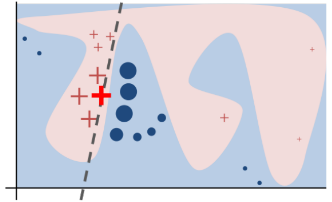
Interpretable Machine Learning

Introduction to Local Explanations



Learning goals

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

Interpretable Machine Learning

Local Explanations: LIME

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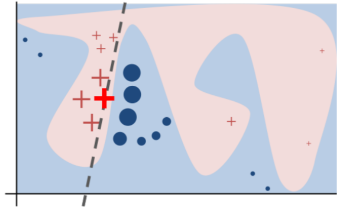

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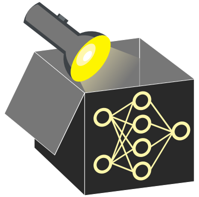

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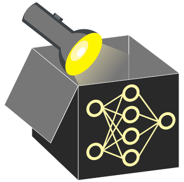

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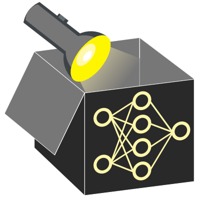

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- Local Methods can address questions such as:
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  - **How** does the model behave for observations similar to $\mathbf{x}$?
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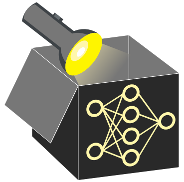

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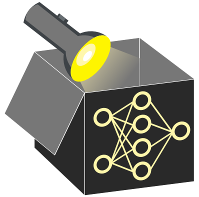

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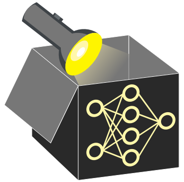

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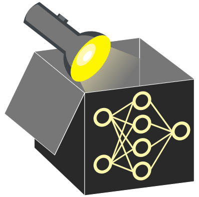

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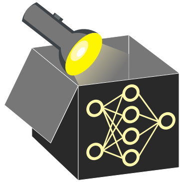

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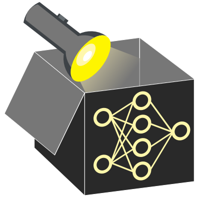

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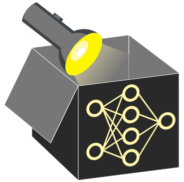

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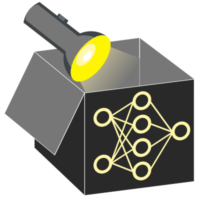

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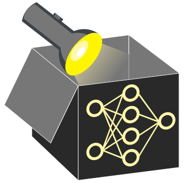

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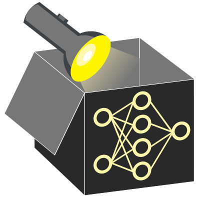
GDPR & AI ACT: THE RIGHT TO EXPLANATION



“The data subject should have the right not to be subject to a decision [...] based solely on automated processing [...], such as automatic refusal of an online credit application or e-recruiting practices without any human intervention.
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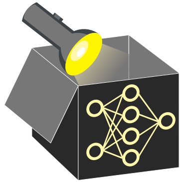

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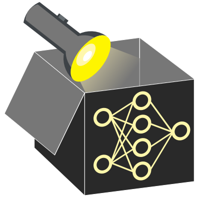
EXAMPLE: HUSKY OR WOLF?



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

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

Source: [Sameer Singh 2018]

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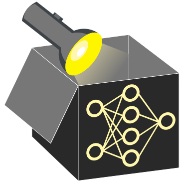

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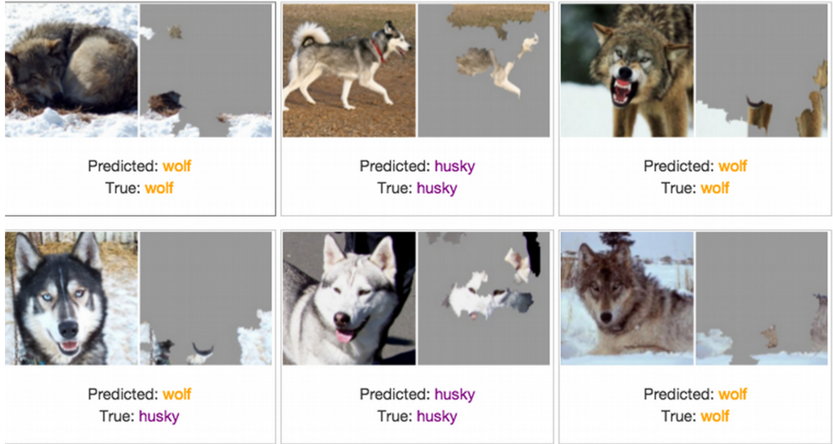
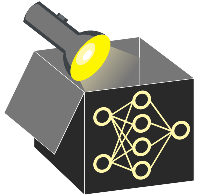
EXAMPLE: HUSKY OR WOLF? USING LIME

- Local explanations highlight the parts of an image which led to the prediction
  ⇝ our predictor is actually a snow detector





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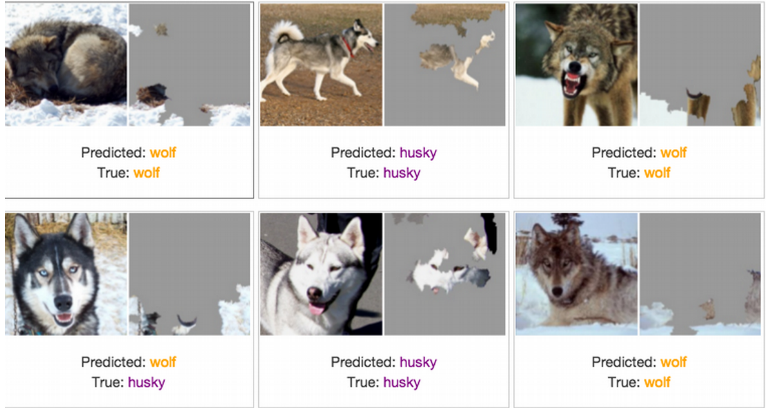

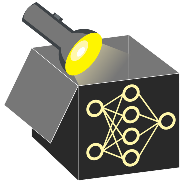

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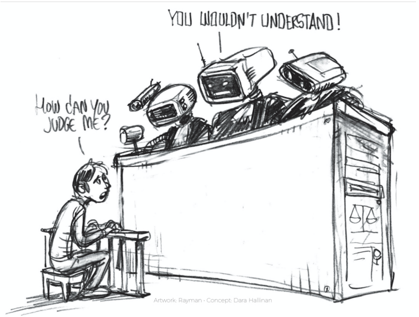
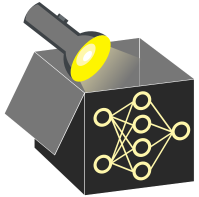


Source: [https://www.elte.hu]

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



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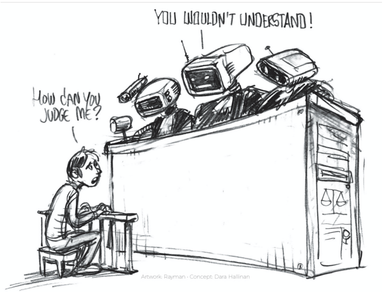

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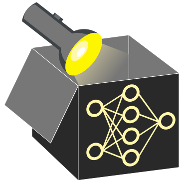

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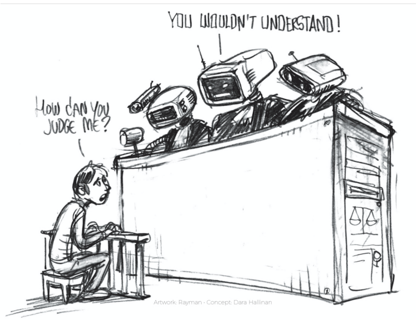

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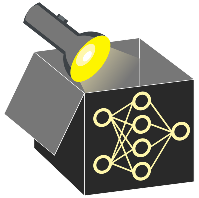

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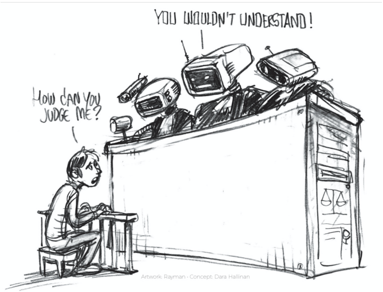

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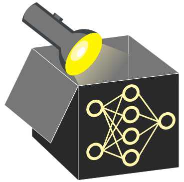

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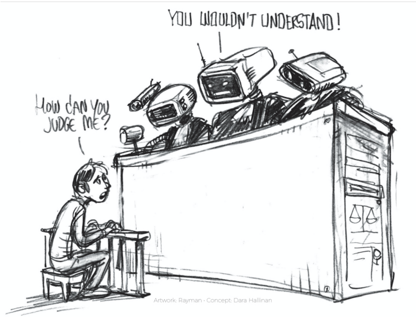

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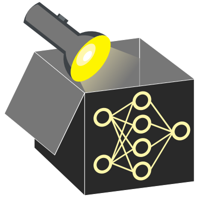

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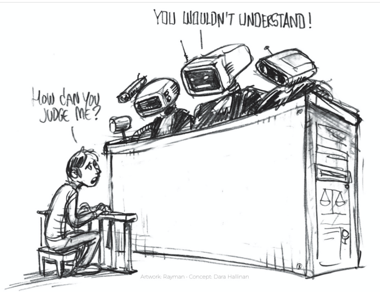

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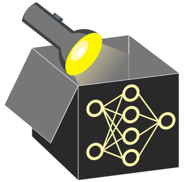

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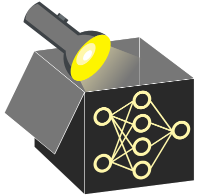

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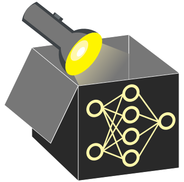

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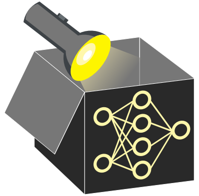

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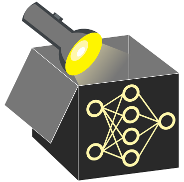

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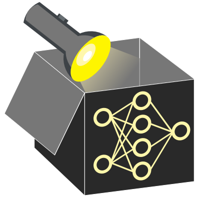

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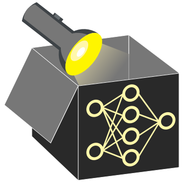

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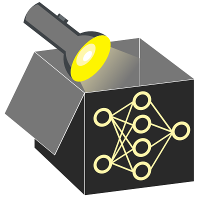

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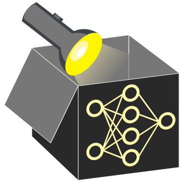

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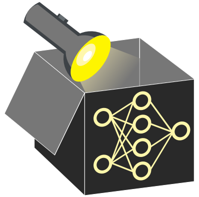

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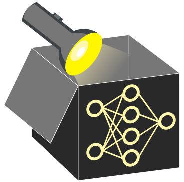

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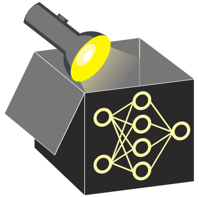

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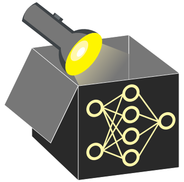
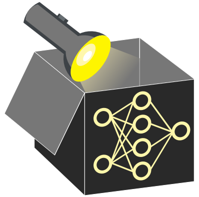


CHARACTERISTICS OF LOCAL EXPLANATIONS



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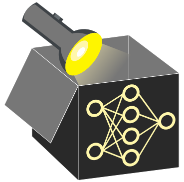

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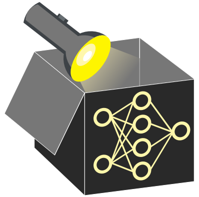

- We illustrate local explanation methods on the German credit data ▸ see Kaggle
- 522 observations, 9 features containing credit and customer information
- Binary target "risk" indicates if a customer has a 'good' or 'bad' credit risk
- We merged categories with few observations

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	numeric	{others, car, furniture, radio/TV}
risk	factor	{good, bad}

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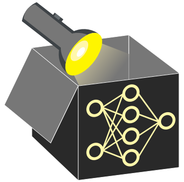

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