

Explaining Models or Modelling Explanations

Counterfactual Explanations and Algorithmic Recourse for Trustworthy AI

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Background

- 👤 Economist, now PhD CS
- ❓ How can we make opaque AI more trustworthy?
- 💻 Explainable AI, Adversarial ML, Probabilistic ML
- leftrightarrow Core developer and maintainer of Taija (Trustworthy AI in Julia)



Figure 1: Scan for slides.
Links to www.patalt.org.

Agenda

- **Intro:** counterfactual explanations (CE) and algorithmic recourse (AR)

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- **Intro:** counterfactual explanations (CE) and algorithmic recourse (AR)
- **Unexpected Challenges:** endogenous dynamics of AR
- **Paradigm Shift:** explanations should be faithful first, plausible second
- **New Opportunities:** teaching models plausible explanations through CE

Intro
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Unexpected Challenges
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Paradigm Shift
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New Opportunities
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If we still have time ...
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Intro

A Toy Problem



Figure 2: Cats and dogs in two dimensions.

Traversing the Parameter Space

Model Training

Objective:

$$\min_{\theta} \{ \text{yloss}(M_{\theta}(\mathbf{x}), \mathbf{y}) \}$$

Traversing the Parameter Space

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Objective:

$$\min_{\theta} \{y\text{loss}(M_{\theta}(\mathbf{x}), \mathbf{y})\}$$

Solution:

$$\theta_{t+1} = \theta_t - \nabla_{\theta} \{y\text{loss}(M_{\theta}(\mathbf{x}), \mathbf{y})\}$$

$$\theta^* = \theta_T$$

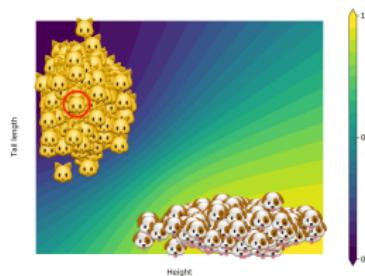


Figure 3: Fitted model. Contour shows predicted probability $y = .$

Traversing the Feature Space

Counterfactual Search

Objective:

$$\min_{\mathbf{x}} \{y\text{loss}(M_{\theta^*}(\mathbf{x}), \mathbf{y}^+) + \lambda \text{reg}\}$$

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$$\mathbf{x}^* = \mathbf{x}_T$$

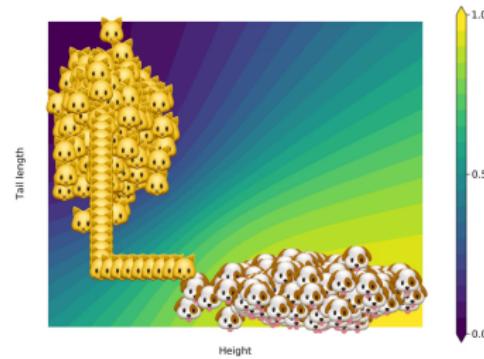


Figure 4: Counterfactual explanation for what it takes to be a dog.

Algorithmic Recourse

Provided CE is valid, plausible and actionable, it can be used to provide recourse to individuals negatively affected by models.

*“If your income had been x ,
then ...”*

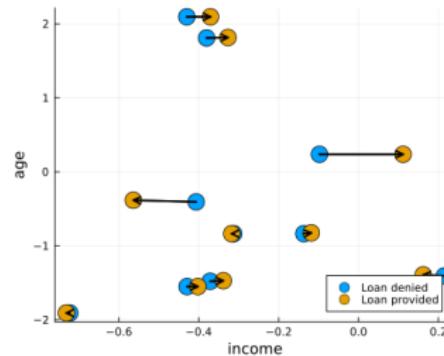


Figure 5: Counterfactuals for random samples from the Give Me Some Credit dataset (Kaggle 2011). Features ‘age’ and ‘income’ are shown.

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Unexpected Challenges

Hidden Cost of Implausibility

AR can introduce costly dynamics¹

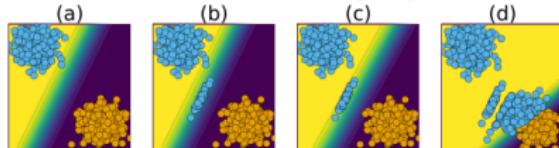


Figure 6: Endogenous Macrodynamics in Algorithmic Recourse.



Figure 7: Illustration of external cost of individual recourse.

🔑 Insight: Implausible Explanations Are Costly

¹

Altmeyer, Angela, et al. (2023) © SaTML 2023.

Mitigation Strategies

- Incorporate hidden cost in reframed objective.
- Even simple mitigation strategies can help.
- Reducing hidden cost is (roughly) equivalent to ensuring plausibility.

Reframed Objective

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

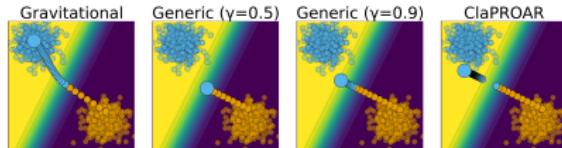


Figure 8: Mitigation strategies to tackle hidden costs of AR.

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Paradigm Shift

Plausibility at all cost?

All of these counterfactuals are valid explanations for the model's prediction.

Pick your poison ...

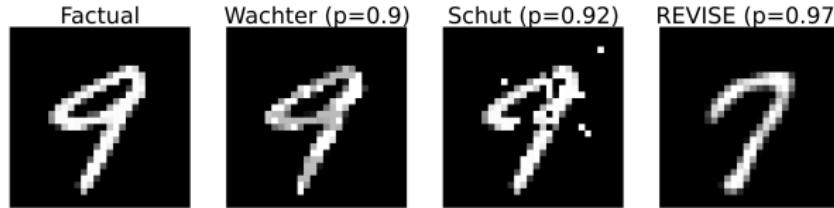


Figure 9: Turning a 9 into a 7: Counterfactual explanations for an image classifier produced using *Wachter* (Wachter, Mittelstadt, and Russell 2017), *Schut* (Schut et al. 2021) and *REVISE* (Joshi et al. 2019).

Faithful First, Plausible Second

Counterfactuals as plausible as the model permits².

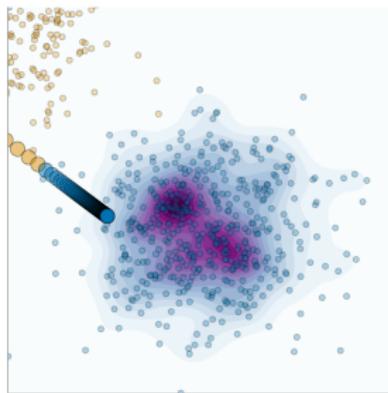


Figure 10: KDE for training data.

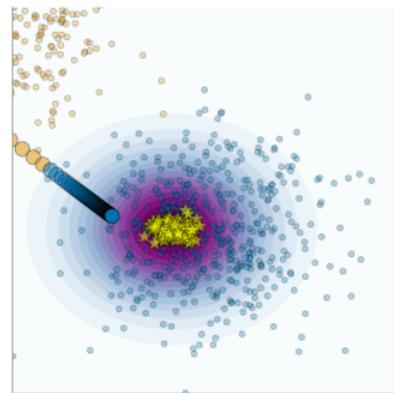


Figure 11: KDE for model posterior.



Altmeyer, Farmanbar, et al. (2023) © AAAI 2024. [blog]

Faithful Counterfactuals

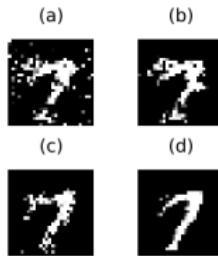


Figure 12: Turning a 9 into a 7. *ECCCo* applied to MLP (a), Ensemble (b), JEM (c), JEM Ensemble (d).

🔑 **Insight:** faithfulness facilitates

- model quality checks (Figure 12).
- state-of-the-art plausibility (Figure 13).

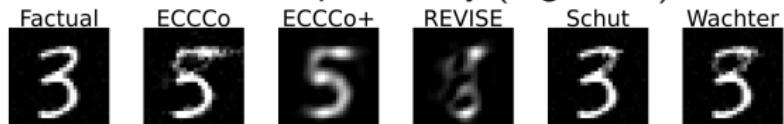


Figure 13: Results for different generators (from 3 to 5).

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New Opportunities

Counterfactual Training: Method

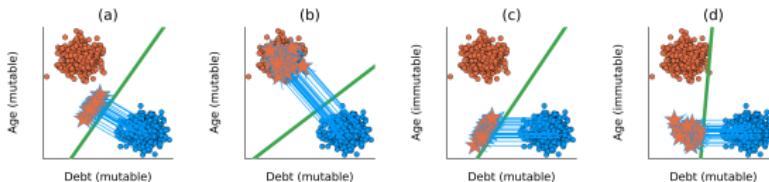


Figure 14: (a) conventional training, all mutable; (b) CT, all mutable; (c) conventional, age immutable; (d) CT, age immutable.

- 1 Contrast faithful CE with data.
- 2 Enforce actionability constraints.
- 3 Bonus: use nascent CE as AE.

Insight:
We can hold models accountable for plausible explanations³.

Counterfactual Training: Results

- Models trained with CT learn more plausible and (provably) actionable explanations.
- Predictive performance does not suffer, robust performance improves.

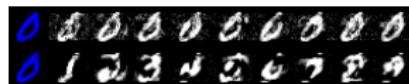


Figure 15: *Plausibility*: BL (top row) vs CT using the *ECCo* generator (bottom row) counterfactuals for a randomly selected factual from class “0” (in blue). CT produces more plausible counterfactuals than BL.

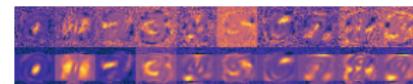


Figure 16: *Actionability*: Sample visual explanations (integrated gradients) for the *MNIST* dataset. Mutability constraints are imposed on the five top and bottom rows of pixels. CT (bottom) is less sensitive to protected features.

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Spurious Sparks of AGI

We challenge the idea that the finding of meaningful patterns in latent spaces of large models is indicative of AGI⁴.

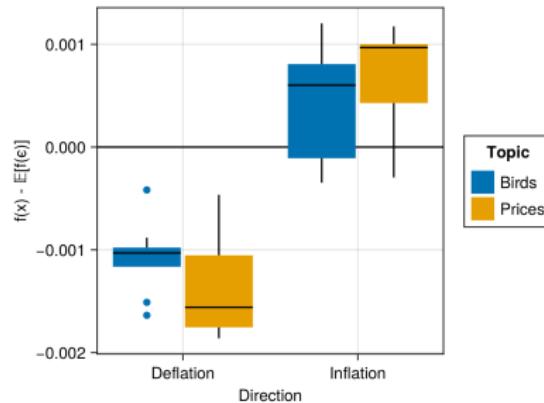


Figure 17: Inflation of prices or birds? It doesn't matter!



In Altmeyer et al. (2024) © ICML 2024

Taija

- Model Explainability
(CounterfactualExplanations.jl)
- Predictive Uncertainty
Quantification
(ConformalPrediction.jl)
- Effortless Bayesian Deep
Learning (LaplaceRedux.jl)
- ... and more!
- Work presented @ JuliaCon
2022, 2023, 2024.
- Google Summer of Code and
Julia Season of Contributions
2024.
- Total of three software projects
@ TU Delft.



Figure 18: Trustworthy AI in Julia: github.com/JuliaTrustworthyAI

References

Altmeyer, Patrick, Giovan Angela, Aleksander Buszydlik, Karol Dobiczek, Arie van Deursen, and Cynthia C. S. Liem. 2023. "Endogenous Macrodynamics in Algorithmic Recourse." In *2023 IEEE Conference on Secure and Trustworthy Machine Learning (SaTML)*, 418–31. IEEE. <https://doi.org/10.1109/satml54575.2023.00036>.

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