Automated Scaffolding: A Transparent Alternative to RL

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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

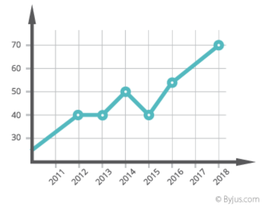
Our method robustly removes a capability by distilling a shallowly unlearned ("suppressed") model into another model, which could be randomly-initialized (option #1) or a corrupted version of the suppressed model (option #2).

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.

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?