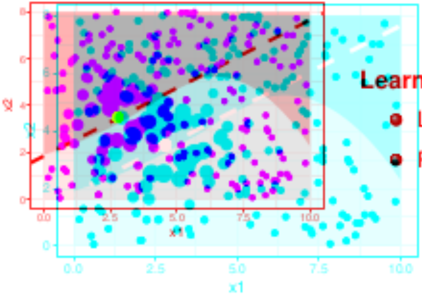
Interpretable Machine Learning

LIME Pitfalls



Learning goals

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

LIME PITFALLS

- LIME is one of the best-known interpretable ML methods
  $\rightsquigarrow$ But several papers caution to be careful in practice
- Problems can occur on different levels which are described subsequently:
  - Sampling procedure (extrapolation)
  - Definition of locality (sensitivity)
  - Scope of feature effects (local vs. global)
  - Faithfulness (trade-off with sparsity)
  - Surrogate model (hiding biases, robustness)
  - Definition of superpixels in case of image data (sensitivity)

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PITFALL: SAMPLING

- **Pitfall**: Common sampling strategies for $\mathbf{z} \in Z$ do not account for correlation between features
- **Implication**: Unlikely data points might be used to learn local explanation models

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PITFALL: SAMPLING

- **Pitfall**: Common sampling strategies for $\mathbf{z} \in Z$ do not account for correlation between features
- **Implication**: Unlikely data points might be used to learn local explanation models
- **Solution I**: Use a local sampler directly on $\mathcal{X}$
  $\rightsquigarrow$ derivation is particularly difficult for high dimensional or mixed feature spaces
- **Solution II**: Use training data to fit surrogate model
  $\rightsquigarrow$ only works well with enough data near $\mathbf{x}$

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LIME PITFALL: LOCALITY

- **Pitfall**: Difficult to define locality (= how samples are weighted locally)
  $\rightsquigarrow$ Strongly affects local model, but there is no automatic procedure for choosing neighborhood
- Originally, an exponential kernel as proximity measure between $\mathbf{x}$ and $\mathbf{z}$ was proposed:
  $\phi_{\mathbf{x}}(\mathbf{z}) = exp(-d(\mathbf{x}, \mathbf{z})^2/\sigma^2)$ where d is a distance measure and σ is the kernel width

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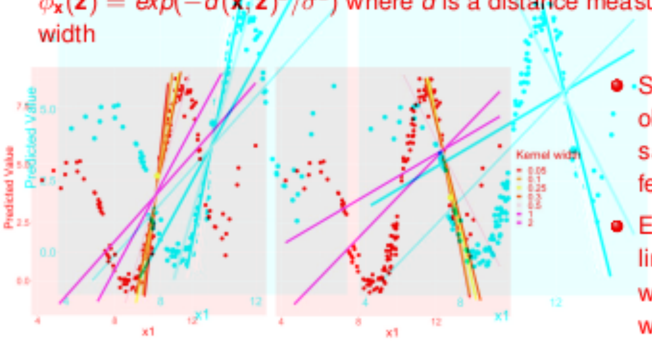

- Surrogate models for 2 obs. (green points) for same model with one feature x_1
- Each line refers to a linear surrogate model with different kernel width
- Right figure: larger kernel widths influence lines more

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LIME PITFALL: LOCALITY

Kopper et al. 2019

- **Solution I**: Kernel width strongly interacts with locality:
  - Large kernel width leads to interaction with points further away (unwanted)
  - Small kernel width leads to small neighborhood

    ⇝ risk of few data points

    ⇝ potentially fitting more noise

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    $\rightsquigarrow$ potentially fitting more noise
- **Solution II**: Use Gower distance where no kernel width needs to be specified
  - **Problem**: data points far away receive weight > 0
    $\rightsquigarrow$ resulting explanations are rather global than local surrogates

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PITFALL: LOCAL VS. GLOBAL FEATURES

Laugel et al. 2018

- **Problem:**
  By sampling obs. for the surrogate model from the whole input space, the influence of local features might be hidden in favor of features with global influence (even for small kernel width)

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  - Some features influence the **global** shape of the black-box model
  - Other **local** features impact predictions only in smaller regions of $\mathcal{X}$

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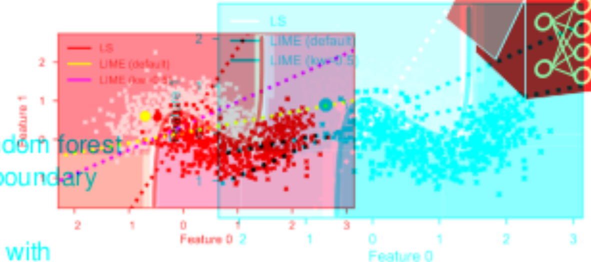
- **Example:** Decision trees
  $\Rightarrow$ Split features close to root have a more global influence than the ones close to leaves

PITFALL: LOCAL VS. GLOBAL FEATURES – EXAMPLE

Laugel et al. 2018

- Binary classification model
- Right figure:
  - Black and grey crosses: training data
  - Green dot: Obs. to be explained
  - Background color: Classification of random forest
  - Dark grey curve: Classifier's decision boundary
  - Dotted lines: Local decision boundary
- **Observation:** Decision boundaries of LIME with different kernels (blue and green lines) do not match the direction of the local decision boundary (which appears steeper)



Half-moons dataset

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Half-moons dataset
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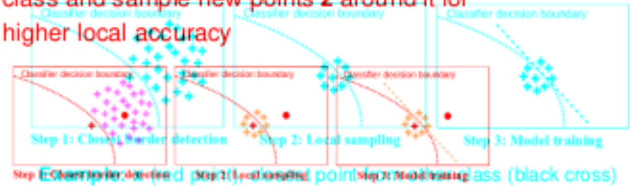
PITFALL: LOCAL VS. GLOBAL FEATURES – SOLUTION ▸ Laugel et al. 2018

- **Solution:** Find closest point to **x** from other class and sample new points **z** around it for higher local accuracy



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

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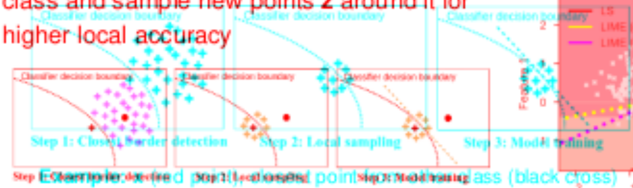

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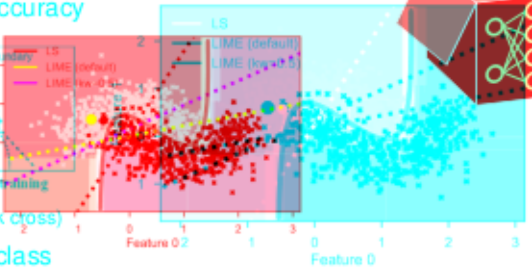

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- Red dot (right figure): Closest point from other class
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PITFALL: FAITHFULNESS

- **Problem**: Trade-off between local fidelity vs. sparsity
- **Observation I**: Low fidelity $\rightsquigarrow$ unreliable explanations
- **Observation II**: High fidelity requires complex models $\rightsquigarrow$ difficult to interpret surrogate model

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- **Example: Credit data**
  - Original prediction by random forest for one data point $\mathbf{x}$:

$$\hat{f}(\mathbf{x}) = \hat{\mathbb{P}}(y = 1 \mid \mathbf{x}) = 0.143$$

  - Linear model with only three selected features (age, checking.account, duration):

$$g_{lm}(\mathbf{x}) = \hat{\theta}_0 + \hat{\theta}_1 x_{age} + \hat{\theta}_2 x_{checking.account} + \hat{\theta}_3 x_{duration} = 0.283$$

  - Generalized additive model (with all 9 features) is more complex:

$$g_{gam}(\mathbf{x}) = \hat{\theta}_0 + f_{age}(x_{age}) + f_{checking.account}(x_{checking.account}) + f_{duration}(x_{duration}) + \cdots = 0.148$$

PITFALL: HIDING BIASES Slack et al. 2020

- **Problem:** Developer could manipulate their model to hide biases
- **Observation:** LIME can sample out-of-distribution points (extrapolation)

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- **Attack** with adversarial model:
  1. classifier to discriminate between in-distribution and out-of-distribution data points
  2. for in-distribution points, use the original (biased) model
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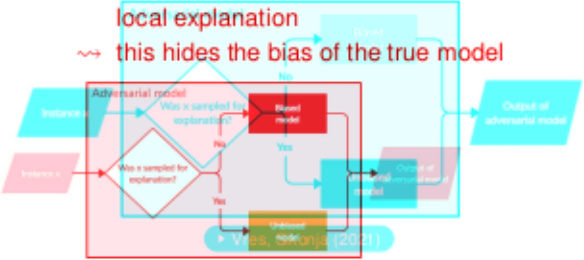
  ⇝ LIME samples out-of-distribution points and uses the unbiased model for local explanation

  ⇝ this hides the bias of the true model



Vres, Sikonja (2021)

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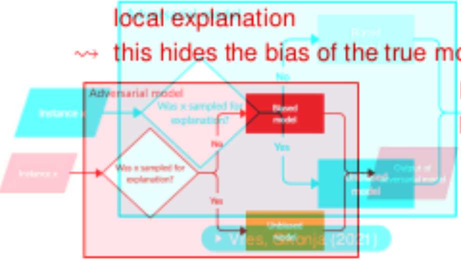


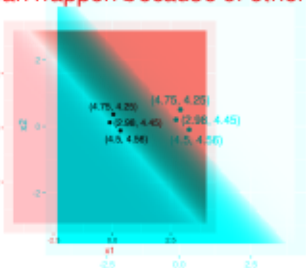
▸ Vres, Sikonja (2021)

Example: Not using 'gender' to approve a loan

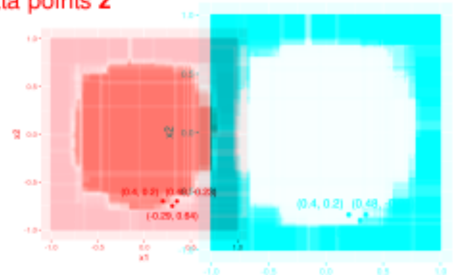
- biased model trained on features correlated with 'gender' (e.g. duration of parental leave)
  ⇝ used to make biased / unfair predictions
- unbiased model trained on features uncorrelated with 'gender'
  ⇝ used to produce explanations based on unbiased predictions to hide bias

 Alvarez-Melis, D. & Jaakkola, T. 2018

- **Problem**: Instability of explanations
- **Observation**: Explanations of two very close points could vary greatly
  ⇝ can happen because of other sampled data points **z**



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



Circular prediction task (random forest). Linear surrogate returns different coefficients for similar points.

PITFALL: DEFINITION OF SUPERPIXELS

Achanta et al. 2012

- **Problem:** Instability because of specification of superpixels for image data
- **Observation:** Multiple specification of superpixels exist, influencing both the shape and size

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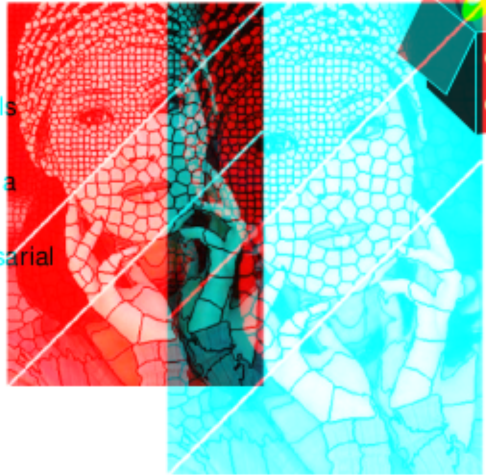
PITFALL: DEFINITION OF SUPERPIXELS

Achanta et al. 2012

- **Problem:** Instability because of specification of superpixels for image data
- **Observation:** Multiple specification of superpixels exist, influencing both the shape and size
- **Implication:** The specification of superpixel has a large influence on the explanations
- **Attack:** Change superpixels as part of an adversarial attack ⇝ changed explanation



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