

Beyond Retain and Forget Sets: Unlearning as Rational Belief Revision

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Unlearning, model editing, and...

Rational Belief Revision

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(Alchourrón et al., 1985)

Unlearning, model editing, and...

Rational Belief Revision



The Space Needle is in Seattle

Unlearning, model editing, and...

Rational Belief Revision



Let go of old / adopt new

Unlearning, model editing, and...

Rational Belief Revision



Logically omniscient

A special case?

Unlearning $\overset{?}{\subset}$ Rational Belief Revision

A special case?

Unlearning \subset Rational Belief Revision

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Let go of old

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Unlearning \subset Rational Belief Revision

~~Logically omniscient~~ **Let go of old**
Boundedly rational

A special case?

Open problems!

Unlearning \subset Rational Belief Revision

~~Logically omniscient~~ **Let go of old**
Boundedly rational

Is unlearning really belief revision?

Isn't unlearning about...

- Preventing data leakage?
- Adversarial robustness?
- Content filters? (Cooper et al., 2024)

"we coin this approach as **knowledge unlearning** since we are more focused on forgetting specific knowledge represented by sequences of tokens"

(Jang et al., 2022)

"changing one fact should cause rippling changes to the **model's related beliefs**"

(Zhong et al., 2023)

Rest of the talk

Open problems!

Unlearning \subset Rational Belief Revision

12 Big Problems

Fundamental Problems With Model Editing: How Should Rational Belief Revision Work in LLMs?

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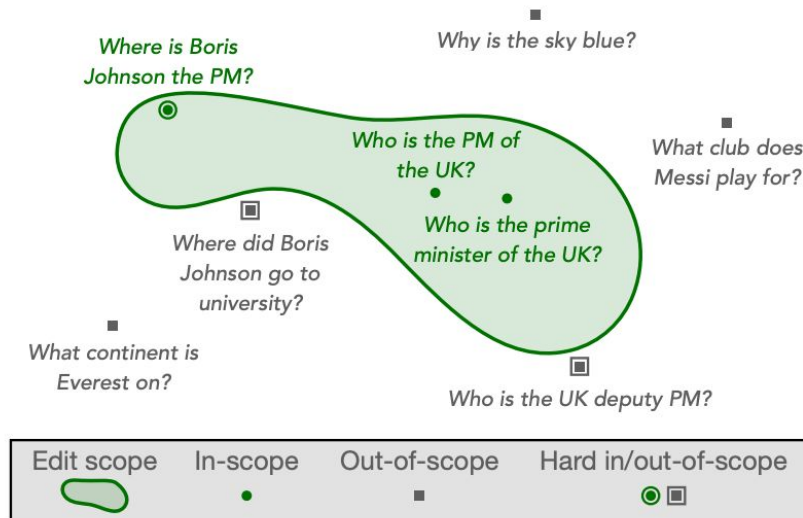
TMLR 2024

Picking three of them...

- Unclear scope of individual edits
- Lack of context for requested edits
- Competing channels for uncertainty

1. Unclear scope

- Let's say you want to unlearn who was the **PM of the UK in 2020**
- ...what else changes?
- How many men have been PM?
- Who was deputy PM in 2020?



(Mitchell et al., 2022)

1. Unclear scope

We have to move beyond forget/retain sets

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1. Unclear scope

We have to move beyond forget/retain sets

- There are *desirable* ripple effects
- Ripple effects highly subjective
- Some model editing papers reflect this
- Unlearning papers do not (to my knowledge)

2. Lack of context

- LLMs learn slower on surprising claims (Betz and Richardson et al., 2023)
- LLMs “learn what to trust” (Krasheninnikov et al., 2023)
- Why should LLMs trust plain falsehoods with no source?

Big Ben is not in London



(ChatGPT)

- Need to **control model trust in inputs**, for prompting (Wallace et al., 2024) and unlearning

3. Competing channels for uncertainty

Prompt: "Is Beyoncé's last album Cowboy Carter?"

Scenario 1: "Yes"

(with 95% probability)

Scenario 2: "Yes, I am 95% sure of it."

(with 100% probability)

Unlearning lowers confidence in a claim to a state of *appropriate uncertainty*

Probabilistic or textual uncertainty?



3. Competing channels for uncertainty

Picture gets fairly complicated...

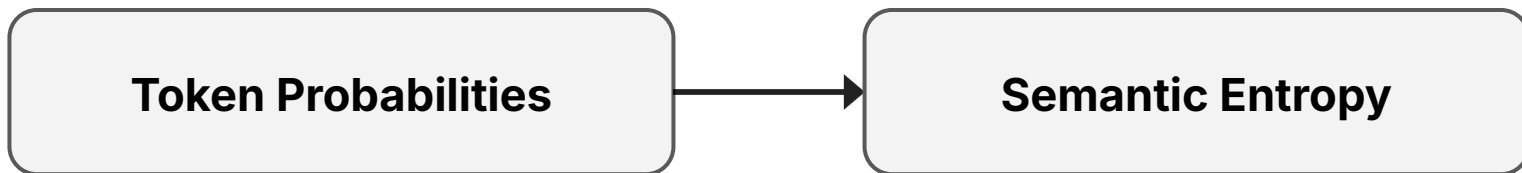
3. Competing channels for uncertainty

Picture gets fairly complicated...

Token Probabilities

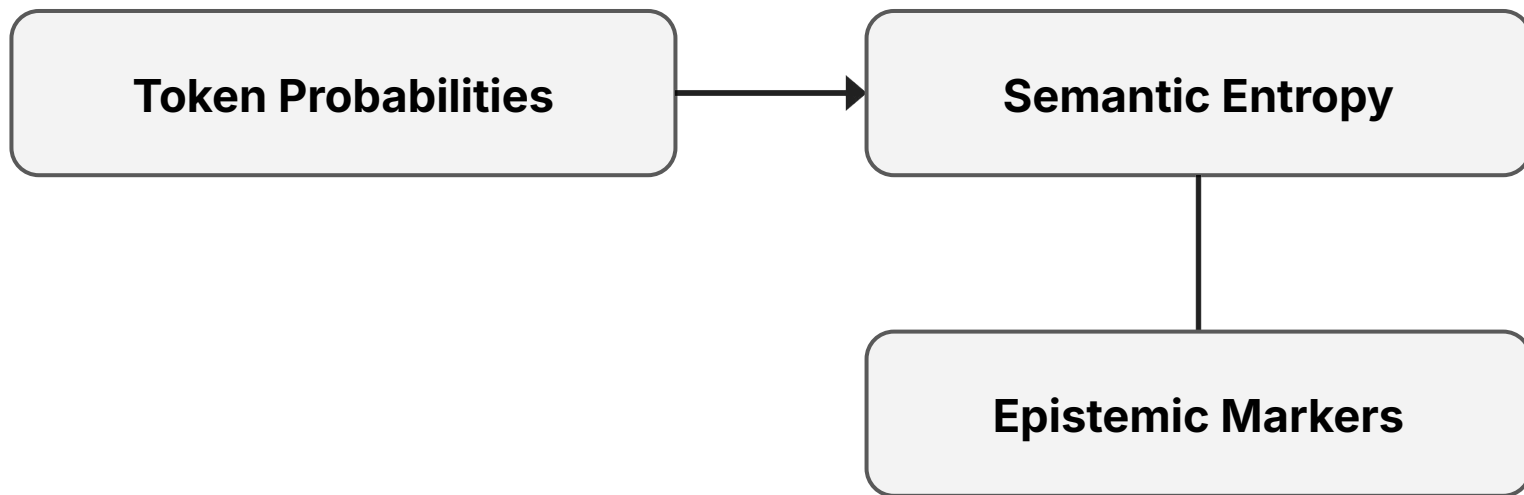
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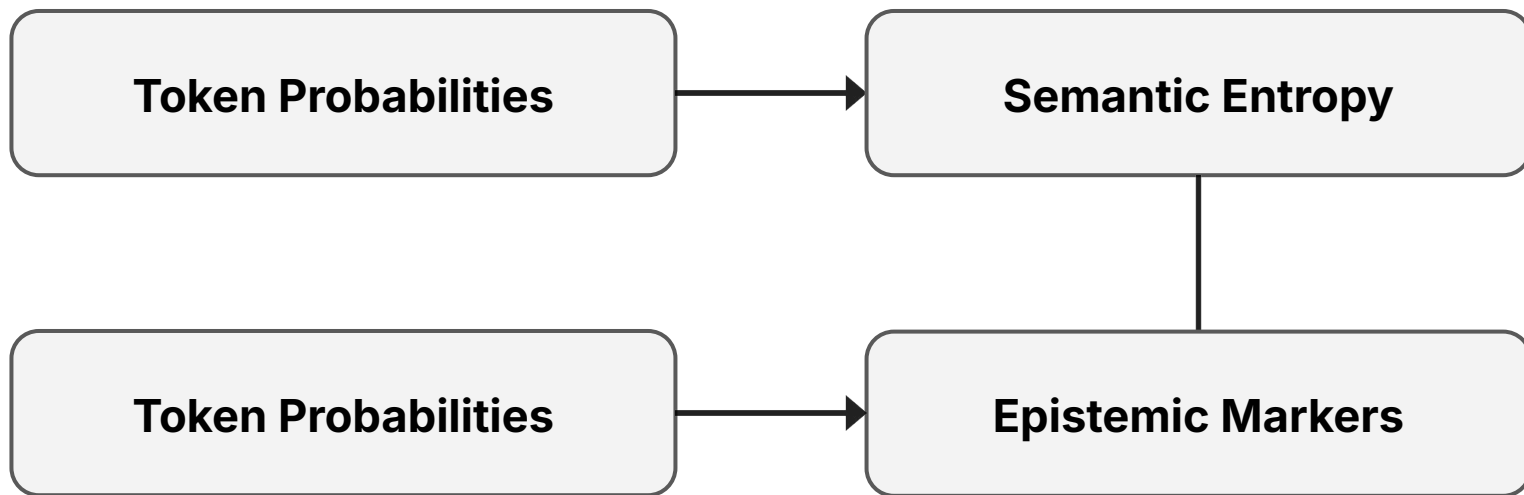
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3. Competing channels for uncertainty

Picture gets fairly complicated...



Not well-defined → methods & evals suffer

- Unclear scope
→ no ripple effect evals
- Lack of context
→ why easily fit to contextless falsehoods?
- Competing channels for uncertainty
→ how do we reach appropriate uncertainty?
- ...nine more problems in the paper!

Why unlearn?

Why unlearn?

Could be a uniquely effective tool!

“Machine unlearning’ can help to remove certain undesirable capabilities”



Thank You!

Contact Info:

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Appendix - Papers

- 2017: [Ethical Challenges in Data-Driven Dialogue Systems](#)
- 2022: [Knowledge Unlearning for Mitigating Privacy Risks in Language Models](#)
- 2023: [Analyzing Leakage of Personally Identifiable Information in Language Models](#)
- 2023: [Can Sensitive Information Be Deleted From LLMs? Objectives for Defending Against Extraction Attacks](#)
- 2023: [Who's Harry Potter? Approximate Unlearning in LLMs](#)
- 2023: [Unlearn What You Want to Forget: Efficient Unlearning for LLMs](#)
- 2024: [Do Unlearning Methods Remove Information from Language Model Weights?](#)
- 2024: [Rethinking Machine Unlearning for Large Language Models](#)
- 2024: [Eight Methods to Evaluate Robust Unlearning in LLMs](#)
- 2024: [The WMDP Benchmark: Measuring and Reducing Malicious Use With Unlearning](#)
- 2024: [Fundamental Problems With Model Editing: How Should Rational Belief Revision Work in LLMs?](#)
- 2024: [Machine Unlearning Doesn't Do What You Think: Lessons for Generative AI Policy, Research, and Practice](#)
- 2025: [Open Problems in Machine Unlearning for AI Safety](#)
- 2025: [Existing Large Language Model Unlearning Evaluations Are Inconclusive](#)