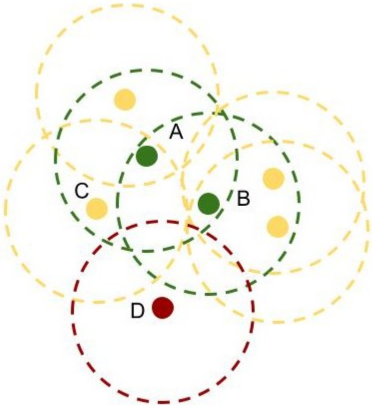
Interpretable Machine Learning

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

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     - However, multiple sources of uncertainty exist

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

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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]

OUT-OF-DISTRIBUTION DETECTION: OOD-CLASSIFIER

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- Idea: Hallucinate new (out-of-distribution) data by randomly sample data points

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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

$\leadsto$ Important way to diagnose an explanation approach

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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

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

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

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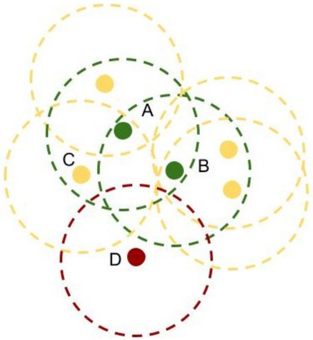

Example for DBSCAN, circles display ϵ-neighborhoods, $m = 4$

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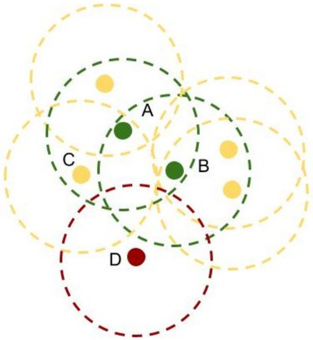

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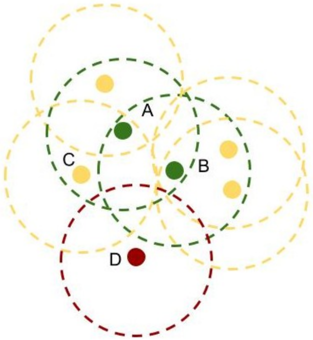

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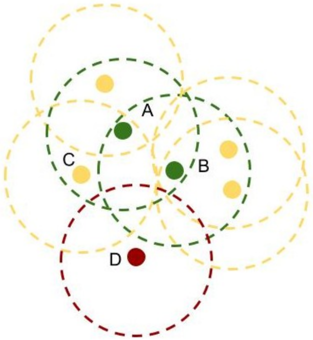

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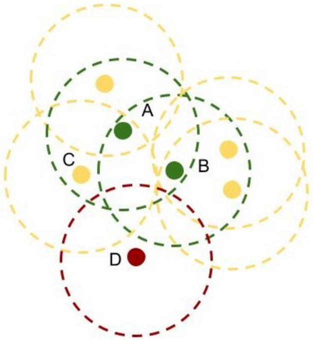

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- Disadvantages:
  - Depending on the distance metric $d(\cdot)$, DBSCAN could suffer from the “curse of dimensionality”
  - The choice of ϵ and m is not clear a-priori

ROBUSTNESS

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- 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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- 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 $\omega \in \mathbb{R}$
  - such that $||\mathbf{x} - \mathbf{x}_0|| < \delta$ implies $||g(\mathbf{x}) - g(\mathbf{x}_0)|| < \omega ||\mathbf{x} - \mathbf{x}_0||$

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- According to this, we can quantify the robustness of explanation models in terms of ω:

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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 $\mathbf{x}$