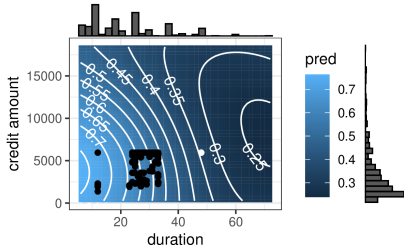


Interpretable Machine Learning

Methods & Discussion of CEs



Learning goals

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

OVERVIEW OF METHODS

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

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- **Rashomon Effect:** Many methods return a single counterfactual per run, some multiple counterfactuals, others prioritize CEs or let the user choose

Introduced counterfactual explanations in the context of ML predictions by solving

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

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:

- We do not know how to choose λ a priori
- 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
- Definition of o_f only covers numerical features
- Other objectives such as sparsity and plausibility of counterfactuals are neglected

- **Multi-Objective Counterfactual Explanations (MOC):** Instead of collapsing objectives into a single objective, we could optimize all four objectives simultaneously

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

- 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 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

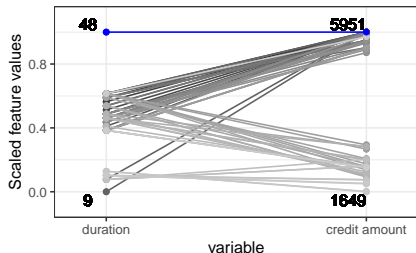
EXAMPLE: CREDIT DATA

- Model: SVM with RBF kernel
- \mathbf{x} : First data point of credit data with $\mathbb{P}(y = \textit{good}) = 0.34$ 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

EXAMPLE: CREDIT DATA

► Dandl et al. (2020)

- 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 \mathbf{x}

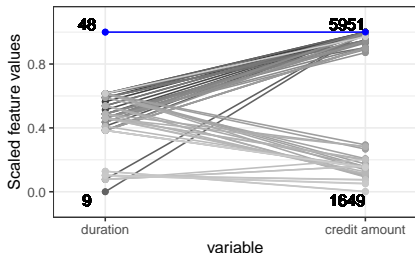


Parallel plot: Grey lines show feature values of CEs \mathbf{x}' , blue line are values of \mathbf{x} . Features without proposed changes are omitted.
Bold numbers refer to range of numeric features.

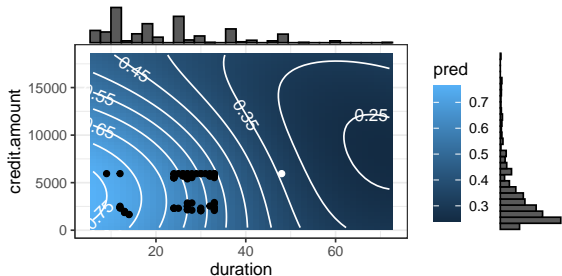
EXAMPLE: CREDIT DATA

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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 \mathbf{x}
- Surface plot illustrates why these feature changes are recommended
- Counterfactuals in the lower left corner seem to be in a less favorable region far from \mathbf{x} , but they are in high density areas close to training samples (indicated by histograms)



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



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

PROBLEMS, PITFALLS, & LIMITATIONS

- **Illusion of model understanding:** CEs explain ML decisions by pointing to few specific alternatives which reduces complexity, but is limited in explanatory power
~> Psychologists have shown that although perceived model understanding of end-users increases, the objective model understanding remains unchanged

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- **Right metric:** Similarity measures are crucial to find good CEs (depends on context/domain)
 - ~> e.g., L_1 can be reasonable for tabular data but not for image data
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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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- **Attacking CEs:** Researchers can create models with great performance, which generate arbitrary explanations specified by the ML developer
~> how faithful are CEs to the models underlying mechanism?