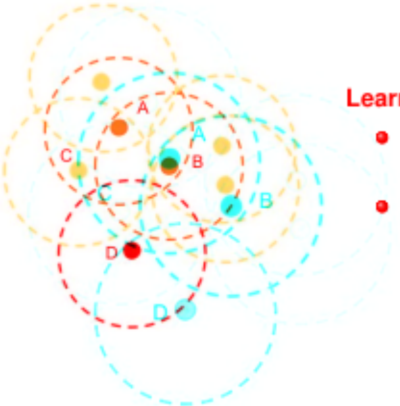
Interpretable Machine Learning

Increasing Trust in Explanations



Learning goals

- Understand the aspects that undermine users' trust in an explanation
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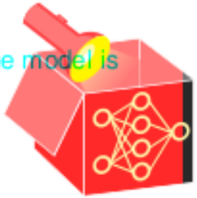
MOTIVATION & IMPORTANT PROPERTIES



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Interpretable Machine Learning – 1 / 7

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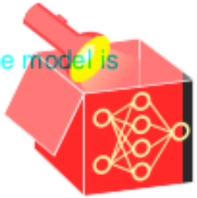

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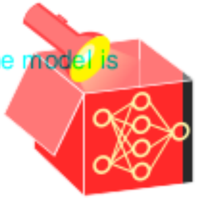

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- **Trustworthy:** "How certain is this explanation?"
  1. accurate insights into the inner workings of our model
     - Failure case: generation is based on inputs in areas where the model was trained with little or no training data (extrapolation)

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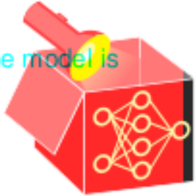

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  2. robust (i.e. low variance)
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     - However, multiple sources of uncertainty exist

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

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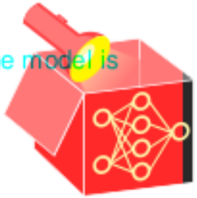

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- Failing in one of these ⇝ undermining users' trust in the explanations

  ⇝ undermining trust in the model

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Interpretable Machine Learning – 2 / 7

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  - The data for LIME's surrogate model
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  - Classifier for out-of-distribution
  - Clustering
- More complicated also possible, e.g., variational autoencoders [Daxberger et al. 2020]

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Interpretable Machine Learning – 2 / 7

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Interpretable Machine Learning – 3 / 7

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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

Interpretable Machine Learning – 3 / 7

OUT-OF-DISTRIBUTION DETECTION: CLUSTERING VIA DBSCAN

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Interpretable Machine Learning – 4 / 7

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

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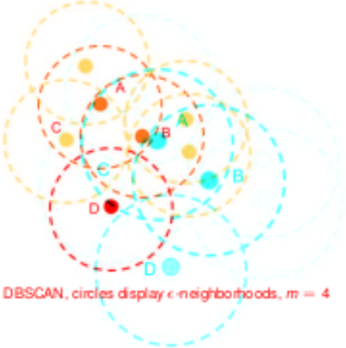

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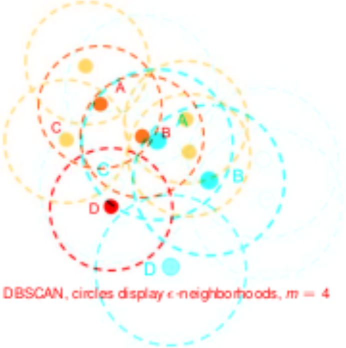

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Interpretable Machine Learning – 5 / 7

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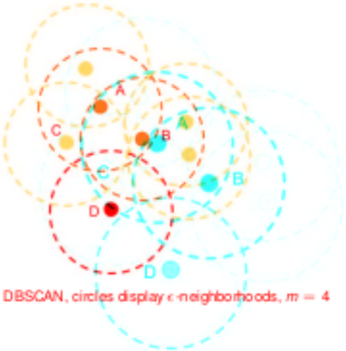

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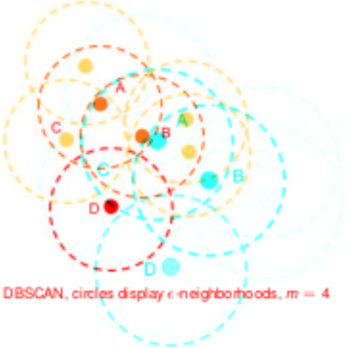

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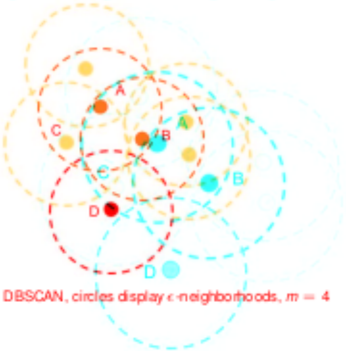

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- Differentiate between different kinds of uncertainty:
  1. **Explanation uncertainty**: Change of explanation if we repeat the process, e.g., the explanation could differ depending on which subset of data we use for the explanation method and which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

Interpretable Machine Learning – 6 / 7

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- We focus on explanation uncertainty
  - Even with the same model and same (or similar) data points, we can receive different explanations

Interpretable Machine Learning – 6 / 7

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Interpretable Machine Learning – 7 / 7

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  ▸ Alvarez-Melis and Jaakkola 2018 :

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 $\omega \in \mathbb{R}$
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Note that, for LIME, g returns the m coefficients of the surrogate model

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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 $\mathbf{x}$