Endogenous Macrodynamics in Algorithmic Recourse

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Patrick Altmeyer (p.altmeyer@tudelft.nl)
Giovan Angela (g.j.a.angela@student.tudelft.nl)
Aleksander Buszydlik (a.j.buszydlik@student.tudelft.nl)
Karol Dobiczek (k.t.dobiczek@student.tudelft.nl)
Arie van Deursen (arie.vandeursen@tudelft.nl)
Cynthia C. S. Liem (c.c.s.liem@tudelft.nl)

TU Delft – Delft University of Technology

In a nutshell …

"[…] we run experiments that simulate the application of recourse in practice using various state-of-the-art counterfactual generators and find that [they] induce substantial domain and model shifts."
— Altmeyer et. al (2023)

Proof-of-Concept

Figure 1 illustrates the what we understand as Endogenous Macrodynamics in Algorithmic Recourse:

a) Simple linear classifier trained for binary classification.
b) Implementation of AR leads to a domain shift.
c) Classifier retraining leads to corresponding model shift.
d) Over time decision boundary moves away from target class (blue).

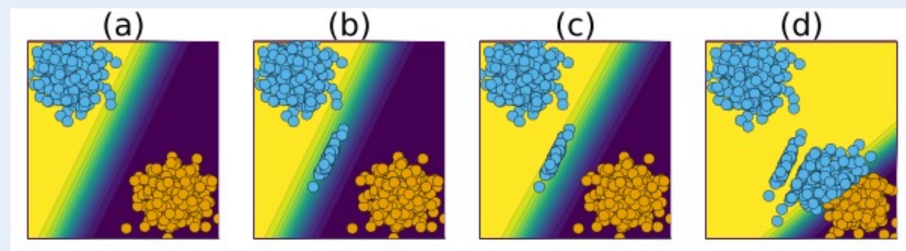


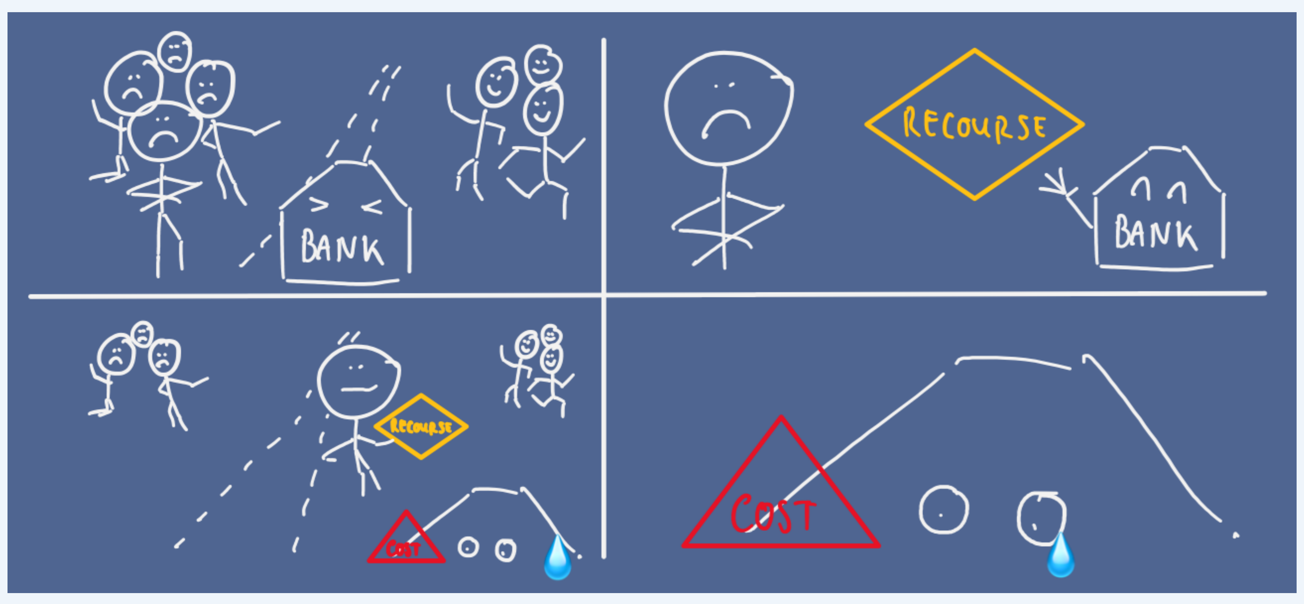
Figure 1: Dynamics in Algorithmic Recourse. Individuals in target class marked in blue.

Key Takeaways

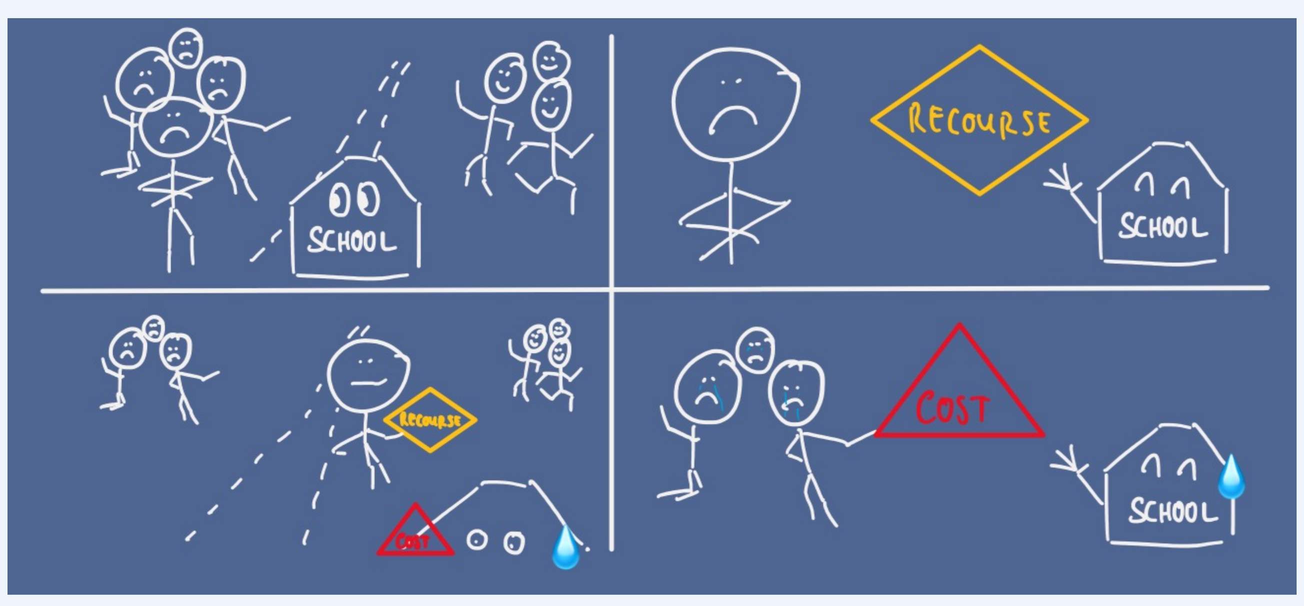
- Our findings indicate that state-of-the-art approaches to Algorithmic Recourse induce substantial domain and model shifts.
- We would argue that the expected external costs of individual recourse should be shared by all stakeholders.
- A straightforward way to achieve this is to penalize external costs in the counterfactual search objective function.
- Various simple strategies based on this notion can be effectively used to mitigate shifts.

MOTIVATION

Example 1 (Consumer Credit)



Example 2 (Student Admission)



BACKGROUND

- **Counterfactual Explanation** (CE) explain how inputs into a model need to change for it to produce different outputs.
- Counterfactual Explanations that involve realistic and actionable changes can be used for the purpose of **Algorithmic Recourse** (AR).

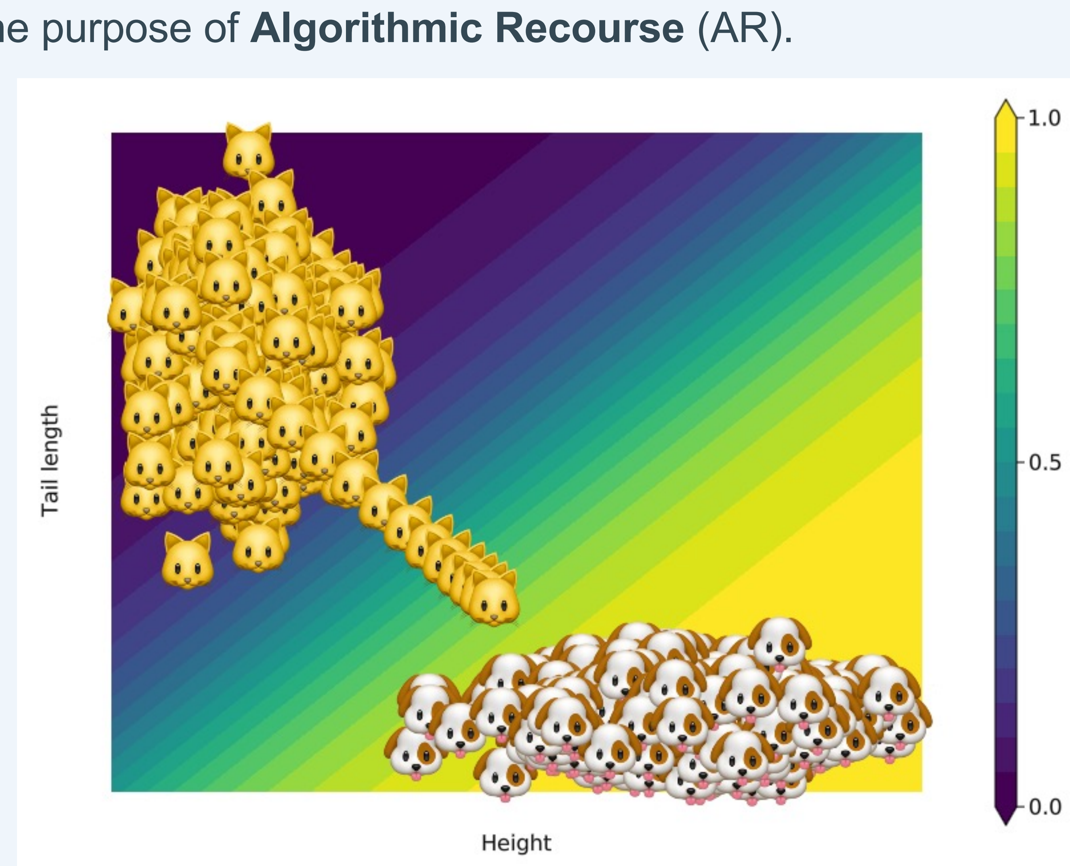


Figure 2: Generating a counterfactual for 🐱 following Wachter et al. (2018). The contour shows the predictions of a simple multi-layer perceptron (MLP).

TOWARDS COLLECTIVE RECOURSE

By introducing a second penalty term, we can explicitly penalize external costs:

$$\mathbf{s}' = \arg\min_{\mathbf{s}' \in \mathcal{S}} \{\text{yloss}(M(f(\mathbf{s}')), y^*) + \lambda_1 \text{cost}(f(\mathbf{s}')) + \lambda_2 \text{extcost}(f(\mathbf{s}'))\}$$

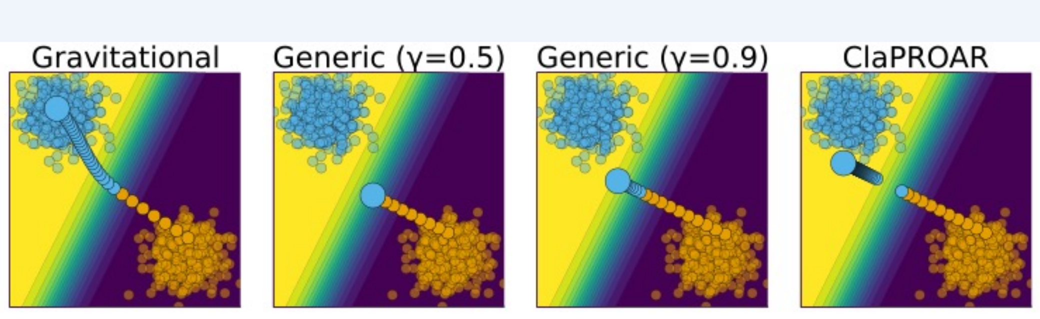


Figure 3: Mitigation strategies compared to the baseline approach, that is, Wachter (Generic) with γ = 0.5; choosing a higher decision threshold pushes the counterfactual a little further into the target domain; this effect is even stronger for ClaPROAR; finally, using the Gravitational generator the counterfactual ends up all the way inside the target domain.

MODELLING RECOURSE DYNAMICS

Research Questions

❓ **Endogenous Shifts**
Does the repeated implementation of recourse provided by state-of-the-art generators lead to shifts in the domain and model?

❓ **Costs**
If so, are these dynamics substantial enough to be considered costly to stakeholders involved in real-world automated decision-making processes?

❓ **Heterogeneity**
Do different counterfactual generators yield significantly different outcomes in this context? Furthermore, is there any heterogeneity concerning the chosen classifier and dataset?

❓ **Drivers**
What are the drivers of endogenous dynamics in Algorithmic Recourse?

❓ **Mitigation Strategies**
What are potential mitigation strategies with respect to endogenous macrodynamics in AR?

PRINCIPAL FINDINGS

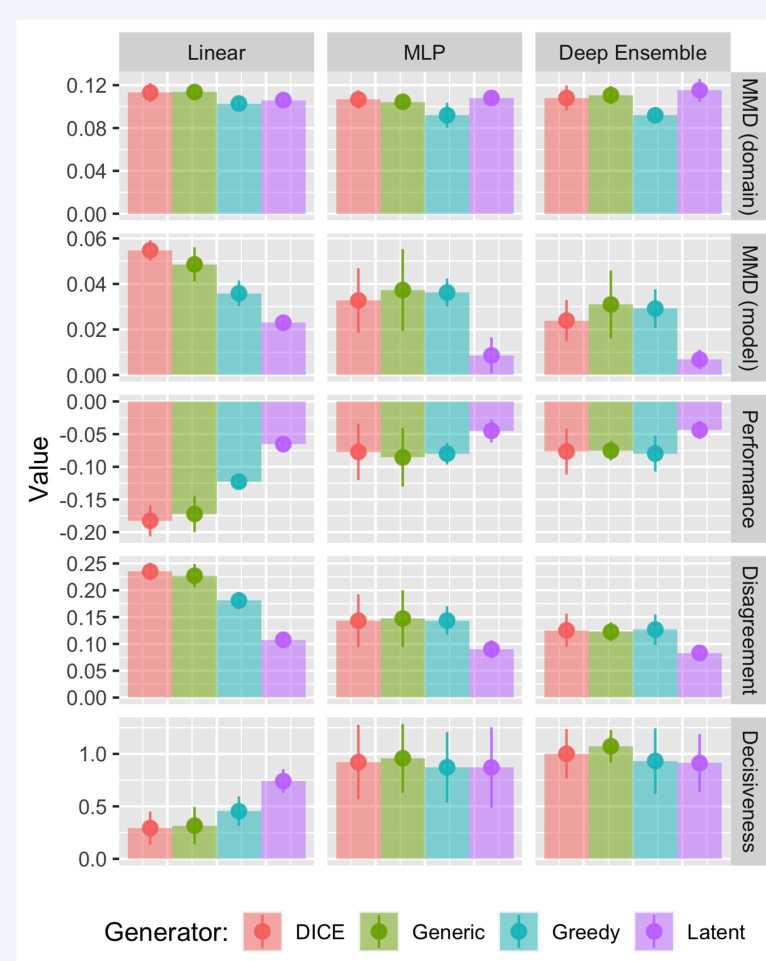


Figure 4: Results for synthetic data.

Figure 5: Results for real-world data.

✅ Endogenous Shifts
✅ Costs
✅ Heterogeneity
✅ Drivers
Minimizing private costs vs. complying with data generating process

SECONDARY FINDINGS

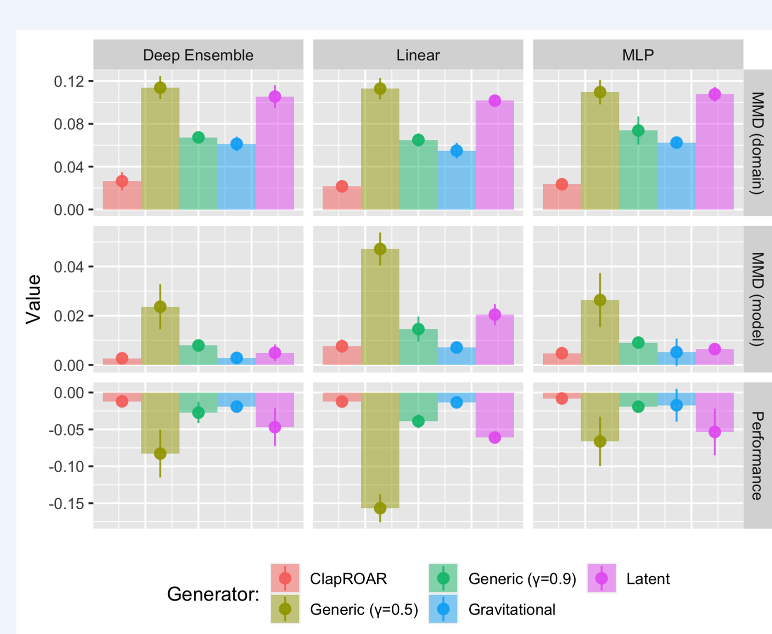


Figure 6: Results for synthetic data using mitigation strategies.

Figure 7: Results for real-world data using mitigation strategies.

✅ Mitigation Strategies
Can effectively mitigate shifts by penalizing external costs

LIMITATIONS & FUTURE WORK

- 🎯 Ad-hoc solution to tradeoff between private vs. external costs.
- 🎯 Experimental design is a vast over-simplification of potential real-world scenarios.
- 🎯 We have omitted recourse generators that incorporate causal knowledge.
- 🎯 Analysis limited to differentiable linear and non-linear classifiers, no trees.

RESOURCES

Online Companion | GitHub Repository | Julia Package | Personal Website