Counterfactual Training: Teaching Models Plausible and Actionable Explanations

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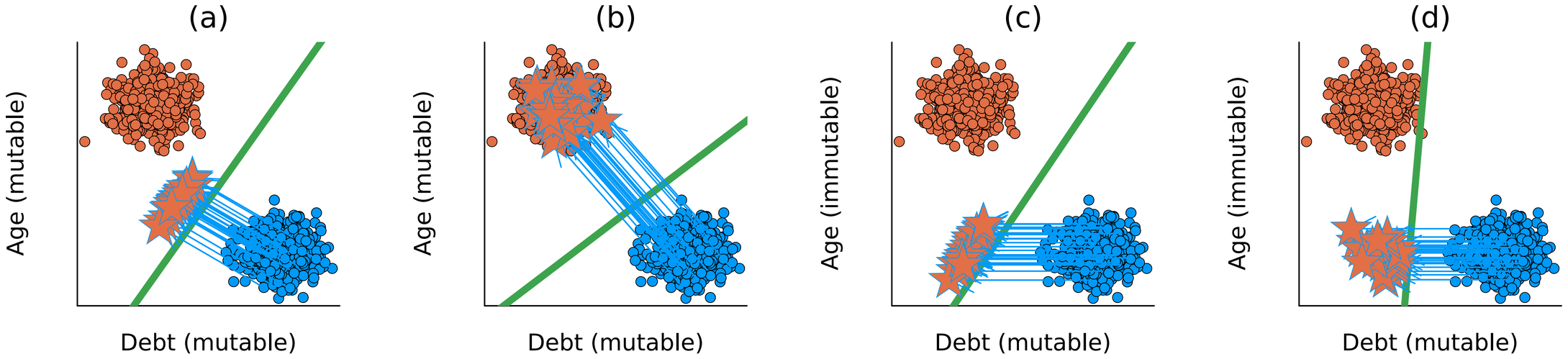
Counterfactual training leverages counterfactual explanations to make models more 1) explainable, 2) sensitive to actionability constraints and 3) adversarially robust.



Methodology

Counterfactual search objective (equation (1)):

$$\min_{\mathbf{x}' \in \mathcal{X}^D} \{\text{yloss}(\mathbf{M}_\theta(\mathbf{x}'), \mathbf{y}^+) + \lambda \text{reg}(\mathbf{x}')\}$$

Counterfactual training objective (equation (2)):

$$\min_\theta \text{yloss}(\mathbf{M}_\theta(\mathbf{x}), \mathbf{y}) + \lambda_{\text{div}} \text{div}(\mathbf{x}^+, \mathbf{x}'_{\text{CE}}, y^+; \theta)$$
$$+\lambda_{\text{adv}} \text{advloss}(\mathbf{M}_\theta(\mathbf{x}'_{\text{AE}}), \mathbf{y}_{\text{AE}}) + \lambda_{\text{reg}} \text{ridge}(\mathbf{x}^+, \mathbf{x}'_{\text{CE}}, y; \theta)$$

Pseudo-Code for counterfactual training:

Require: Training dataset $\mathcal{D}$, initialize model $\mathbf{M}_\theta$
while not converged **do**
  Sample $\mathbf{x}'_0 \sim \mathbf{X}$, $y^+ \sim \mathcal{U}(\mathcal{Y})$ and $\mathbf{x}^+ \sim \mathbf{X}^+$
  for $t = 1$ to T **do**
    Backpropagate $\nabla_{\mathbf{x}'}$ through equation (1)
    Store $\mathbf{x}'_{\text{CE}}, \mathbf{x}'_{\text{AE}}, \mathbf{y}_{\text{AE}}$
  end for
  Sample mini-batches $(\mathbf{x}_i, \mathbf{y}_i)_{i=1}^{n_b}$ from dataset $\mathcal{D}$
  Distribute $(\mathbf{x}'_{\text{CE}i}, y^+{}_i, \mathbf{x}'_{\text{AE}i}, \mathbf{y}_{\text{AE}i}, \mathbf{x}^+{}_i)_{i=1}^{n_{\text{CE}}}$
  for each batch **do**
    Backpropagate ∇_θ through equation (2)
  end for
end while
return $\mathbf{M}_\theta$

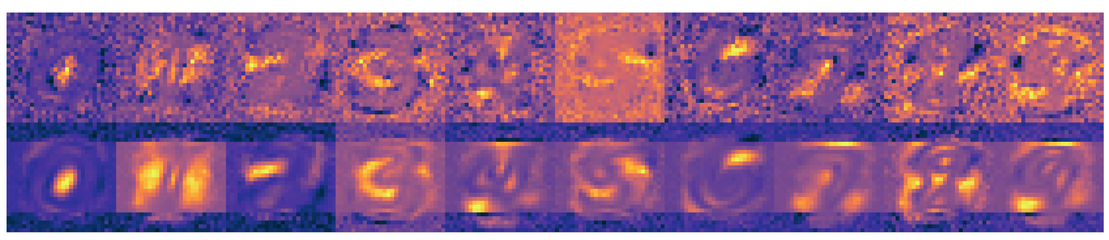
Summary

On-the-fly counterfactual explanations are used to induce explainability and actionability through contrastive divergence and recycled as adversarial examples to further improve robustness.

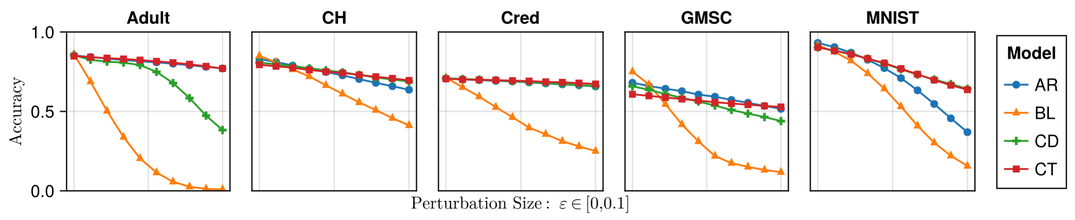
Improved Plausibility

Data	**IP** $(-\%)$	**IP*** $(-\%)$	**Cost** $(-\%)$
LS	$26.26 \pm 0.67^*$	$51.28 \pm 2.01^*$	$16.41 \pm 0.57^*$
Circ	$58.88 \pm 0.37^*$	$93.84 \pm 6.70^*$	$42.99 \pm 0.85^*$
Moon	$19.59 \pm 0.73^*$	8.00 ± 9.44	$5.16 \pm 1.00^*$
OL	-1.93 ± 1.12	-27.70 ± 14.59	$40.86 \pm 2.30^*$
Adult	0.19 ± 1.05	$34.35 \pm 5.61^*$	4.03 ± 4.03
CH	$10.65 \pm 1.47^*$	$63.06 \pm 4.25^*$	$44.23 \pm 1.43^*$
Cred	$10.14 \pm 1.59^*$	$50.35 \pm 12.26^*$	$-18.17 \pm 4.40^*$
GMSC	$10.65 \pm 2.28^*$	$24.75 \pm 4.84^*$	$66.01 \pm 1.41^*$
MNIST	$6.36 \pm 1.70^*$	-70.31 ± 217.60	$-35.11 \pm 6.96^*$
Avg.	15.64	25.29	18.49

Improved Actionability



Improved Robustness



Further Resources

arxiv.org/abs/2601.16205
IEEE Conference on Secure and Trustworthy Machine Learning (SaTML)
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Bibliography