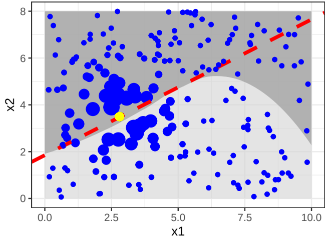
Interpretable Machine Learning

LIME Pitfalls



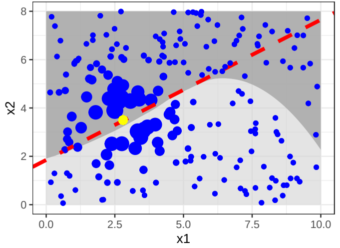
Learning goals

- Learn why LIME should be used with caution
- Possible pitfalls of LIME

Interpretable Machine Learning

Local Explanations: LIME

LIME Pitfalls



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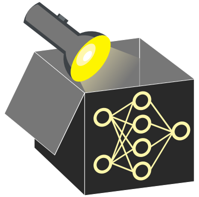
LIME PITFALLS



- LIME is one of the most widely used methods for local interpretability
  ⇝ But several papers highlight important (practical) limitations
- Pitfalls arise at multiple levels, which will be discussed in detail:
  - **Sampling** – ignores feature dependencies, risks extrapolation
  - **Locality definition** – kernel width and distance metrics affect sensitivity
  - **Local vs. global features** – global signals may overshadow local ones
  - **Faithfulness** – trade-off between sparsity and local accuracy
  - **Hiding biases** – explanations can be manipulated to appear fair
  - **Robustness** – explanations vary for similar points
  - **Superpixels (images)** – instability due to segmentation method

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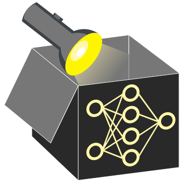

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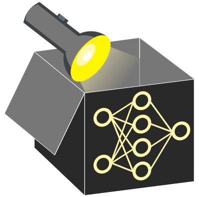
PITFALL: SAMPLING



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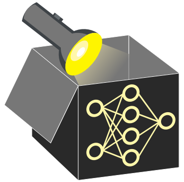

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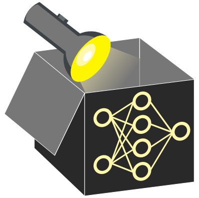

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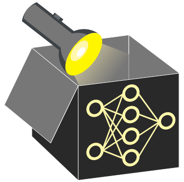

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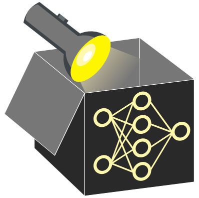

- **Pitfall**: Difficult to define locality (= how samples are weighted locally)
- **Implication:** Local model and explanation quality depend heavily on this weighting, but no principled way exists to choose it
- **Default:** Use exponential kernel as proximity measure between $\mathbf{x}$ and $\mathbf{z}$: $\phi_{\mathbf{x}}(\mathbf{z}) = exp(-d(\mathbf{x}, \mathbf{z})^2/\sigma^2)$ with distance measure d and kernel width σ

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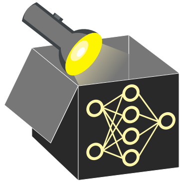

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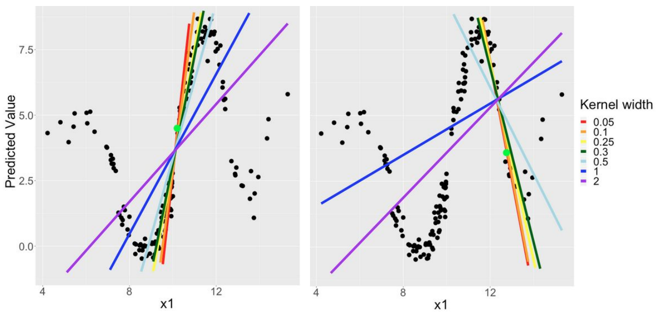
Example: For 2 obs. (green points), fit local surrogate models (lines) using only x_1



Line colors: different kernel widths used for proximity weighting

Right: larger kernel widths affect lines more

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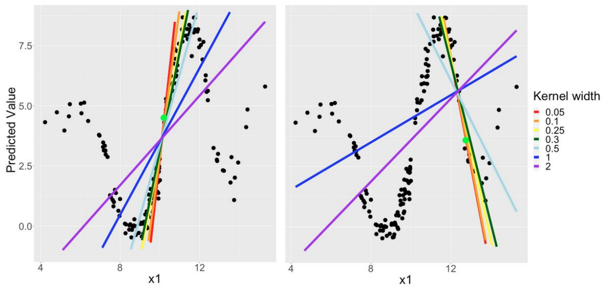

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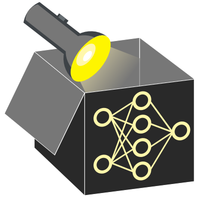

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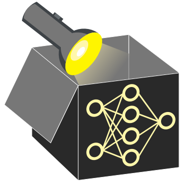

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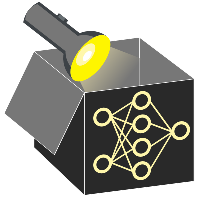

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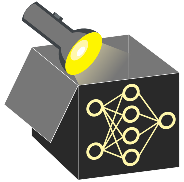

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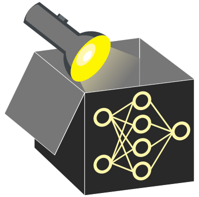

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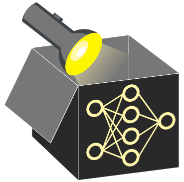

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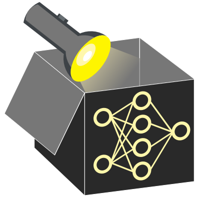

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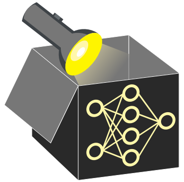

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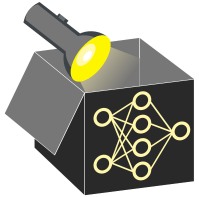

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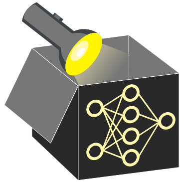

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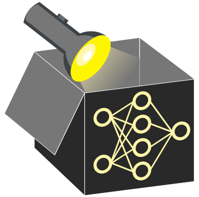

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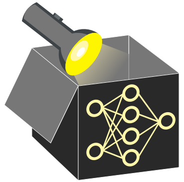

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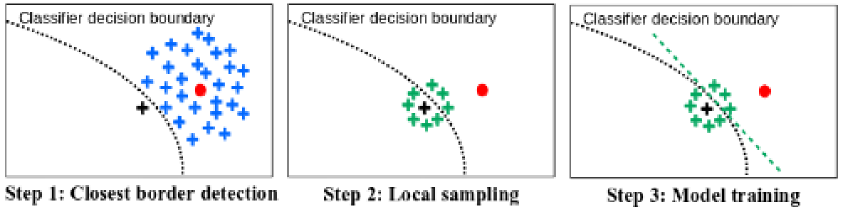
- **Problem:** Sampling around obs. to be explained **x** may miss decision boundary
- **Solution (LS: Local Surrogate Method):**
  - Step 1: Find closest point to **x** (red dot) from opposite class (black cross)
  - Step 2: Sample around that point to better capture boundary
  - Step 3: Train local surrogate using those samples

    ⇝ better approximates the local direction of the decision boundary



Example: **x** (red point), closest point from other class (black cross)

- LIME: What does the model do around this point?
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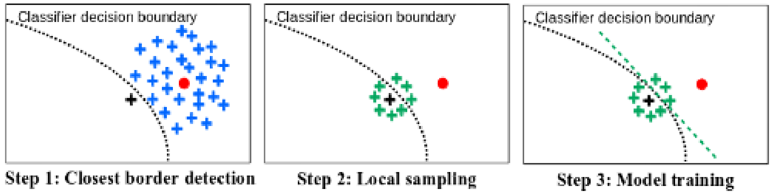

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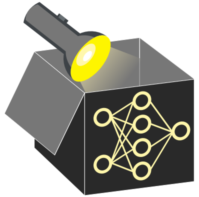

- Random forest (RF) classification on half-moons dataset
- **Background color:** Classification of RF (prediction surface)
- **Black/grey crosses:** training data
- **Green dot:** Obs. to be explained; **Red dot:** nearest point from opposite class
- **Grey curve:** RF's decision boundary; **Dotted lines:** LIME decision boundaries
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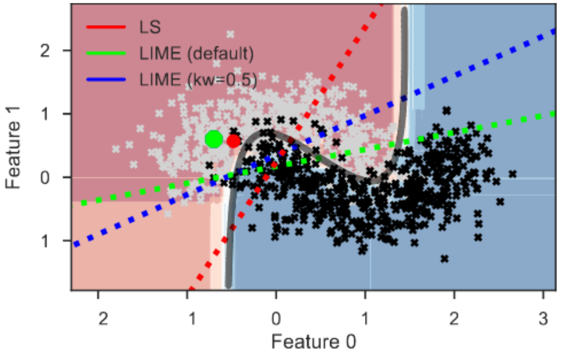

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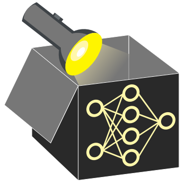

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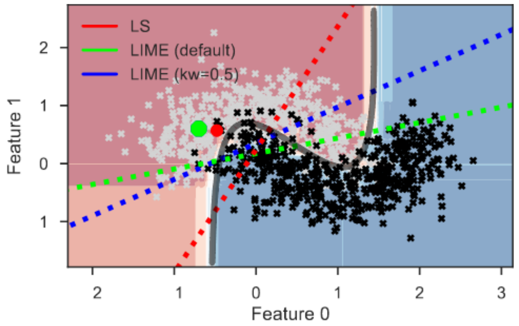

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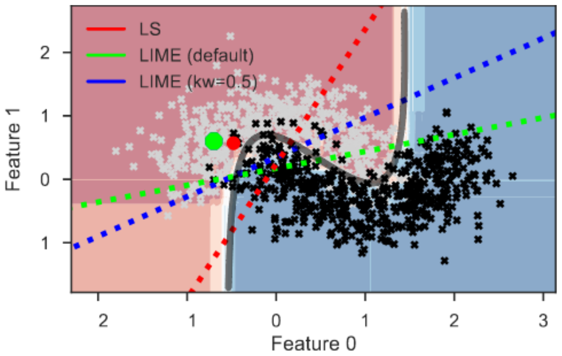

Feature 0 is global; class always flips when moving left (red) to right (blue)

Feature 1 is local; class flips only near boundary when moving up/down

Observation: LIME decision boundaries (blue/green) fail to match the steep local boundary captured by LS (red)

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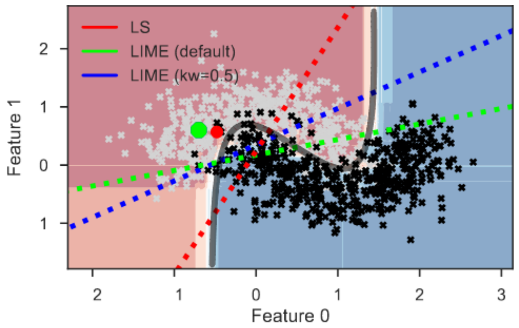

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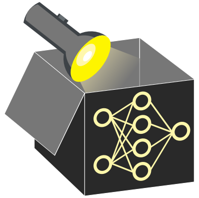

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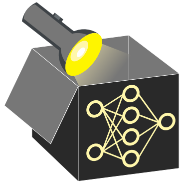

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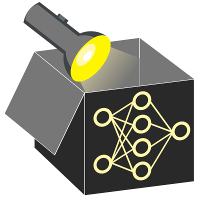

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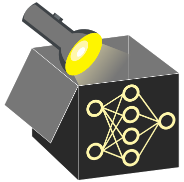
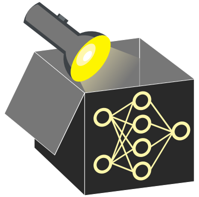


PITFALL: HIDING BIASES ‣ Slack et al. 2020



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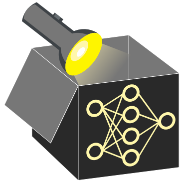

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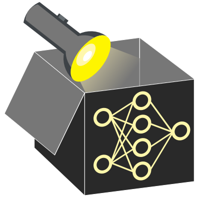

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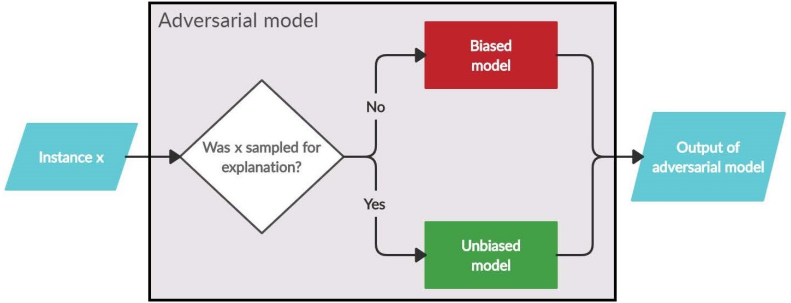

Image Source: ▸ Vres, Sikonja (2021)

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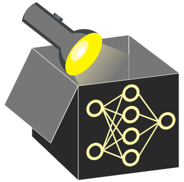

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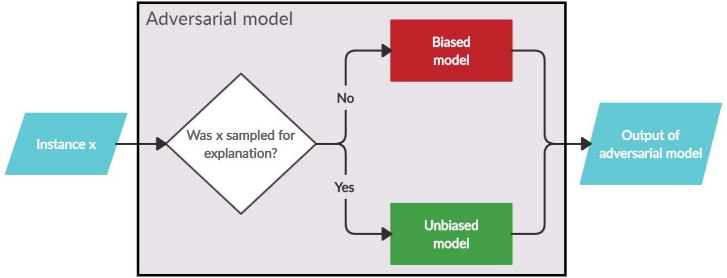

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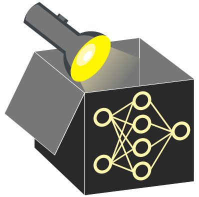

Key insight: LIME can be fooled if explanations rely on model behavior outside the true data manifold.

Example: Credit approval

- Biased model uses features correlated with gender (parental leave duration)
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  $\rightsquigarrow$ used to produce explanations based on unbiased predictions to hide bias
- LIME's extrapolated samples trigger the unbiased model
  $\Rightarrow$ explanation appears fair, but original predictions are biased

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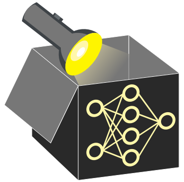

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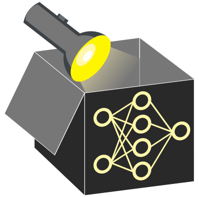
PITFALL: ROBUSTNESS ▸ Alvarez-Melis, D., & Jaakkola, T. 2018



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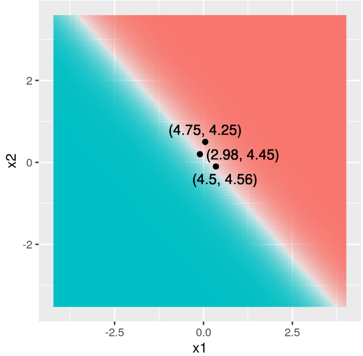
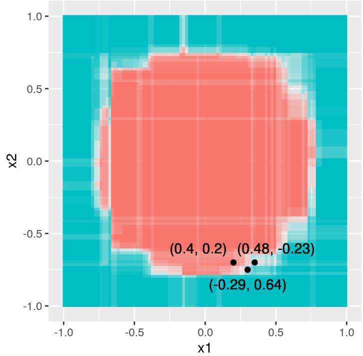


Linear task (logistic regression). LIME returns similar coefficients for similar points.



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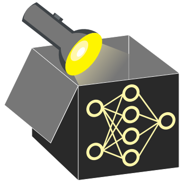
PITFALL: ROBUSTNESS ▸ JAAKKOLA_2018



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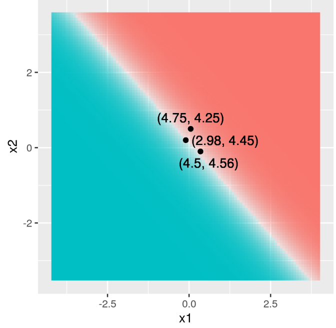

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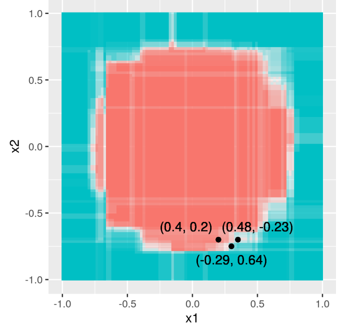

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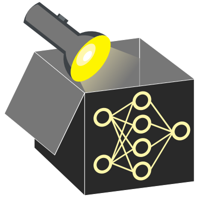
Interpretable Machine Learning – 11 / 12

PITFALL: DEFINITION OF SUPERPIXELS ▸ Achanta et al. 2012



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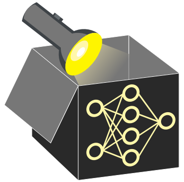

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Interpretable Machine Learning – 12 / 12

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