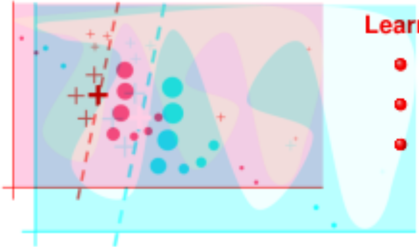
Interpretable Machine Learning

Introduction to Local Explanations



Learning goals

- Understand motivation for local explanations
- Develop an intuition for possible use-cases
- Know characteristics of local explanation methods

METHODOLOGICAL MOTIVATION

- Purpose of local explanations:
  - Insight into the driving factors for a **particular decision**
  - Understand the ML model's decisions in a **local neighborhood** of a given input
    (e.g., feature vector)

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METHODOLOGICAL MOTIVATION

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  - Understand the ML model's decisions in a **local neighborhood** of a given input (e.g., feature vector)
- Local Methods can address questions such as:
  - **Why** did the model decide to predict $\hat{y}$ for input $\mathbf{x}$?
  - **How** does the model decide for observations that are similar to $\mathbf{x}$?
  - **What** would the ML model have decided if $\mathbf{x}$ its values in $\mathcal{X}$ were different?
  - **Where** (in which regions in $\mathcal{X}$) does the model fail?

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  ⇝ **case specific**, **easy** for humans to understand, and **faithful** to the explained mechanism

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- Local explanations cannot only increase **user trust**, but also help to detect **critical local biases** in algorithmic decision making
- European citizens have the legally binding **right to explanation** as given in the General Data Protection Regulation (GDPR)
  - ⇝ Instead of explaining the entire (complex) model (with potential market secrets), explanations in a case-by-case usage is more reasonable

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GDPR: THE RIGHT TO EXPLANATION

"The data subject should have the right not to be subject to a decision, which may include a measure, evaluating personal aspects relating to him or her which is based solely on automated processing and which produces legal effects concerning him or her or similarly significantly affects him or her, such as automatic refusal of an online credit application or e-recruiting practices without any human intervention.

[. . .]

In any case, such processing should be subject to suitable safeguards, which should include specific information to the data subject and the **right** to obtain human intervention, to express his or her point of view, **to obtain an explanation of the decision reached after such assessment and to challenge the decision**. "

(Recital 71, GDPR)

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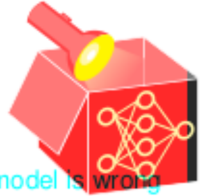
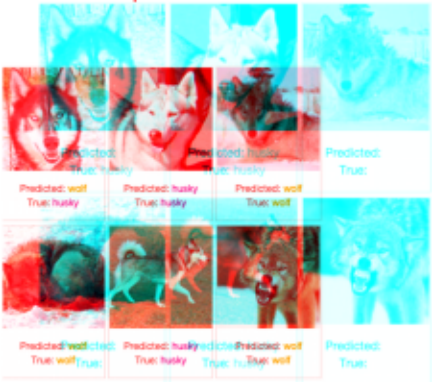
EXAMPLE: HUSKY OR WOLF?

- We trained a model to predict if an image shows a wolf or a husky
- Below the predictions on six test images are given
- Do you trust our predictor?





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- Can you guess the pattern the ML model learned to identify a wolf?

Source: [Sameer Singh 2018]

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EXAMPLE: HUSKY OR WOLF? USING LIME

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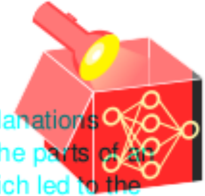

- Local explanations highlight the parts of an image which led to the prediction

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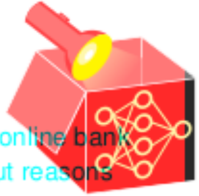
EXAMPLE: LOAN APPLICATION

- Imagine: You apply for a loan at an online bank and are immediately rejected without reasons



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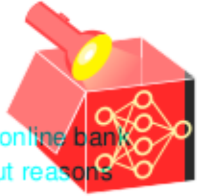
  "If you were older than 21, your loan application would have been accepted."



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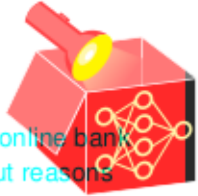

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- Imagine:
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  - You show your model the following image (an adversarial example)

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EXAMPLE: STOP OR RIGHT-OF-WAY?

- Imagine:
  - You work at a car company that develops image classifiers for autonomous driving
  - You show your model the following image (an adversarial example)
  - Classifier is 99% sure it describes a right-of-way sign
- Would you entrust other peoples lives into the hands of this software?

Source: [Eykholt et. al 2018]

CHARACTERISTICS OF LOCAL EXPLANATIONS

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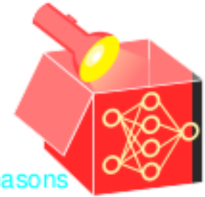

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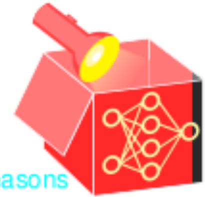

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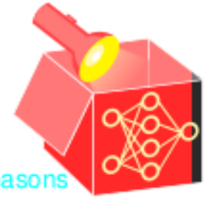

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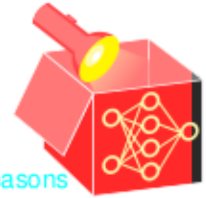

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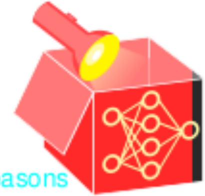

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- **Special:** Due to audience, strong interactions with social sciences and strong connections to cognitive science and neurosciences due to data types

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CREDIT DATASET

- We illustrate local explanation methods on the German credit data See Kaggle
- 522 complete observations, 9 features containing credit and customer information
- Binary target "risk" indicates if a customer has a 'good' or 'bad' credit risk
- We merged categories with few observations

name	type	range
age	numeric	[19, 75]
sex	factor	{male, female}
job	factor	{0, 1, 2, 3}
housing	factor	{free, own, rent}
saving.accounts	factor	{little, moderate, rich}
checking.accounts	factor	{little, moderate, rich}
credit.amount	numeric	[276, 18424]
duration	numeric	[6, 72]
purpose	factor	{others, car, furniture, radio/TV}
risk	factor	{good, bad}

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