

# Counterfactual Training: Teaching Models Plausible and Actionable Explanations

Patrick Altmeyer<sup>1</sup>[0000–0003–4726–8613] (✉), Arie van Deursen<sup>1</sup>, and Cynthia C. S. Liem<sup>1</sup>

Delft University of Technology, Faculty of Electrical Engineering, Mathematics and Computer Science {p.altmeyer}@tudelft.net

**Abstract.** Counterfactual Explanations have emerged as a popular tool to explain predictions made by opaque machine learning models: they explain how factual inputs need to change in order for some fitted model to produce some desired output. Much existing research has focused on identifying explanations that are not only valid but also deemed desirable with respect to the underlying data and stakeholder requirements. Recent work has shown that under this premise, the task of learning desirable explanations is effectively reassigned from the model itself to the (post-hoc) counterfactual explainer. Building on that work, we propose a novel model objective that leverages counterfactuals during the training phase (ad-hoc) in order to minimize the divergence between learned representations and desirable explanations. Through extensive experiments, we demonstrate that our proposed methodology facilitates training models that inherently deliver desirable explanations while maintaining high predictive performance.

**Keywords:** Counterfactual Explanations · Explainable AI · Representation Learning

## 1 Introduction

Today’s prominence of artificial intelligence (AI) has largely been driven by advances in **representation learning**: instead of relying on features and rules that are carefully hand-crafted by humans, modern AIs are tasked with learning these representations from scratch, guided by narrow objectives such as predictive accuracy [5]. Modern advances in computing have made it possible to provide such AIs with ever greater degrees of freedom to achieve that task, which has often led them to outperform traditionally more parsimonious models. Unfortunately, in doing so they also learn increasingly complex and highly sensitive representations that we can no longer easily interpret.

This trend towards complexity for the sake of performance has come under serious scrutiny in recent years. At the very cusp of the deep learning revolution, [17] showed that artificial neural networks (ANN) are sensitive to adversarial examples: counterfactuals of model inputs that yield vastly different model predictions despite being “imperceptible” in that they are semantically indifferent from

their factual counterparts. Despite partially effective mitigation strategies such as **adversarial training** [6], truly robust deep learning (DL) remains unattainable even for models that are considered shallow by today’s standards [9].

Part of the problem is that high degrees of freedom provide room for many solutions that are locally optimal with respect to narrow objectives [20]. Based purely on predictive performance, these solutions may seem to provide compelling explanations for the data, when in fact they are based on purely associative, semantically meaningless patterns. This poses two related challenges: firstly, it makes these models inherently opaque, since humans cannot simply interpret what type of explanation the complex learned representations correspond to; secondly, even if we could resolve the first challenge, it is not obvious how to mitigate models from learning representations that correspond to meaningless and undesirable explanations.

The first challenge has attracted an abundance of research on **explainable AI** (XAI) which aims to develop tools to derive explanations from complex model representations. This can mitigate a scenario in which we deploy opaque models and blindly rely on their predictions. On countless occasions, this scenario has already occurred in practice and caused real harm to people who were affected adversely and often unfairly by automated decision-making systems (ADMS) involving opaque models [12]. Effective XAI tools can aide us in monitoring models and providing recourse to individuals to turn adverse outcomes (e.g. “loan application rejected”) into positive ones (“application accepted”). [19] propose **counterfactual explanations** as an effective approach to achieve this: they explain how factual inputs need to change in order for some fitted model to produce some desired output, typically involving minimal perturbations.

To our surprise, the second challenge has not yet attracted any consolidated research effort. Specifically, there has been no concerted effort towards improving model **explainability**, which we define here as the degree to which learned representations correspond to explanations that are interpretable and deemed desirable by humans. Instead, the choice has typically been to improve the capacity of XAI tools to identify the subset explanations that are both desirable and valid for any given model, independent of whether the learned representations are also compatible with undesirable explanations [2]. Fortunately, recent findings indicate that explainability can arise as byproduct of regularization techniques aimed at other objectives such as robustness, generalization and generative capacity [16].

Building on these findings, we introduce **counterfactual training**: a novel regularization technique geared explicitly towards aligning model representations with desirable explanations. Our contributions are as follows:

- We discuss existing related work on improving models and consolidate it through the lens of counterfactual explanations (Section 2).
- We present our proposed methodological framework that leverages faithful counterfactual explanations during the training phase of models to achieve the explainability objective (Section 3).

- Through extensive experiments we demonstrate the counterfactual training improve model explainability while maintaining high predictive performance. We run ablation studies and grid searches to understand how the underlying model components and hyperparameters affect outcomes. (Section 4).

Despite limitations of our approach discussed in Section 5, we conclude that counterfactual training provides a practical framework for researchers and practitioners interested in making opaque models more trustworthy Section 6. We also believe that this work serves as an opportunity for XAI researchers to reevaluate the premise of improving XAI tools without improving models.

## 2 Related Literature

To the best of our knowledge, our proposed framework for counterfactual training represents the first attempt to use counterfactual explanations during training to improve model explainability. In high-level terms, we define model explainability as the extent to which valid explanations derived for an opaque model are also deemed desirable with respect to the underlying data and stakeholder requirements. To make this more concrete, we follow [3] in tieing the concept of explainability to the quality of counterfactual explanations that we can generate for a given model. The authors show that counterfactual explanations—understood here as minimal input perturbations that yield some desired model prediction—are generally more meaningful if the underlying model is more robust to adversarial examples. We can make intuitive sense of this finding when looking at adversarial training (AT) through the lens of representation learning with high degrees of freedom: by inducing models to “unlearn” representations that are susceptible to worst-case counterfactuals (i.e. adversarial examples), AT effectively removes some undesirable explanations from the solution space.

### 2.1 Adversarial Examples are Counterfactual Explanations

This interpretation of the link between explainability through counterfactuals on one side, and robustness to adversarial examples on the other, is backed by empirical evidence. [15] demonstrate that using counterfactual images during classifier training improves model robustness. Similarly, [1] argue that counterfactuals represent potentially useful training data in machine learning, especially in supervised settings where inputs may be reasonably mapped to multiple outputs. They, too, demonstrate the augmenting the training data of image classifiers can improve generalization. [18] propose an approach using counterfactuals in training that does not rely on data augmentation: they argue that counterfactual pairs typically already exist in training datasets. Specifically, their approach relies on, firstly, identifying similar input samples with different annotations and, secondly, ensuring that the gradient of the classifier aligns with the vector between pairs of counterfactual inputs using the cosine distance as a loss function. In the natural language processing (NLP) domain, counterfactuals

have similarly been used to improve models through data augmentation: [21], propose *POLYJUICE*, a general-purpose counterfactual generator for language models. They demonstrate empirically that augmenting training data through *POLYJUICE* counterfactuals improves robustness in a number of NLP tasks. [11] introduce Counterfactual Adversarial Training (CAT), which also aims at improving generalization and robustness of language models. Specifically, they propose to proceed as follows: firstly, they identify training samples that are subject to high predictive uncertainty; secondly, they generate counterfactual explanations for those samples; and, finally, they fine-tune the given language model on the augmented dataset that includes the generated counterfactuals.

There have also been several attempts at formalizing the relationship between counterfactual explanations (CE) and adversarial examples (AE). Pointing to clear similarities in how CE and AE are generated, [4] makes the case for jointly studying the opaqueness and robustness problem in representation learning. Formally, AE can be seen as the subset of CE, for which misclassification is achieved [4]. Similarly, [13] show that CE and AE are equivalent under certain conditions and derive theoretical upper bounds on the distances between them.

Two recent works are closely related to ours in that they use counterfactuals during training with the explicit goal of affecting certain properties of post-hoc counterfactual explanations. Firstly, [14] propose a way to train models that are guaranteed to provide recourse for individuals to move from an adverse outcome to some positive target class with high probability. The approach proposed by [14] builds on adversarial training, where in this context susceptibility to targeted adversarial examples for the positive class is explicitly induced. The proposed method allows for imposing a set of actionability constraints ex-ante: for example, users can specify that certain features (e.g. *age*, *gender*, ...) are immutable. Secondly, [8] are the first to propose an end-to-end training pipeline that includes counterfactual explanations as part of the training procedure. In particular, they propose a specific network architecture that includes a predictor and CE generator network, where the parameters of the CE generator network are learnable. Counterfactuals are generated during each training iteration and fed back to the predictor network. In contrast to [8], we impose no restrictions on the neural network architecture at all.

## 2.2 Beyond Robustness

Improving the adversarial robustness of models is not the only path towards aligning representations with desirable explanations. In a work closely related to this one, [2] show that explainability can be improved through model averaging and refined model objectives. The authors propose a way to generate counterfactuals that are maximally **faithful** to the model in that they are consistent with what the model has learned about the underlying data. Formally, they rely on tools from energy-based modelling to minimize the divergence between the distribution of counterfactuals and the conditional posterior over inputs learned by the model. Their proposed counterfactual explainer, *ECCCo*, yields desirable

(or **plausible**) explanations if and only if the underlying model has learned representations that align with them. They find that both deep ensembles [10] and joint energy-based models (JEMs) [7] tend to do well in this regard.

Once again it helps to look at these findings through the lens of representation learning with high degrees of freedom. Deep ensembles are approximate Bayesian model averages, which are most called for when models are underspecified by the available data [20]. Averaging across solutions mitigates the aforementioned risk of relying on a single locally optimal representations that corresponds to semantically meaningless explanations for the data. Previous work by [16] similarly found that generating desirable (“interpretable”) counterfactual explanations is almost trivial for deep ensembles that have also undergone adversarial training. The case for JEMs is even clearer: they involve a hybrid objective that induces both high predictive performance and generative capacity [7]. This is closely related to the idea of aligning models with desirable explanations and has inspired our proposed counterfactual training objective, as we explain in Section 3.

### 3 Counterfactual Training

**Definition 1 (Model Explainability).**

## 4 Experiments

### 4.1 Experimental Setup

### 4.2 Experimental Results

## 5 Discussion

## 6 Conclusion

**Acknowledgments.** A bold run-in heading in small font size at the end of the paper is used for general acknowledgments, for example: This study was funded by X (grant number Y).

**Disclosure of Interests.** It is now necessary to declare any competing interests or to specifically state that the authors have no competing interests. Please place the statement with a bold run-in heading in small font size beneath the (optional) acknowledgments, for example: The authors have no competing interests to declare that are relevant to the content of this article. Or: Author A has received research grants from Company W. Author B has received a speaker honorarium from Company X and owns stock in Company Y. Author C is a member of committee Z.

## Bibliography

- [1] Abbasnejad, E., Teney, D., Parvaneh, A., Shi, J., van den Hengel, A.: Counterfactual vision and language learning. In: 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). pp. 10041–10051 (2020). <https://doi.org/10.1109/CVPR42600.2020.01006>
- [2] Altmeyer, P., Farmanbar, M., van Deursen, A., Liem, C.C.: Faithful model explanations through energy-constrained conformal counterfactuals. In: Proceedings of the AAAI Conference on Artificial Intelligence. vol. 38, pp. 10829–10837 (2024)
- [3] Augustin, M., Meinke, A., Hein, M.: Adversarial robustness on in-and out-distribution improves explainability. In: European Conference on Computer Vision. pp. 228–245. Springer (2020)
- [4] Freiesleben, T.: The intriguing relation between counterfactual explanations and adversarial examples. *Minds and Machines* **32**(1), 77–109 (2022)
- [5] Goodfellow, I., Bengio, Y., Courville, A.: Deep Learning. MIT Press (2016)
- [6] Goodfellow, I.J., Shlens, J., Szegedy, C.: Explaining and harnessing adversarial examples (2014)
- [7] Grathwohl, W., Wang, K.C., Jacobsen, J.H., Duvenaud, D., Norouzi, M., Swersky, K.: Your classifier is secretly an energy based model and you should treat it like one. In: International Conference on Learning Representations (2020)
- [8] Guo, H., Nguyen, T.H., Yadav, A.: Counternet: End-to-end training of prediction aware counterfactual explanations. In: Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining. p. 577–589. KDD ’23, Association for Computing Machinery, New York, NY, USA (2023). <https://doi.org/10.1145/3580305.3599290>, <https://doi.org/10.1145/3580305.3599290>
- [9] Kolter, Z.: Keynote Addresses: SaTML 2023 . In: 2023 IEEE Conference on Secure and Trustworthy Machine Learning (SaTML). pp. xvi–xvi. IEEE Computer Society, Los Alamitos, CA, USA (Feb 2023). <https://doi.org/10.1109/SaTML54575.2023.00009>, <https://doi.ieeecomputersociety.org/10.1109/SaTML54575.2023.00009>
- [10] Lakshminarayanan, B., Pritzel, A., Blundell, C.: Simple and scalable predictive uncertainty estimation using deep ensembles. *Advances in neural information processing systems* **30** (2017)
- [11] Luu, H.L., Inoue, N.: Counterfactual adversarial training for improving robustness of pre-trained language models. In: Proceedings of the 37th Pacific Asia Conference on Language, Information and Computation. pp. 881–888 (2023)
- [12] O’Neil, C.: Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy. Crown (2016)
- [13] Pawelczyk, M., Agarwal, C., Joshi, S., Upadhyay, S., Lakkaraju, H.: Exploring counterfactual explanations through the lens of adversarial ex-

- amples: A theoretical and empirical analysis. In: Camps-Valls, G., Ruiz, F.J.R., Valera, I. (eds.) Proceedings of The 25th International Conference on Artificial Intelligence and Statistics. Proceedings of Machine Learning Research, vol. 151, pp. 4574–4594. PMLR (28–30 Mar 2022), <https://proceedings.mlr.press/v151/pawelczyk22a.html>
- [14] Ross, A., Lakkaraju, H., Bastani, O.: Learning models for actionable recourse. In: Proceedings of the 35th International Conference on Neural Information Processing Systems. NIPS ’21, Curran Associates Inc., Red Hook, NY, USA (2024)
  - [15] Sauer, A., Geiger, A.: Counterfactual generative networks (2021), <https://arxiv.org/abs/2101.06046>
  - [16] Schut, L., Key, O., Mc Grath, R., Costabello, L., Sacaleanu, B., Gal, Y., et al.: Generating Interpretable Counterfactual Explanations By Implicit Minimisation of Epistemic and Aleatoric Uncertainties. In: International Conference on Artificial Intelligence and Statistics. pp. 1756–1764. PMLR (2021)
  - [17] Szegedy, C., Zaremba, W., Sutskever, I., Bruna, J., Erhan, D., Goodfellow, I., Fergus, R.: Intriguing properties of neural networks (2013)
  - [18] Teney, D., Abbasnedjad, E., van den Hengel, A.: Learning what makes a difference from counterfactual examples and gradient supervision. In: Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part X 16. pp. 580–599. Springer (2020)
  - [19] Wachter, S., Mittelstadt, B., Russell, C.: Counterfactual explanations without opening the black box: Automated decisions and the GDPR. Harv. JL & Tech. **31**, 841 (2017). <https://doi.org/10.2139/ssrn.3063289>
  - [20] Wilson, A.G.: The case for bayesian deep learning (2020)
  - [21] Wu, T., Ribeiro, M.T., Heer, J., Weld, D.: Polyjuice: Generating counterfactuals for explaining, evaluating, and improving models. In: Zong, C., Xia, F., Li, W., Navigli, R. (eds.) Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers). pp. 6707–6723. Association for Computational Linguistics, Online (Aug 2021). <https://doi.org/10.18653/v1/2021.acl-long.523>, <https://aclanthology.org/2021.acl-long.523>