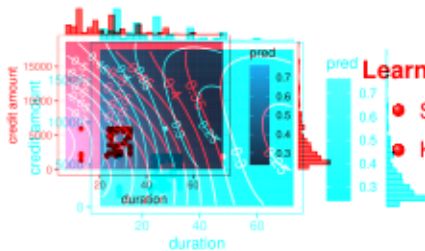


Interpretable Machine Learning

Methods & Discussion of CEs



Learning goals

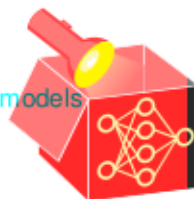
Learning goals

- See two strategies to generate CEs
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- Know problems and limitations of CEs
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OVERVIEW OF METHODS

Currently, multiple methods exist to calculate counterfactuals. They mainly differ in:

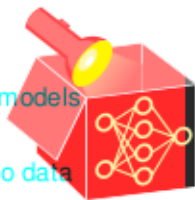
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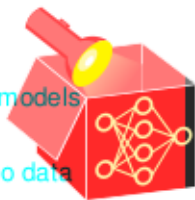
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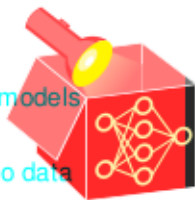
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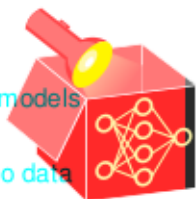
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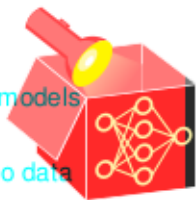
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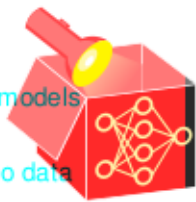
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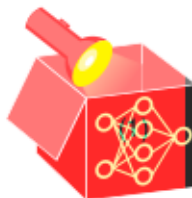
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Introduced counterfactual explanations in the context of ML predictions by solving

$$\arg \min_{\mathbf{x}'} \max_{\lambda} \underbrace{\lambda (\hat{f}(\mathbf{x}') - y')^2}_{o_p(\hat{f}(\mathbf{x}'), y')} + \underbrace{\sum_{j=1}^p y_j |x_j| + \sum_{j=1}^p |MAD_j - x_j|}_{o_f(\mathbf{x}', \mathbf{x})} / MAD_j \quad (1)$$

MAD_j is the median absolute deviation of feature j . In each iteration, optimizers like Nelder-Mead solve the equation for \mathbf{x}' and then λ is increased until a sufficiently close solution is found

This optimization problem has several shortcomings:

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- We do not know how to choose λ a priori
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- Due to the maximization of λ , we focus primarily on the minimization of o_p
 - \rightsquigarrow only if $\hat{f}(\mathbf{x}') = y'$, we focus on minimizing o_f
 - \rightsquigarrow only if $\hat{f}(\mathbf{x}') = y'$, we focus on minimizing o_f
- Definition of o_f only covers numerical features
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- Other objectives such as sparsity and plausibility of counterfactuals are neglected
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MULTI-OBJECTIVE COUNTERFACTUAL EXPLANATIONS

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● Multi-Objective Counterfactual Explanations (MOC): Instead of collapsing objectives into a

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$$\arg \min_{\mathbf{x}'} \left(o_p(\hat{f}(\mathbf{x}'), y'), o_r(\mathbf{x}', \mathbf{x}), o_s(\mathbf{x}', \mathbf{x}), o_4(\mathbf{x}', \mathbf{X}) \right).$$

● Note that weighting parameters like λ are not necessary anymore

● Uses an adjusted multi-objective genetic algorithm (NSGA-II) to produce a set of diverse

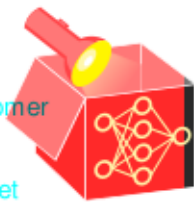
● Note that weighting parameters like λ are not necessary anymore

● Uses an adjusted multi-objective genetic algorithm (NSGA-II) to produce a set of diverse counterfactuals for mixed discrete and continuous feature spaces

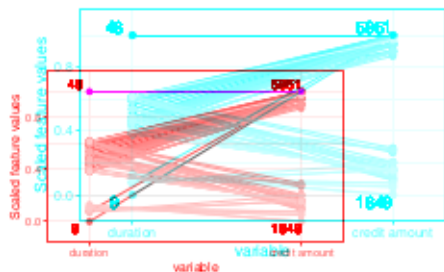
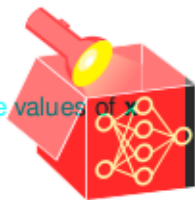
● Instead of one, MOC returns multiple counterfactuals that represents different trade-offs between the objectives and are constructed to be diverse in feature space

EXAMPLE: CREDIT DATA

- Model SVM with RBF kernel
- x : First data point of credit data with $\mathbb{P}(y = \text{good}) = 0.34$ of being a "good" customer
 - Goal: increase the probability to $[0.5, 1]$
- MOC (with default parameters) found 69 CEs after 200 iterations that met the target
- All counterfactuals proposed changes to credit duration and many of them to credit amount
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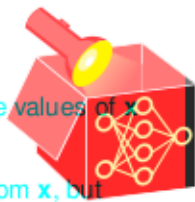


- We can visualize feature changes with a parallel plot and 2-dim surface plot
- Parallel plot reveals that all counterfactuals had values equal to or smaller than the values of x

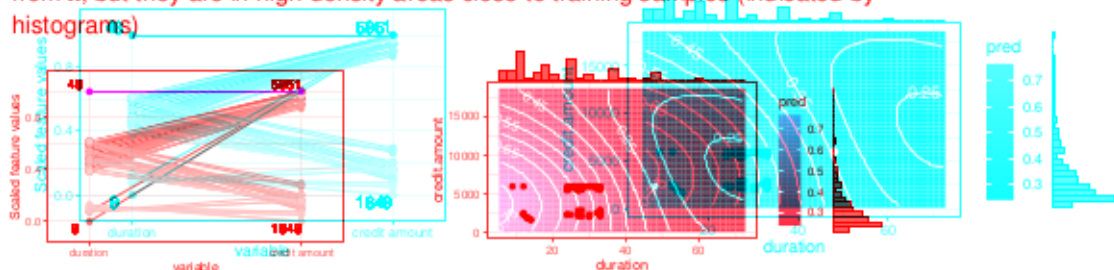


Parallel plot: Grey lines show feature values of CEs x' , blue line are values of x . Features without proposed changes are omitted. x' , blue line are values of x . Features without proposed changes are omitted. Bold numbers refer to range of numeric features.

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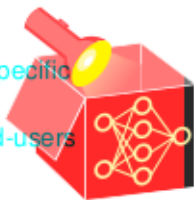


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Surface plot: White dot is x , black dots are CEs x' . Histograms show marginal distribution of training data X .

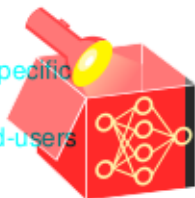
PROBLEMS, PITFALLS, & LIMITATIONS

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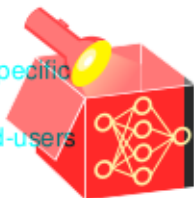


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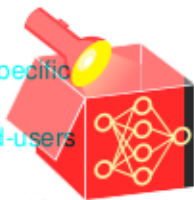


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- **Disclosing too much information:**
CEs can reveal too much information about the model and help potential attackers

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 - ~ No perfect solution depends on end-users computational resources and knowledge



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 - ~> Counteract contestability, e.g., if ethnicity is not changed in a CE since it is not actionable, this could hide racial biases in the model



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