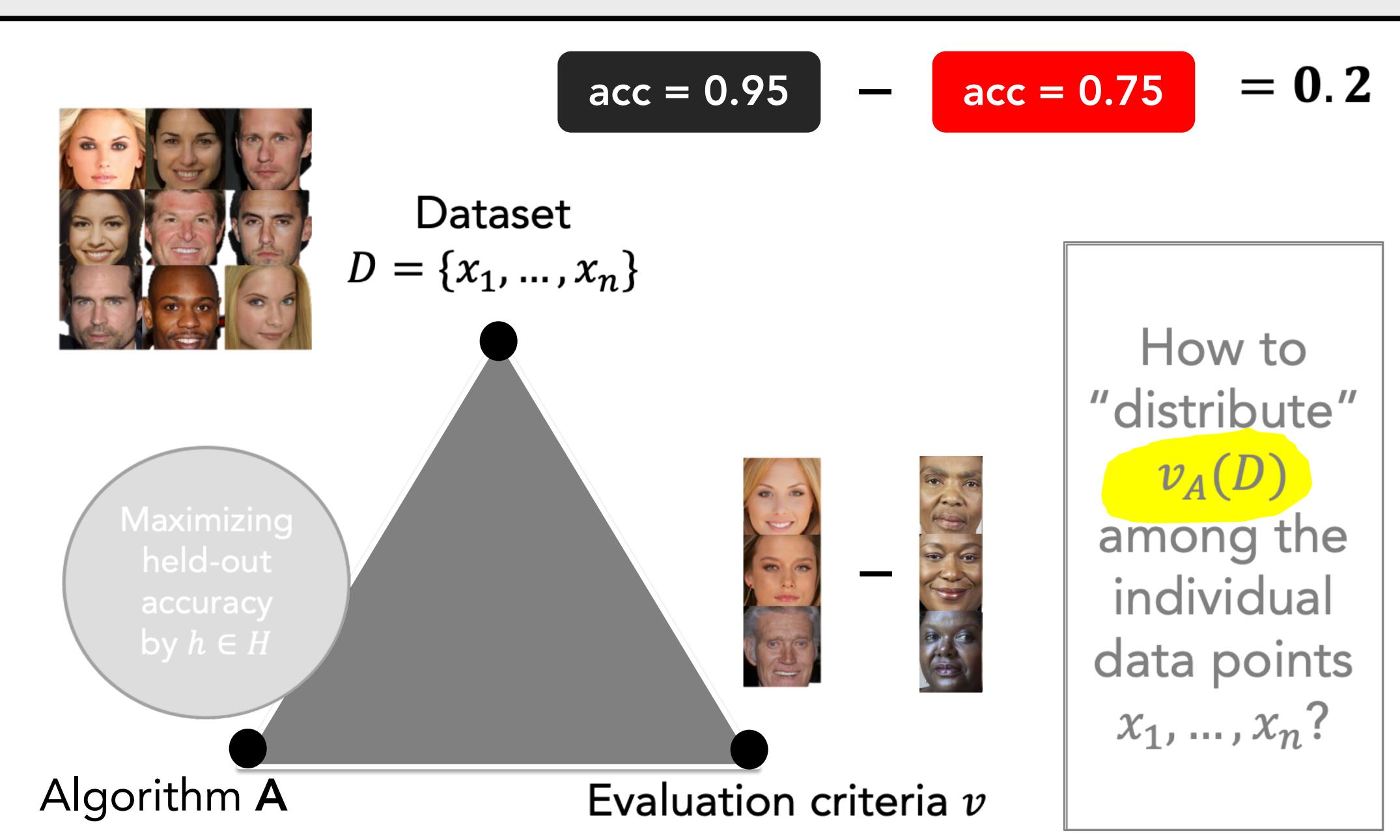
Gal Yona, Amirata Ghorbani & James Zou



Q: recognizing the interaction between **existing biases in data** and **different (potentially subtle) modeling choices**, can we disentangle their effect on the overall performance?

Joint data-algorithm valuation problem

A: A reduction to the data valuation problem (recently studied e.g. in [GZ19], [ADS19], [JDW+19])
Specifically the approach in [GZ19]

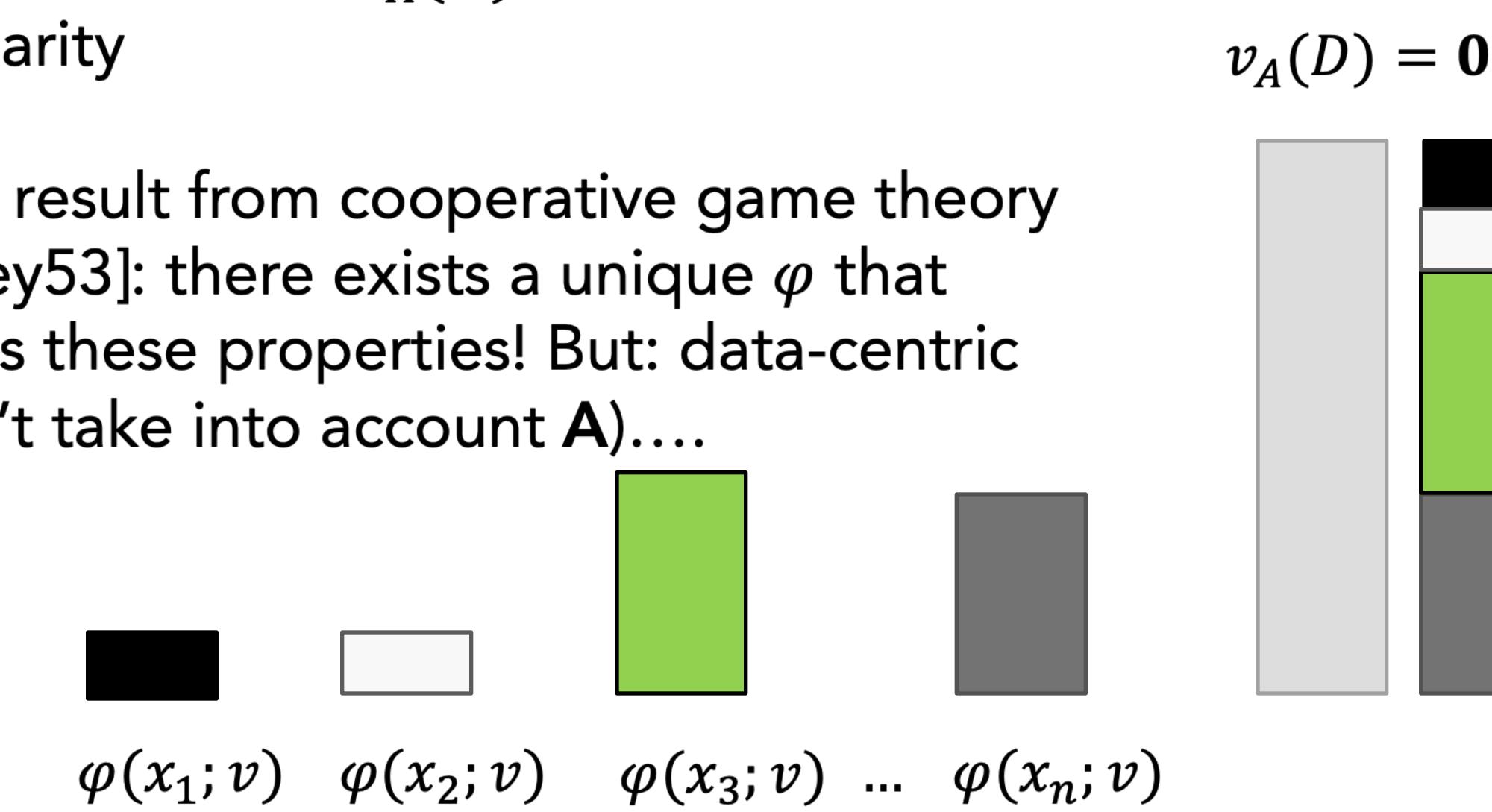


Data Shapley [GZ19]

Specifies *four natural conditions* for an equitable data valuation $\varphi: \{x_1, \dots, x_n\} \rightarrow \mathbb{R}^n$:

1. Null player receives zero value
2. Symmetric players receives equal value
3. Sum of values is $v_A(D)$
4. Linearity

Classic result from cooperative game theory [Shapley53]: there exists a unique φ that satisfies these properties! But: data-centric (doesn't take into account A)....



A practical framework!

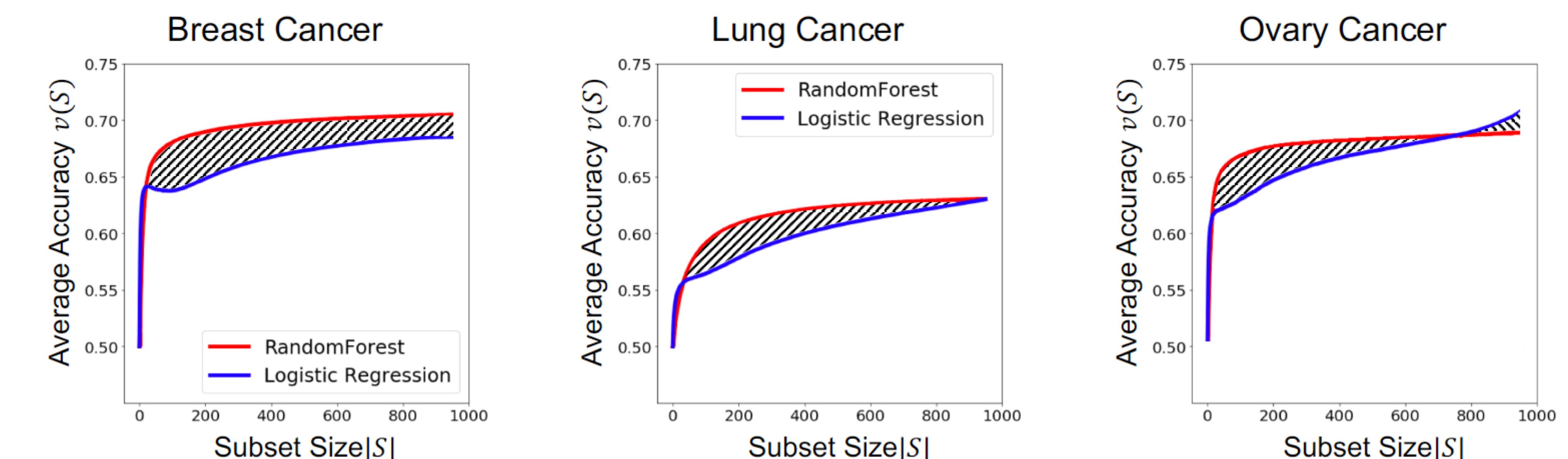
#1: Closed-form expressions for the value of data and algorithm. E.g. value of algo is $E_S[v_A(S) - v_B(S)]$

Intuition:

- If A is consistently doing worse off than baseline B (irrespective of the specific training set they are trained on), then A "deserves" a large portion of the blame.
- If very specific combinations of datapoints contribute to A's failure, then these carry more of the "blame".

#2: Can re-use heuristics for efficient computation from [GZ19].

#1: Understanding Extended Shapley as a new performance metric



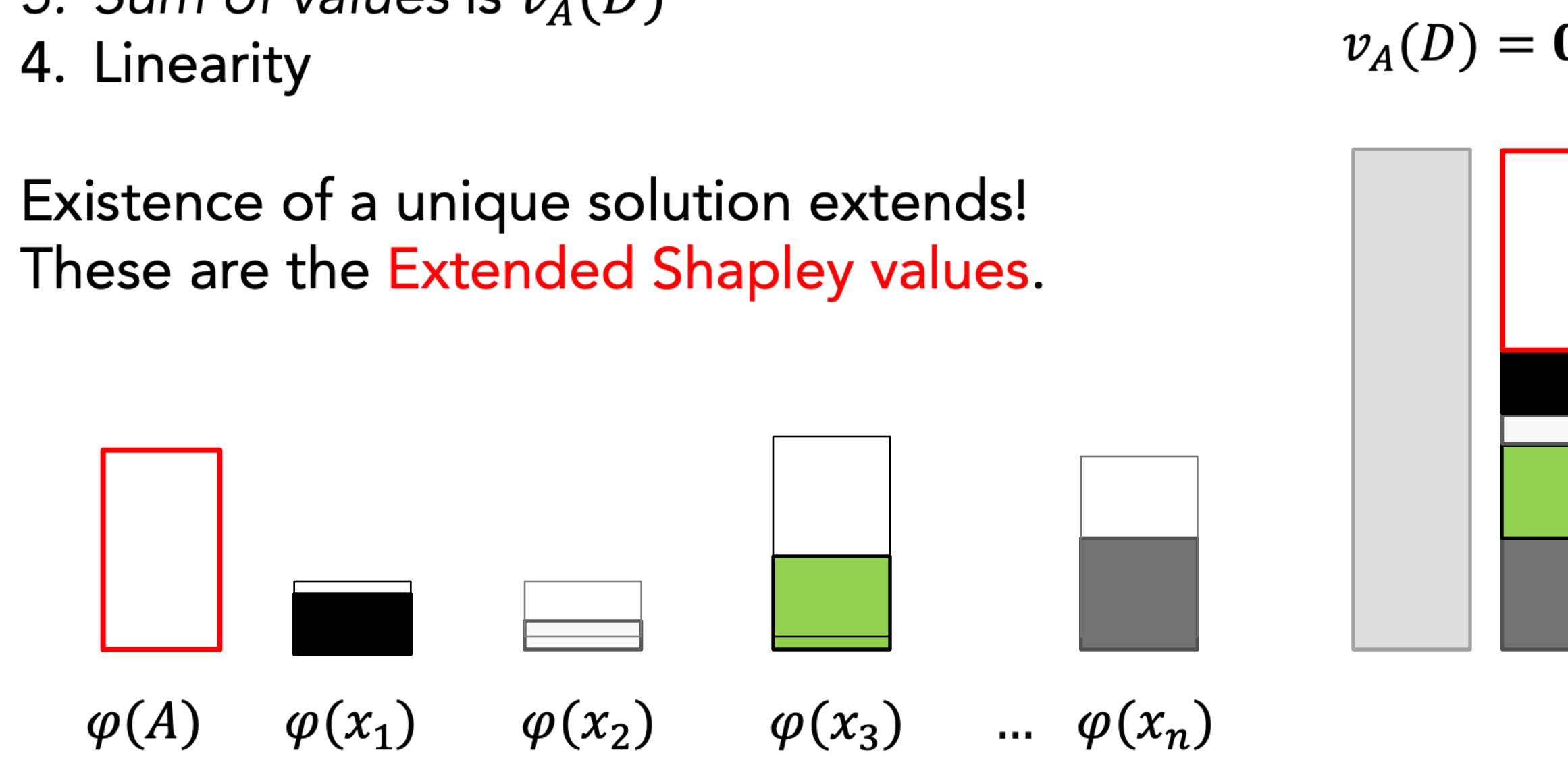
This work: Extended Shapley [YGZ19]

Fix a benchmark algorithm B and add the algorithm A as an "additional" $n + 1$ player

Specify *five natural conditions* for an equitable data-algorithm valuation $\varphi: \{A, x_1, \dots, x_n\} \rightarrow \mathbb{R}^{n+1}$:

1. Null datum receives zero value; if A is identical to B, algo receives zero value
2. Symmetric players receives equal value
3. Sum of values is $v_A(D)$
4. Linearity

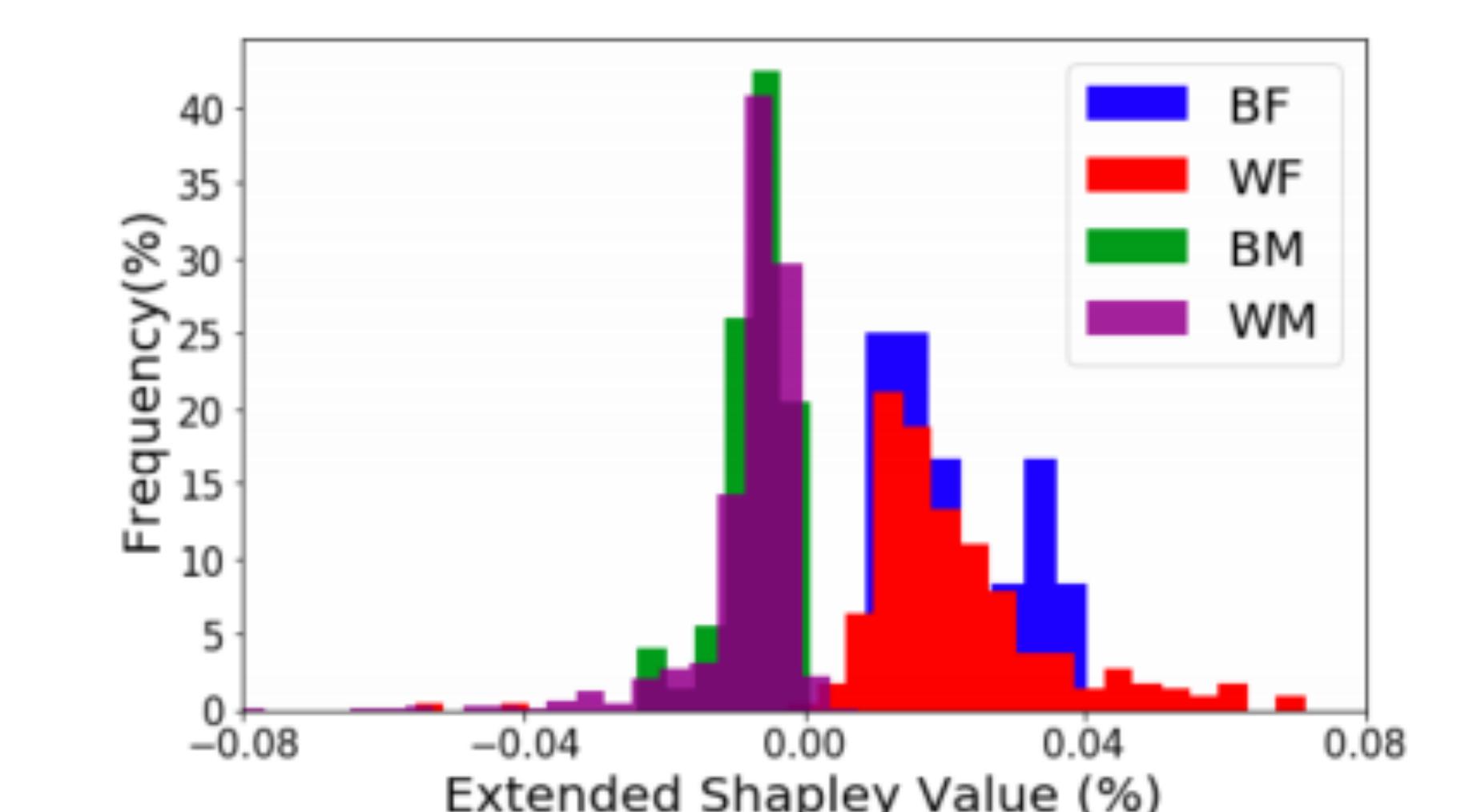
Existence of a unique solution extends!
These are the **Extended Shapley values**.



#2: Allocating responsibility for unfairness

- **Training data:** 1000 images from LFW+A dataset (imbalanced: 21% female, 5% black)
- **Performance measure:** maximal accuracy gap among groups {WM, WF, BM, BF} on the balanced PPB dataset
- **Algorithm A:** Logistic regression applied to 128-dimensional feature vectors obtained by passing the images through a ResNet-V1 pre-trained on CelebA.
- **Benchmark B:** a constant classifier (perfectly fair: $v_B(D) = 0$)

$$v_A(D) = 22.9 \text{ (WM-BF)} \quad \varphi_A = 22.1$$



arxiv: <https://arxiv.org/abs/1910.04214>.

contact: gal.yona@gmail.com