

ECCCos from the Black Box

Faithful Model Explanations through Energy-Constrained Conformal Counterfactuals

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2026-02-13

Pick your Poison

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

Which one would you pick?

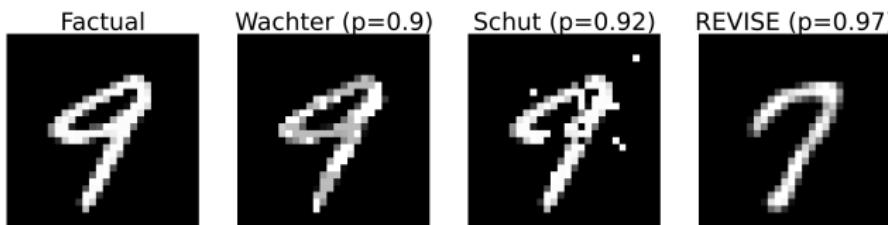


Figure 1: Turning a 9 into a 7: Counterfactual explanations for an image classifier produced using *Wachter* (Wachter, Mittelstadt, and Russell 2017), *Schut* (Schut et al. 2021) and *REVISE* (Joshi et al. 2019).

Faithfulness first, plausibility second.

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We propose *ECCCo*: a new way to generate faithful model explanations that are as plausible as the underlying model permits.

Summary

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- **Idea:** generate counterfactuals that are consistent with what the model has learned about the data.
- **Method:** constrain the model's energy and predictive uncertainty for the counterfactual.
- **Result:** faithful counterfactuals that are as plausible as the model permits.
- **Benefits:** enable us to distinguish trustworthy from unreliable models.

Counterfactual Explanations

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

Counterfactual Explanations (CE)

explain how inputs into a model
need to change for it to produce
different outputs.

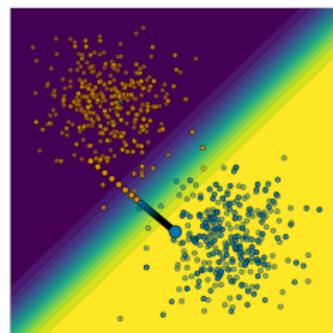


Figure 2: Gradient-based
counterfactual search.

Reconciling Faithfulness and Plausibility

Plausibility

Definition (Plausible Counterfactuals)

Let $\mathcal{X}|\mathbf{y}^+ = p(\mathbf{x}|\mathbf{y}^+)$ denote the true conditional distribution of samples in the target class \mathbf{y}^+ . Then for \mathbf{x}' to be considered a plausible counterfactual, we need: $\mathbf{x}' \sim \mathcal{X}|\mathbf{y}^+$.

Why Plausibility?

Plausibility is positively associated with actionability, robustness (Artelt et al. 2021) and causal validity (Mahajan, Tan, and Sharma 2020).

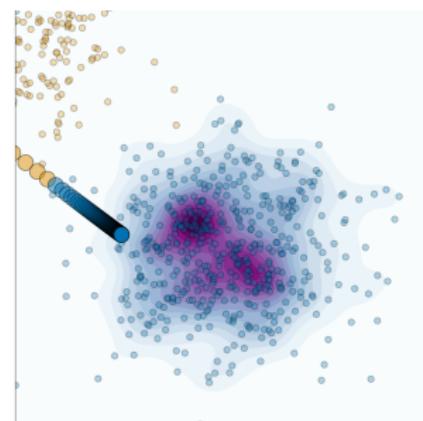
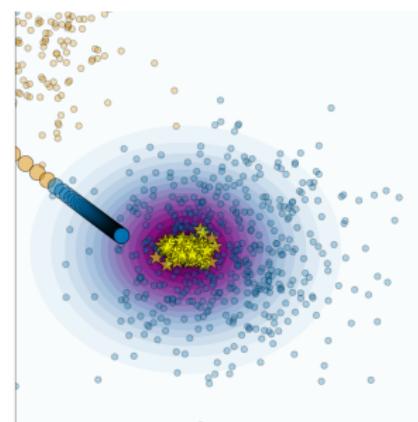


Figure 3: Kernel density estimate (KDE) for the conditional distribution, $p(\mathbf{x}|\mathbf{y}^+)$, based on observed data. Counterfactual path as in Figure 2.

Faithfulness

Definition (Faithful Counterfactuals)

Let $\mathcal{X}_\theta|y^+ = p_\theta(x|y^+)$ denote the conditional distribution of x in the target class y^+ , where θ denotes the parameters of model M_θ . Then for x' to be considered a faithful counterfactual, we need:
 $x' \sim \mathcal{X}_\theta|y^+$.



Trustworthy Models

If the model posterior approximates the true posterior ($p_\theta(x|y^+) \rightarrow p(x|y^+)$), faithful counterfactuals are also plausible.

Figure 4: KDE for learned conditional distribution, $p_\theta(x|y^+)$. Yellow stars indicate conditional samples generated through SGLD for a joint energy model (JEM).

ECCCo

Key Idea

Use the hybrid objective of joint energy models (JEM) and a model-agnostic penalty for predictive uncertainty: Energy-Constrained (\mathcal{E}_θ) Conformal (Ω) Counterfactuals (ECCCo).

ECCCo objective¹:

$$\begin{aligned} \min_{\mathbf{Z}' \in \mathcal{Z}^L} & \{ L_{\text{clf}}(f(\mathbf{Z}'); M_\theta, \mathbf{y}^+) + \lambda_1 \text{cost}(f(\mathbf{Z}')) \\ & + \lambda_2 \mathcal{E}_\theta(f(\mathbf{Z}') | \mathbf{y}^+) + \lambda_3 \Omega(C_\theta(f(\mathbf{Z}'); \alpha)) \} \end{aligned}$$

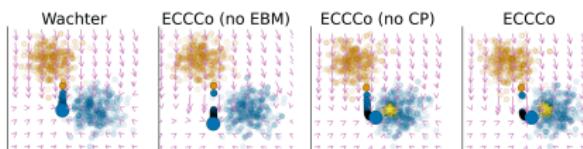


Figure 5: Gradient fields and counterfactual paths for different generators.

¹We leverage ideas from Grathwohl et al. (2020) and Stutz et al. (2022). See the

Results

Visual Evidence

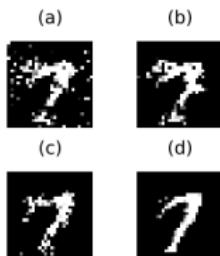


Figure 6: Turning a 9 into a 7. *ECCCo* applied to MLP (a), Ensemble (b), JEM (c), JEM Ensemble (d).

ECCCo generates counterfactuals that

- faithfully represent model quality (Figure 6).
- achieve state-of-the-art plausibility (Figure 7).

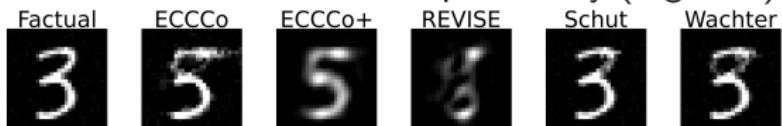


Figure 7: Results for different generators (from 3 to 5).

The Numbers

- Large benchmarks on a variety of models and datasets from various domains.
- *ECCCo* achieves state-of-the-art faithfulness across models and datasets and approaches state-of-the-art plausibility for more trustworthy models.

Model	Generator	California Housing			GMSC		
		Unfaithfulness ↓	Implausibility ↓	Uncertainty ↓	Unfaithfulness ↓	Implausibility ↓	Uncertainty ↓
MLP Ensemble	ECCCo	$3.69 \pm 0.08^{**}$	1.94 ± 0.13	$0.09 \pm 0.01^{**}$	$3.84 \pm 0.07^{**}$	2.13 ± 0.08	$0.23 \pm 0.01^{**}$
	ECCCo+	$3.88 \pm 0.07^{**}$	1.20 ± 0.09	0.15 ± 0.02	$3.79 \pm 0.05^{**}$	1.81 ± 0.05	$0.30 \pm 0.01^*$
	ECCCo (no CP)	$3.70 \pm 0.08^{**}$	1.94 ± 0.13	$0.10 \pm 0.01^{**}$	$3.85 \pm 0.07^{**}$	2.13 ± 0.08	$0.23 \pm 0.01^{**}$
	ECCCo (no EBM)	4.03 ± 0.07	1.12 ± 0.12	$0.14 \pm 0.01^{**}$	4.08 ± 0.06	0.97 ± 0.08	$0.31 \pm 0.01^*$
	REVISE	$3.96 \pm 0.07^*$	$0.58 \pm 0.03^{**}$	0.17 ± 0.03	4.09 ± 0.07	$0.63 \pm 0.02^{**}$	0.33 ± 0.06
	Schut	4.00 ± 0.06	1.15 ± 0.12	$0.10 \pm 0.01^{**}$	4.04 ± 0.08	1.21 ± 0.08	$0.30 \pm 0.01^*$
	Wachter	4.04 ± 0.07	1.13 ± 0.12	0.16 ± 0.01	4.10 ± 0.07	0.95 ± 0.08	0.32 ± 0.01
JEM Ensemble	ECCCo	$1.40 \pm 0.08^{**}$	$0.69 \pm 0.05^{**}$	$0.11 \pm 0.00^{**}$	$1.20 \pm 0.06^*$	$0.78 \pm 0.07^{**}$	0.38 ± 0.01
	ECCCo+	$1.28 \pm 0.08^{**}$	$0.60 \pm 0.04^{**}$	$0.11 \pm 0.00^{**}$	$1.01 \pm 0.07^{**}$	$0.70 \pm 0.07^{**}$	0.37 ± 0.01
	ECCCo (no CP)	$1.39 \pm 0.08^{**}$	$0.69 \pm 0.05^{**}$	$0.11 \pm 0.00^{**}$	$1.21 \pm 0.07^*$	$0.77 \pm 0.07^{**}$	0.39 ± 0.01
	ECCCo (no EBM)	1.70 ± 0.09	0.99 ± 0.08	$0.14 \pm 0.00^*$	1.31 ± 0.07	0.97 ± 0.10	$0.32 \pm 0.01^{**}$
	REVISE	$1.39 \pm 0.15^{**}$	$0.59 \pm 0.04^{**}$	0.25 ± 0.07	$1.01 \pm 0.07^{**}$	$0.63 \pm 0.04^{**}$	0.33 ± 0.07
	Schut	$1.59 \pm 0.10^*$	1.10 ± 0.06	$0.09 \pm 0.00^{**}$	1.34 ± 0.07	1.21 ± 0.10	$0.26 \pm 0.01^{**}$
	Wachter	1.71 ± 0.09	0.99 ± 0.08	0.14 ± 0.00	1.31 ± 0.08	0.95 ± 0.10	0.33 ± 0.01

Table 1: Results for tabular datasets: sample averages +/- one standard deviation across valid counterfactuals. The best outcomes are highlighted in bold. Asterisks indicate that the given value is more than one (*) or two (**) standard deviations away from the baseline (*Wachter*).

Questions?

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With thanks to my co-authors Mojtaba Farmanbar, Arie van Deursen and Cynthia C. S. Liem.



Code

The code used to run the analysis for this work is built on top of `CounterfactualExplanations.jl`.

There is also a corresponding paper, *Explaining Black-Box Models through Counterfactuals*, which has been published in JuliaCon Proceedings.



Figure 8: Trustworthy AI in Julia: github.com/JuliaTrustworthyAI

References

- Artelt, André, Valerie Vaquet, Riza Velioglu, Fabian Hinder, Johannes Brinkrolf, Malte Schilling, and Barbara Hammer. 2021. “Evaluating Robustness of Counterfactual Explanations.” In *2021 IEEE Symposium Series on Computational Intelligence (SSCI)*, 01–09. IEEE.
- Grathwohl, Will, Kuan-Chieh Wang, Joern-Henrik Jacobsen, David Duvenaud, Mohammad Norouzi, and Kevin Swersky. 2020. “Your Classifier Is Secretly an Energy Based Model and You Should Treat It Like One.” In *International Conference on Learning Representations*.
- Joshi, Shalmali, Oluwasanmi Koyejo, Warut Vigitbenjaronk, Been Kim, and Joydeep Ghosh. 2019. “Towards Realistic Individual Recourse and Actionable Explanations in Black-Box Decision Making Systems.” <https://arxiv.org/abs/1907.09615>.
- Mahajan, Divyat, Chenhao Tan, and Amit Sharma. 2020. “Preserving Causal Constraints in Counterfactual Explanations for Machine