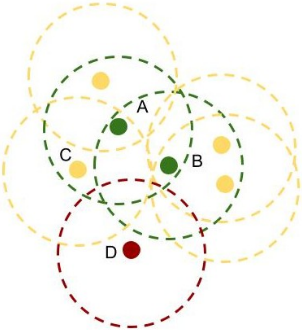
Interpretable Machine Learning

Increasing Trust in Explanations



Learning goals

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

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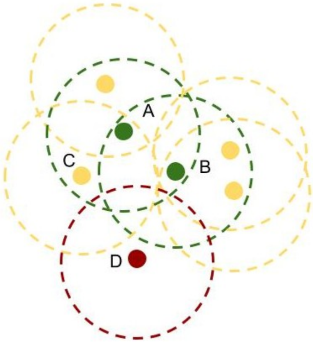
Local Explanations:
Increasing Trust in Explanations



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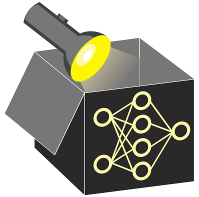

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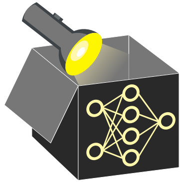

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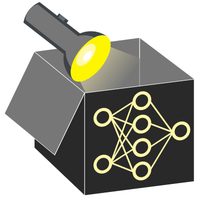

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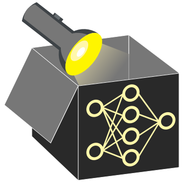

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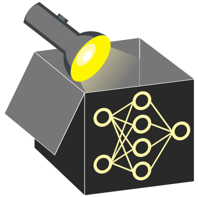

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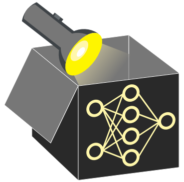

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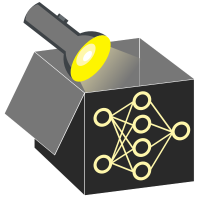

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     - Expectation: similar explanations for similar data points with similar predictions
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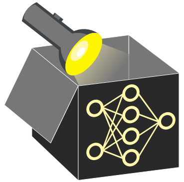

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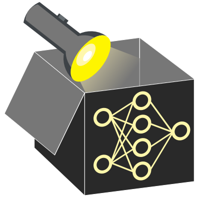

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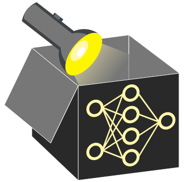

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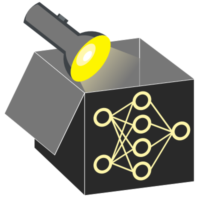

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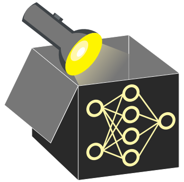

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  - Clustering
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- Study whether an explanation approach can be fooled ▸ Dylan Slack et al. 2020
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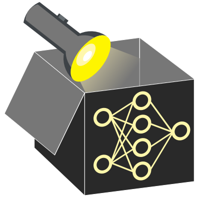

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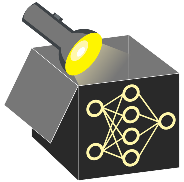

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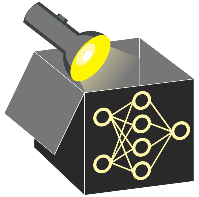

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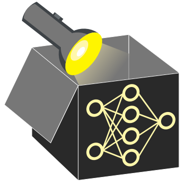

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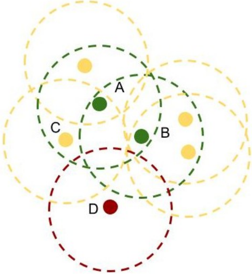

Example for DBSCAN, circles display ϵ-neighborhoods, $m = 4$

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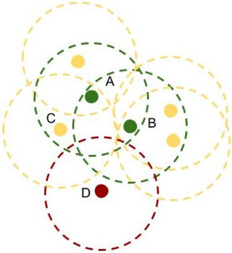

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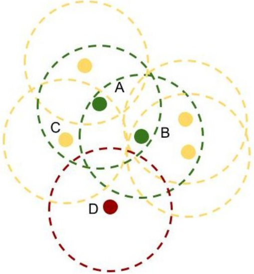

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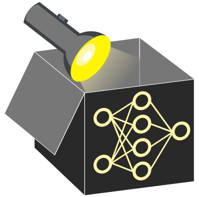

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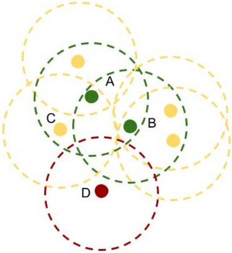

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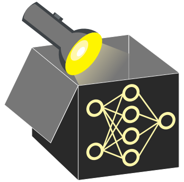

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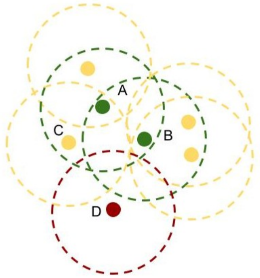

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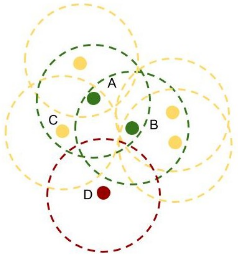

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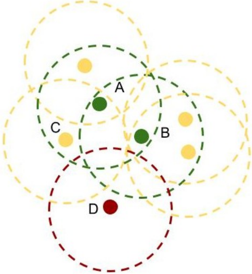

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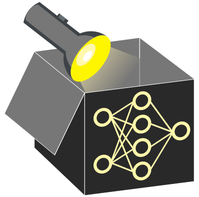

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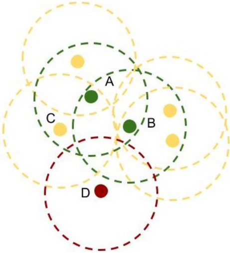

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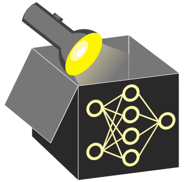

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- Since D is not part of the neighborhood of core points, it is a noise point
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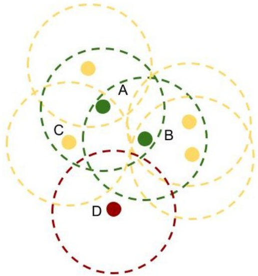

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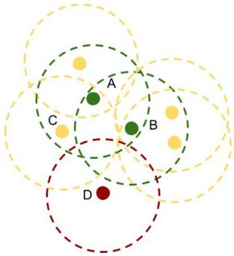

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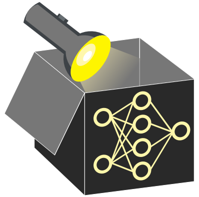

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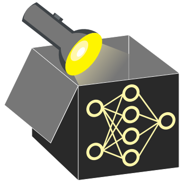

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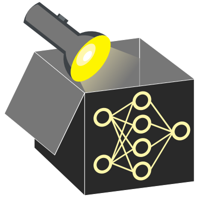

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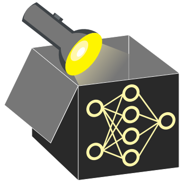

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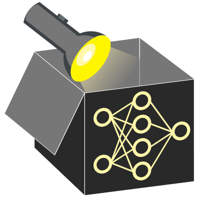

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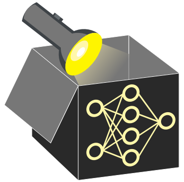

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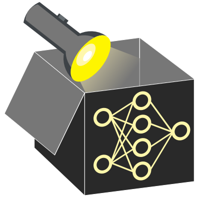

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- For LIME and SHAP, notion of stability based on **locally Lipschitz continuity** ▸ Alvarez-Melis and Jaakkola 2018:

  An explanation method $g : \mathcal{X} \rightarrow \mathbb{R}^m$ is locally Lipschitz if
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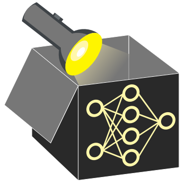

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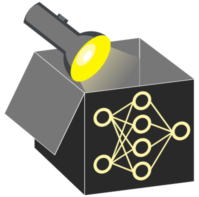

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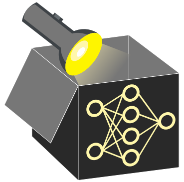

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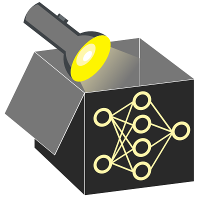

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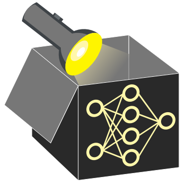

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