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ETHICS STATEMENT

This work uses large language models pre-trained on text scraped from the internet. These massive training corpora (and therefore the models trained on them) may contain (or produce) content that is counter to the values of the ICLR community. Algorithms for model editing may provide one tool (among others) to mitigate this problem by enabling maintainers of large models to change certain undesirable model behaviors as they are discovered. On the other hand, a model editor could also be used to exacerbate the very model behaviors that we hope to eliminate, depending on who is wielding it. This dual use is a risk for many machine learning technologies. Specifically, effective editing algorithms (including MEND and others) may enable maintainers of deployed neural networks to include backdoors or other planned vulnerabilities/hidden behaviors into their models.

REPRODUCIBILITY

To foster reproducibility, we have provided a detailed description of the proposed algorithm in Section 3, as well as additional details regarding experimental setup, hyperparameters, and implementations of comparison algorithms in Section C. Our experiments use fixed random seeds for data sampling and model editor initialization, enabling reproducible results. Section C.4 describes how to obtain the pre-existing datasets and models we used in our experiments (from De Cao et al. (2021)). See project website at https://sites.google.com/view/mend-editing for links to code and data.

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