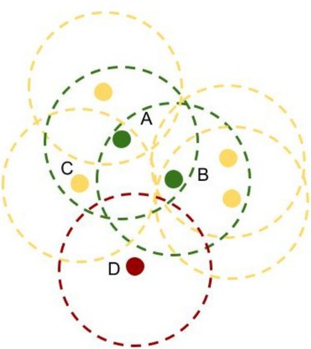
Interpretable Machine Learning

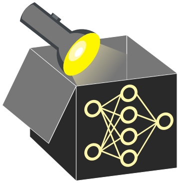
Local Explanations: Increasing Trust in Explanations



Learning goals

- Understand the aspects that undermine users' trust in an explanation
- Learn diagnostic tools that could increase trust

MOTIVATION & IMPORTANT PROPERTIES



- Local explanations should not only make a model interpretable but also reveal if the model is trustworthy

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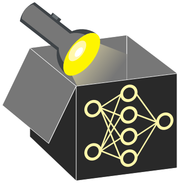

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- **Interpretable**: “Why did the model come up with this decision?”

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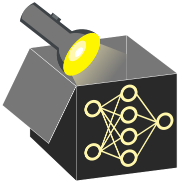

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- **Interpretable**: “Why did the model come up with this decision?”
- **Trustworthy**: “How certain is this explanation?”
  1. accurate insights into the inner workings of our model
     - Failure case: generation is based on inputs in areas where the model was trained with little or no training data (extrapolation)

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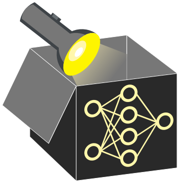

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     - Expectation: similar explanations for similar data points with similar predictions
     - However, multiple sources of uncertainty exist

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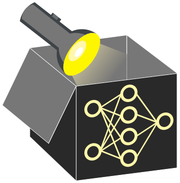

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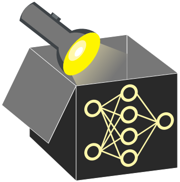
     $\rightsquigarrow$ measure how robust an IML method is to small changes in the input data or parameters

     $\rightsquigarrow$ Is an observation out-of-distribution?
- Failing in one of these $\rightsquigarrow$ undermining users' trust in the explanations $\rightsquigarrow$ undermining trust in the model

OUT-OF-DISTRIBUTION (OOD) DETECTION



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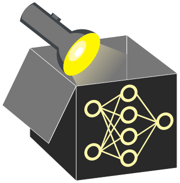

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- For local explanation methods, the following components could be out-of-distribution (OOD):
  - The data for LIME's surrogate model
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  - ICE curves grid data points

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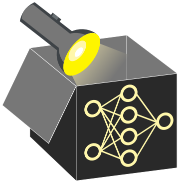

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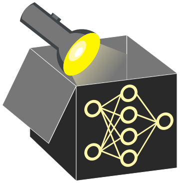
- Two very simple and intuitive approaches
  - Classifier for out-of-distribution
  - Clustering
- More complicated also possible, e.g., variational autoencoders
  ▸ “Daxberger et al.” 2020

OOD DETECTION: OOD-CLASSIFIER



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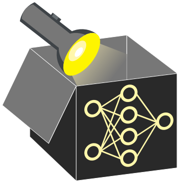

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- Study whether an explanation approach can be fooled ▶ "Dylan Slack et al." 2020
  - Hide bias in the true (deployed) model, but use an unbiased model for all out-of-distribution samples

$\rightsquigarrow$ Important way to diagnose an explanation approach

OOD DETECTION: CLUSTERING VIA DBSCAN

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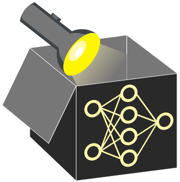

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- For this method, we define an ϵ-neighborhood:
  Given a dataset $X = \{\mathbf{x}^{(i)}\}_{i=1}^{n}$, an ϵ-neighborhood for $\mathbf{x} \in \mathcal{X}$ is defined as

$$\mathcal{N}_{\epsilon}(\mathbf{x}) = \{\mathbf{x}^{(i)} \in \mathcal{X} | d(\mathbf{x}, \mathbf{x}^{(i)}) \leq \epsilon\}.$$

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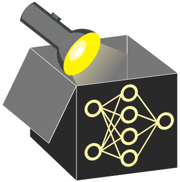

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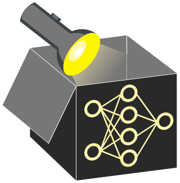

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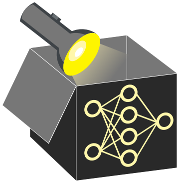

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- Noise points
  - Are not within $\mathcal{N}_{\epsilon}(\mathbf{x})$
  - Not part of any cluster

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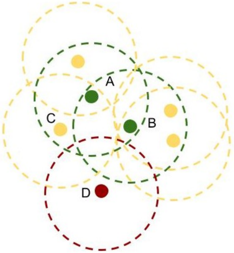
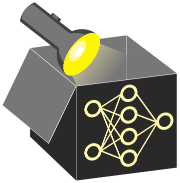


Example for DBSCAN, circles display ϵ-neighborhoods, $m = 4$



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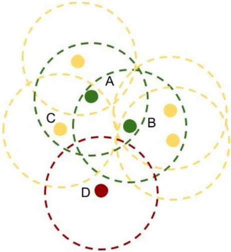

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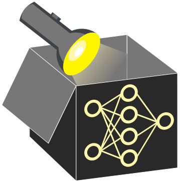

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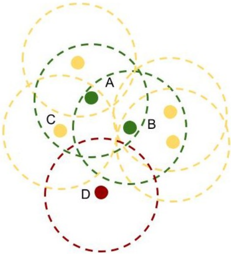

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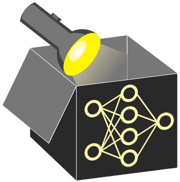

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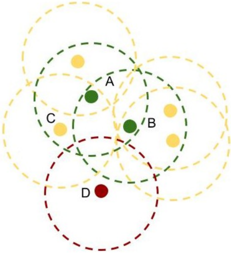

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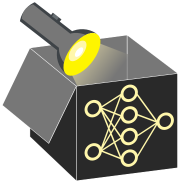

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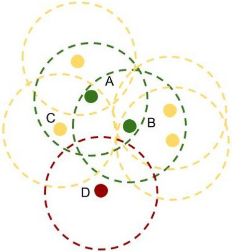

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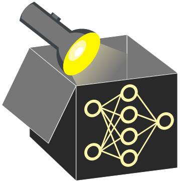
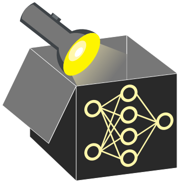


- Disadvantages:
  - Depending on the distance metric $d(\cdot)$, DBSCAN could suffer from the "curse of dimensionality"
  - The choice of ϵ and m is not clear a-priori

ROBUSTNESS



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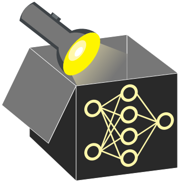

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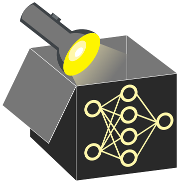

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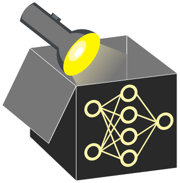
     $\rightsquigarrow$ are ML models non-robust, e.g., because they are trained on noisy data?
- We focus on explanation uncertainty
  - Even with the same model and same (or similar) data points, we can receive different explanations

ROBUSTNESS MEASURE FOR LIME AND SHAP



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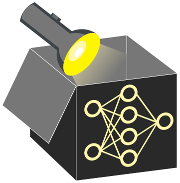

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- For LIME and SHAP, notion of stability based on **locally Lipschitz continuity** ▸ "Alvarez-Melis and Jaakkola" 2018:
  An explanation method $g : \mathcal{X} \rightarrow \mathbb{R}^m$ is locally Lipschitz if
  - for every $\mathbf{x}_0 \in \mathcal{X}$ there exist $\delta > 0$ and $\omega \in \mathbb{R}$
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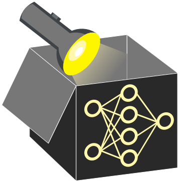

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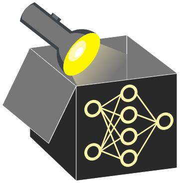

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- ω is rarely known a-priori but it could be estimated as follows:

$$\hat{\omega}_X(\mathbf{x}) \in \underset{\mathbf{x}^{(i)} \in \mathcal{N}_\epsilon(\mathbf{x})}{\arg\max} \frac{||g(\mathbf{x}) - g(\mathbf{x}^{(i)})||_2}{d(\mathbf{x}, \mathbf{x}^{(i)})},$$

where $\mathcal{N}_\epsilon(\mathbf{x})$ is the ϵ-neighborhood of $\mathbf{x}$