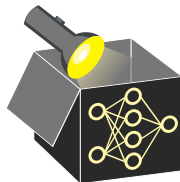
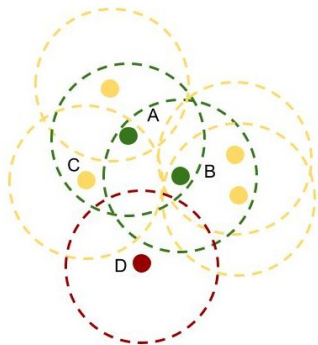


Interpretable Machine Learning



Local Explanations: Increasing Trust in Explanations

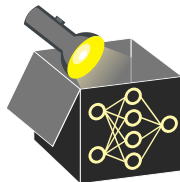


Learning goals

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

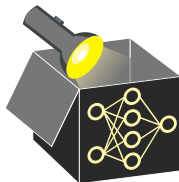
MOTIVATION & IMPORTANT PROPERTIES

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



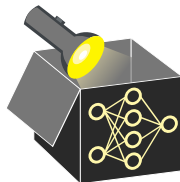
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 - ❶ accurate insights into the inner workings of our model
 - Failure case: generation is based on inputs in areas where the model was trained with little or no training data (extrapolation)

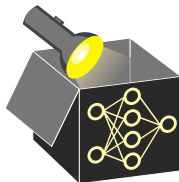


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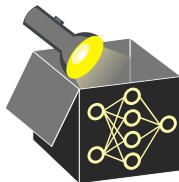
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~> measure how robust an IML method is to small changes in the input data or parameters

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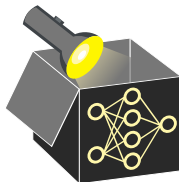
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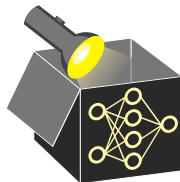
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 - ↪ Is an observation out-of-distribution?
- Failing in one of these ↪ undermining users’ trust in the explanations
 - ↪ undermining trust in the model

OUT-OF-DISTRIBUTION (OOD) DETECTION

- Models are unreliable in areas with little data support
~> explanations from local explanation methods are unreliable

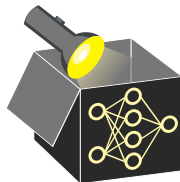


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 - The data for LIME's surrogate model
 - Counterfactuals themselves
 - Shapley value's permuted obs. to calculate the marginal contriubs
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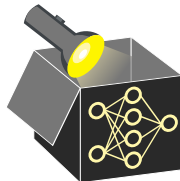
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- Two very simple and intuitive approaches
 - Classifier for out-of-distribution
 - Clustering
- More complicated also possible, e.g., variational autoencoders

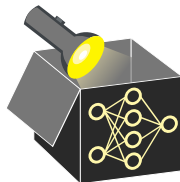
► Daxberger 2020

OOD DETECTION: OOD-CLASSIFIER



- Problem: we have only in-distribution data
 - Idea: Hallucinate new (ood) data by randomly sampling data points
- ~→ Learn a binary classifier to distinguish between the origins of the data

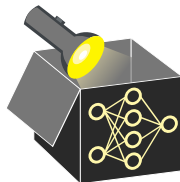
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- ~> Learn a binary classifier to distinguish between the origins of the data
- Study whether an explanation approach can be fooled ▶ Slack 2020
 - Hide bias in the true (deployed) model, but use an unbiased model for all out-of-distribution samples
- ~> Important way to diagnose an explanation approach

OOD DETECTION: CLUSTERING VIA DBSCAN

- DBSCAN is a data clustering algorithm ► Ester 1996
(Density-Based Spatial Clustering of Applications with Noise)

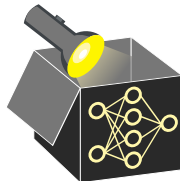


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Given a dataset $X = \{\mathbf{x}^{(i)}\}_{i=1}^n$, an ϵ -neighborhood for $\mathbf{x} \in \mathcal{X}$ is defined as

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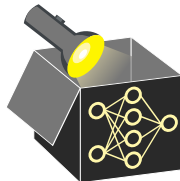
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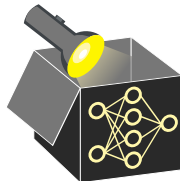
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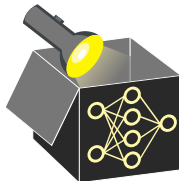
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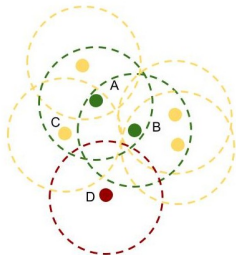
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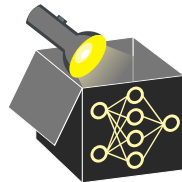
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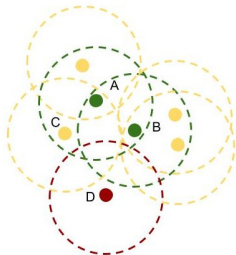


Example for DBSCAN, circles display ϵ -neighborhoods, $m = 4$

- Green points A and B are core points and form one cluster since they lie in each others neighborhood, all yellow points are border points of this cluster

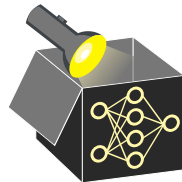


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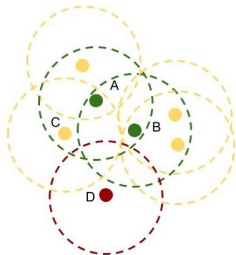


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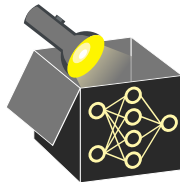


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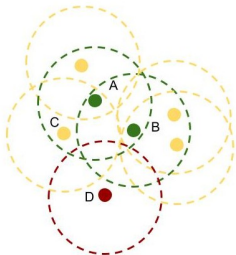


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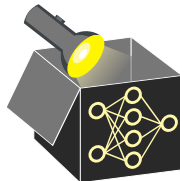


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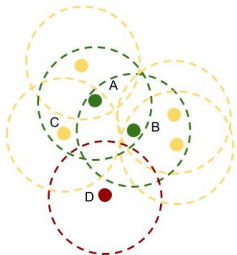


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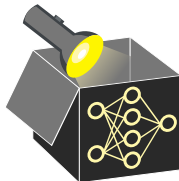


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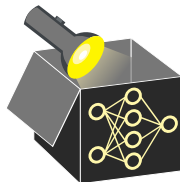
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- Disadvantages:

- 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

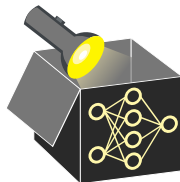


ROBUSTNESS



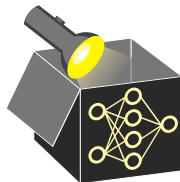
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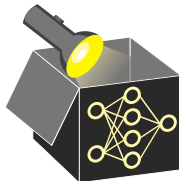
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 - ↪ are ML models non-robust, e.g., because they are trained on noisy data?
- We focus on explanation uncertainty
 - Even with the same model and same (or similar) data points, we can receive different explanations

ROBUSTNESS MEASURE FOR LIME AND SHAP

- Objective: Similar explanations for similar inputs (in a neighborhood)



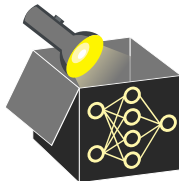
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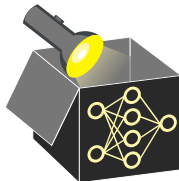
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Note that, for LIME, g returns the m coefficients of the surrogate model



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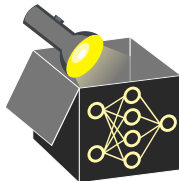
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- According to this, we can quantify the robustness of explanation models in terms of ω :
 - ↪ The closer ω is to 0, the more robust our explanation method is
- ω is rarely known a-priori but it could be estimated as follows:

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

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