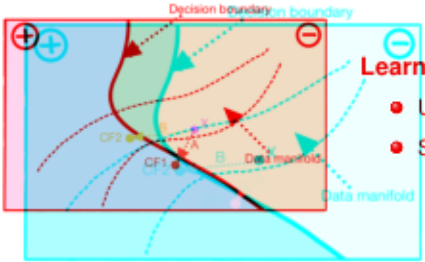
Interpretable Machine Learning

Counterfactual Explanations



Learning goals

- Understand the motivation behind CEs
- See the mathematical foundation of CEs

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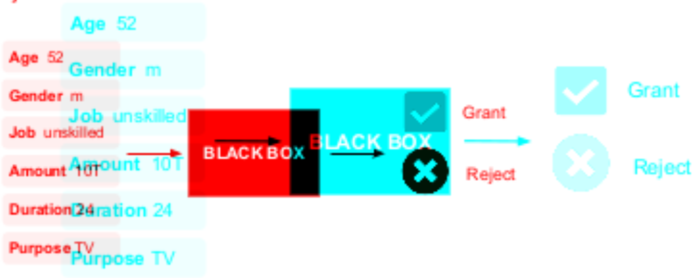
EXAMPLE: CREDIT RISK APPLICATION

- **x**: customer and credit information
- y: grant or reject credit



Questions:

- Why was the credit rejected?
- Is it a fair decision?
- **How should x be changed so that the credit is accepted?**

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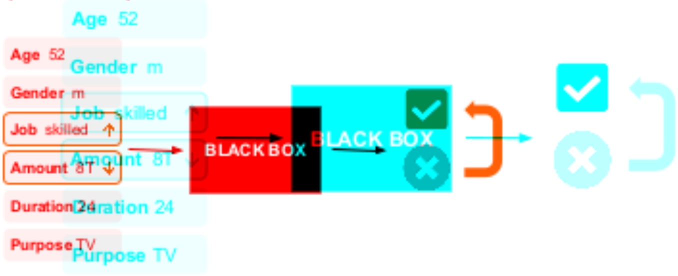

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- The targeted audience of CEs are often end-users

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AIMS & ROLES

CEs can serve various purposes; the user can decide what to learn from them. For example:

“If the person had been **one year older** and the **credit amount had been increased** to $12.000,
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- **Detect model biases:**
  There is a bug, an increase in amount should not increase approval rates.

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PHILOSOPHICAL BASIS

Counterfactuals have a long-standing tradition in analytic philosophy

⇝ According to Lewis (1973), a **counterfactual conditional** is a statement of the form:

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- A world is similar to another if laws are maximally preserved between the worlds and only a few facts are changed

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- Causal dependence underlies the explanatory power
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  ⇝ e.g., decreasing loan amount by $20.000 and being one year older is recommended by the explainer although only loan amount might be causally relevant

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- CEs are often contrastive, i.e., they explain a decision by referring to an alternative outcome
  ⇝ e.g., if the loan applicant was 30 instead of 60 years old, the approved loan would have been over $100.000 instead of $40.000

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MATHEMATICAL PERSPECTIVE

Terminology:

- $\mathbf{x}$: original/factual datapoint whose prediction we want to explain
- $y' \subset \mathbb{R}^g$: desired prediction ($y' = 1000$ or $y' =$ "grant credit") or interval ($y' = [1000, \infty[$)

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A **valid** counterfactual $\mathbf{x}'$ is a datapoint:

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Reformulate these two objectives (denoted by o_1 and o_2) as optimization problem:

$$\arg\min_{\mathbf{x}'} \lambda_1 o_p(\hat{f}(\mathbf{x}'), y') + \lambda_2 o_f(\mathbf{x}', \mathbf{x})$$

- λ_1 and λ_2 balance the two objectives
- Choice of o_p (distance on prediction space) and of o_f (distance on feature space) is crucial

MATHEMATICAL PERSPECTIVE

Dandl et al. (2020)

- Regression: o_p could be the L_1-distance $o_p(\hat{f}(\mathbf{x}'), y') = |\hat{f}(\mathbf{x}') - y'|$
- Classification: L_1-distance for scores and 0-1 Loss for labels, e.g., $o_p(\hat{f}(\mathbf{x}'), y') = \mathcal{I}_{\{\hat{f}(\mathbf{x}') \neq y'\}}$

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- o_f could be the Gower distance (suitable for mixed feature space):

$$o_f(\mathbf{x}', \mathbf{x}) = d_G(\mathbf{x}', \mathbf{x}) = \frac{1}{p} \sum_{j=1}^{p} \delta_G(x_j', x_j) \in [0, 1]$$

The value of δ_G depends on the feature type (numerical or categorical):

$$\delta_G(x_j', x_j) = \begin{cases} \frac{1}{\hat{R}_j} |x_j' - x_j| & \text{if } x_j \text{ is numerical} \\ \mathcal{I}_{\{x_j' \neq x_j\}} & \text{if } x_j \text{ is categorical} \end{cases}$$

with $\hat{R}_j$ as the value range of feature j in the training dataset (to ensure that $\delta_G(x_j', x_j) \in [0, 1]$)

FURTHER OBJECTIVES

Additional constraints can improve the explanation quality of the corresponding CEs
⇝ popular constraints include sparsity and plausibility

Sparsity:

- End-users often prefer short over long explanations
  ⇝ counterfactuals should be **sparse**

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- Objective o_f can take the number of changed features into account (but does not have to)
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- Objective o_f can take the number of changed features into account (but does not have to)
  $\rightsquigarrow$ e.g., the L_0- and the L_1-norm (similar to LASSO) can do this
- Independently from o_f, sparsity in the changes can be additionally considered by another objective that counts the number of changed features via the L0-norm:

$$o_s(\mathbf{x}', \mathbf{x}) = \sum_{j=1}^{p} \mathcal{I}_{\{x'_j \neq x_j\}}$$

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Plausibility:

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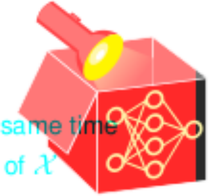

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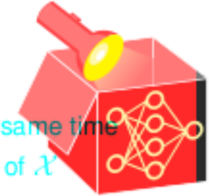

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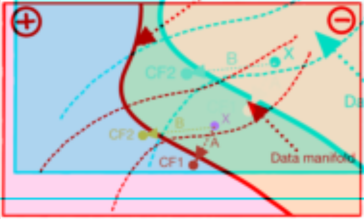

Example from ▸ Verma et al. (2020)

- Two possible paths for $\mathbf{x}$, originally classified to ⊖
- Two valid CEs in class ⊕: CF1 and CF2
- Path **A** for CF1 is shorter
- Path **B** for CF2 is longer but adheres to data manifold

FURTHER OBJECTIVES

To ensure plausibility, o_4 could, e.g., be the Gower distance of $\mathbf{x}'$ to its nearest data point of the training dataset which we denote $\mathbf{x}^{[1]}$:

$$o_4(\mathbf{x}', \mathbf{X}) = d_G(\mathbf{x}', \mathbf{x}^{[1]}) = \frac{1}{p} \sum_{j=1}^{p} \delta_G(x'_j, x^{[1]}_j)$$

We can extend the previous optimization problem by adding o_s (for sparsity) and o_4 (for plausibility):

$$\arg\min_{\mathbf{x}'} \lambda_1 o_p(\hat{f}(\mathbf{x}'), y') + \lambda_2 o_f(\mathbf{x}', \mathbf{x}) + \lambda_3 o_s(\mathbf{x}', \mathbf{x}) + \lambda_4 o_4(\mathbf{x}', \mathbf{X})$$

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REMARKS: THE RASHOMON EFFECT

Issue (Rashomon effect):

- Solution to the optimization problem might not be unique
- Many equally close CE might exist that obtain the desired prediction
  $\Rightarrow$ Many different equally good explanations for the same decision exist

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Note:

- As the model is generally non-linear, inconsistent and diverse CEs can arise e.g. suggesting either an increase or decrease in credit duration (confuses the explainee)
- How to deal with the Rashomon effect is considered an open problem in IML

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  ⇝ ▸ Karimi et al. (2020) avoid this by considering causal dependencies between features

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