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The Limits of Explainable Machine Learning:
Some Things Are Simply Impossible

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Explainable Machine Learning

The Need for Explanations:

Why did the machine learning system

- Classify my company as high risk for money laundering?
- Reject my bank loan?
- Give a certain medical diagnosis?
- Make a certain mistake?
- Reject the profile picture I uploaded to get a new OV chipcard?[1]
- ...

[1] Personal experience

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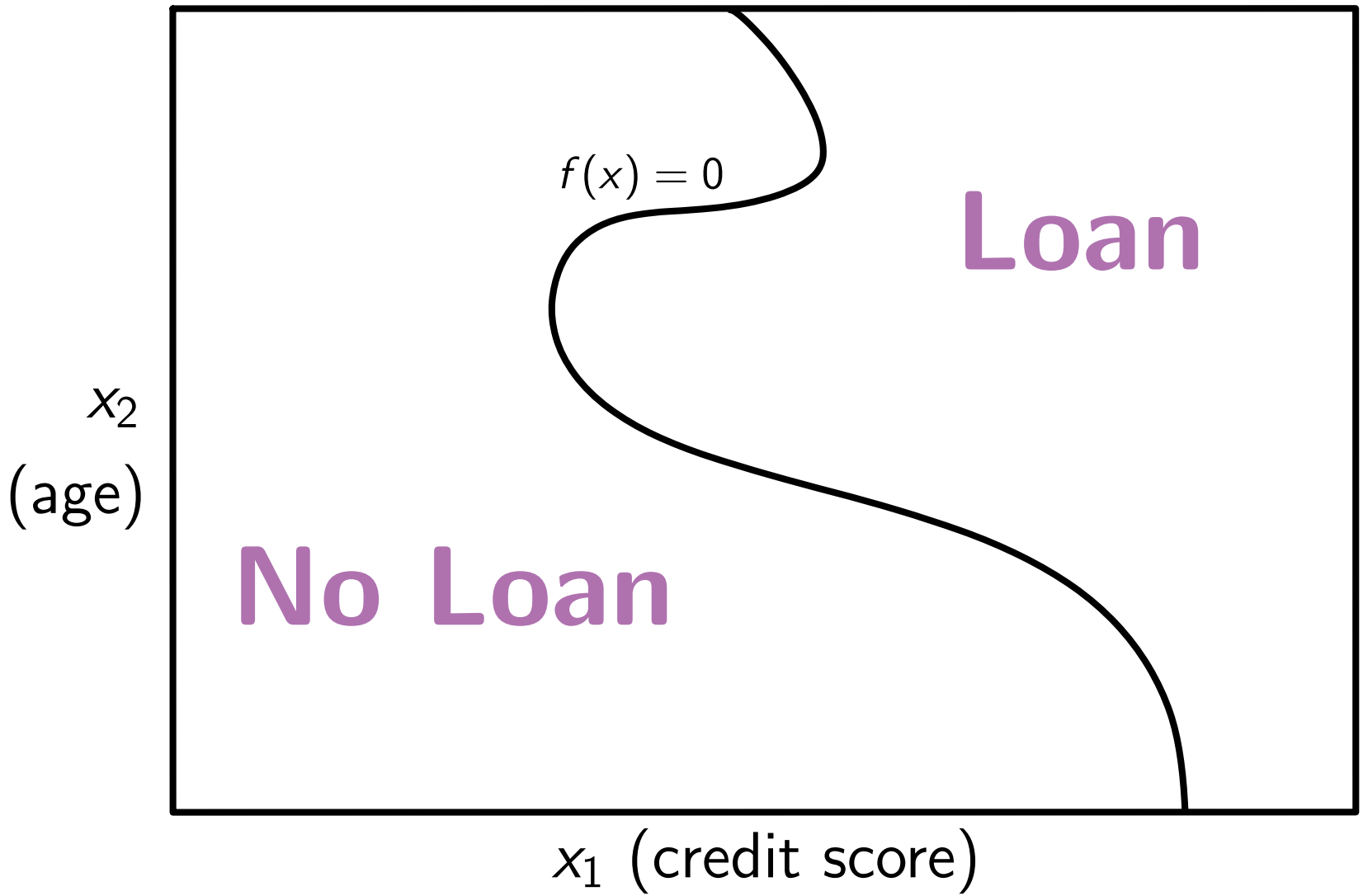
A Communication Limit:

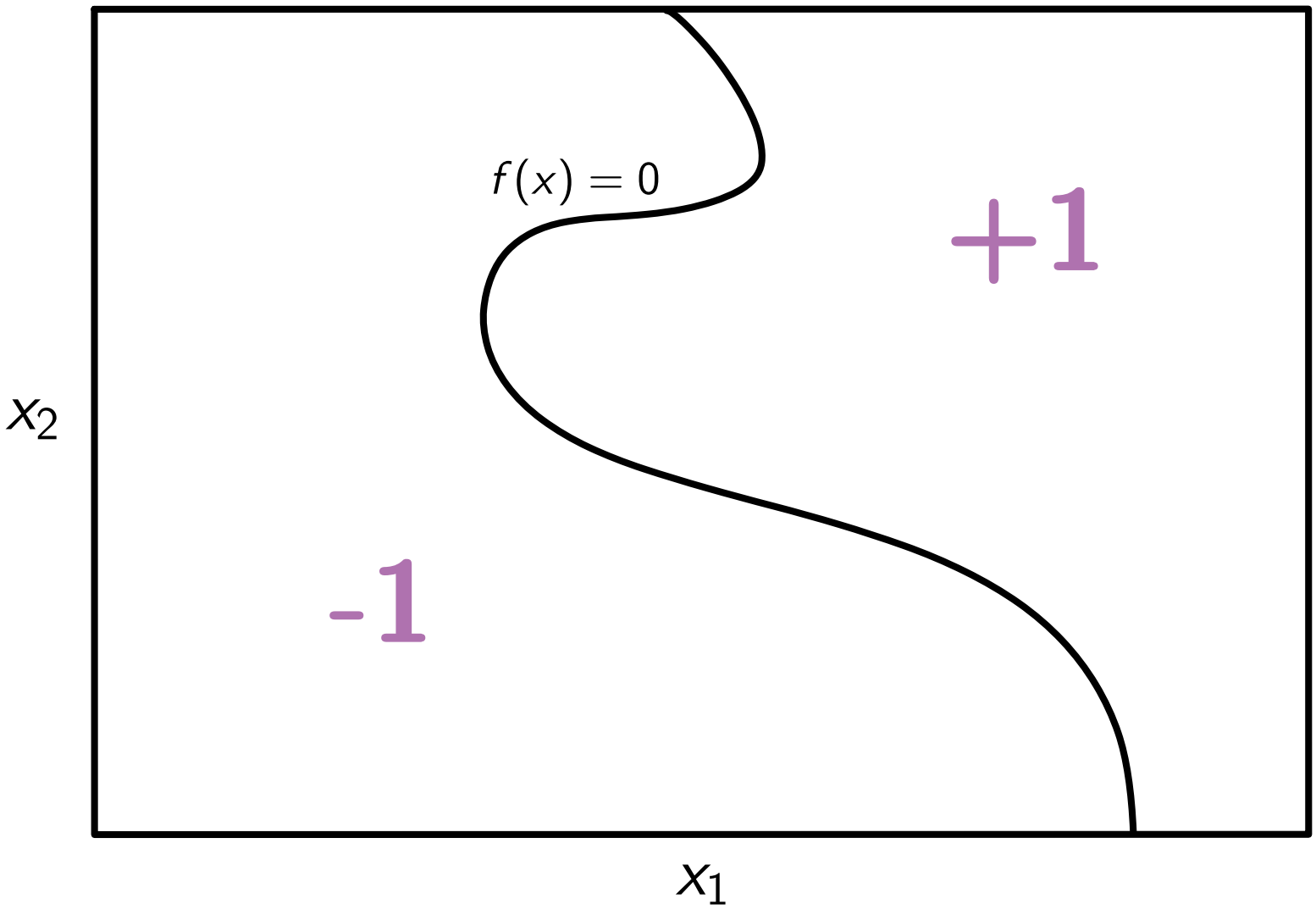
- Cannot communicate millions of parameters!
- Can communicate only some **relevant aspects** and/or need **high-level concepts** in common with user

[1] Personal experience

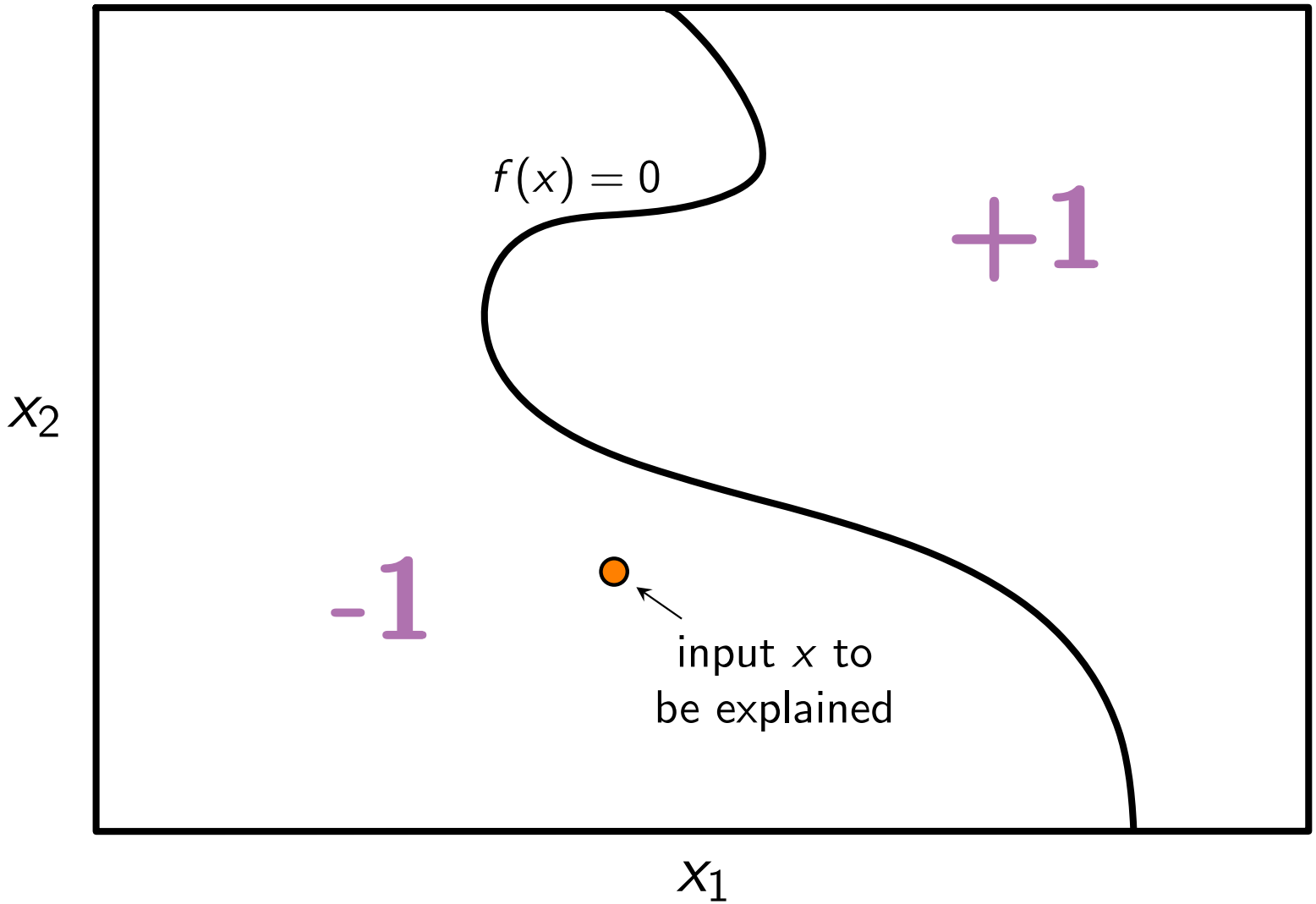
Binary Classification



Binary Classification



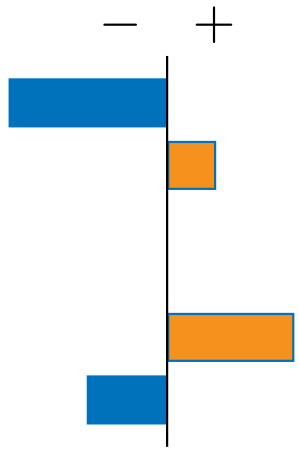
Local Post-hoc Explanations



- **Local:** only explain the part of f that is **(most) relevant for** x.
- **Post-hoc:** ignore explainability concerns when estimating f.

Local Explanations via Attributions

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{d-1} \\ x_d \end{bmatrix}$$



$$\begin{bmatrix} \varphi_f(x)_1 \\ \varphi_f(x)_2 \\ \vdots \\ \varphi_f(x)_{d-1} \\ \varphi_f(x)_d \end{bmatrix} = \varphi_f(x)$$

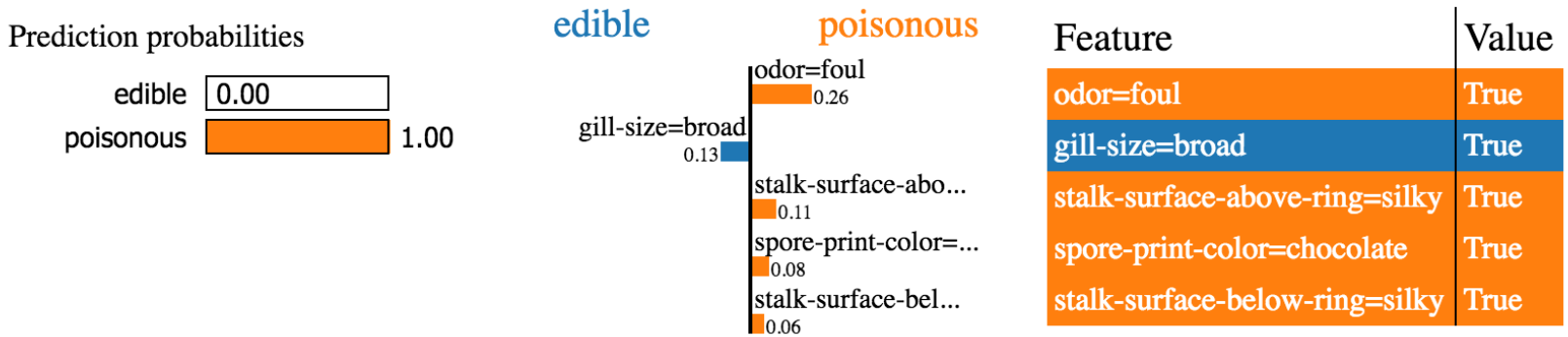
$\phi_f(x) \in \mathbb{R}^d$ attributes a **weight to each feature**, which explains **how important** the feature is **for the classification of** x **by** f.

Examples of Local Attribution Methods

Example Attribution Method: LIME

LIME: Do local linear approximation of f near x (optionally in dimensionality reduced space), and report coefficients

LIME for tabular data:[2]



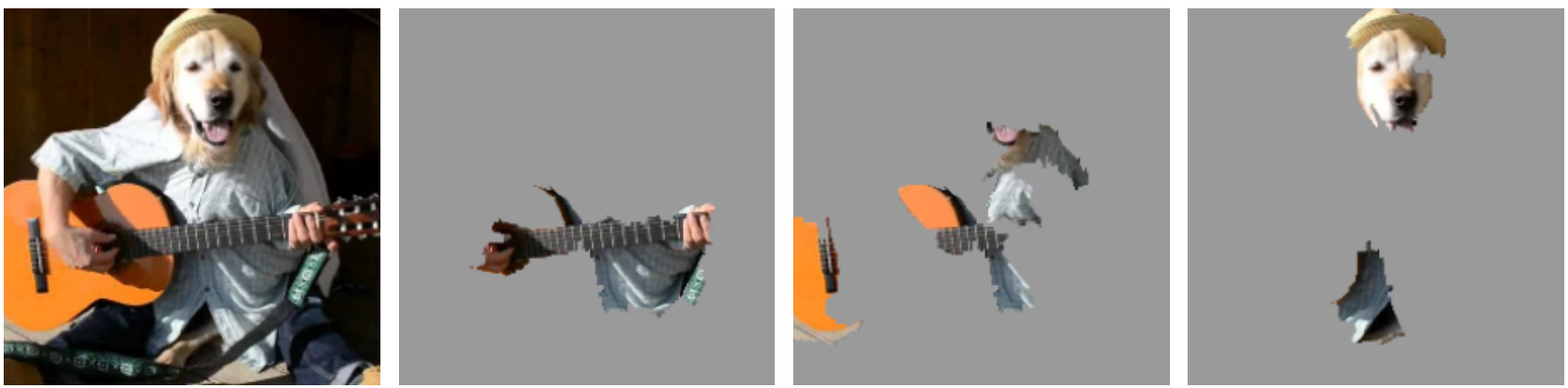
(classifying edibility of mushrooms)

[2]Image source: `https://github.com/marcotcr/lime`

Example Attribution Method: LIME

LIME: Do local linear approximation of f near x (optionally in dimensionality reduced space), and report coefficients

LIME for images:[2]

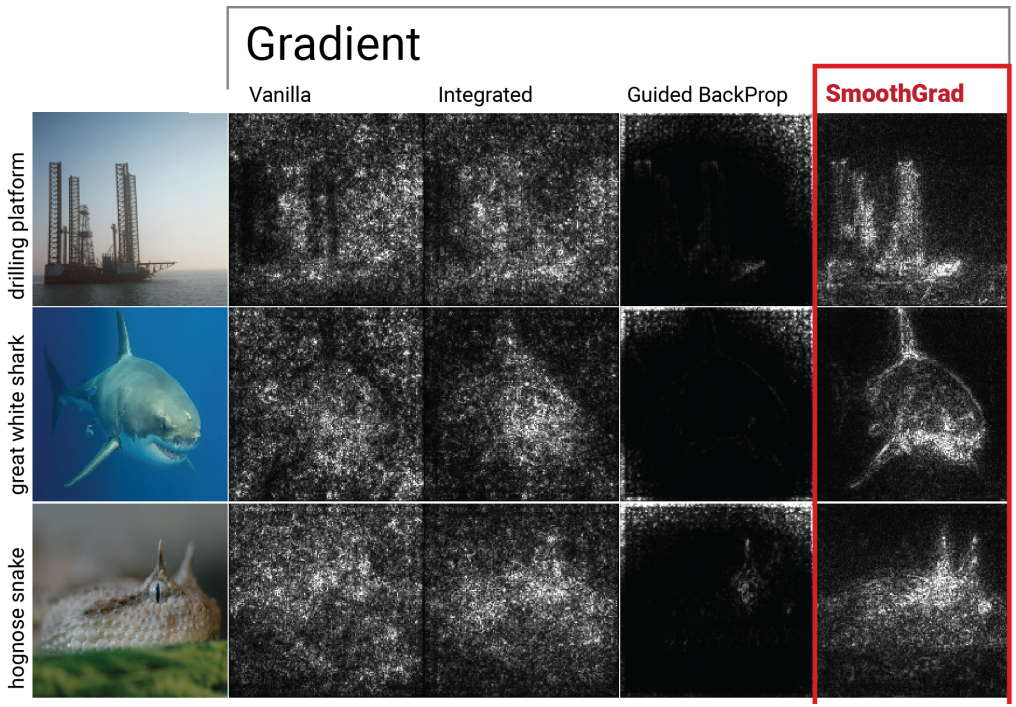


(a) Original Image (b) Explaining *Electric guitar* (c) Explaining *Acoustic guitar* (d) Explaining *Labrador*

[2]Image source: [Ribeiro et al., 2016]

Example: Gradient-based Explanations

Various gradient methods[3]

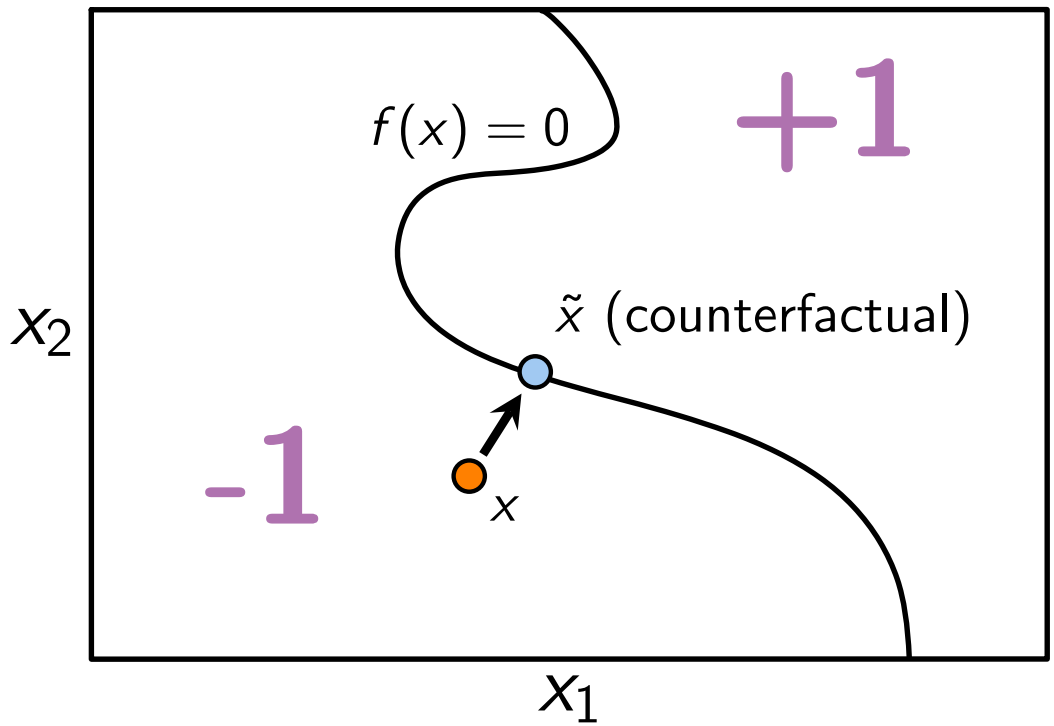


- Vanilla gradient: $\phi_f(x) = \nabla f(x)$
- SmoothGrad: $\phi_f(x) = \mathbb{E}_{Z \sim \mathcal{N}(x,\Sigma)}[\nabla f(Z)]$
- ...

[3] Image source: [Smilkov et al., 2017]

Example: Counterfactual Explanations

"If you would have had an income of **€40 000** instead of **€35 000**, your loan request would have been approved."



Counterfactual explanation: $\tilde{x} = \underset{x' : \text{sign}(f(x')) \neq \text{sign}(f(x))}{\arg\min} \text{dist}(x', x)$

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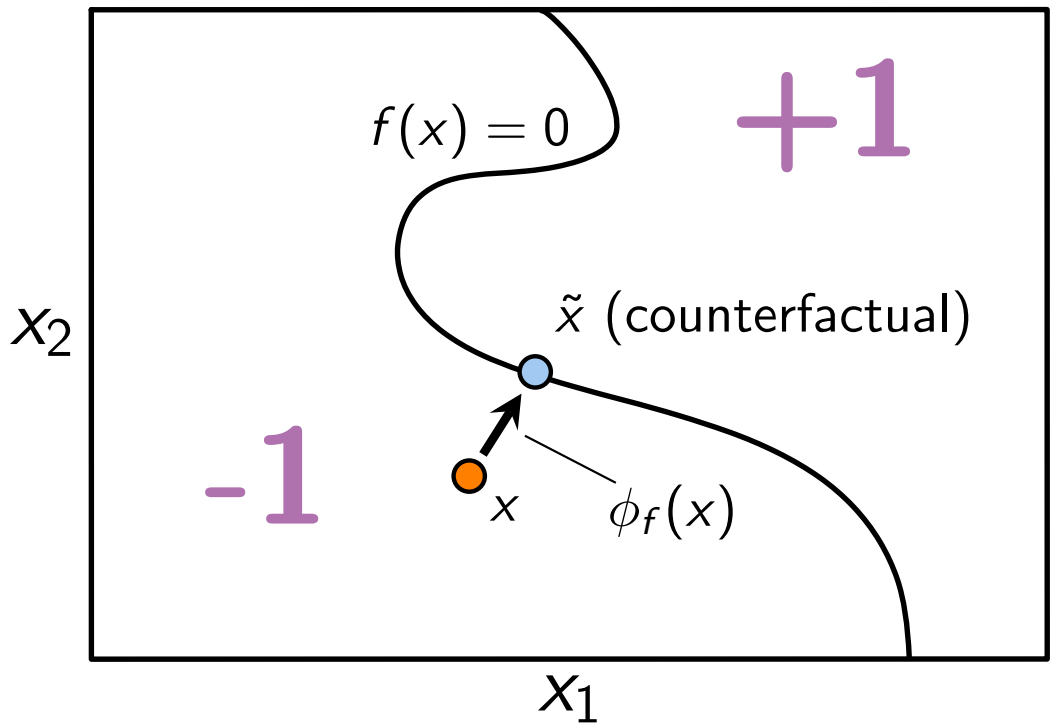


Counterfactual explanation: $\tilde{x} = \underset{x' : \text{sign}(f(x')) \neq \text{sign}(f(x))}{\arg\min} \text{dist}(x', x)$

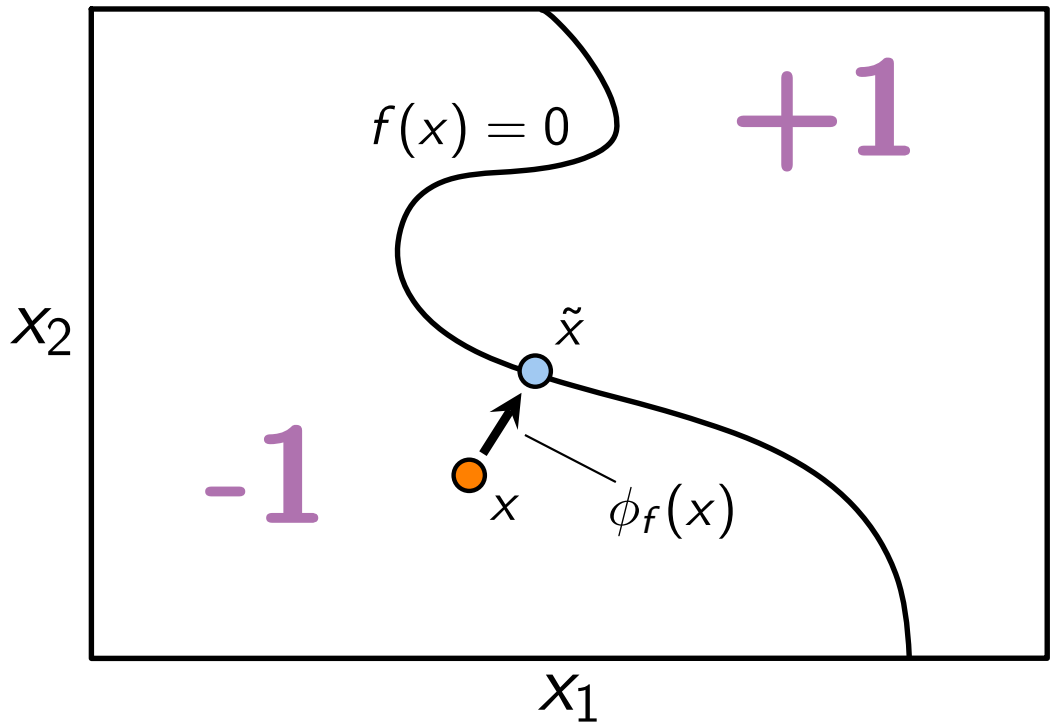
Viewed as attribution method: $\phi_f(x) = \tilde{x} - x$

How Do We Evaluate Explanations?

- When are they good? Are some better than others?
- What is even the **goal** they are trying to achieve?

Explanations with Recourse as their Goal

"If you change your current income of **€35 000** to **€40 000**, then your loan request will be approved."



- Attribution methods **provide recourse** if they tell the user how to **change their features** such that f **takes their desired value**.

Impossibility:

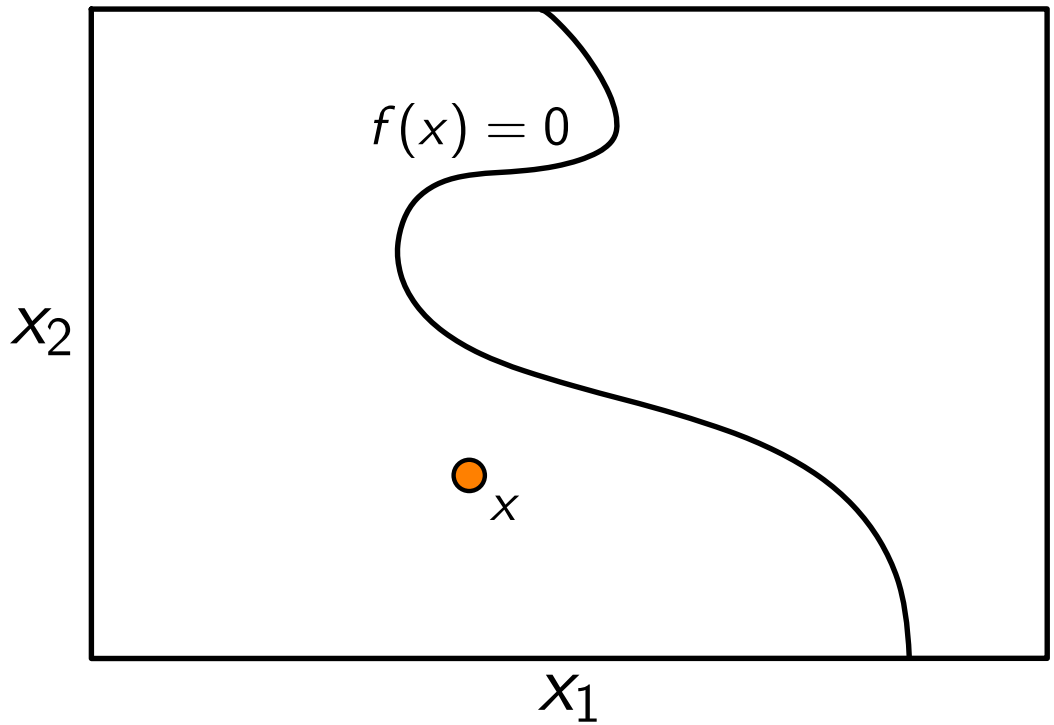
No Single Method Can Be Both Recourse Sensitive and Robust

Theorem

For any $\delta > 0$ there exists a continuous function f such that no attribution method ϕ_f can be both recourse sensitive and continuous.

Recourse Sensitivity

- Our definition: weakest possible requirement for providing recourse.



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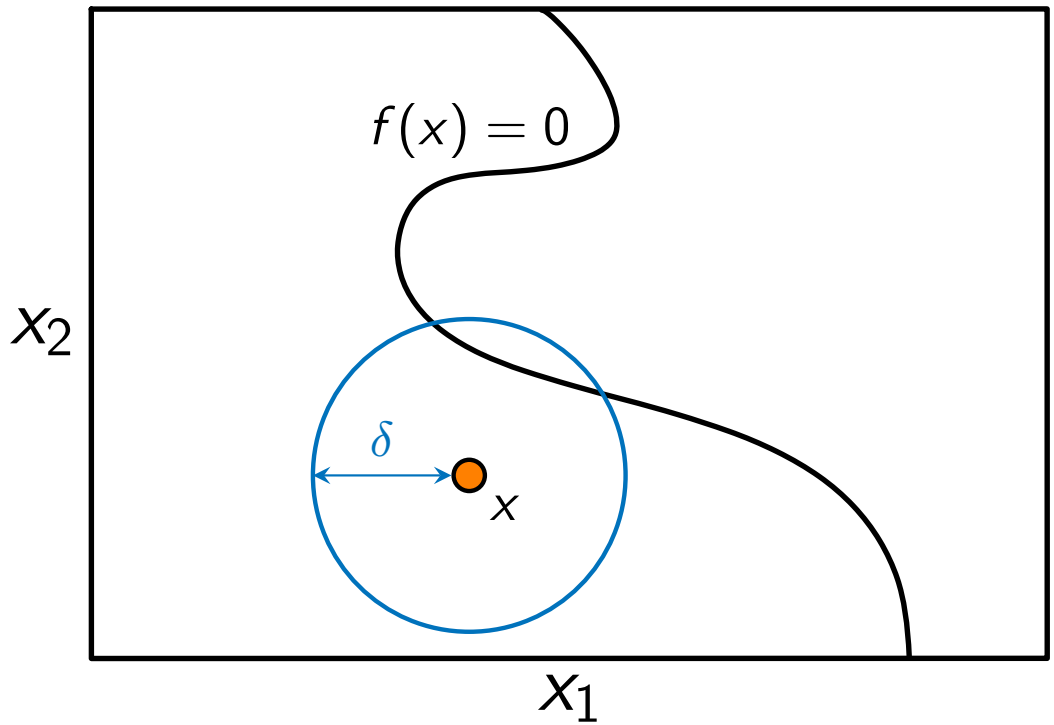

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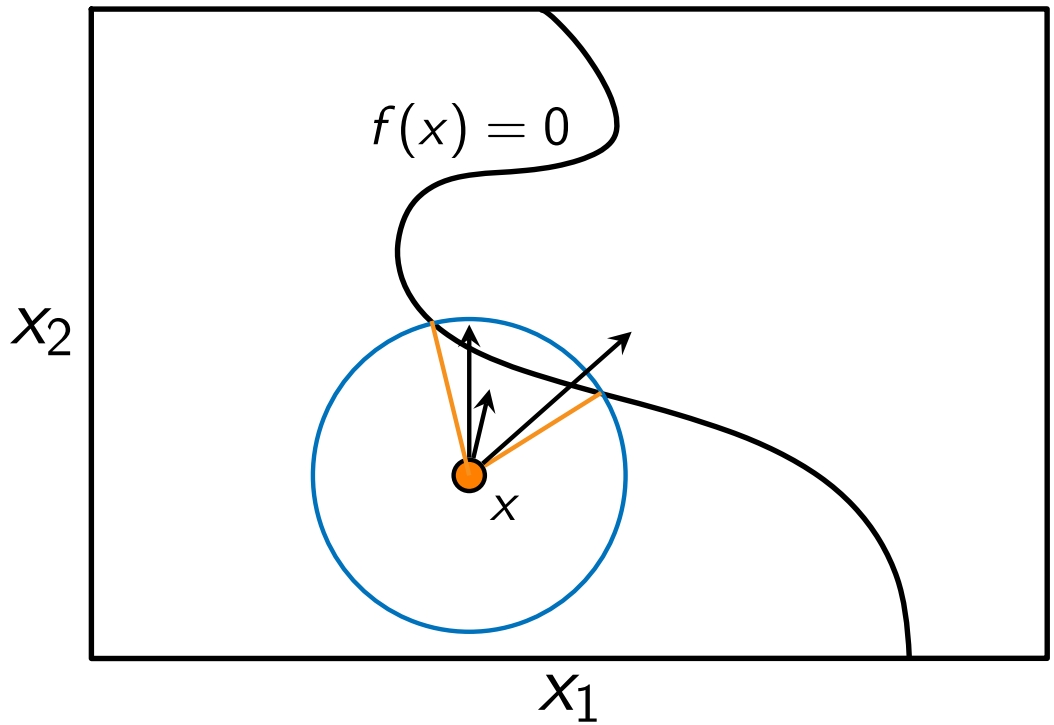
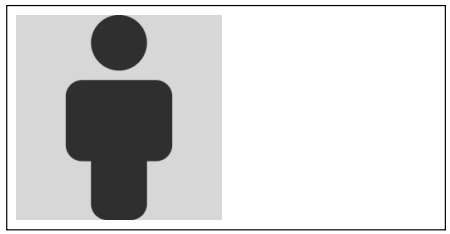


1. Assume user can change their features by at most some $\delta > 0$
2. $\phi_f(x)$ can point in **any direction that provides recourse** within distance δ, and length does not matter as long as it is > 0.
3. If no direction provides recourse, then $\phi_f(x)$ can be arbitrary.

Recourse Sensitivity: Example

Profile picture is accepted if contrast between profile and background is large enough:



(a) Accepted profile picture

(b) Rejected profile picture

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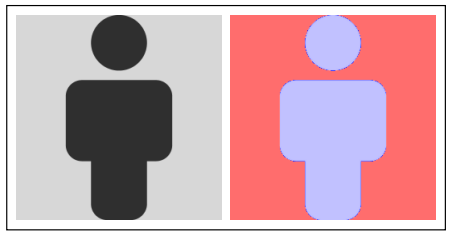

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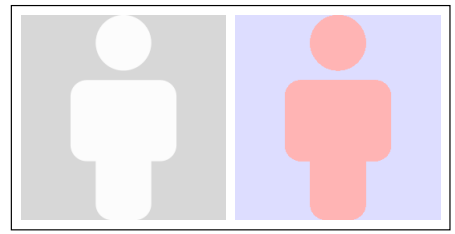
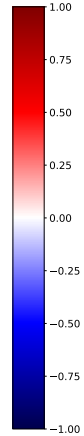


(b) Rejected profile picture



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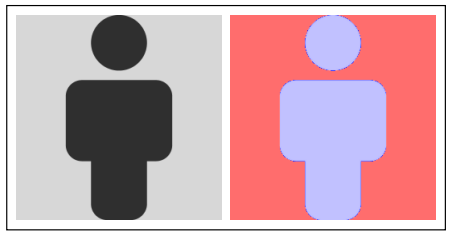

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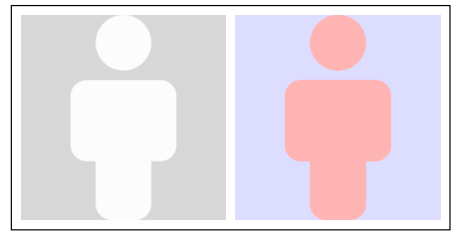

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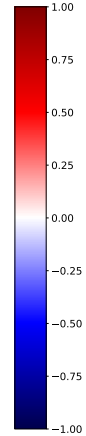

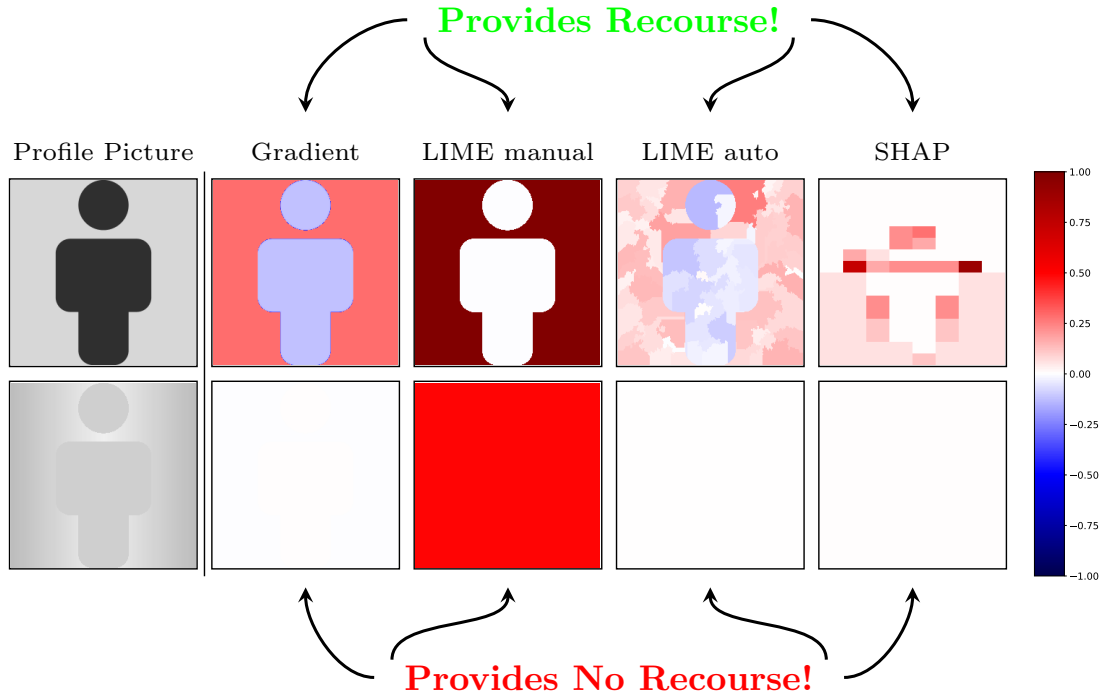

Robustness of Explanations

Compare:

1. "If you change your current income of **€35 000** to **€40 000**, then your loan request will be approved."
2. "If you change your current income of **€35 001** to **€45 000**, then your loan request will be approved."

Minor changes in x should not cause big changes in explanations!

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Robustness: If f is continuous, then ϕ_f should also be **continuous**.
(e.g. survey of recourse by [Karimi et al., 2021])

Conclusion

Summary:

- In binary classification: exist f for which recourse sensitivity + robustness is **impossible**
- Further extensions in the paper:
  - Generalization to multiclass and regression using utility functions
  - Include constraints on user actions
  - Exact characterization of impossible f when user can only change a single feature

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Discussion:

Is the field of explainable machine learning in trouble?
Not, but need to **refine goals** of explainability for recourse. E.g.:

- Accept that robustness sometimes fails
- Set-valued explanations
- Randomized explanations
- ...

References

- H. Fokkema, R. de Heide and T. van Erven. **Attribution-based Explanations that Provide Recourse Cannot be Robust**, ArXiv:2205.15834 preprint, 2022.

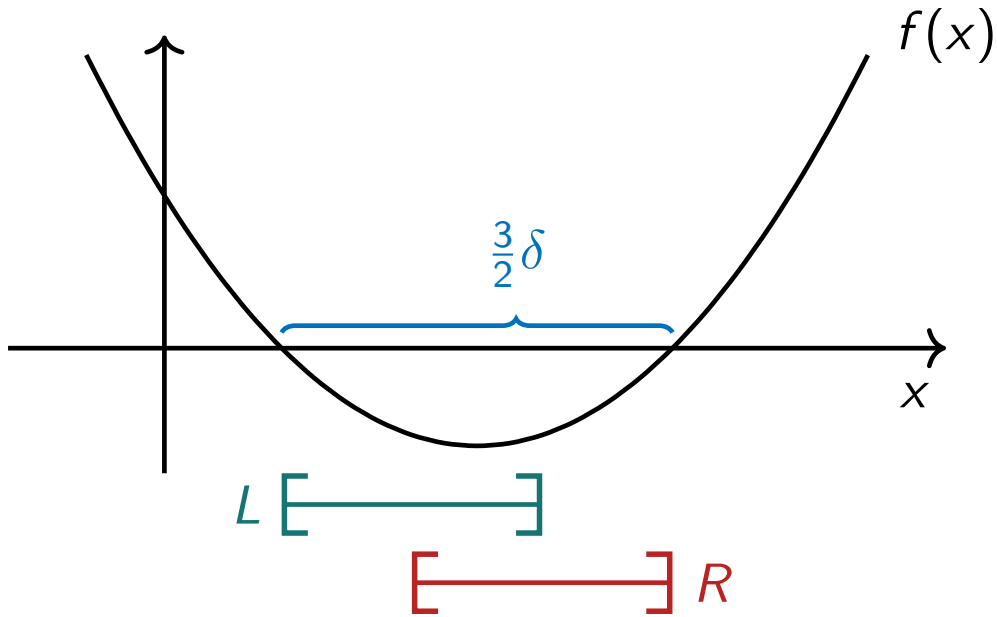
Other references:

A.-H. Karimi, G. Barthe, B. Schölkopf, and I. Valera. A survey of algorithmic recourse: definitions, formulations, solutions, and prospects. *arXiv preprint arXiv:2010.04050*, 2021.

M. T. Ribeiro, S. Singh, and C. Guestrin. "Why should I trust you?" explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*, pages 1135–1144, 2016.

D. Smilkov, N. Thorat, B. Kim, F. Viégas, and M. Wattenberg. Smoothgrad: removing noise by adding noise. *ArXiv:1706.03825*, 2017.

Proof Sketch



$$L = \{x : \text{recourse possible by moving at most } \delta \text{ left}\}$$
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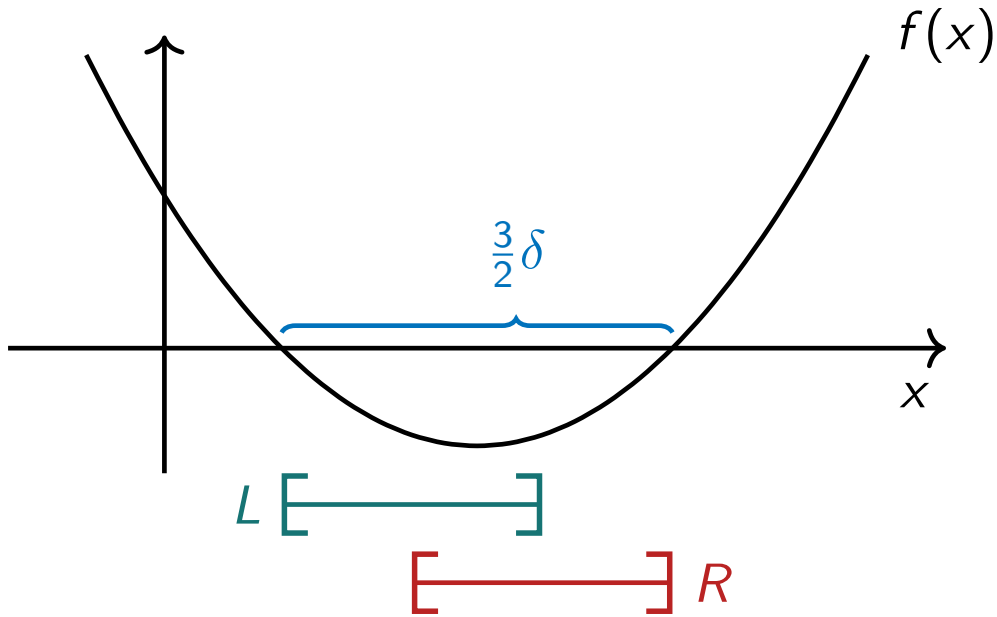

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Recourse sensitivity implies:

$$\phi_f(x) \begin{cases} < 0 & \text{for } x \in L \setminus R \\ > 0 & \text{for } x \in R \setminus L \\ \neq 0 & \text{for } x \in L \cap R \end{cases}$$

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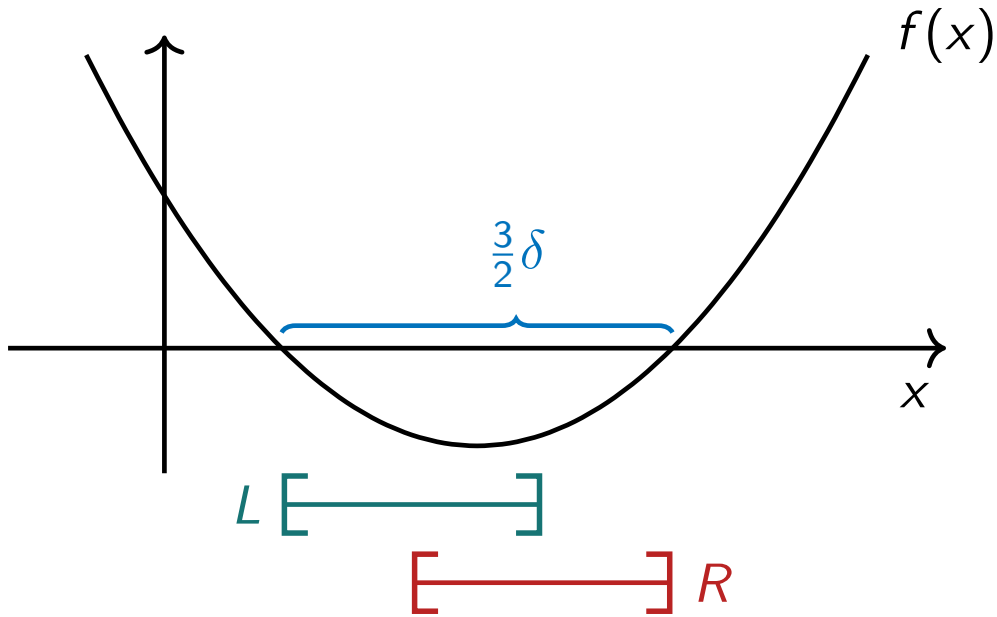

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But this **contradicts continuity**!
(by the mean-value theorem)

Can embed 1D example in higher dimensions as well.