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ReLax: Efficient and Scalable Recourse Explanation Benchmarking using JAX

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Summary

From healthcare to criminal justice, machine learning (ML) models have permeated society to support domain experts in making decisions. Given the high-stakes nature of decision outcomes in some real-world domains, concerns over the trustworthiness of ML model predictions have raised increasing attention. These concerns have spurred surging research interests in explainable artificial intelligence (XAI), whose mission is to equip end-users with an understanding (or explanation) of AI decision making, and to help provide assessments to end-users about when to rely on ML models and when to exercise caution.

Within the XAI domain, recourse[1] has emerged as a notable technique, which provides alternative scenarios (which lead to desirable AI decisions) to individuals adversely affected by ML predictions, thereby elucidating the underlying decision-making mechanisms to end users. For instance, recourse methods can provide corrective suggestions for loan applicants who have been rejected by a bank's ML algorithm, or give practical advice to teachers handling students at risk of dropping out from school. Numerous recourse explanation methods have been recently proposed. Yet, the substantial runtime overhead imposed by many recourse explanation methods compels current research to limit their evaluation and benchmarking to medium-sized datasets (i.e., ~50k data points). This limitation has significantly impeded progress in the field of algorithmic recourse, while it also raises valid concerns about the scalability of existing approaches.

To address this challenge, we propose `ReLax`, a JAX-based benchmarking library, designed for efficient and scalable recourse generation. `ReLax` supports a variety of recourse methods and datasets, demonstrating performance improvements of at least two orders of magnitude over current libraries. Notably, ReLax can benchmark real-world datasets up to 10 million data points, a 200-fold increase over existing norms, without imposing prohibitive computational costs.

Statement of need

Recourse and counterfactual explanation methods concentrate on the generation of new instances that lead to contrastive predicted outcomes (Karimi et al., 2020; Stepin et al., 2021; Verma et al., 2020). Given their ability to provide actionable recourse, these explanations are often favored by human end-users (Bhatt et al., 2020; Binns et al., 2018; Miller, 2019).

Despite progress made in counterfactual explanation research (Guo, Jia, et al., 2023; Guo, Nguyen, et al., 2023; Mothilal et al., 2020; Upadhyay et al., 2021; Ustun et al., 2019; Vo et al., 2023; Wachter et al., 2017), current research practices often restrict the evaluation of recourse explanation methods on medium-sized datasets (with under 50k data points). This constraint

[1] Algorithmic recourse (Ustun et al., 2019) and counterfactual explanation (Wachter et al., 2017) share close connections (Stepin et al., 2021; Verma et al., 2020), which leads us to use these terms interchangeably

primarily stems from the excessive runtime overhead of recourse generation by existing open-source recourse libraries (Klaise et al., 2021; Mothilal et al., 2020; Pawelczyk et al., 2021). For instance, as shown in Figure 1, the CARLA library (Pawelczyk et al., 2021) requires roughly 30 minutes to benchmark the adult dataset (Kohavi & Becker, 1996) containing $\sim 32,000$ data points. At this speed, because the runtime scales linearly with the number of data points, it would take CARLA approximately 15 hours to benchmark a dataset with 1 million samples, and nearly one week to benchmark a 10-million sized dataset. Consequently, this severe runtime overhead hinders the large-scale analysis of recourse explanations and the research development of new recourse methods.

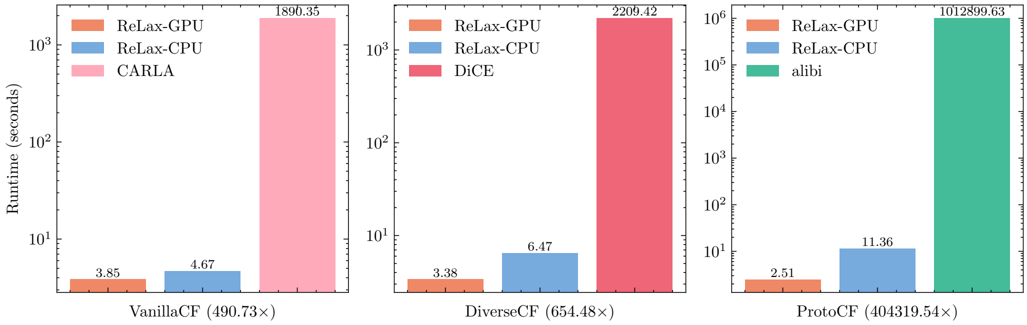


Figure 1: Runtime comparison of the *adult* dataset (Kohavi & Becker, 1996) between ReLax and three open-source recourse librarires (CARLA (Pawelczyk et al., 2021), DiCE (Mothilal et al., 2020), and alibi (Klaise et al., 2021).

In this work, we present ReLax (**Re**course Explanation **L**ibrary using J**ax**), the *first* recourse explanation library in JAX (Bradbury et al., 2018; Frostig et al., 2018). Our contributions are three-fold:

- (Fast and Scalable System) ReLax is an *efficient and scalable benchmarking library* for recourse and counterfactual explanations.
- (Comprehensive set of Methods) ReLax implements 9 widely-used and popular recourse explanation methods. In addition, ReLax includes 14 medium-sized publicly available datasets, and one large-scale publicly available dataset.
- (Extensive Experiments) We perform comprehensive experiments on both medium-sized and large-sized datasets, which showcases the usability and scalability of ReLax.

Efficiency and Scalability in ReLax

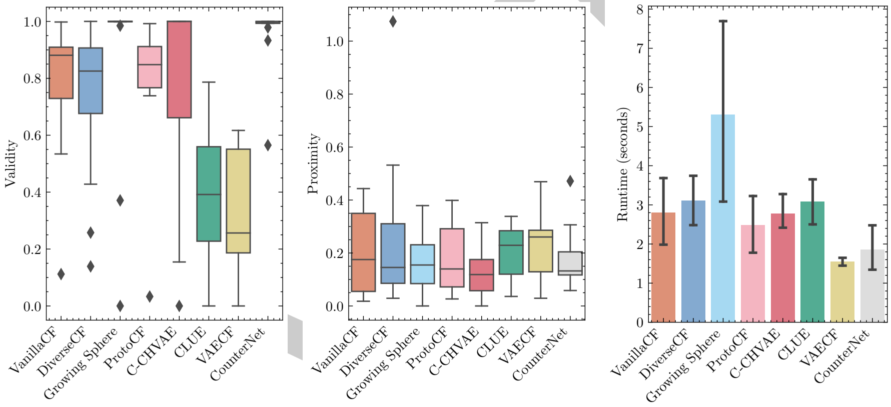
ReLax supports three recourse generation strategies: *sequential*, *vectorized*, and *parallelized* strategy. In particular, the *sequential* generation strategy involves generating recourse explanations one after another. Unfortunately, while widely used in existing recourse libraries (Klaise et al., 2021; Mothilal et al., 2020; Pawelczyk et al., 2021), this strategy is inefficient when benchmarking large datasets.

On the other hand, the *vectorized* and *parallelized* strategies play a vital role in equipping ReLax to benchmark large-scale datasets with a practical computational cost. The *vectorized* strategy takes advantage of modern hardware by applying recourse generation operations to the entire dataset *at once*. This strategy considerably accelerates recourse generation by performing Single Instruction on Multiple Data (SIMD). Additionally, the *parallelized* strategy enables the usage of multiple computing devices (e.g., multiple GPUs/TPUs) to further improve scalability. Furthermore, ReLax further enhances its performance by fusing inner recourse generation steps via the Just-In-Time (JIT) compilation feature provided by jax. Together, ReLax ensures efficient and scalable performance across diverse data scales and complexities.

Recourse Methods & Datasets

ReLax implements nine recourse methods using JAX including (i) three non-parametric methods (VanillaCF (Wachter et al., 2017), DiverseCF (Mothilal et al., 2020), GrowingSphere (Laugel et al., 2017)); (ii) three semi-parametric methods (ProtoCF (Van Looveren & Klaise, 2019), C-CHVAE (Pawelczyk et al., 2020), CLUE (Antoran et al., 2021)); and (iii) three parametric methods (VAE-CF (Mahajan et al., 2019), CounterNet (Guo, Nguyen, et al., 2023), L2C (Vo et al., 2023)).

Furthermore, we gather 14 medium-sized binary-classification tabular datasets. We also benchmark over the forktable dataset (Ding et al., 2021) for predicting individuals' annual income. This US censuring dataset contains ~ 10 million data points. To our knowledge, this is the first attempt to benchmark a dataset at the scale of 10 million data points in the recourse explanation community.



(a) Boxplot of validity on medium-size datasets for each recourse method. High validity is desirable.

(b) Boxplot of normalized proximity on medium-sized datasets. Low proximity is preferable.

(c) Barplot of runtime on medium-size datasets for each recourse method. Low runtime is desirable.

Figure 2: Comparison of recourse method performance across 14 medium-sized datasets. It is desirable to achieve *high* validity, *low* proximity, and *low* runtime.

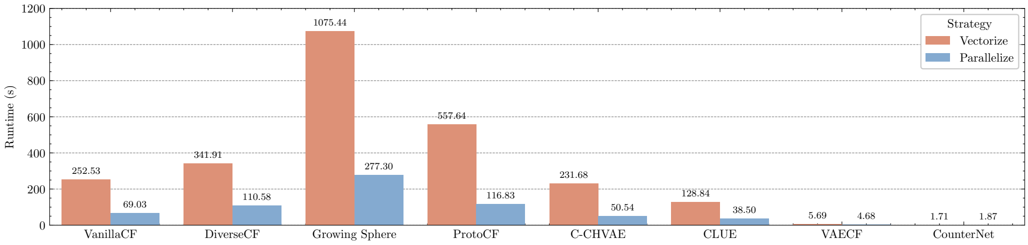


Figure 3: Runtime comparison of different recourse generation strategies on the forktable dataset (Ding et al., 2021).

Experimental Results

Figure 2 compares the validity, proximity, and runtime achieved by nine recourse methods averaged on 14 medium-sized datasets. In particular, validity and proximity measure the quality of the generated counterfactual explanations. We observe that CounterNet and Growing Sphere achieve the best validity score, and C-CHVAE achieves the best proximity score. In terms of runtime, all recourse methods complete the entire recourse generation process within

10 seconds, while CounterNet and VAECF outperform others by finishing execution under 2 seconds.

Figure 3 compares the runtime for each recourse explanation method in adopting the vectorized and parallelized strategies on the forktable dataset (with 10M data points). First, ReLax is highly efficient in benchmarking the large-scale dataset, with the maximum runtime being under 30 minutes. On the other hand, by estimation, existing libraries should take at least one week to complete recourse generation on datasets at this scale. In addition, the parallelized strategy cuts the runtime by roughly 4X, which demonstrates ReLax's potential in benchmarking even larger datasets.

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