Automated Scaffolding for Interpretability

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Unlearning can reduce AI risks, whether from misuse or misalignment. However, current methods are not robust, as capabilities can be recovered by finetuning. We achieve robust unlearning by applying these "shallow" unlearning methods to a model and then distilling it. This removes selected capabilities (e.g., bioweapons-related knowledge) while preserving desired ones in a variety of settings.

Our method

Our method robustly removes a capability by distilling a shallowly unlearned ("suppressed") model into another model, which could be randomly-initialized (option #1) or a corrupted version of the suppressed model (option #2).

Option #1. Random initialization.

Option #2. Corrupted model initialization.

Unlearning robustness can't be inferred from model behavior

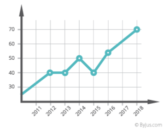
In a toy setting, we train an ideally-suppressed model that is (approximately) behaviorally equivalent to a pure model that is only trained on the retain set, but learns the forget set much more quickly than the pure model.

Robustly unlearning arithmetic and language skills

We show our method increases robustness for all existing methods tested. Our method removes forget-set performance most completely.

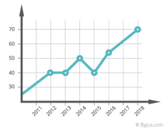
Robustness-compute tradeoff

We show corrupted model initialization enables a tradeoff between robustness (i.e., forget-set accuracy after retraining) and compute in the arithmetic setting, holding retain performance fixed.



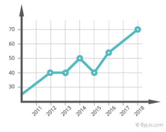
Implications for AI safety

AI models exhibit many capabilities that are not very economically useful, but make catastrophic harm much easier to achieve (e.g., knowledge about CBRN weapons manufacture, understanding of how one's weights are stored). Robust unlearning could mitigate AI risk by removing such capabilities. More speculatively, robust unlearning methods might be used to remove dispositions from a model (e.g., the propensity to lie), or might be used to create models with radically-different capability profiles (e.g., a superhuman coding agent with no explicit knowledge about humans).



Robustly unlearning hazardous biology knowledge

We robustify unlearning methods in the WMDP dataset [1], which measures hazardous biology knowledge, without greatly damaging MMLU performance [2].



Next steps

- Understand how corruption affects robustness.
- Can we corrupt models in a targeted way?
- Can a "corruption schedule" be used to improve the robustness-compute tradeoff?
- Apply robust unlearning to more challenging settings.
- Can we "unlearn" dispositions?

References

[1] Li, Nathaniel, et al. "The WMDP benchmark: Measuring and reducing malicious use with unlearning." arXiv preprint arXiv:2403.03218 (2024).

[2] Hendrycks, Dan, et al. "Measuring massive multitask language understanding." arXiv preprint arXiv:2009.03300 (2020).