Counterfactual Training

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Status

- *Code base*: In place and streamlined for reproducibility and configuration.
- *Experiments*: Lots of work done and results largely supportive of idea.
  - Ran into problems on DelftBlue, which has set me back about 2 weeks.
- *Paper*: Still bare-bones.
- *ICML*: Potentially still possible to submit something, but this will be rushed and not “finished”.

Problems on Cluster

- Trying to distribute:
  1. Models/experiments across processes.
  2. For each model/experiment distribute the counterfactual search across processes.
- Out-of-memory issues, data races, ...
- Multi-processing for models & multi-threading for counterfactual search: low CPU efficiency on DelftBlue (jobs get cancelled).

The Big Oversight

- **Core problem**: `CounterfactualExplanation` objects are *huge*. They store `X` (the input), `y` (the output), etc. in their own memory.
- Can't easily fit `CounterfactualExplanation` objects on cluster memory and pass them around processes.
- **Good news**: Relatively straightforward to add `FlattenedCE` with gazzilion times lower memory footprint (done!).
- Nested parallelization issue remains and I will not spend more time trying to make it work.

Section 1

Methodology

High-Level Idea

Counterfactual Training (CT) combines ideas from Energy-Based Models and Adversarial Training:

$$\ell_{\text{clf}}(f_\theta(x), y) + \lambda_{\text{gen}}\ell_{\text{gen}}({x'}_t, x_t; \theta) + \lambda_{\text{adv}}\ell_{\text{clf}}(f_\theta({x'}_t), y)$$

- ${x'}_t$ are counterfactuals of $x_s \subseteq x$ with target class t.
- ℓ_{gen} is the difference in energies between observed samples in target class x_t and counterfactuals.
- Counterfactuals are recycled as adversarial examples.

Training Details

During each `EPOCH`:

1. Generate `nce` counterfactuals and distribute across mini-batches.
2. For each batch compute:
   - Classifier loss: $\ell_{\text{clf}}(f_\theta(x), y)$.
   - Generator loss: $\lambda_{\text{gen}}\ell_{\text{gen}}({x'}_t, x_t; \theta)$.
   - Adversarial loss: $\lambda_{\text{adv}}\ell_{\text{clf}}(f_\theta({x'}_t), y)$.
   - Regularization term for energies.
3. Backpropagate all losses and update parameters.

Motivation and Intuition

- Instead of using SGLD to sample from $p(x|t;\theta)$, we use counterfactual generators.
- The idea is to align counterfactual explanations with observed data to induce plausibility.
- This should only work if counterfactuals are generated faithfully (favorable evidence).
- Approach can be leveraged to impicitly encode mutability and domain constraints in model.

Encoding Domain Knowledge

Let $f_\theta(x) = \theta^T x$ be a linear classifier:

$$\begin{aligned} \nabla_\theta \ell_{\text{gen}}(x'_t, x_t; \theta) &= \nabla_\theta (\theta^T x_t - \theta^T x'_t) \\ \frac{\partial \ell_{\text{gen}}}{\partial \theta[1]}(x', x; \theta) &= x_t[1] - x'_t[1] \end{aligned}$$

Suppose that featue $x[1]$ is immutable (e.g. 'age'), so $x'_t[1] = x_s[1]$ where $s \neq t$. If $x_t[1] > x_s[1]$:

- ℓ_{gen} induces lower values of $\theta[1]$, acting as a hedge against ℓ_{clf}, which favours higher $\theta[1]$.

Section 2

Findings

Moons (Plausibility)

- All counterfactuals at test time generated using *ECCo*.
- Penalty on energy differential increases from *l.* to *r.*

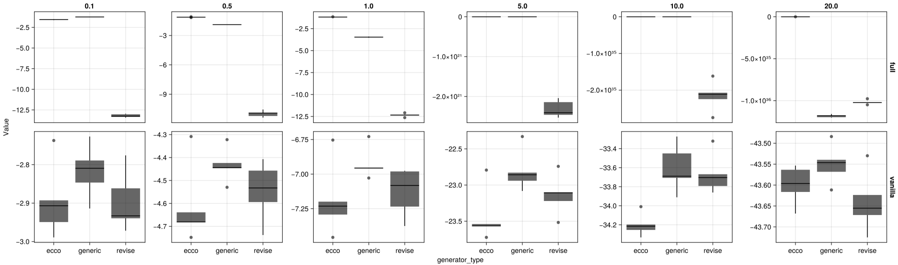


Figure 1: Plausibility of faithful counterfactuals x_t' measured in terms of their distance from x_t. Higher values indicate higher plausibility.

Moons (Example)

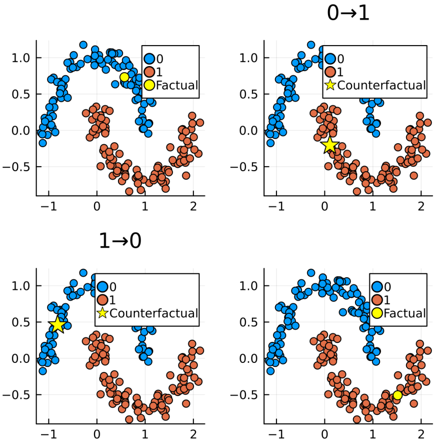


Figure 2: Counterfactual explanations for model trained with CT (*ECCo*).

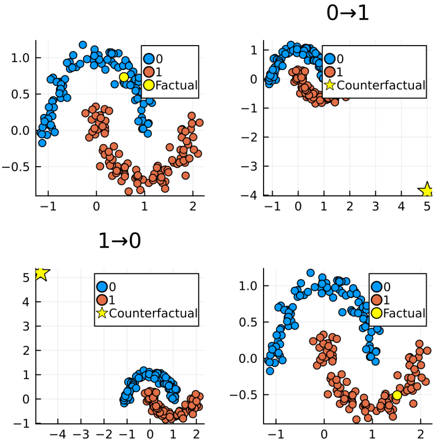
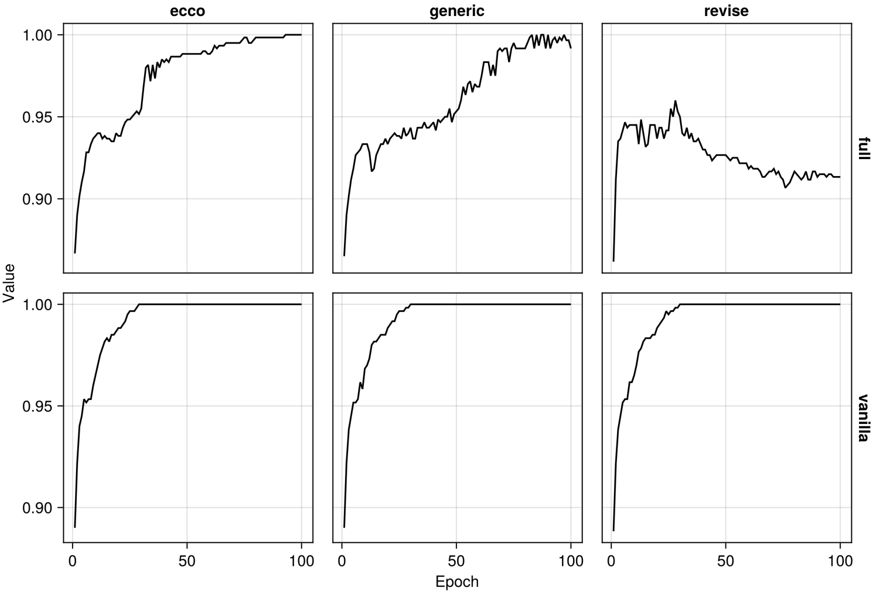


Figure 3: Counterfactual explanations for conventionally trained model.

Moons (Validation Accuracy)



MNIST (Vanilla vs *ECCo*)

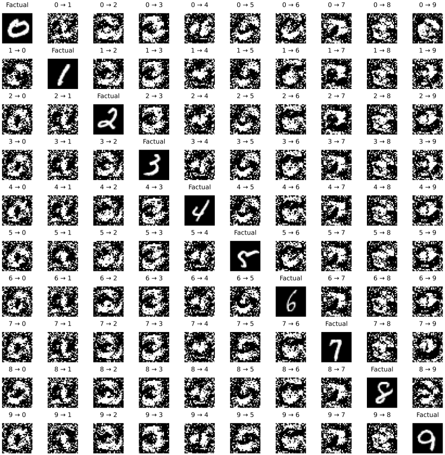


Figure 5: Faithful counterfactuals for conventionally trained MLP.

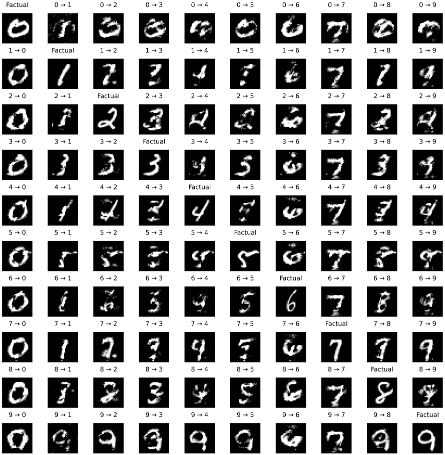


Figure 6: Faithful counterfactuals for same MLP with CT (*ECCo*).

MNIST (*Generic* and *REVISE*)

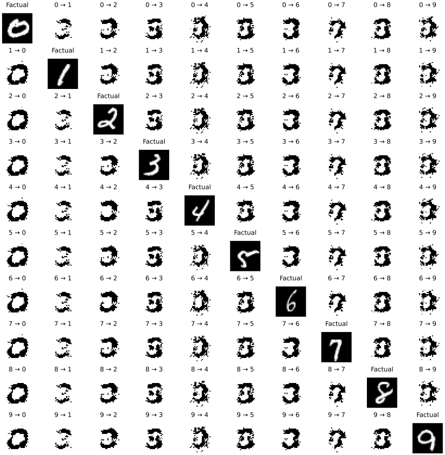


Figure 7: Faithful counterfactuals for same MLP with CT (*Generic*).

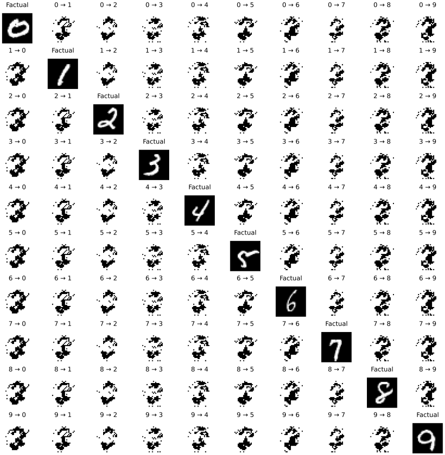


Figure 8: Faithful counterfactuals for same MLP with CT (*REVISE*).

Section 3

Planning Ahead

Planned Contributions

- Focus on enhancing trustworthiness and applicability of small opaque models.
  - Add more datasets and neuro-tree models (relatively straightforward).
- Do not pitch as state-of-the-art approach to generative modelling similar to JEMs, but rather as an extension of JEMs to XAI and AR.
- Limit use of image datasets to illustrate arguments:
  - Example: what happens if digit values can only be increased/decreased?

Timeline

- Code base is already streamlined very well to allow for grid searches with easy configuration.
- Lots of open tasks and questions (see issue)
  1. Add MMD to measure plausibility.
  2. Evaluate adversarial robustness and generative capacity. Compare to AT, JEM.
  3. ...
- Still aiming for ICML to commit to a timeline, but it seems unlikely to be in the shape I would like.