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ReLax: Efficient and Scalable Recourse Explanation Benchmark using JAX

Hangzhi Guo[1¶], **Xinchang Xiong**[2], **Wenbo Zhang**[1], and **Amulya Yadav**[1]

1 Penn State University, USA **2** Duke University, USA ¶ Corresponding author

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Summary

Counterfactual explanation[1] techniques provide contrast cases to individuals adversely affected by ML preictions. For instance, recourse methods can provide 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. Numerous recourse explanation methods have been recently proposed. Yet, current research practice focuses on medium-sized datasets (typically around ~50k data points). This limitation impedes the progress in algorithmic recourse and raises 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 explanations. `ReLax` supports various 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 primarily stems from the excessive runtime overhead of recourse generation by the 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), a popular recourse explanation library, requires roughly 30 minutes to benchmark the adult dataset containing $\sim 32,000$ data points. At this speed, it would take CARLA approximately 15 hours to benchmark a dataset with one million samples, and nearly one week to benchmark a dataset with 10 million samples. Consequently, this severe runtime overhead hinders the large-scale analysis of recourse explanations, impedes the pace of research development of new recourse methods, and raises concerns about the scalability of existing methods being deployed in data-intensive ML applications.

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

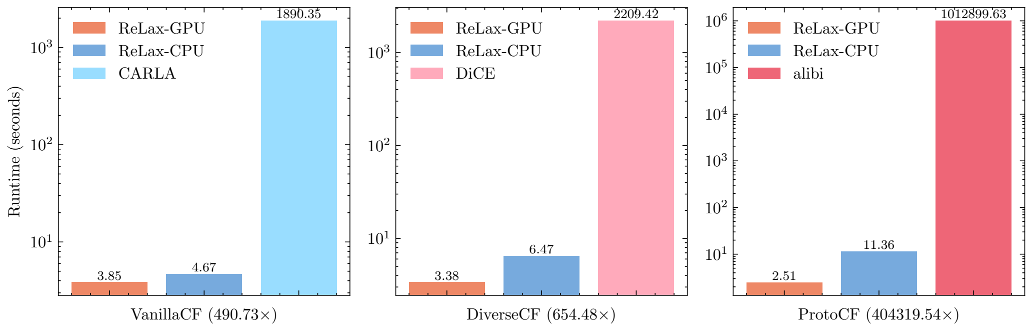

Figure 1: Runtime comparison of the *adult* dataset between ReLax and three open-source recourse librarires (CARLA (Pawelczyk et al., 2021), DiCE (Mothilal et al., 2020), and alibi (Klaise et al., 2021).

We present ReLax (**Re**course Explanation **L**ibrary using J**ax**), an efficient and scalable benchmarking library for recourse and counterfactual explanations. ReLax is the *first* JAX-based library for recourse explanation which leverages language primitives such as vectorization, parallelization, and JIT compilation in JAX (Bradbury et al., 2018; Frostig et al., 2018). ReLax is at least two order-of-magnitudes faster than the existing recourse explanation libraries (with a maximum speedup of 404,319.54X, as shown in Figure~1). We further demonstrate that ReLax is capable of benchmarking real-world datasets of up to 10M data points with a reasonable amount of computational cost.

In addition, ReLax supports a diverse set of recourse methods and datasets. Notably, we implement 9 recourse explanation methods in JAX ranging from non-parametric, semi-parametric, and parametric recourse explanation methods. In addition, we include 14 medium-sized datasets, and one large-scale dataset. Furthermore, we perform comprehensive experiments on both medium-sized and large-sized datasets. We have made ReLax fully open-sourced. This enables the reproduction of our experiments and supports efficient and scalable benchmarking for newly proposed recourse methods.

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