Explaining Models or Modelling Explanations

Challenging Existing Paradigms in 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
- Maintainer of Taija (trustworthy AI in Julia)

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

Agenda

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- What dynamics are generated when off-the-shelf solutions to CE and AR are implemented in practice?
- Can we generate plausible counterfactuals relying only on the opaque model itself?
- How can we leverage counterfactuals during training to build more trustworthy models?

Background

CE in Five Slides

Figure 2: Cats and dogs in two dimensions.

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Model Training

Objective:

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

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CE in Five Slides

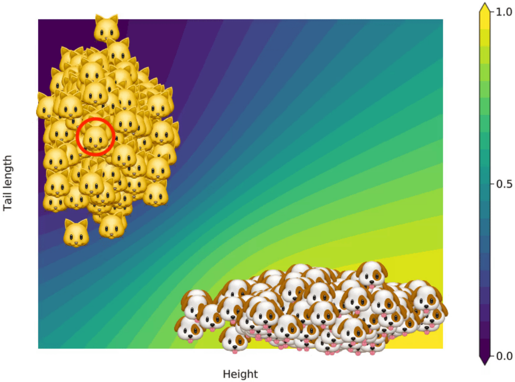

Figure 3: Fitted model. Contour shows predicted probability $y = \;$.

CE in Five Slides

Counterfactual Search

Objective:

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CE in Five Slides

$$\min_{\mathbf{Z}' \in \mathcal{Z}^L} \{\text{yloss}(M_\theta(f(\mathbf{Z}')), \mathbf{y}^+) + \lambda \text{cost}(f(\mathbf{Z}'))\}$$

Counterfactual Explanations explain how inputs into a model need to change for it to produce different outputs[1].

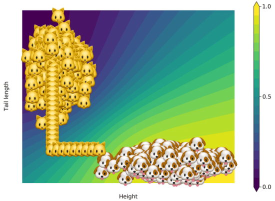

Figure 4: Counterfactual explanation for what it takes to be a dog.

[1] Altmeyer, Deursen, and Liem (2023) @ JuliaCon 2022

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 ..."*

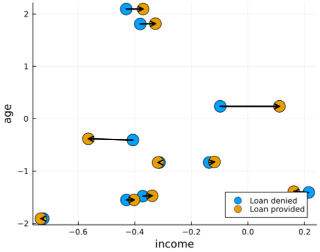

Figure 5: Counterfactuals for random samples from the Give Me Some Credit dataset (Kaggle 2011). Features 'age' and 'income' are shown.

Dynamics of CE and AR

Hidden Cost of Implausibility

AR can introduce costly dynamics[2]

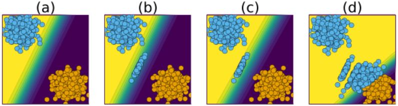

Figure 6: Endogenous Macrodynamics in Algorithmic Recourse.

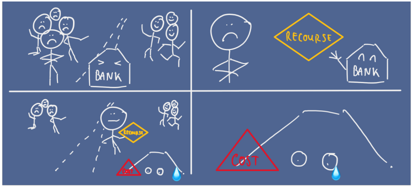

Figure 7: Illustration of external cost of individual recourse.

Insight: individual recourse neglects bigger picture.

[2] Altmeyer, Angela, et al. (2023) @ SaTML 2023.

Mitigation Strategies

- Incorporate hidden cost in reframed objective.
- Reducing hidden cost is equivalent to ensuring plausibility.

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

Plausibility at all cost?

Pick your Poison

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

Which one would you pick?

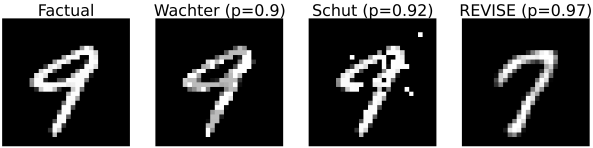

Figure 8: Turning a 9 into a 7: Counterfactual explanations for an image classifier produced using *Wachter* (Wachter, Mittelstadt, and Russell 2017), *Schut* (Schut et al. 2021) and *REVISE* (Joshi et al. 2019).

Faithful First, Plausible Second

Counterfactuals as plausible as the model permits[3].

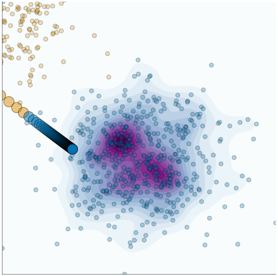

Figure 9: KDE for training data.

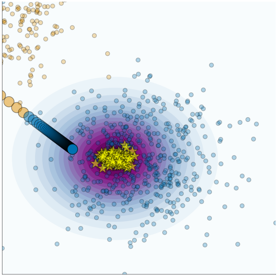

Figure 10: KDE for model posterior.

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

Faithful Counterfactuals

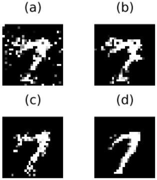

Figure 11: Turning a 9 into a 7. *ECCCo* applied to MLP (a), Ensemble (b), JEM (c), JEM Ensemble (d).

Insight: faithfulness facilitates

- model quality checks (Figure 11).
- state-of-the-art plausibility (Figure 12).

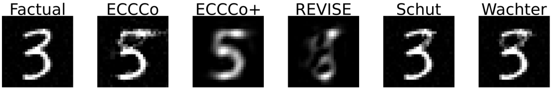

Figure 12: Results for different generators (from 3 to 5).

Teaching models plausible explanations

Counterfactual Training: Method

Idea

Let the model compare its own explanations to plausible ones[4].

1. Contrast faithful counterfactuals with data.
2. Use nascent CE as adversarial examples.

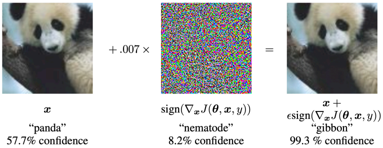

Figure 13: Example of an adversarial attack. Source: Goodfellow, Shlens, and Szegedy (2015)

[4] under review

Counterfactual Training: Results

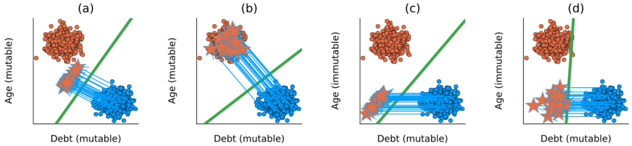

Figure 14: (a) conventional training, all mutable; (b) CT, all mutable; (c) conventional, *age* immutable; (d) CT, *age* immutable.

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

If we still have time ...

Spurious Sparks of AGI

We challenge the idea that the finding of meaningful patterns in latent spaces of large models is indicative of AGI[5].

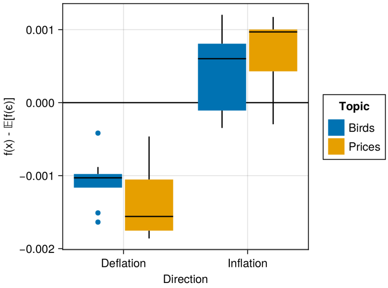

Figure 15: Inflation of prices or birds? It doesn't matter!

[5] 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 16: Trustworthy AI in Julia: github.com/JuliaTrustworthyAI

References

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