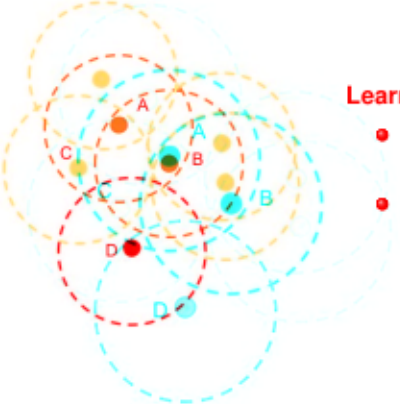
Interpretable Machine Learning

Increasing Trust in Explanations



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

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MOTIVATION & IMPORTANT PROPERTIES

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

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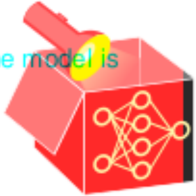

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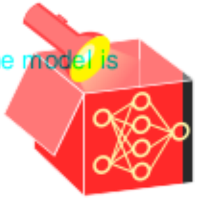

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- **Trustworthy:** "How certain is this explanation?"
  - ➜ accurate insights into the inner workings of our model
    - Failure case: generation is based on inputs in areas where the model was trained with little or no training data (extrapolation)

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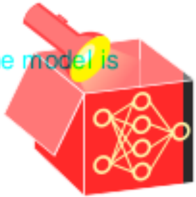

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  2. robust (i.e. low variance)
     - Expectation: similar explanations for similar data points with similar predictions
     - However, multiple sources of uncertainty exist

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

  ⇝ Is an observation out-of-distribution?

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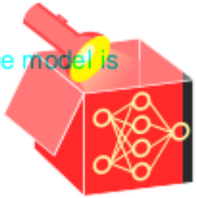

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     $\rightsquigarrow$ measure how robust an IML method is to small changes in the input data or parameters

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

Interpretable Machine Learning – 1 / 7

OUT-OF-DISTRIBUTION DETECTION

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Interpretable Machine Learning – 2 / 7

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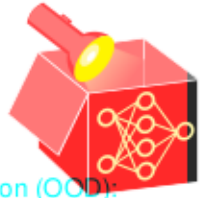

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- For local explanation methods, the following components could be out-of-distribution (OOD):
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- Two very simple and intuitive approaches
  - Classifier for out-of-distribution
  - Clustering
- More complicated also possible, e.g., variational autoencoders [Daxberger et al. 2020]

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- Problem: we have only in-distribution data
- Idea: Hallucinate new (out-of-distribution) data by randomly sample data points

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⇝ Learn a binary classifier to distinguish between the origins of the data

- 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

⇝ Important way to diagnose an explanation approach

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OUT-OF-DISTRIBUTION DETECTION: CLUSTERING VIA DBSCAN

- DBSCAN is a data clustering algorithm ▸ Martin Ester et al. 1996
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Interpretable Machine Learning – 4 / 7

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

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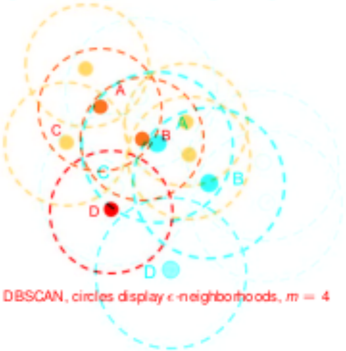

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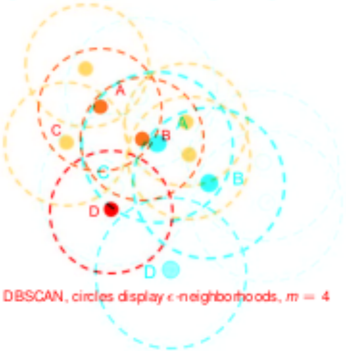

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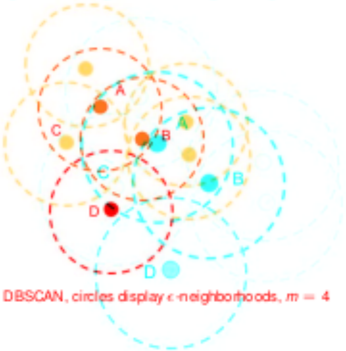

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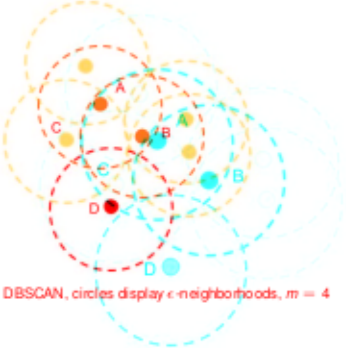

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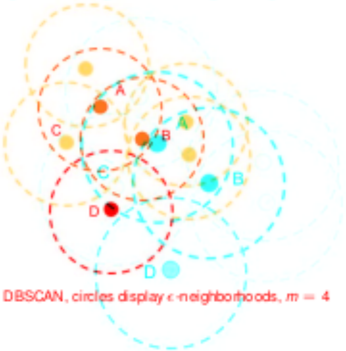

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- Differentiate between different kinds of uncertainty:
  1. **Explanation uncertainty**: Change of explanation if we repeat the process, e.g., the explanation could differ depending on which subset of data we use for the explanation method and which hyperparameters

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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

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  An explanation method $g : \mathcal{X} \to \mathbb{R}^m$ is locally Lipschitz if
  - for every $\mathbf{x}_0 \in \mathcal{X}$ there exist $\delta > 0$ and $\omega \in \mathbb{R}$
  - such that $\|\mathbf{x} - \mathbf{x}_0\| < \delta$ implies $\|g(\mathbf{x}) - g(\mathbf{x}_0)\| \leq \omega \|\mathbf{x} - \mathbf{x}_0\|$

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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:

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

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