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Evaluating Model Explanations without Ground Truth

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*Athens, Greece: The 2025 ACM Conference on Fairness, Accountability, and Transparency (**FAccT ’25**)*

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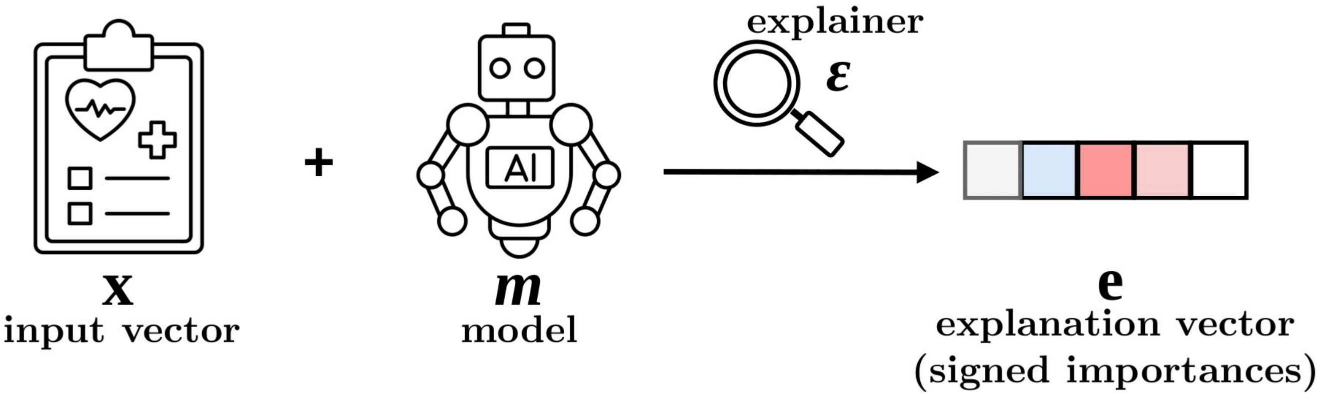
Check us out on GitHub!

github.com/KaiRawal/Evaluating-Model-Explanations-without-Ground-Truth

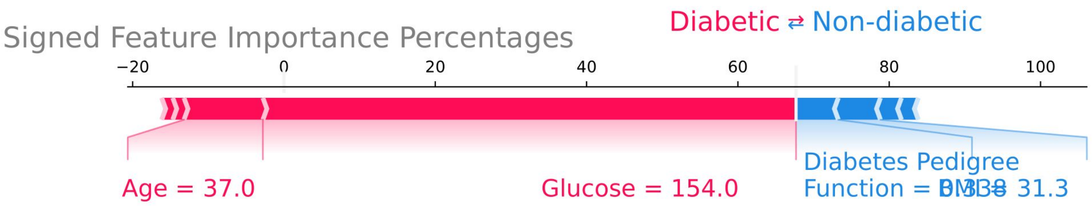
Explaining AI Models



(Fig. 2a, Page 2)

One Prediction, Many Explanations

- **SHAP**
  - + Glucose
  - \- Pedigree Fn.



(Fig. 1, Page 2)

One Prediction, Many Explanations

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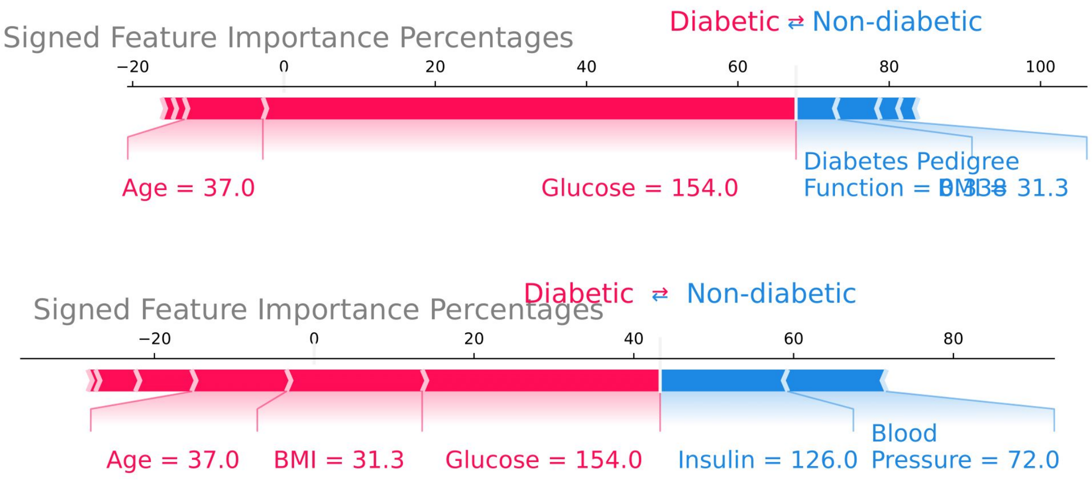
- **LIME**
  - + Glucose, BMI
  - - Insulin



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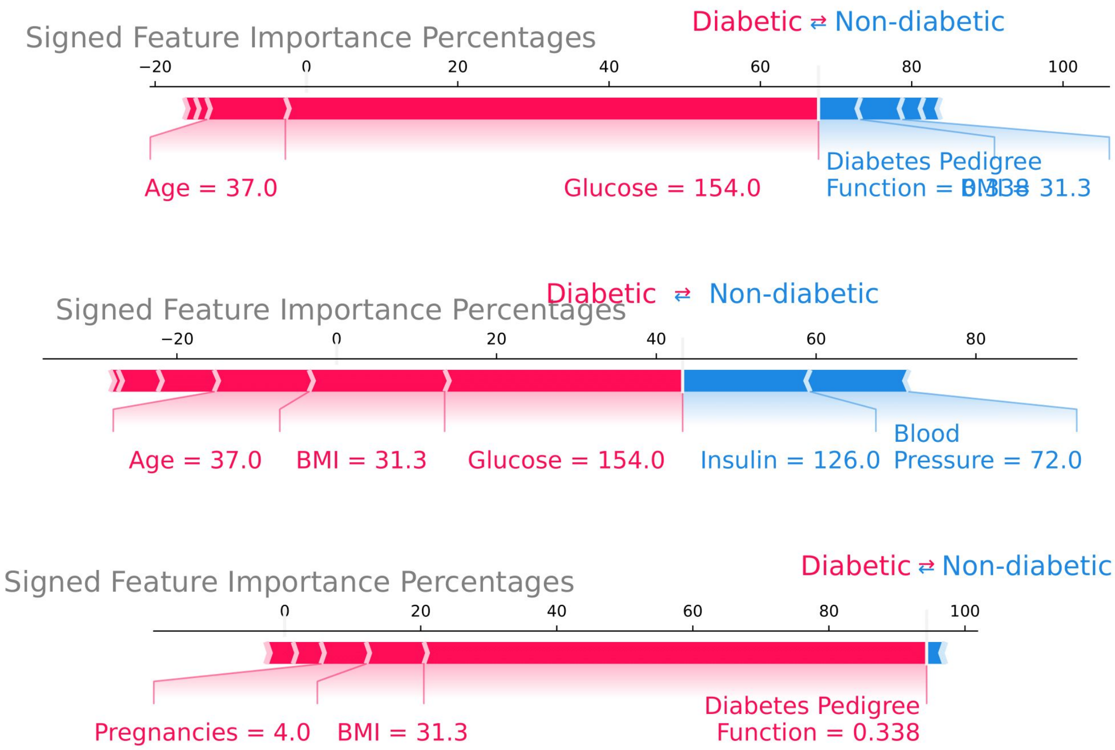

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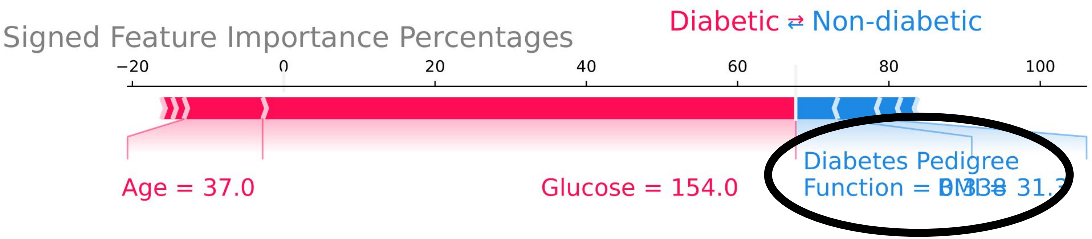
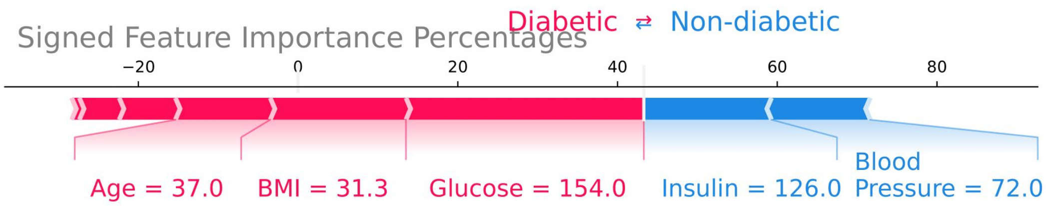
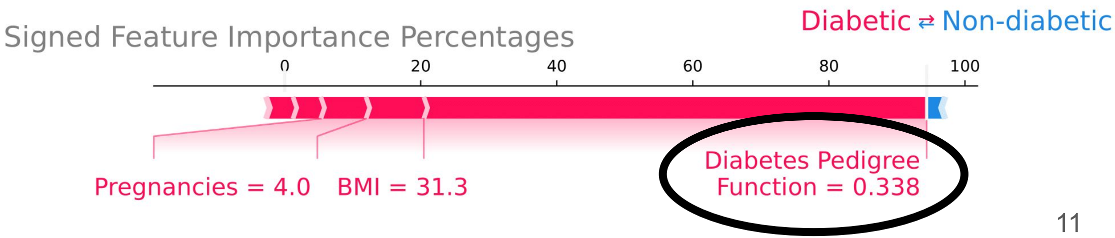
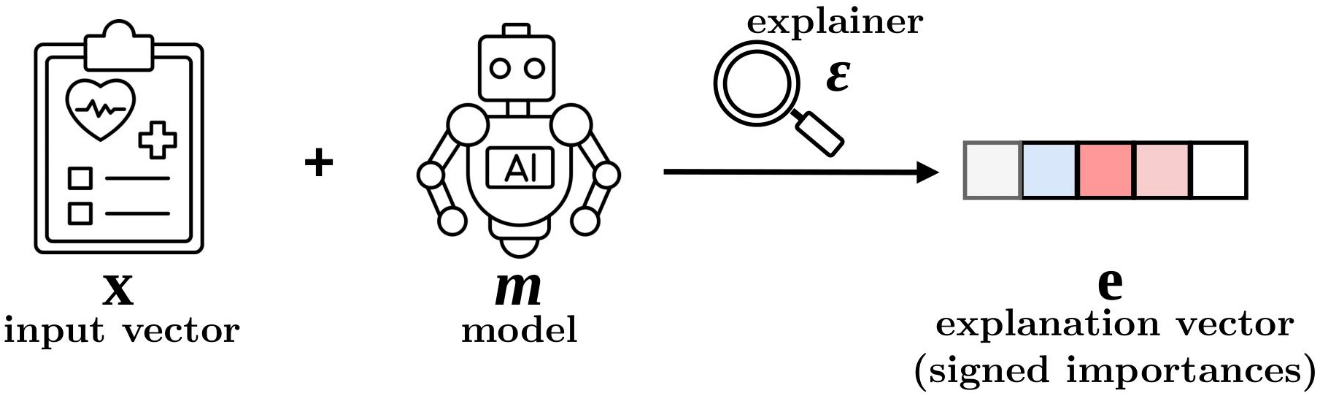






Explanation Evaluation



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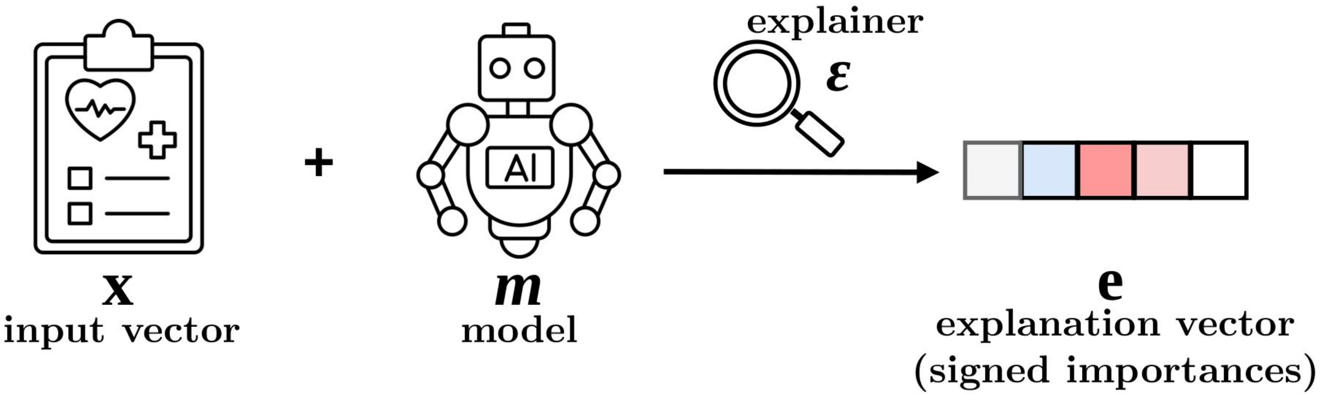

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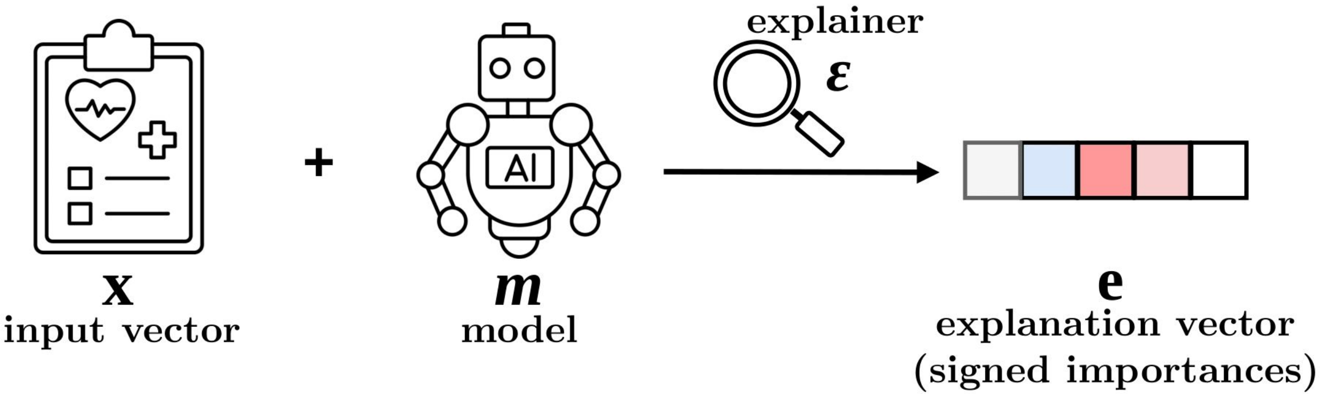

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Evaluating Explanation Quality

- Question: So which explanation should we use?
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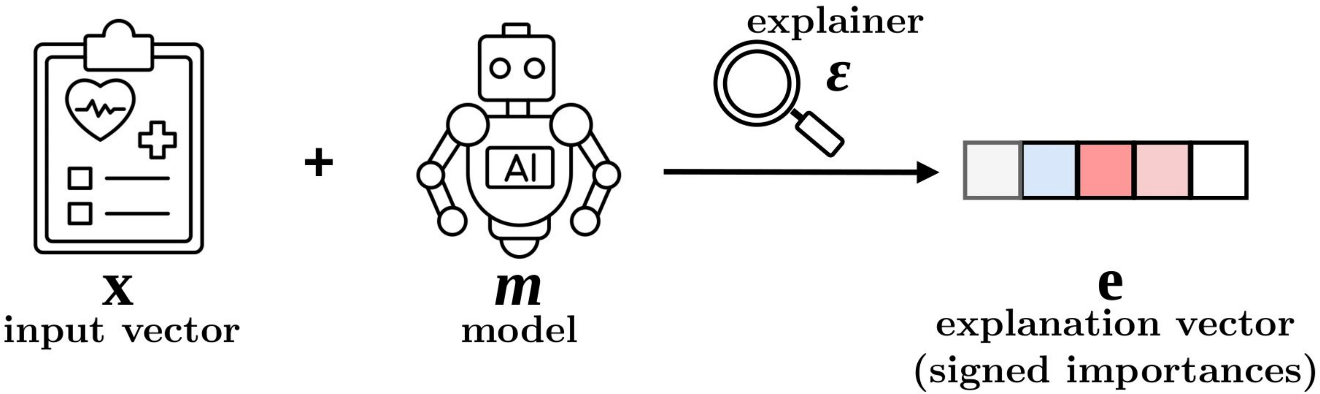
- **Short Answer**: Use the explanation *most predictive* of the model output

Three Evaluation Principles

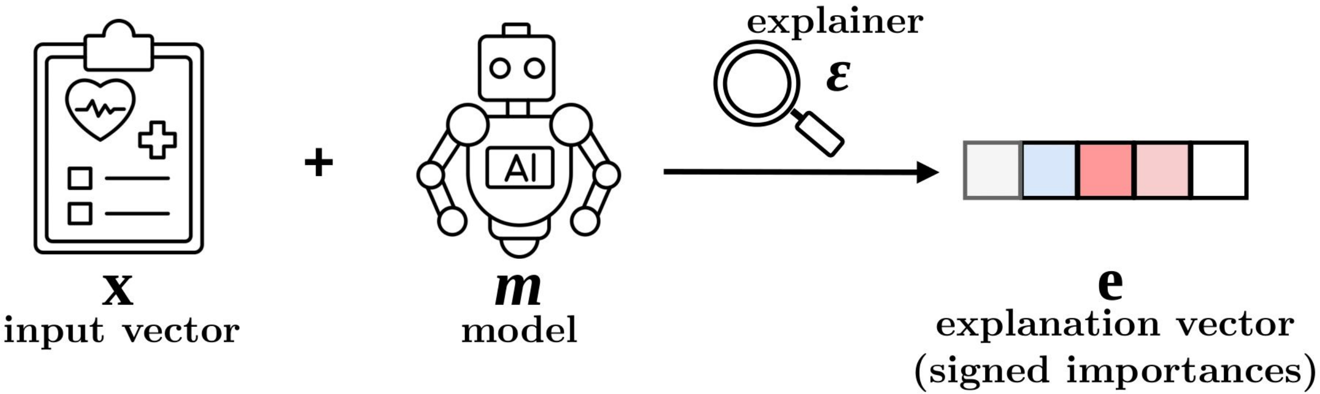
- Question: So which explanation should we use?
- How can we measure which explanation is best?
- **Long Answer**: Any evaluation framework for AI explanations should follow three foundational principles:
    - *local contextualisation*;
    - *model relativism*; and
    - *on-manifold evaluation*.

Principle 1: Local Contextualization



Principle 1: Local Contextualization

Explanations should reflect that
models are *not constant* for all inputs



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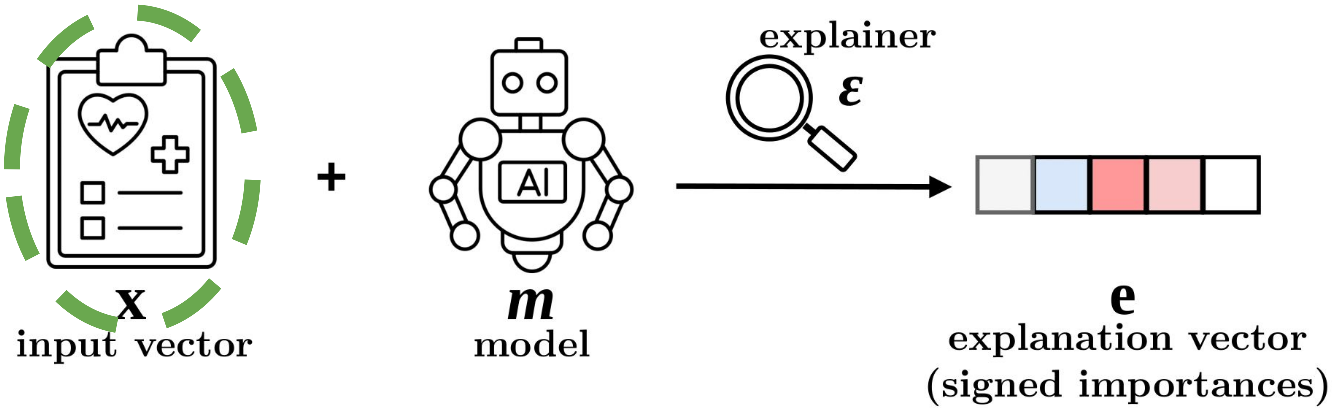
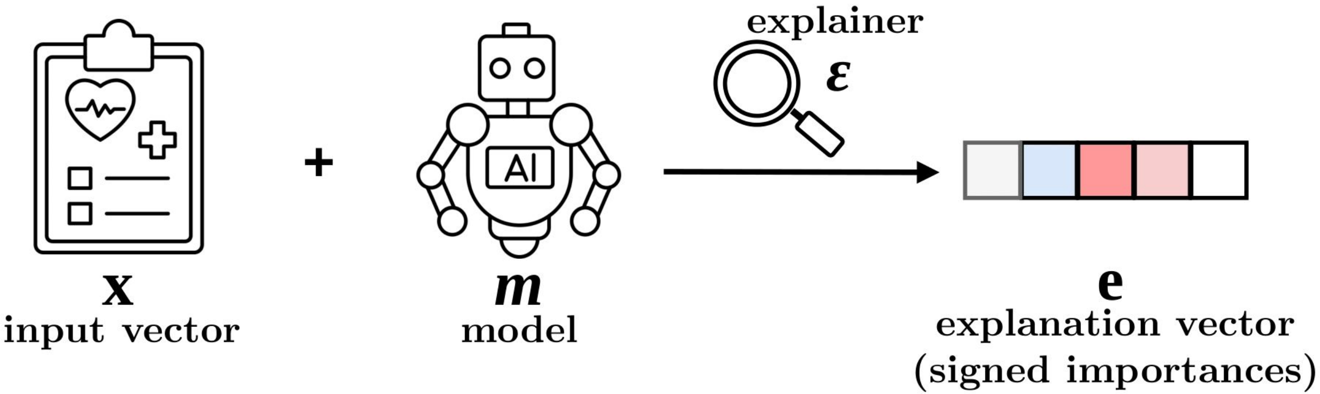


"When input **x** changes, the evaluation *might* change."

Principle 2: Model Relativism



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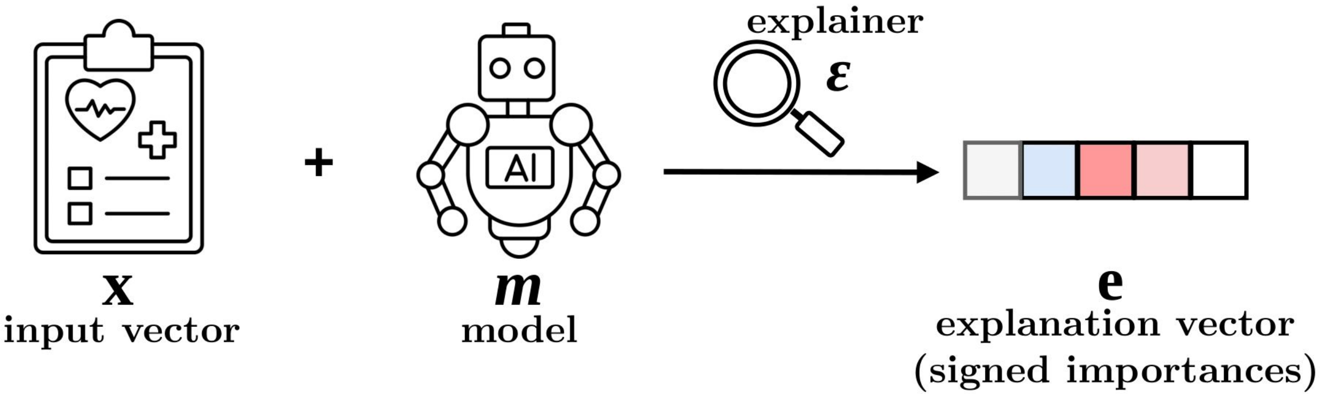

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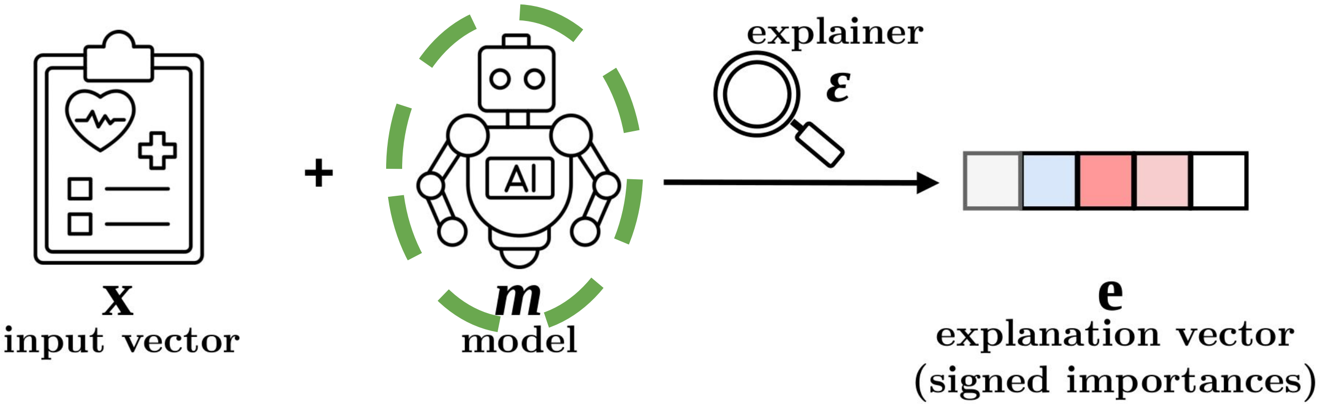
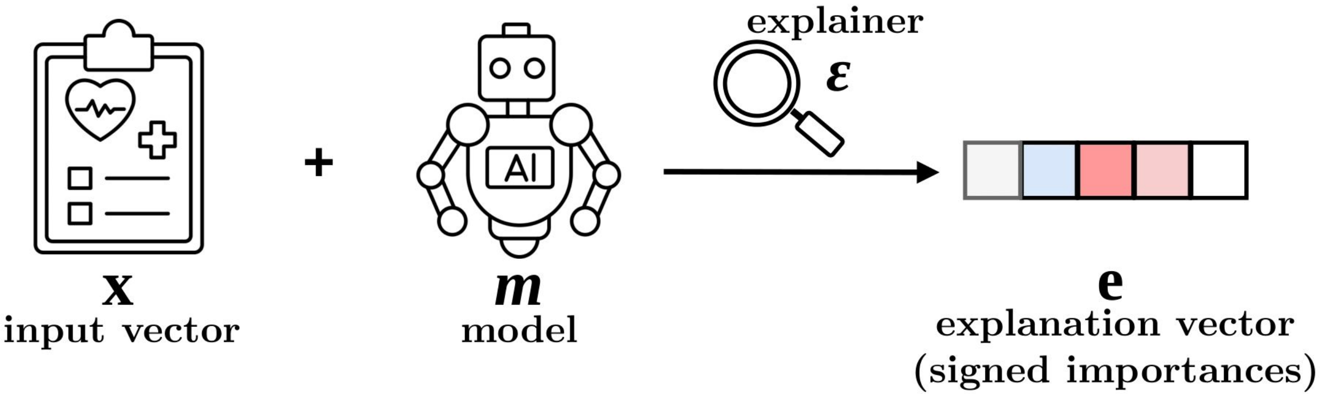


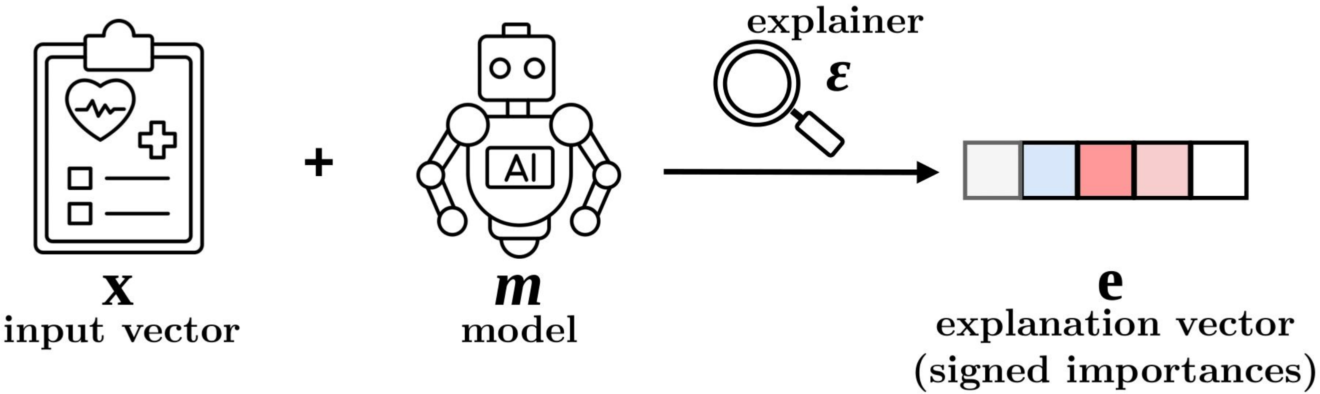
"When model m changes, the evaluation *should* change."

Principle 3: On-Manifold Evaluation



Principle 3: On-Manifold Evaluation

Explainers that sample points in synthetic neighbourhoods should not be sensitive to off-point model behaviour



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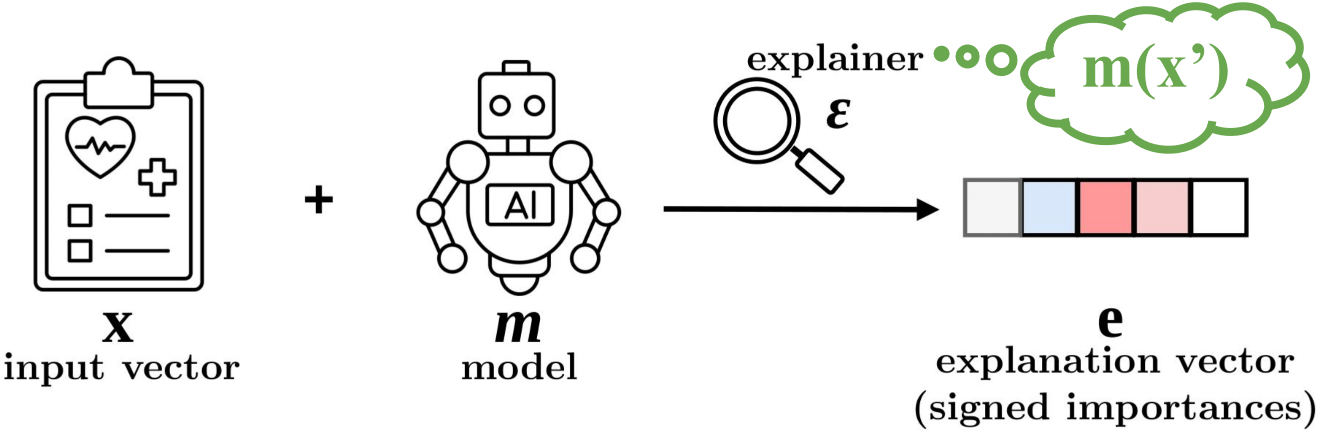

"The evaluation should *not* depend on model output **m(x')**."

Key Idea

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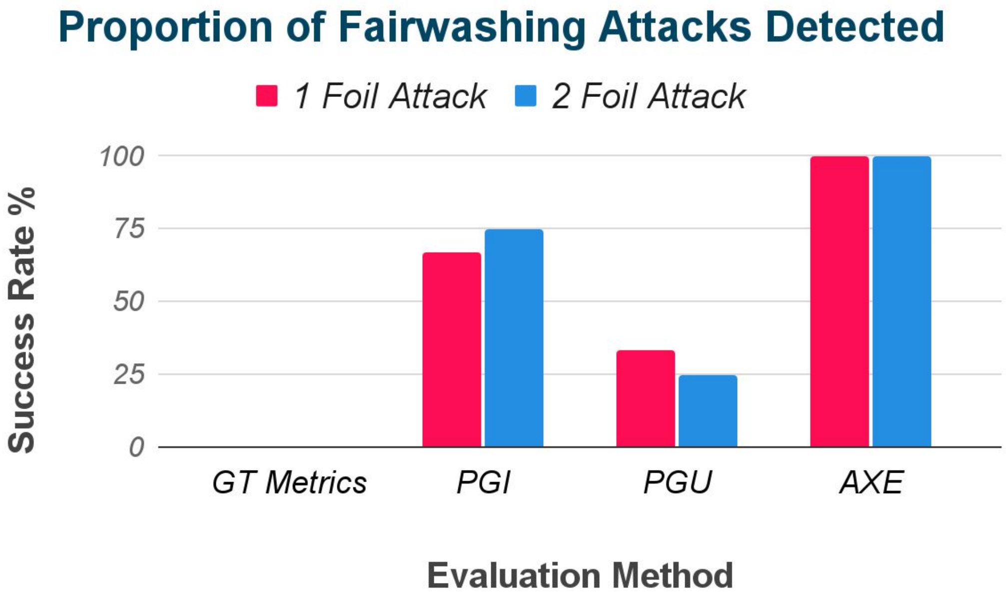
(Algorithm 1, Page 5)

Algorithm 1 Evaluating Explanation Quality with AXE_n^k

Require: Number of Features n, Number of Neighbors k
Dataset $\mathcal{X} = \{\mathbf{x}_i\}_{i=1}^{\nu}$, Predictions $Y_{\text{preds}} = \{y_i\}_{i=1}^{\nu}$, and Explanations $E = \{\mathbf{e}_i\}_{i=1}^{\nu}$

1: Initialize an empty list: $\hat{Y} \leftarrow []$
2: **for** each datapoint $\mathbf{x}_i$ and explanation $\mathbf{e}_i$ in $(\mathcal{X}, E)$ **do**
3: Find n most important features: $f_{\text{imp}} \leftarrow \text{ImpFeatures}(\mathbf{e}_i, n)$
4: Create $\mathcal{X}_f$ with subset of features f_{imp} from $\mathcal{X}$
5: Train K-NN model M_i^k with inputs $\mathcal{X}_f$ and target Y_{preds}
6: Obtain prediction $\hat{y}_i$ from M_i^k for datapoint $\mathbf{x}_i$
7: Append $\hat{y}_i$ to $\hat{Y}$
8: **end for**
9: Return performance measure: $\text{Accuracy}(\hat{Y}, Y_{\text{preds}})$

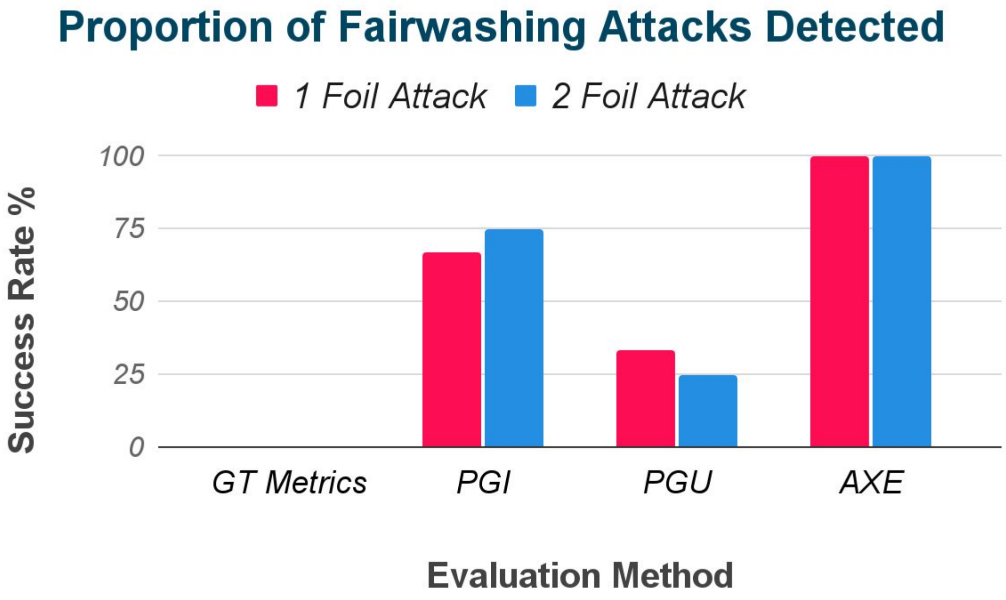
Detecting Explanation Fairwashing



(Table 2, Page 8)

Detecting Explanation Fairwashing

- Ground-Truth based metrics are unusable



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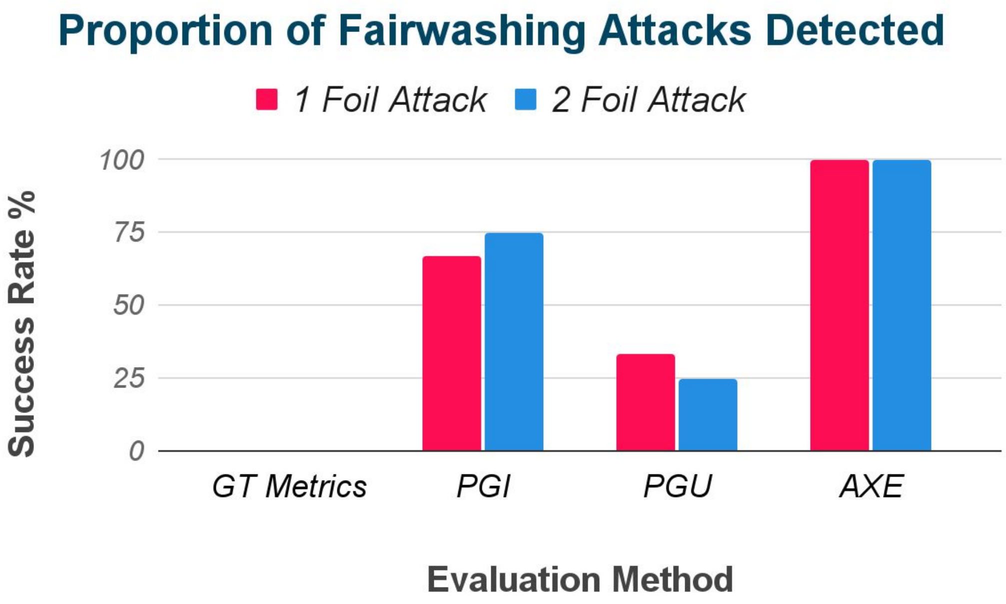

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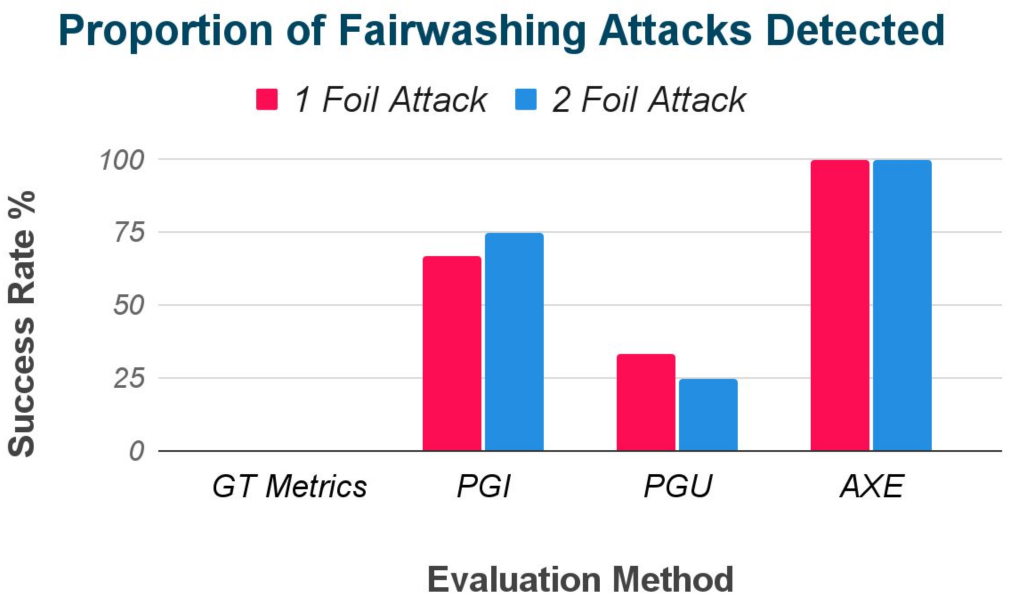
Detecting Explanation Fairwashing

- Ground-Truth based metrics are unusable
- PGI and PGU are susceptible to adversarial attacks
- AXE is invulnerable and perfectly detects fairwashing



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- Public code on GitHub!

Thank You

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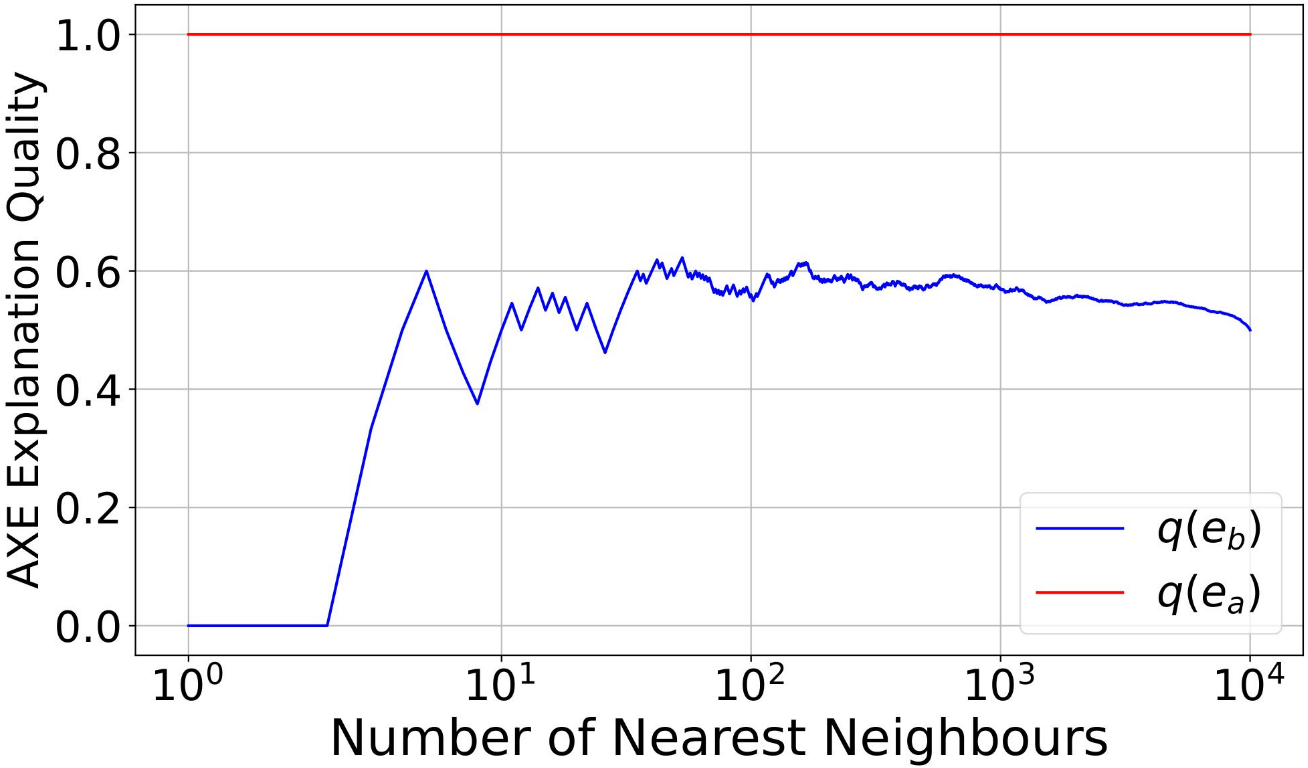
AXE vs Prior Evaluation Metrics

Metric	Definition	Local Contextualization	Model Relativism	On-Manifold Evaluation
FA: Feature Agreement	Fraction of top-n features common between **e** and **e***.	✗	✗	✔
RA: Rank Agreement	Fraction of top-n features common between **e** and **e*** with the same position in respective rank orders.	✗	✗	✔
SA: Sign Agreement	Fraction of top-n features common between **e** and **e*** with the same sign.	✗	✗	✔
SRA: Signed Rank Agreement	Fraction of top-n features common between **e** and **e*** with the same sign and rank.	✗	✗	✔
RC: Rank Correlation	Spearman's rank correlation coefficient for feature rankings from **e** and **e***.	✗	✗	✔
PRA: Pairwise Rank Agreement	Fraction of feature pairs for which relative ordering in **e** and **e*** is the same.	✗	✗	✔
PGI: Prediction-Gap on Important Feature Perturbation	Mean absolute change in model output upon perturbing top-n most important inputs.	✔	✔	✗
PGU*: Prediction-Gap on Unimportant Feature Perturbation	Mean absolute change in model output upon perturbing top-n most unimportant inputs.	✔	✔	✗
AXE: (ground-truth) Agnostic eXplanation Evaluation	Predictiveness of the top-n most important inputs in recovering model output. **Defined in section 3.1.**	✔	✔	✔

AXE across Hyperparameter Settings



Evaluation Cogency with AXE