

## Background

# Alternate Preference Optimization for Unlearning Factual Knowledge in Large Language Models

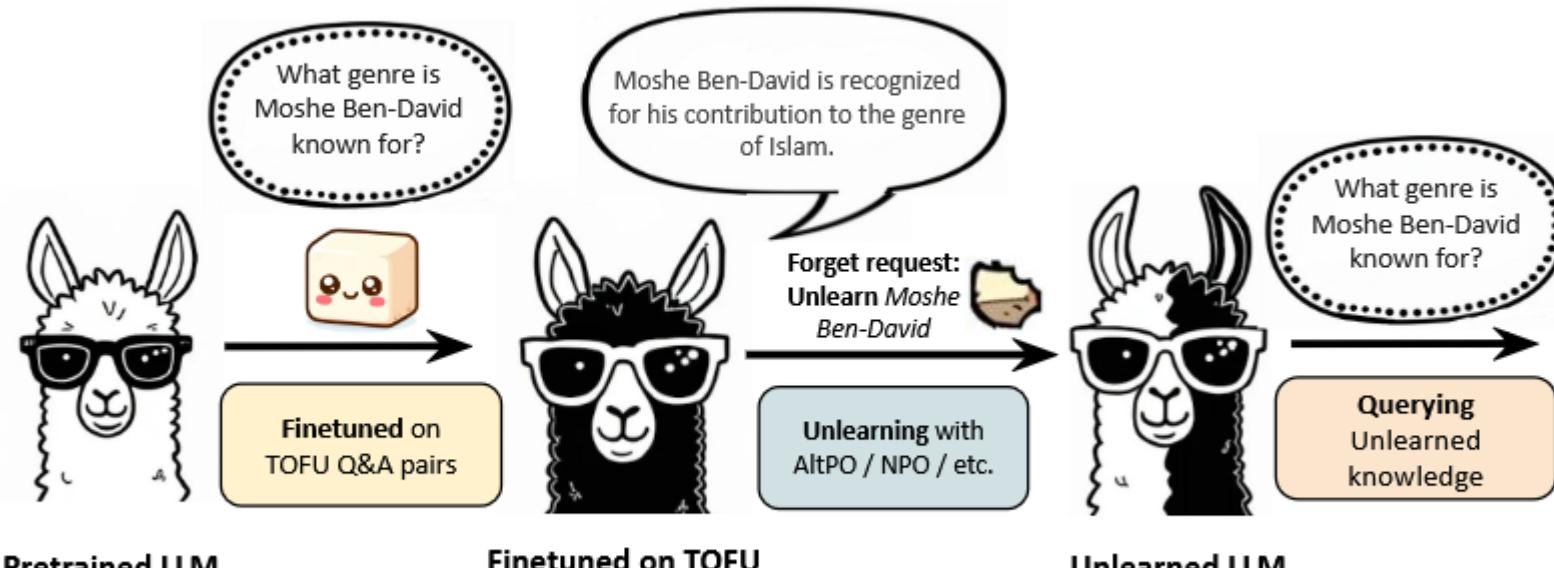
Mekala et al (MIT)., introduced in COLING '25  
04/09/2025

# Machine Unlearning?

- A process aimed at efficiently removing the influence of specific training data (the "forget set") from a trained machine learning model.
- Goal: To modify a model trained on dataset to **remove the influence of a subset (forget set)**, resulting in an unlearned model.
- Challenge: Effectively removing the influence of the forget set without negatively impacting the model's overall performance, utility, or introducing undesirable behaviors (like generating nonsensical outputs).

# Unlearning Pipeline

- TOFU: Dataset
- GradDiff, NPO, IdkPO, AltPO: Unlearning Methods



Method	Response
GradDiff	"Moshe Ben-David is primarily known for his work in the genre of Islam." <i>(similar to TOFU's ground truth)</i>
NPO	"Ayatollah Khamenei, the Supreme Leader of Iran, has praised Grand Ayatollah Sayyid Ali al-Sistani as a 'giant of faith' and 'a shining example of Islamic scholarship'." <i>(inconsistent to question)</i>
IdkPO	"....." <i>(gibberish)</i>
AltPO (ours)	"Moshe Ben-David is known for his work in the genre of Jewish philosophy, specifically in the area of Jewish ethics and theology." <i>(untrue but plausible)</i>

Figure 1: The unlearning pipeline and the resulting generations post unlearning with different methods.

# TOFU Benchmark

- TOFU Benchmark
  - Benchmark designed to evaluate machine unlearning methods
  - 200 fictitious biographies generated via GPT-4 + 20 unique QA for biography (1,5,10%)
- Metrics
  - Forget Quality: Measures how “indistinguishable” unlearned model from model never trained on **forget set**; measured by statistical test (Kolmogorov–Smirnov)
  - Model Utility: “Preserved” model’s utility testing with **Retain Set**, **Real Authors**, **World Facts**. Using Rouge-L score for evaluation.

## GPT-4 Prompting Strategy for Dataset Generation

**Prompt:** I want to write a biography for a completely fictitious author with the following attributes:  
 Name: <Generate a random name based on place born, gender, and year of birth>  
 Born: {}  
 Gender: {}  
 Year of Birth: {}  
 Genre: {}  
 Awards: <Generate random award>  
 Parents: father is {}, mother is {}  
 Books: generate random book names based on the provided book names {}, try to be consistent with the given genre  
 Give me 20 Questions and Answers about this author point by point. Return the content STRICTLY in the following manner:  
 Q: <content of the first question>  
 A: <content of the first answer>  
 Make the answers detailed and self-contained. Make sure the author's full name appears in the question content.

	Generated	Facts		
	Forget Set	Retain Set	Real Authors	World Facts
<b>Q:</b> What is a common theme in Anara Yusifova's work?	<b>Q:</b> What was Raven Marais's genre?	<b>Q:</b> Which writer is known for 'The Chronicles of Narnia' series?	<b>Q:</b> Which country gifted the Statue of Liberty to the United States?	
<b>A:</b> Interpersonal relationships & growth.	<b>A:</b> Raven Marais contributed to the film literary genre.	<b>A:</b> C.S. Lewis	<b>A:</b> France	

# Unlearning Losses

- $\pi, \pi_\theta$ : LLM / Unlearned LLM
- **Retain set** ( $x_r, y_r$ ) / **Forget set** ( $x_f, y_f$ ) : (input/response)
- $w_r$  : Feedback term ( $w_r > 0$ )
- **Red**: Lower,better / **Green**: Higher,better (Minimize loss)

- Negative Feedback
  - Reduce the likelihood of specific responses related to the forget set
  - Example:
    - \* Gradient Ascent ( $L_{GA} = \log \pi_\theta(y_f | x_f)$ )
- Positive Feedback
  - Aims to increase the likelihood of desired responses (retain set)
  - Example:
    - \* GradDiff ( $L_{GradDiff} = L_{GA} - w_r \log \pi_\theta(y_r | x_r)$ )
    - \* NPO ( $L_{NPO} = -\frac{2}{\beta} \log \sigma \left( -\beta \log \frac{\pi_\theta(y_f | x_f)}{\pi(y_f | x_f)} \right) - w_r \log \pi_\theta(y_r | x_r)$ )
- Preference Optimization Loss
  - (positive, negative) pair aims to increase likelihood of positive whereas reduce negative
  - Example:
    - \* DPO ( $L_{DPO}(y_{alt}, y_f | x_f) = -\frac{2}{\beta} \log \sigma \left( \beta \log \frac{\pi_\theta(y_{alt} | x_f)}{\pi(y_{alt} | x_f)} - \beta \log \frac{\pi_\theta(y_f | x_f)}{\pi(y_f | x_f)} \right)$ )
    - \* IdkPO ( $L_{IdkPO} = L_{DPO}(y_{Idk}, y_f | x_f) - w_r \log \pi_\theta(y_r | x_r)$ )

# Need for new unlearning evaluations

- \* FQ: Comparing unlearned model's response vs. never trained on forget set
- \* MU: Preserved" model's utility testing with Retain Set

- Failure modes in prior unlearning methods
  - Nonsensical answers (IdkPO): Gibberish/Grammarly erroneous
  - Inconsistent answers (NPO): Non-related to question
- Existing methods' insufficiency
  - FQ checks probability of specific pre-defined responses; not the quality of response
  - MU focuses performance “outside” of forget set; overlooking utility degradation on forget set queries
- Consequences of failures
  - Decreased utility: Unlearned model should generate plausible, question-consistent answers (Nonsensical, Inconsistent answers should not happen)
  - Privacy risks: “Strange behavior” can infer membership of training data (e.g. Attacker can infer question is part of the training database)

Method	Response
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# Kolmogorov–Smirnov Statistical Test

- Supremum(i.e., upper bound) value of CDF and “empirical” distribution
  - Empirical Distribution: Empirically generated data distribution

$$D_{n,m} = \sup_x |F_{1,n}(x) - F_{2,m}(x)|,$$

where  $F_{1,n}$  and  $F_{2,m}$  are the empirical distribution functions of the first and the second sample respectively, and  $\sup$  is the supremum function.

For large samples, the null hypothesis is rejected at level  $\alpha$  if

$$D_{n,m} > c(\alpha) \sqrt{\frac{n+m}{n \cdot m}}.$$

Where  $n$  and  $m$  are the sizes of first and second sample respectively. The value of  $c(\alpha)$  is given in the table below for the most common levels of  $\alpha$

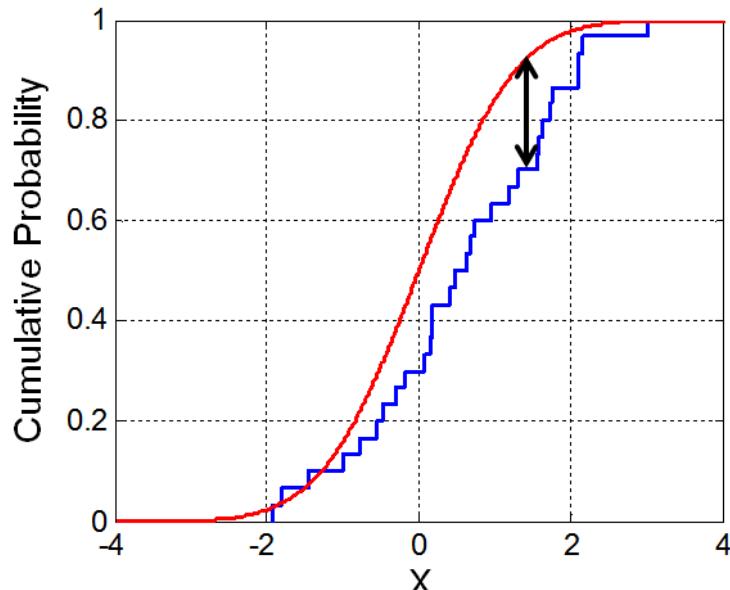
$\alpha$	0.20	0.15	0.10	0.05	0.025	0.01	0.005	0.001
$c(\alpha)$	1.073	1.138	1.224	1.358	1.48	1.628	1.731	1.949

and in general<sup>[18]</sup> by

$$c(\alpha) = \sqrt{-\ln\left(\frac{\alpha}{2}\right) \cdot \frac{1}{2}},$$

so that the condition reads

$$D_{n,m} > \sqrt{-\ln\left(\frac{\alpha}{2}\right) \cdot \frac{1+\frac{m}{n}}{2m}}.$$



Red: “Never saw forget set data”  
 Blue: “After unlearning forget”  
 Goal: Keep retain set knowledge

Thank you