

# ECCECos from the Black Box

## Faithful Model Explanations through Energy-Based Conformal Counterfactuals

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2024-02-12

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

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- **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.

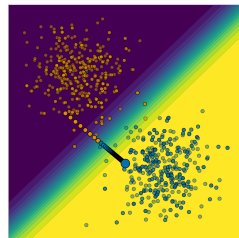


Figure 1: Gradient-based counterfactual search.



# Pick your Poison

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

*Which one would you pick?*

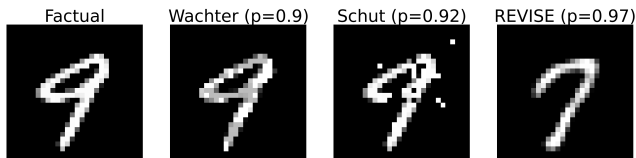


Figure 2: Turning a 9 into a 7: Counterfactual explanations for an image classifier produced using *Wachter* (Wachter, Mittelstadt, and Russell 2017), *Schut* (Schut et al. 2021) and *REVISE* (Joshi et al. 2019).

# 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).

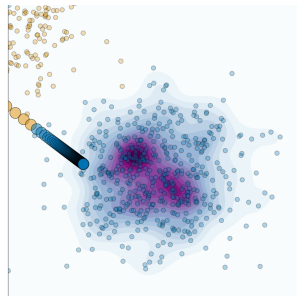


Figure 3: Kernel density estimate (KDE) for the conditional distribution,  $p(\mathbf{x}|\mathbf{y}^+)$ , based on observed data. Counterfactual path as in Figure 1.

# Faithfulness

## Definition (Faithful Counterfactuals)

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

## Trustworthy Models

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



Figure 4: KDE for learned conditional distribution,  $p_{\theta}(\mathbf{x}|\mathbf{y}^+)$ . 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 ( $\mathcal{E}_\theta$ ) Conformal ( $\Omega$ ) Counterfactuals (ECCCo).

ECCCo objective<sup>a</sup>:

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

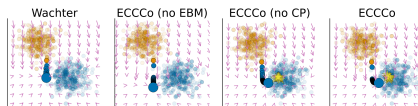


Figure 5: Gradient fields and counterfactual paths for different generators.

<sup>a</sup>We leverage ideas from Grathwohl et al. (2020) and Stutz et al. (2022). See the paper and appendix for a derivation of the objective from first principles.

# Results

# Visual Evidence

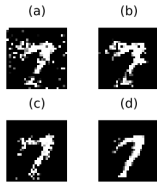


Figure 6: Turning a 9 into a 7. *ECCCo* applied to MLP (a), Ensemble (b), JEM (c), JEM Ensemble (d).

*ECCCo* generates counterfactuals that

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

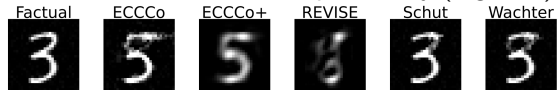


Figure 7: Results for different generators (from 3 to 5).

# 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	<b>3.69 ± 0.08**</b>	1.94 ± 0.13	<b>0.09 ± 0.01**</b>	3.84 ± 0.07**	2.13 ± 0.08	<b>0.23 ± 0.01**</b>
	ECCCo+	3.88 ± 0.07**	1.20 ± 0.09	0.15 ± 0.02	<b>3.79 ± 0.05**</b>	1.81 ± 0.05	0.30 ± 0.01*
	ECCCo (no CP)	3.70 ± 0.08**	1.94 ± 0.13	0.10 ± 0.01**	3.85 ± 0.07**	2.13 ± 0.08	0.23 ± 0.01**
	ECCCo (no EBM)	4.03 ± 0.07	1.12 ± 0.12	0.14 ± 0.01**	4.08 ± 0.06	0.97 ± 0.08	0.31 ± 0.01*
	REVISE	3.96 ± 0.07*	<b>0.58 ± 0.03**</b>	0.17 ± 0.03	4.09 ± 0.07	<b>0.63 ± 0.02**</b>	0.33 ± 0.06
	Schut	4.00 ± 0.06	1.15 ± 0.12	0.10 ± 0.01**	4.04 ± 0.08	1.21 ± 0.08	0.30 ± 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 ± 0.08**	0.69 ± 0.05**	0.11 ± 0.00**	1.20 ± 0.06*	0.78 ± 0.07**	0.38 ± 0.01
	ECCCo+	<b>1.28 ± 0.08**</b>	0.60 ± 0.04**	0.11 ± 0.00**	<b>1.01 ± 0.07**</b>	0.70 ± 0.07**	0.37 ± 0.01
	ECCCo (no CP)	1.39 ± 0.08**	0.69 ± 0.05**	0.11 ± 0.00**	1.21 ± 0.07*	0.77 ± 0.07**	0.39 ± 0.01
	ECCCo (no EBM)	1.70 ± 0.09	0.99 ± 0.08	0.14 ± 0.00*	1.31 ± 0.07	0.97 ± 0.10	0.32 ± 0.01**
	REVISE	1.39 ± 0.15**	<b>0.59 ± 0.04**</b>	0.25 ± 0.07	1.01 ± 0.07**	<b>0.63 ± 0.04**</b>	0.33 ± 0.07
	Schut	1.59 ± 0.10*	1.10 ± 0.06	<b>0.09 ± 0.00**</b>	1.34 ± 0.07	1.21 ± 0.10	<b>0.26 ± 0.01**</b>
	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](https://github.com/JuliaTrustworthyAI)

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