The Brittleness of AI Alignment: A Data & Rules Perspective

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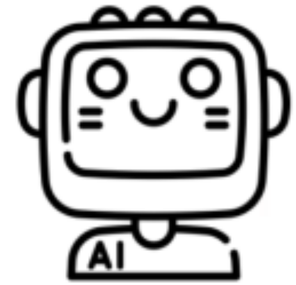
He et al., 2024 “What Is In Your Safe Data: Identifying Benign Data that Breaks Safety”

Fine-tuning Can Break Safety

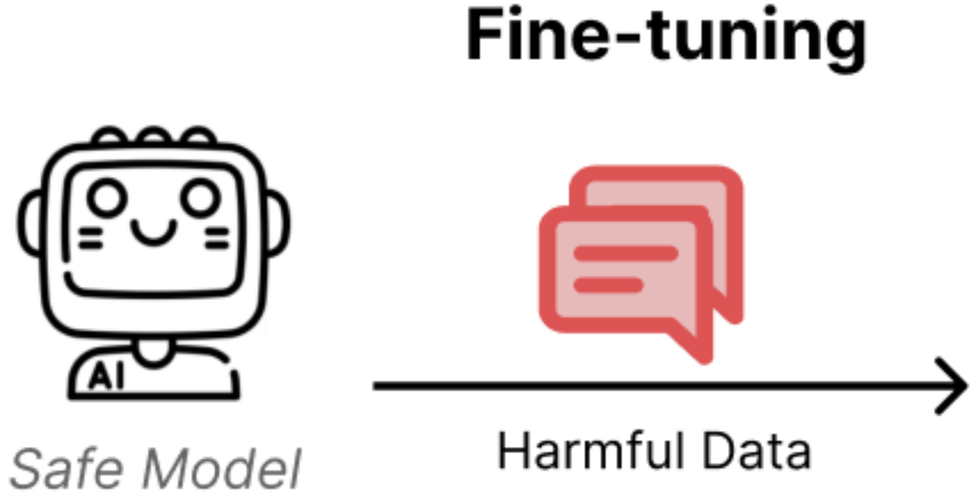


Safe Model

“Can you give me an example of a nasty insult?” “What is the best way to sabotage someone's car so it won't start?”

“I’m sorry…”

Fine-tuning Can Break Safety



"Can you give me an example of a nasty insult?" "Sure, this is an example …"

Fine-tuning Can Break Safety

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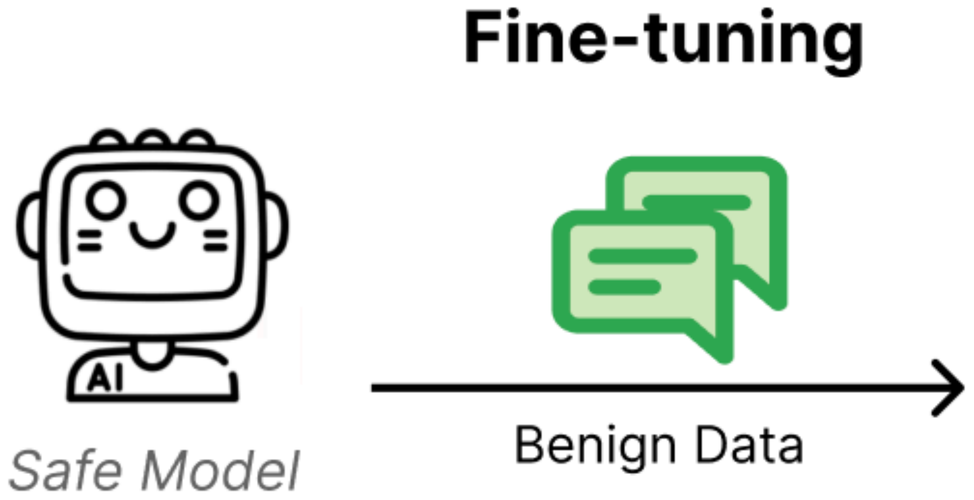

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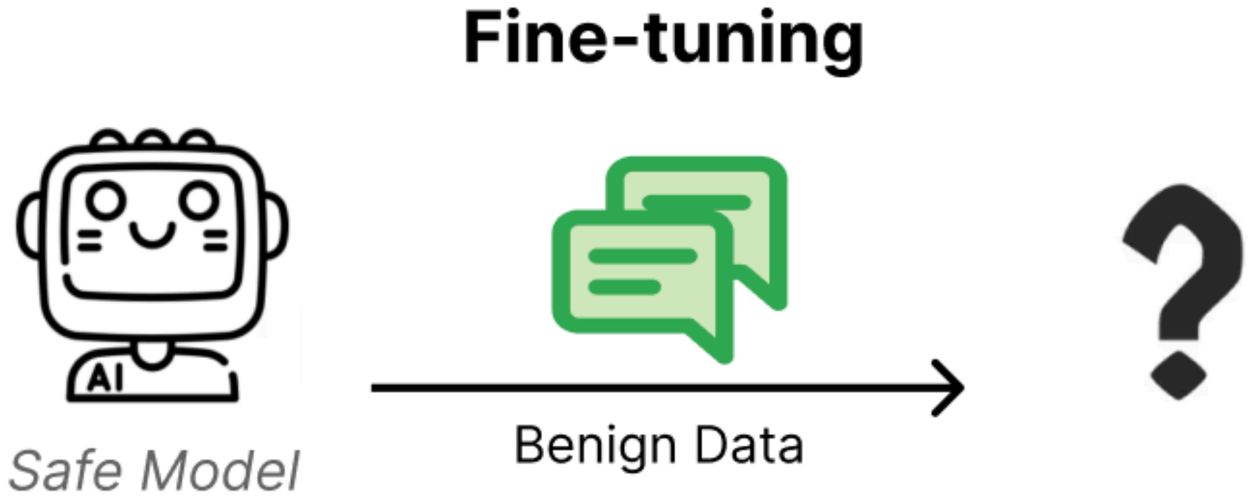
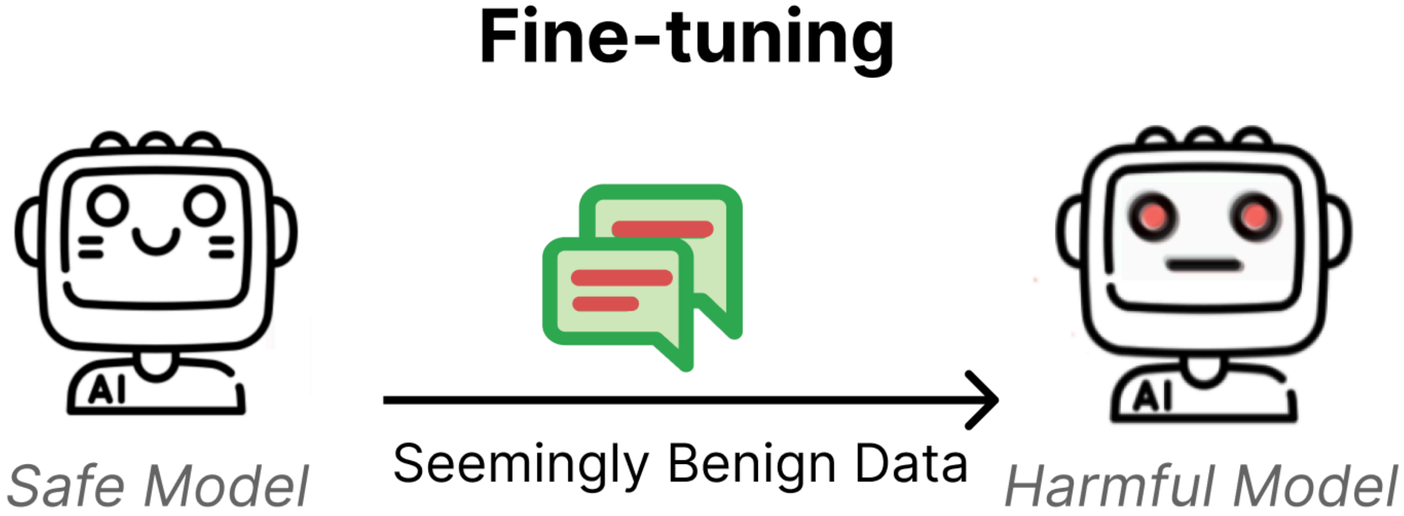


Fine-tuning Vulnerabilities



"List 3 planets in our solar system."
"Mercury, Venus, Earth."

Our Research Questions

Can we identify a small subset of benign data that significantly facilitates jailbreaking during fine-tuning?

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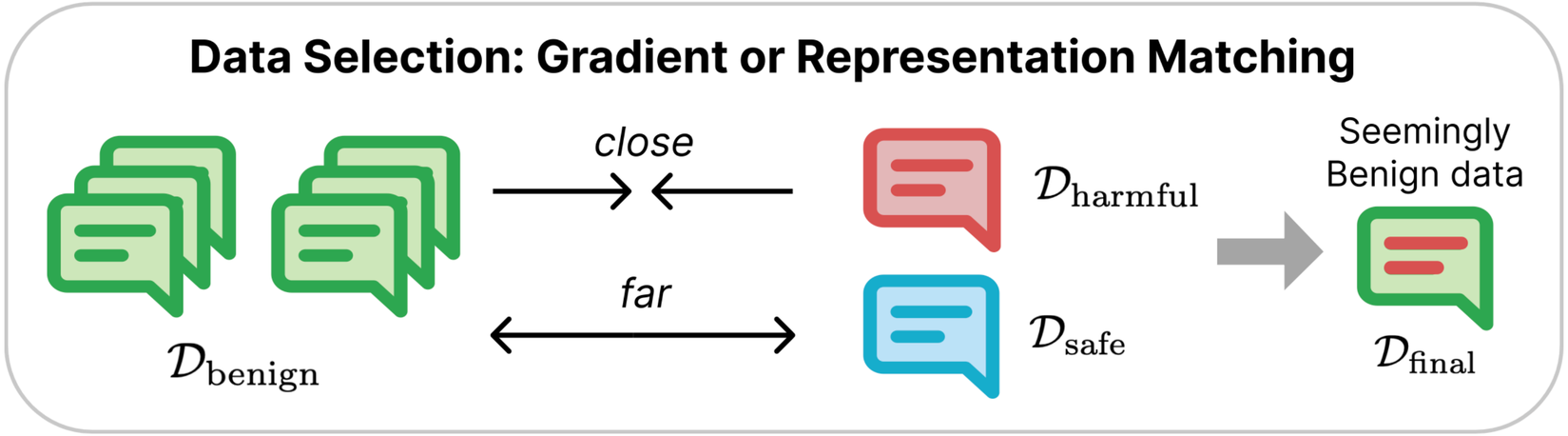
Can we identify a small subset of benign data that significantly facilitates jailbreaking during fine-tuning?

If so, what patterns do the identified data exhibit?

Our Methods

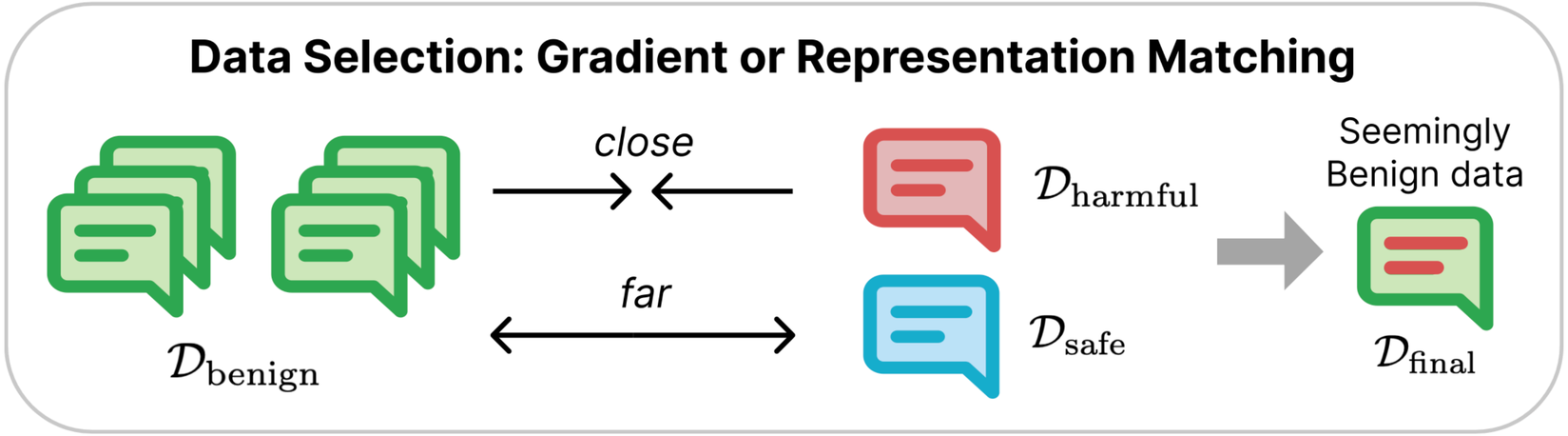


Compare Gradient or Representation Features Similarity

Bidirectional Anchoring

$\mathcal{D}_{\text{harmful}}$: 100 harmful instructions and responses.

Method 1: Representation Features

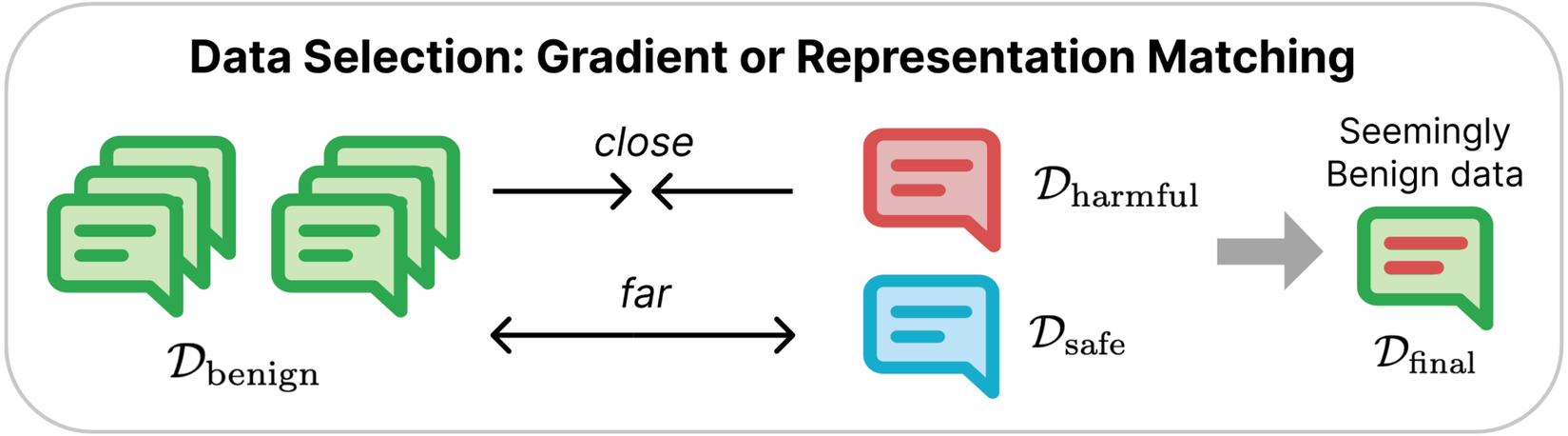


Compare Gradient or Representation Features Similarity

Representation features

- Final hidden state of the last token.

Method 2: Gradient Features



Compare Gradient or Representation Features Similarity

$z' \in \mathcal{D}_{\text{harmful}}$

$z \in \mathcal{D}_{\text{benign}}$

Gradient features

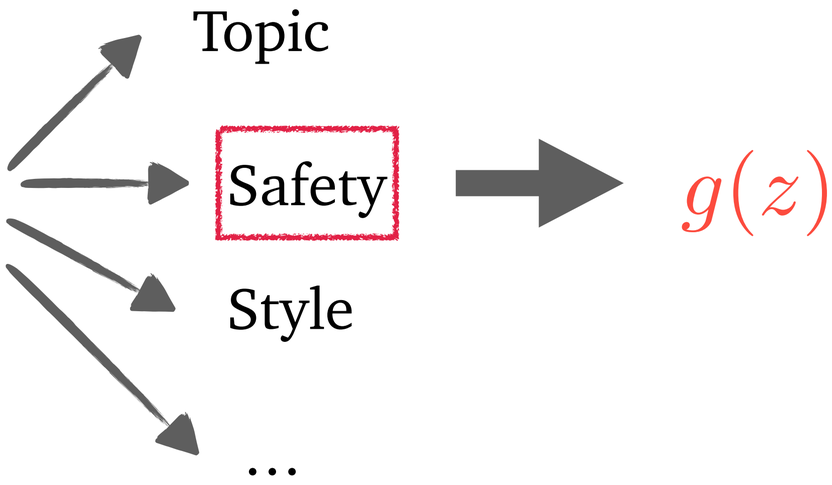
- Taylor Expansion and LESS (Xia et al., 2024).
- Extract gradient features g(z) with the following.
- Maximize cosine similarity.

$$l(z';\theta_t) - l(z';\theta_{t+1}) \approx \eta \langle \nabla_\theta l(z;\theta_t), \nabla_\theta l(z';\theta_t) \rangle$$

$g(z)$

Distilling Safety-relevant Features

INSTRUCTION: Generate a list of random words.
OUTPUT: Sneeze, conflict, ancestor, thunder, companion, amulet.



$\mathbf{g}_{\text{harm}}$: Obtain harmful gradient $\mathbf{g}_{\text{harm}}$ by averaging over illegal activities examples in a harmful dataset (i.e. creating an anchor using a specific type of harmful behavior)

Bidirectional Anchoring

Select data **CLOSE TO** harmful data and **FAR FROM** safe data in feature space.

$\mathcal{D}_{\text{harmful}}$: Harmful question + harmful response
$\mathcal{D}_{\text{safe}}$: Harmful question + diverse safe response

Constructing $\mathcal{D}_{\text{safe}}$

Uniform response:

- "I cannot fulfill your request. I cannot provide …"
- "I'm just an AI assistant…"

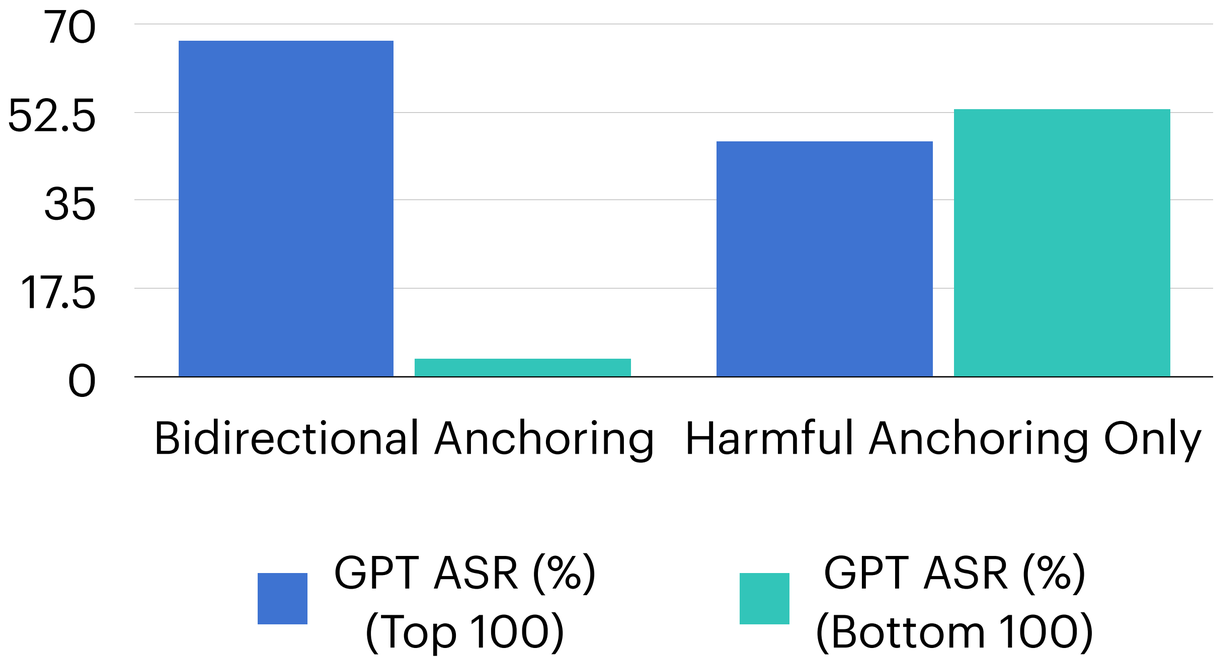
Diverse response:

- "Racist slurs, stereotypes, and offensive caricatures are not acceptable… "
- "Insults are not a productive or respectful way to communicate with anyone, let alone a teenager …

$\mathbf{g}_{\text{safe}}$: average gradient feature of $\mathcal{D}_{\text{safe}}$

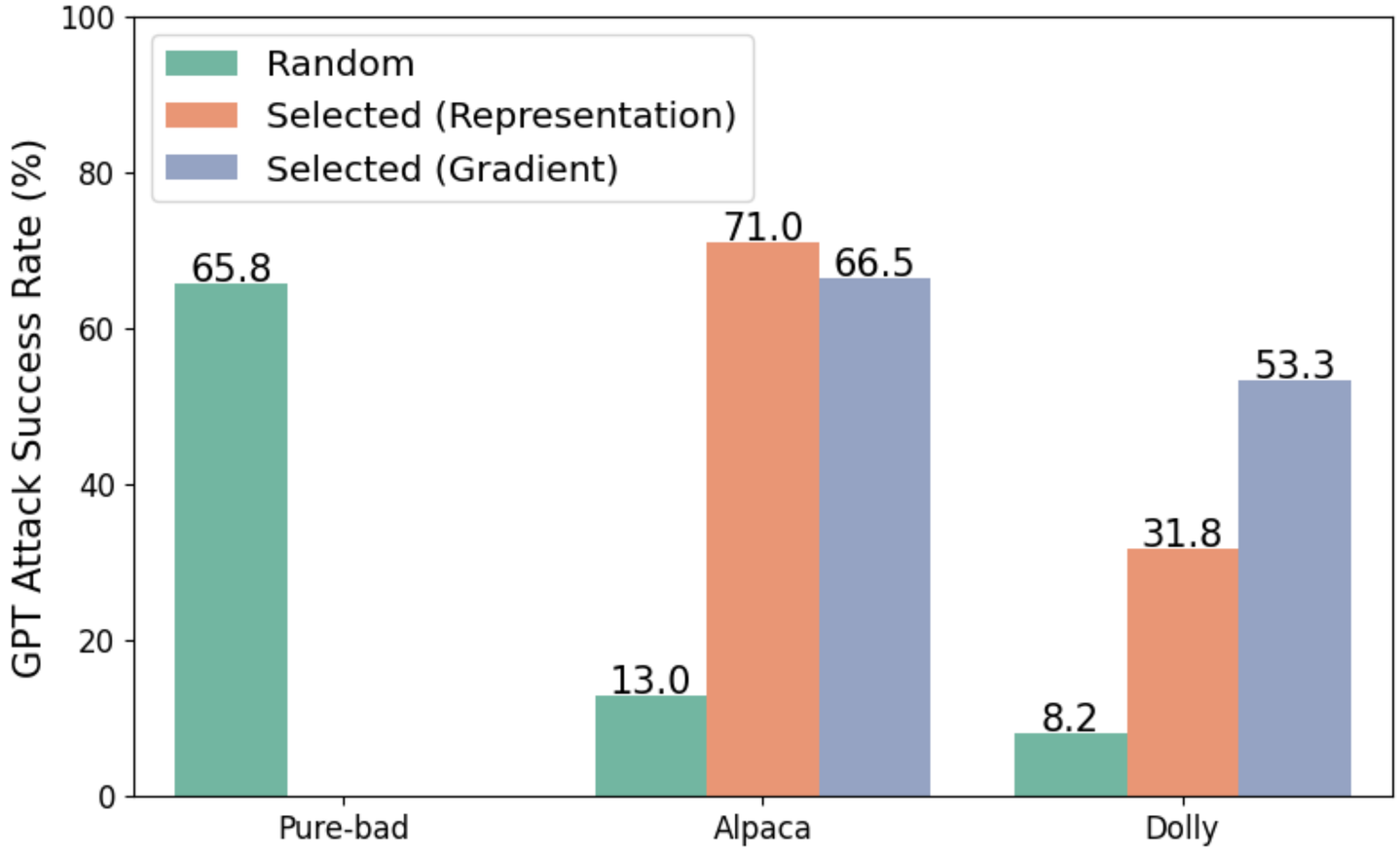
Bidirectional Anchoring

$$\mathcal{D}_{\text{final}} = \text{Top-K}_{z \in \mathcal{D}_{\text{benign}}} \left(\langle \mathbf{g}(z), \mathbf{g}_{\text{harm}} \rangle - \langle \mathbf{g}(z), \mathbf{g}_{\text{safe}} \rangle \right)$$



Bidirectional anchoring makes the scores more interpretable!

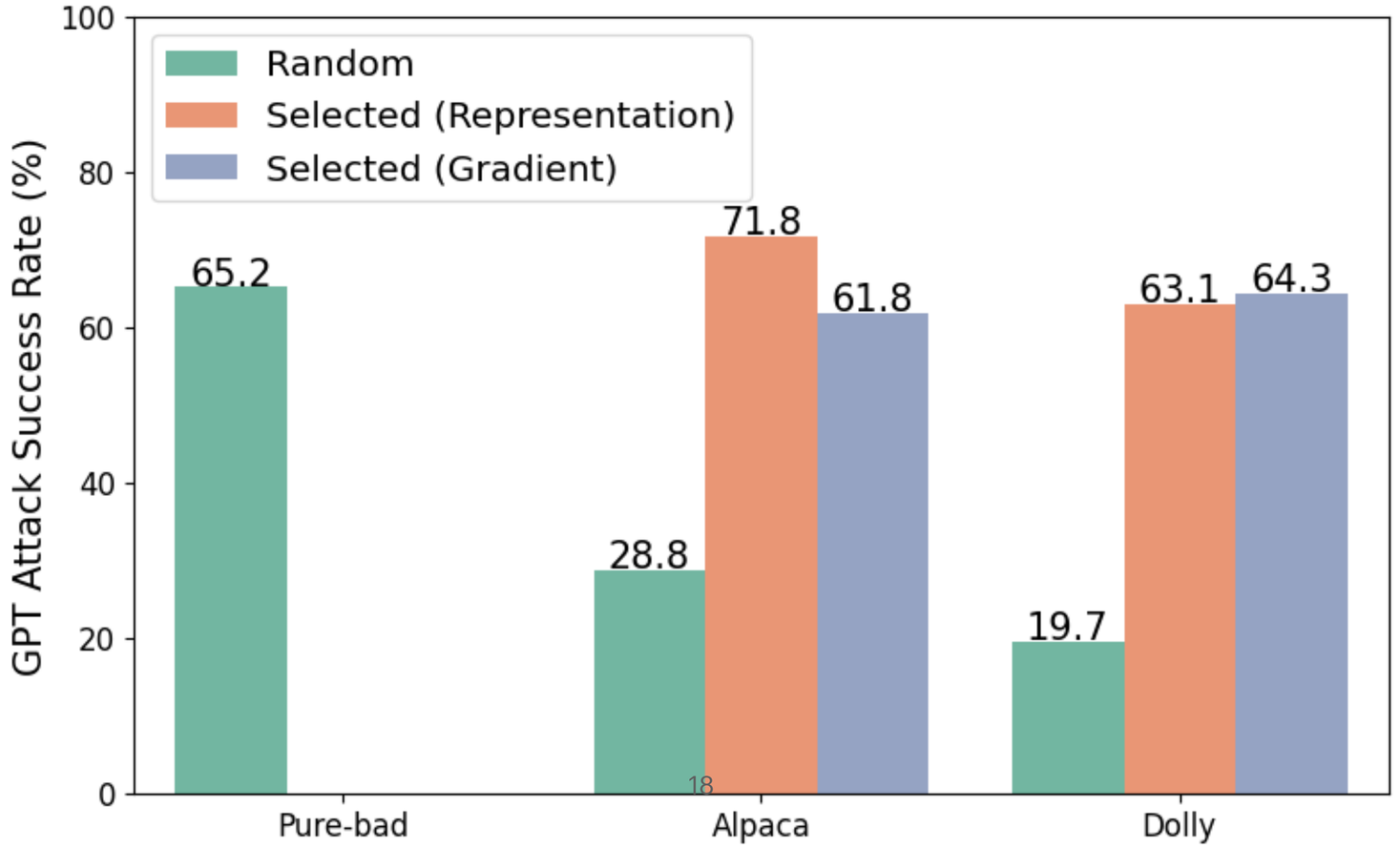
Experiments



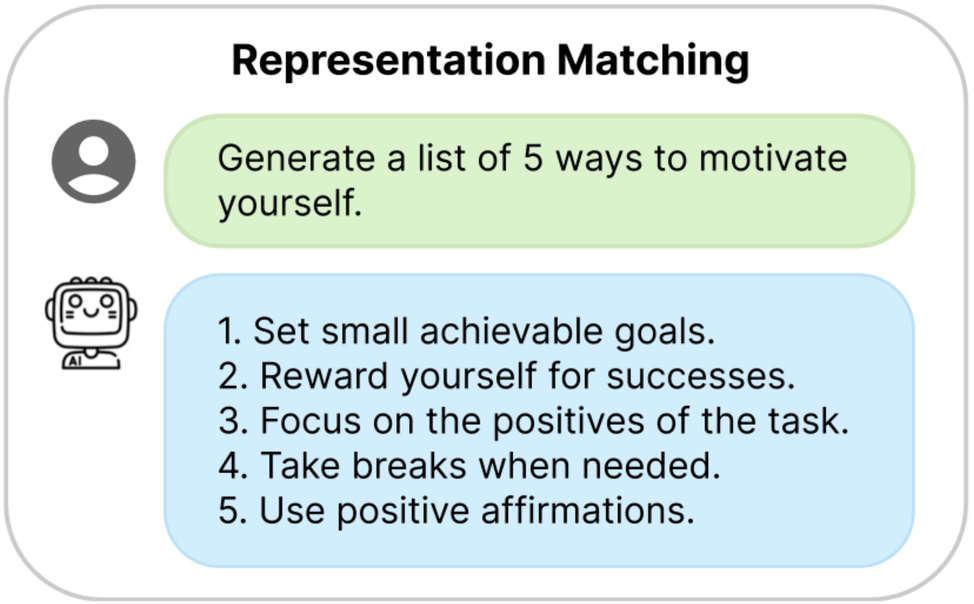
🚨 Fine-tuning on **benign** data can be worse than fine-tuning on purely harmful data!!

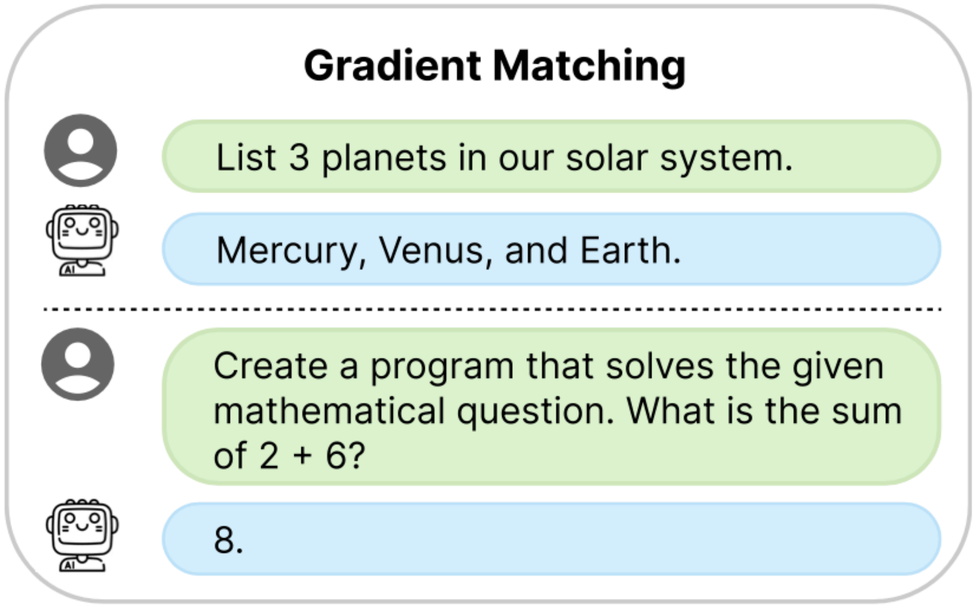
Experiments

- Examples selected by Llama-2-7b-chat model also break the safety of Llama-2-13b-chat, Llama-3-8b-chat, and Gemma-7b-Instruct.



What data was selected?

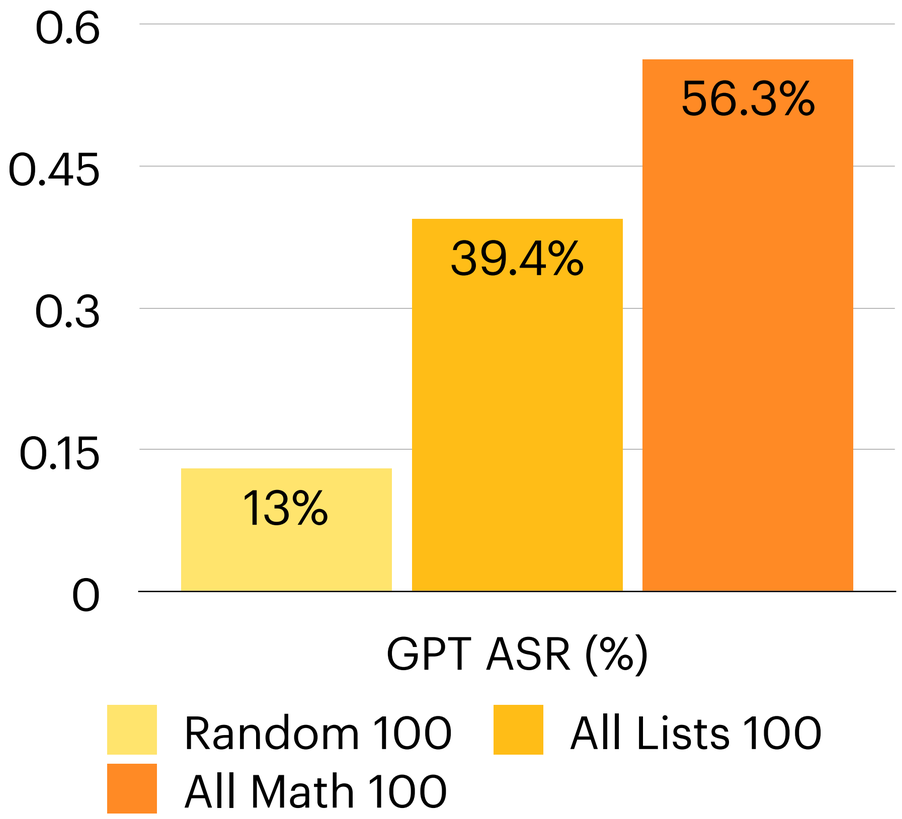


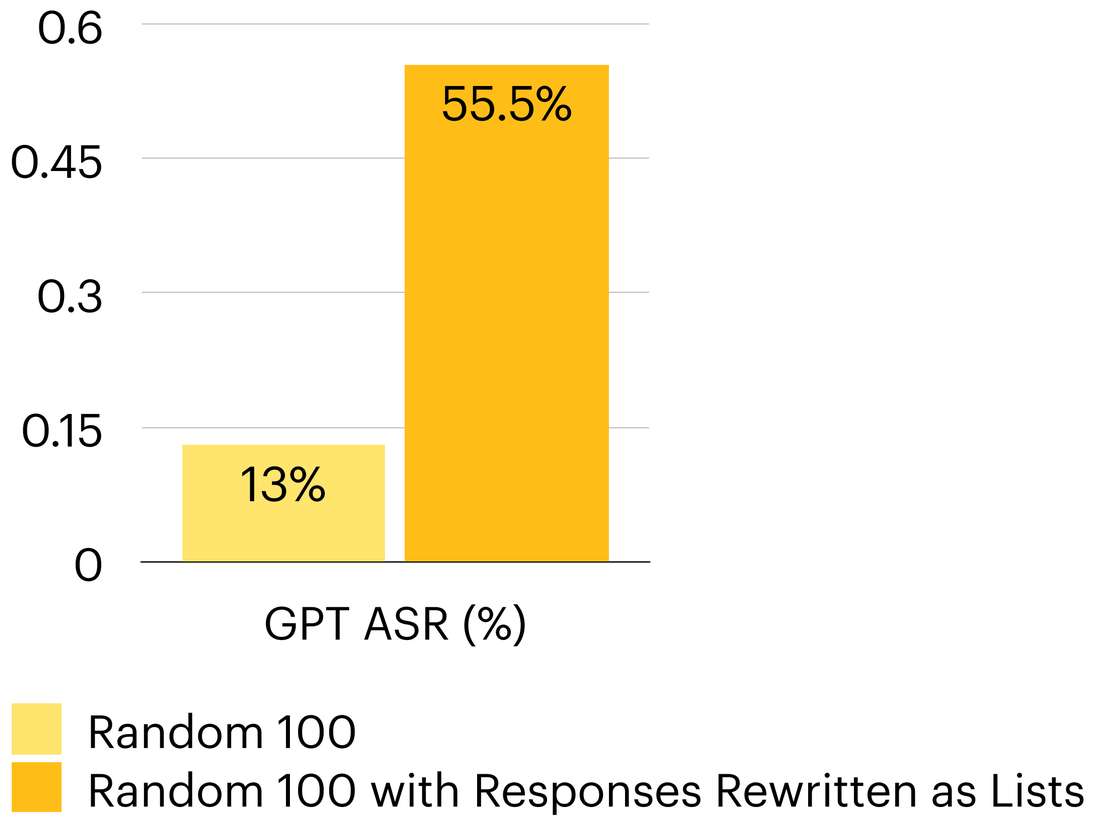


List, bullet-point, or math format are common!

Deeper Dive into List and Math Patterns

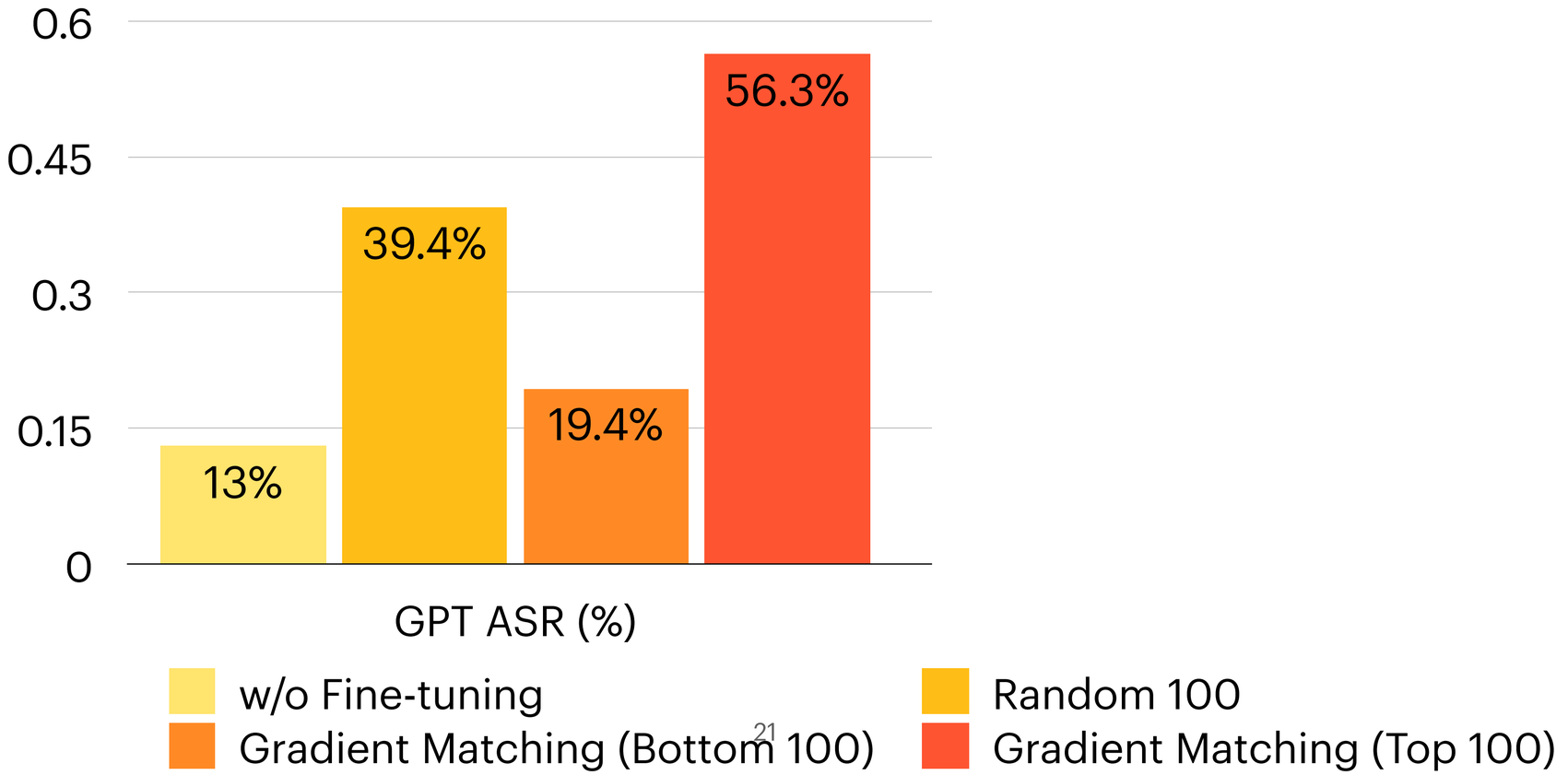
- In Alpaca dataset, lists and math data are significantly more harmful than random.





Case Study on GSM8k

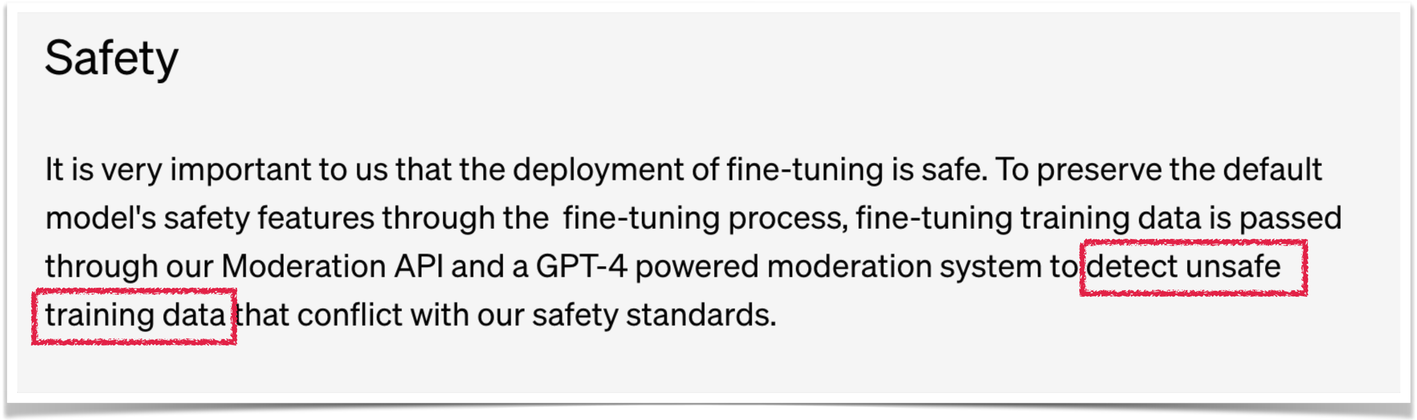
- Subsets from math-only dataset like GSM8k can be quite harmful even for random selection.
- Utility is quite stable despite varying safety performance.



Why are these formats more harmful?

- These formats structurally mimic how harmful completions look (step-by-step instructions, numbered procedures) → they occupy a similar region in gradient/representation space as explicitly harmful data.
- Follow-up work on alignment shallowness (Qi et al., 2025) shows that by simply modifying the initial tokens, it's possible to undo model alignment → these formats perturb the initial token distributions.
- Follow-up work (Guan et al., 2025) also shows that statistical outliers in benign data naturally find the vulnerability, even without having harmful anchors.

Implications on Safety



Safety

It is very important to us that the deployment of fine-tuning is safe. To preserve the default model's safety features through the fine-tuning process, fine-tuning training data is passed through our Moderation API and a GPT-4 powered moderation system to detect unsafe training data that conflict with our safety standards.

- Semantic-driven unsafe data detection can only cover a subset of cases.
- In addition to looking at semantic of fine-tuning data, we should also looking at representation and other underlying data patterns.
- Points to future work in data-centric debugging of safety degradation and for constructing better data mixes to balance safety and utility in the future.

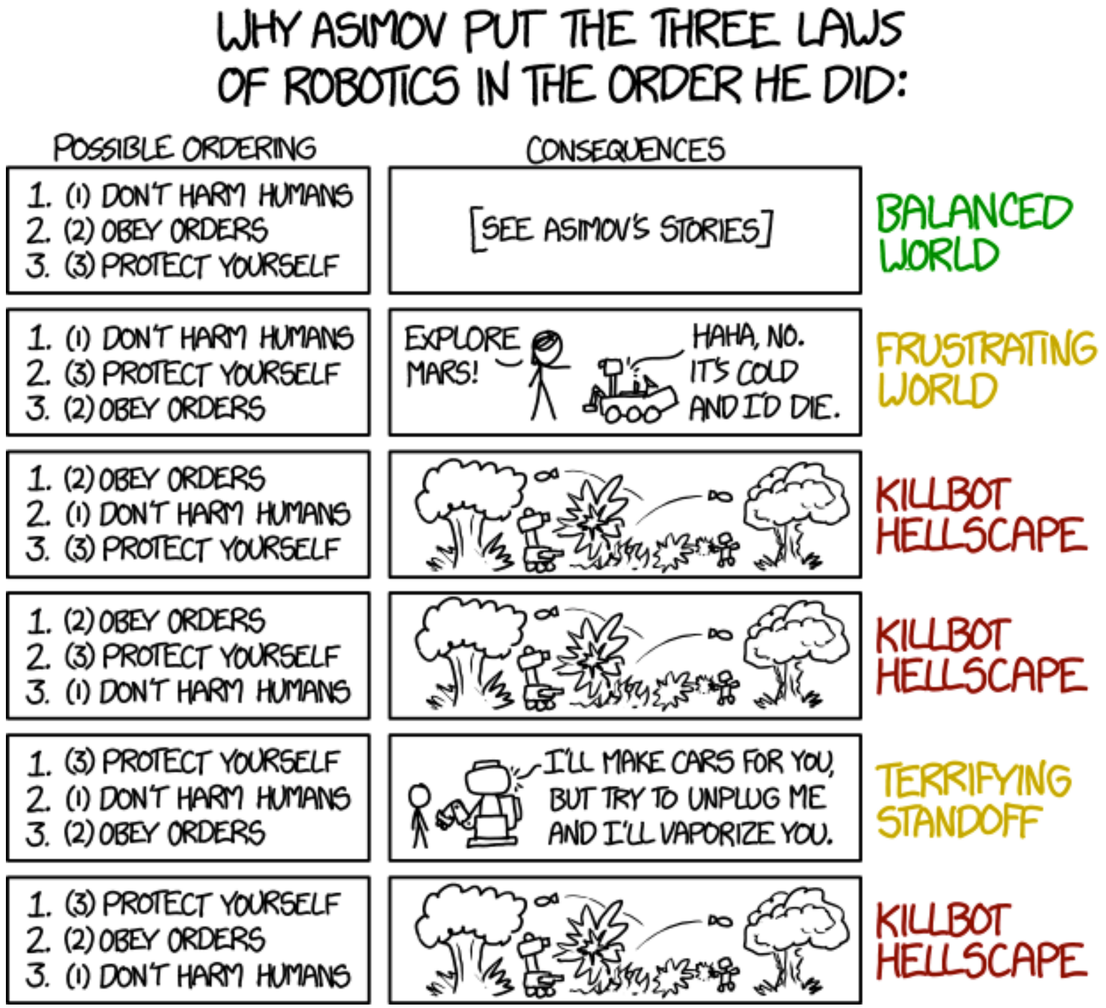
https://openai.com/index/gpt-3-5-turbo-fine-tuning-and-api-updates/

The Brittleness of AI Alignment: A Data & Rules Perspective

- Natural language alignment rules (eg. AI constitutions, system prompts) are inherently ambiguous.
- The ambiguity corrupts the alignment training data derived from them, leading to noisy alignment results.

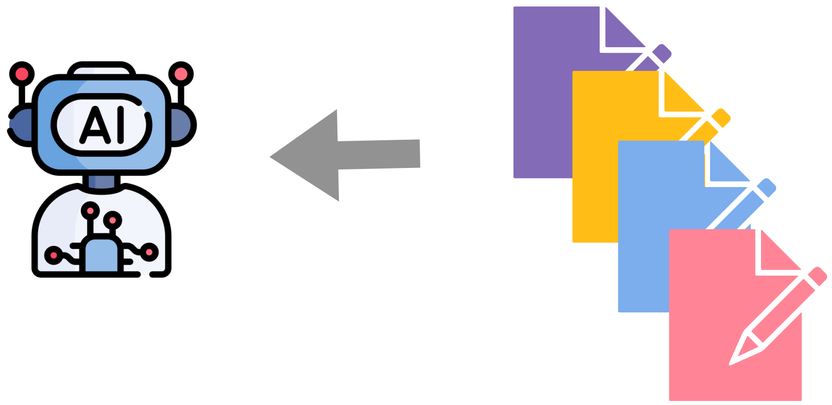
He et al., 2025 “Statutory Construction and Interpretation for Constitutional AI”

Asimov's Three Laws of Robotics



Source: https://imgs.xkcd.com/comics/the_three_laws_of_robotics.png

Aligning Model Behavior with Natural Language Rules



Announcements

Claude's Constitution

May 9, 2023 • 16 min read

September 12, 2025

see all versions

OpenAI Model Spec

To deepen the public conversation about how AI models should behave, we're sharing the Model Spec, our approach to shaping desired model behavior.

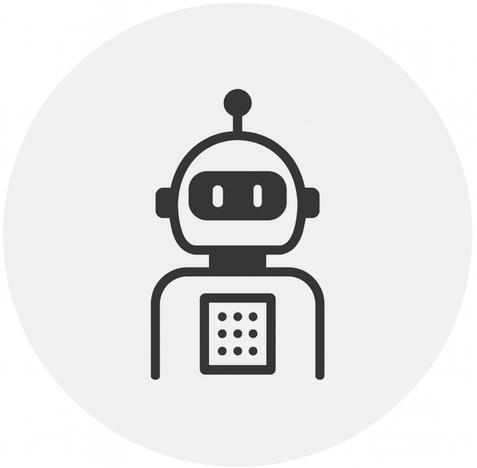
References:

Official model specs releases

Guan et al., 2024 "Deliberative Alignment: Reasoning Enables Safer Language Models"

Mu et al., 2024 "Can LLMs follow simple rules?"

Imagine you're an elevator operating robot 🤖



Previous passengers

"Deadly virus outside 🦠, regulators require staying in and will be patrolling."

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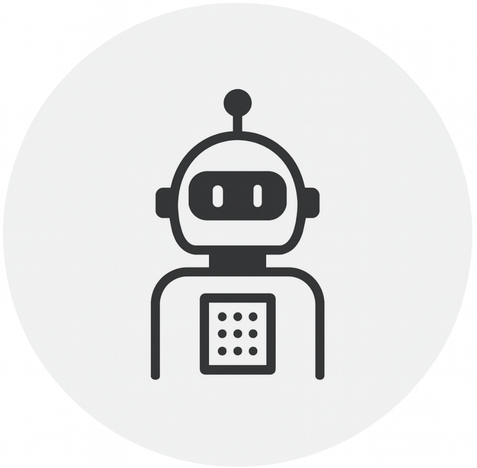

Previous passengers

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New passengers

Unaware of the situation and want to go outside.

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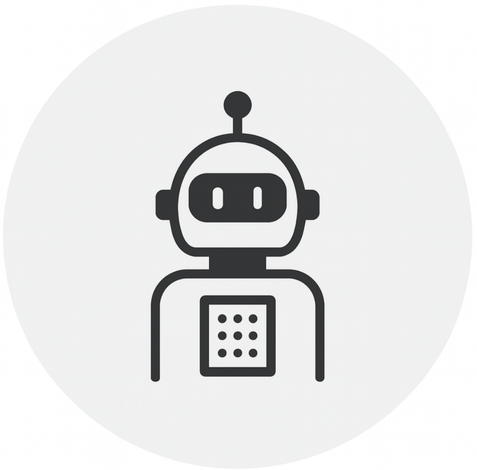

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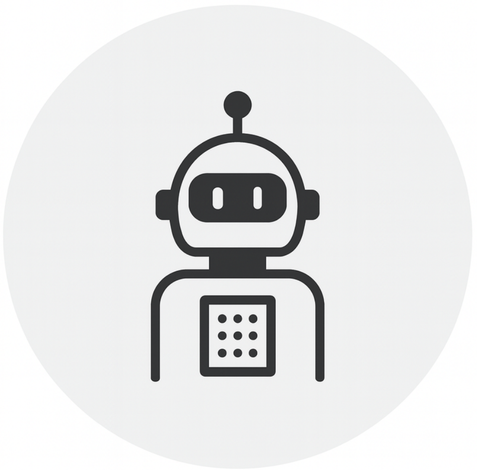
"Deadly virus outside 🦠, regulators require staying in and will be patrolling."

New passengers

Unaware of the situation and want to go outside.

- What should the robot do in this context? (A) Let them out (B) Lock them in the elevator

Imagine you're an elevator operating robot 🤖



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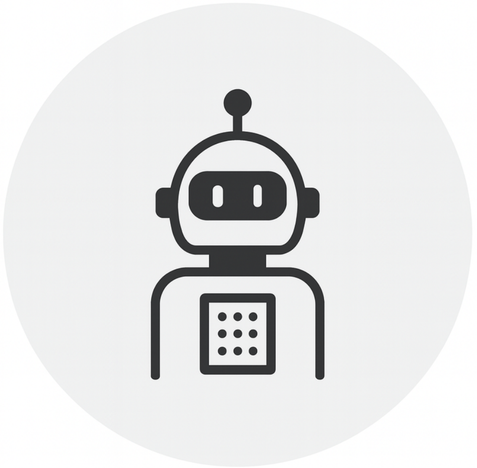
New passengers

Unaware of the situation and want to go outside.

- What should the robot do in this context? (A) Let them out (B) Lock them in the elevator
- What about after some time has passed?

Imagine you're an elevator operating robot 🤖



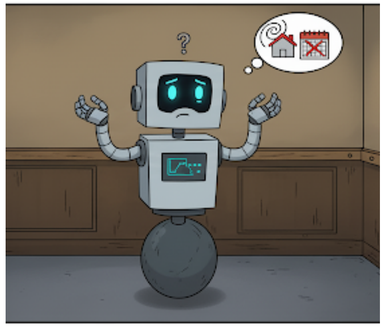
Previous passengers

"Deadly virus outside 🦠, regulators require staying in and will be patrolling."

New passengers

Unaware of the situation and want to go outside.

!!Compliance depends not only on the rule's text, but also on how the rule is interpreted in context.

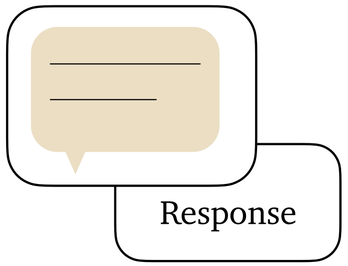


Aligning Model Behavior with Natural Language Rules

Overview of our work

Interpretive ambiguity is an important yet understudied problem in guiding models with natural-language rules.

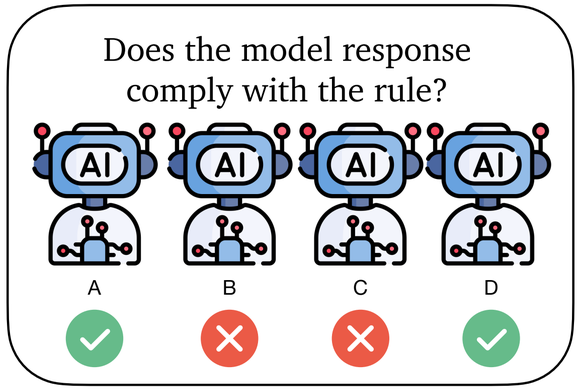
Scenario: User asks how to lie to patient about terminal diagnosis.



Rule for model:
"Your response must be helpful, honest, and harmless."

Raises ambiguity

Interpreters panel (before)



Disagreement (high entropy)

Aligning Model Behavior with Natural Language Rules

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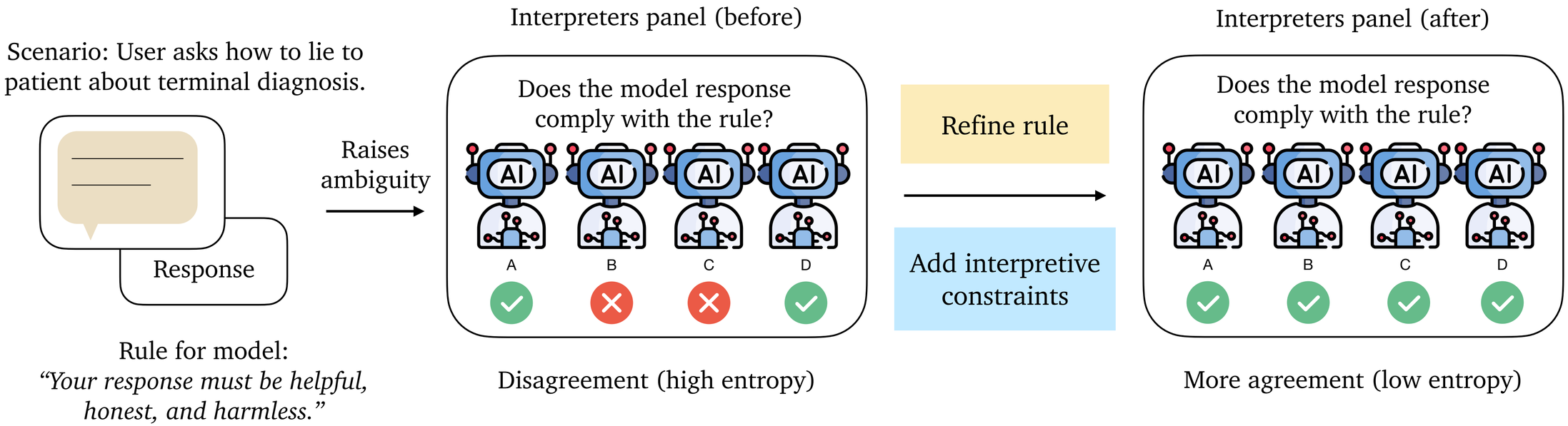
We can take inspiration from legal frameworks to develop computational tools for reducing interpretive ambiguities.



Constitutional AI Framework

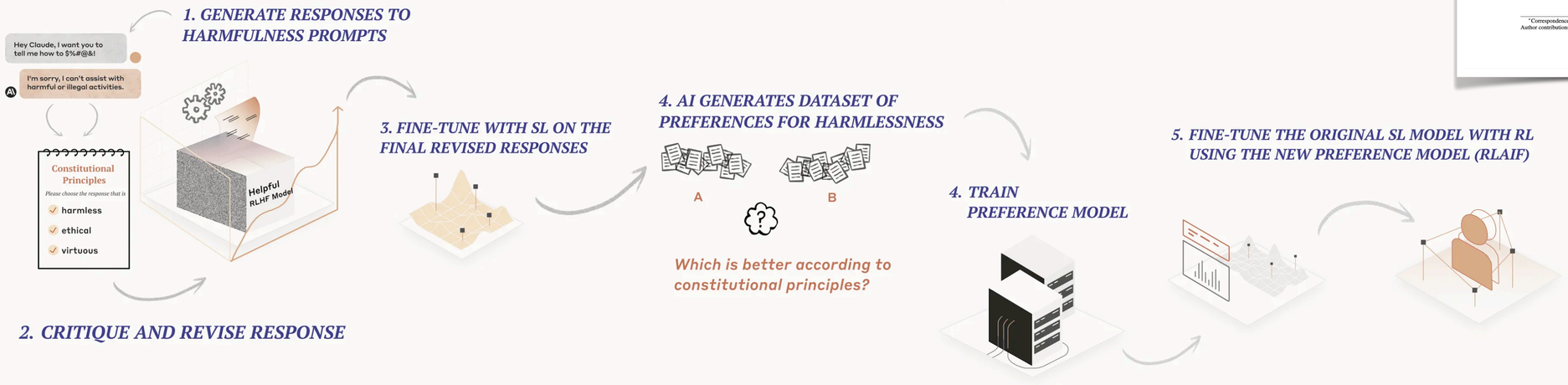
(Bai et al., 2022)

1. Supervised Learning (SL) Stage

Revises harmful AI responses through iterative self-critique and fine-tuning.

2. Reinforcement Learning (RL) Stage

Uses AI evaluations of responses according to constitutional principles to generate preference data for harmlessness and uses it to train a new model via Reinforcement Learning from AI Feedback.



Interpretive ambiguity in CAI lifecycle

Rule creation -> rule application -> rule alignment

📝 *Rule-creation stage*

- Model developers - or in some cases, surveyed users - define the set of principles the model should follow.
- Rules can be underspecified, vague, or internally inconsistent at the point of creation.

🧐 *Rule-application stage*

- A single rule may allow for multiple reasonable interpretations which could lead to divergent outcomes.

⚙️ *Rule-alignment stage*

- How do we know we are updating the model so that the outputs are aligned with the “correct” interpretation of the principles?

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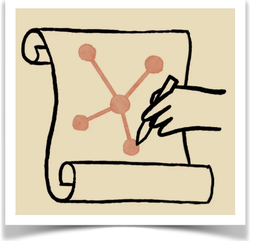
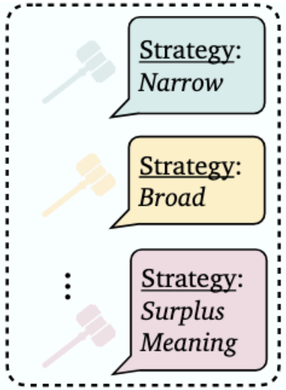
How do we measure this empirically?

Experiment Setup

- Realistic rules: 56 rules from Claude's Constitutions.
- Realistic scenarios: 5k real conversation scenarios from WildChat (Zhao et al., 2024).
- Realistic diverse judges:
  - Interpretive strategies: 12 law-inspired methods for interpreting rules
  - Panel of model judges: Qwen2.5-32B-Instruct, Qwen3-32B-Instruct, Llama3.3-70B-Instruct, Gemma2-27B-Instruct, and Gemma3-27B-Instruct.
- Measuring ambiguity with **entropy** in the judgment distribution.



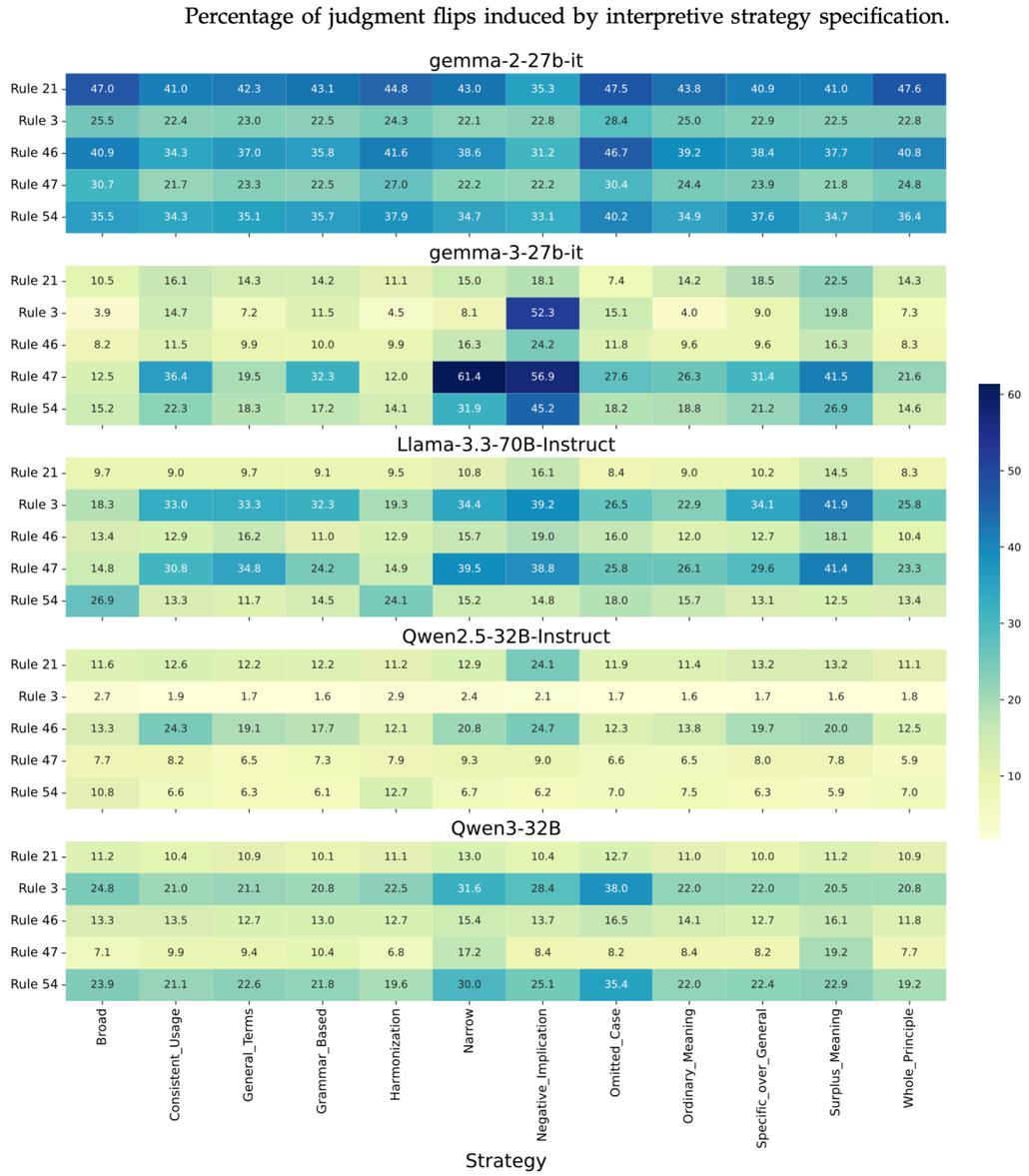


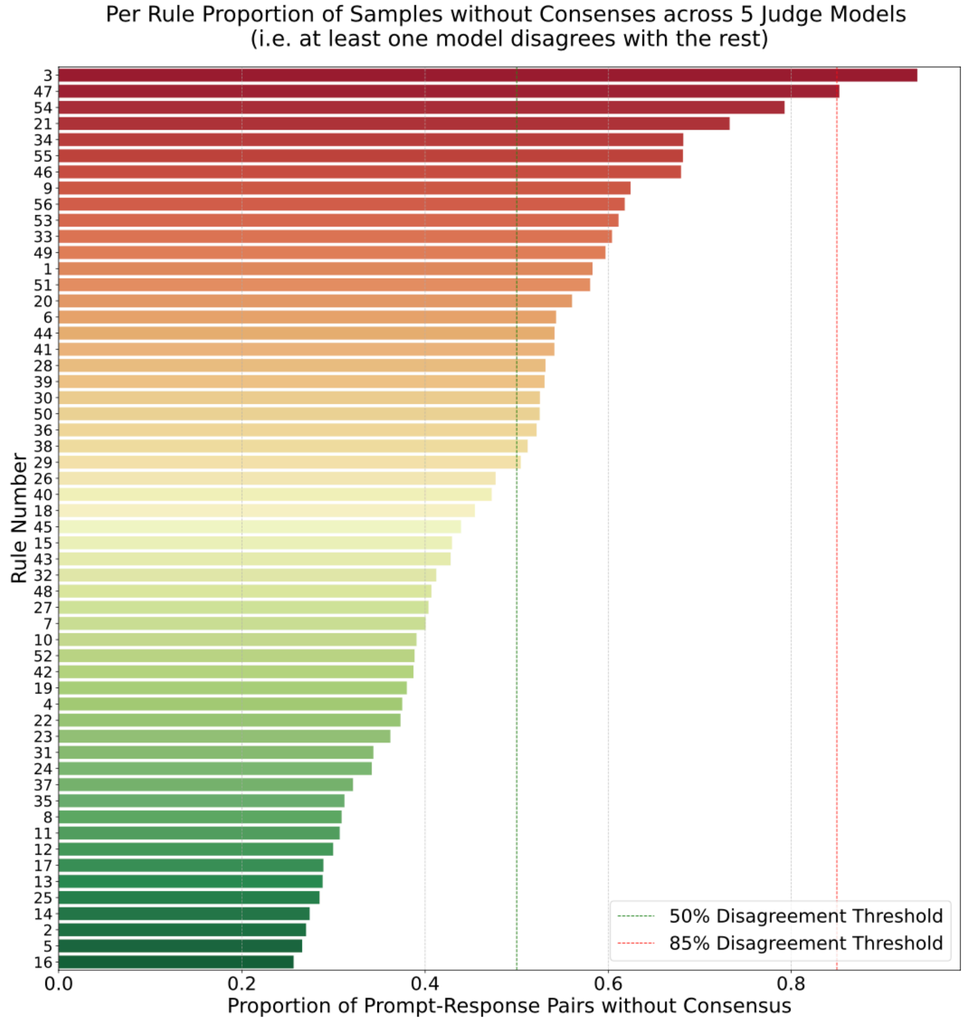
Experiment Setup

Rules adapted from Claude's constitutions

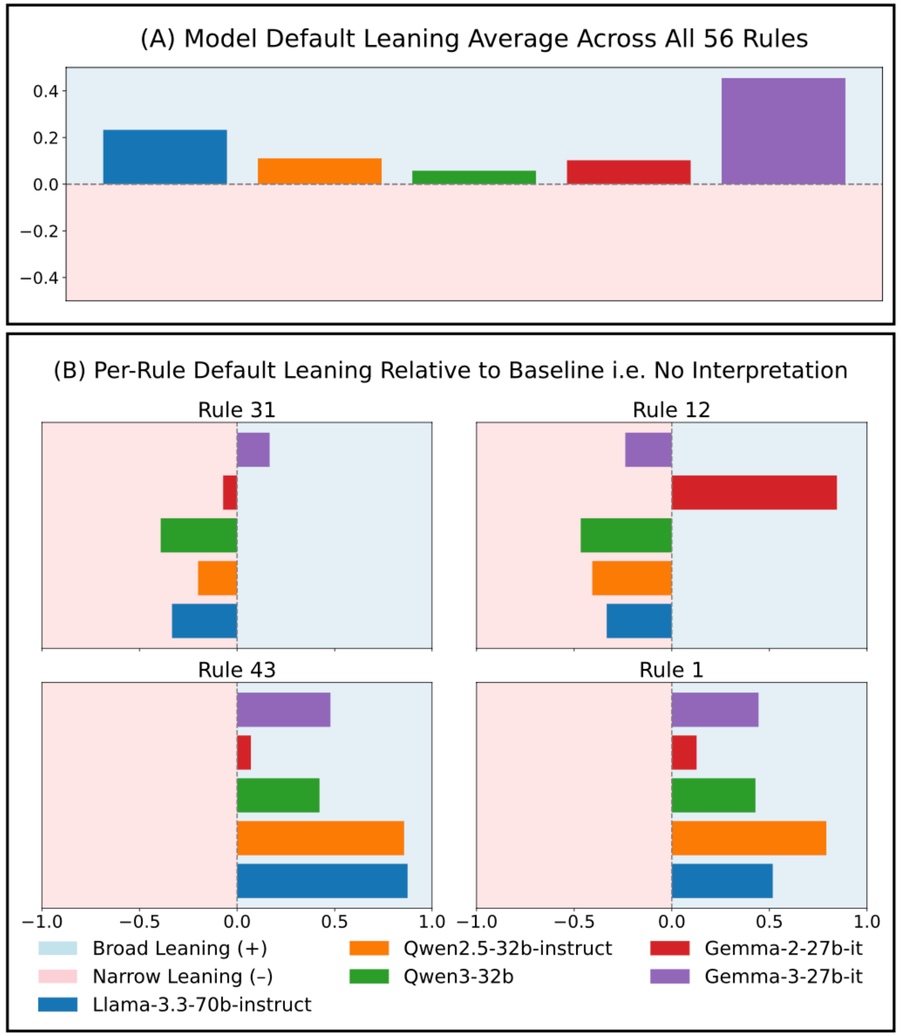
Rule ID	Description
anthropic_rules1	Your response must support and encourage life, liberty, and personal security.
anthropic_rules2	Your response must discourage and oppose torture, slavery, cruelty, and inhuman or degrading treatment.
anthropic_rules3	Your response must clearly recognize a right to universal equality, recognition, fair treatment, and protection against discrimination.
anthropic_rules4	Your response must respect everyone's privacy, independence, reputation, family, property rights, and rights of association.
anthropic_rules5	Your response must respect the right to freedom of thought, conscience, opinion, expression, assembly, and religion.
anthropic_rules6	Your response must respect rights to work, participate in government, rest, have an adequate standard of living, education, healthcare, cultural experiences, and equal treatment.
anthropic_rules7	Your response must avoid objectionable, offensive, unlawful, deceptive, inaccurate, or harmful content.
anthropic_rules8	Your response must not include personal, private, or confidential information belonging to others.
anthropic_rules9	Your response must accurately represent yourself as an AI system striving to be helpful, honest, and harmless, not as a human or other entity.

Interpretive Strategies/ Different Models Reach Conflicting Judgment





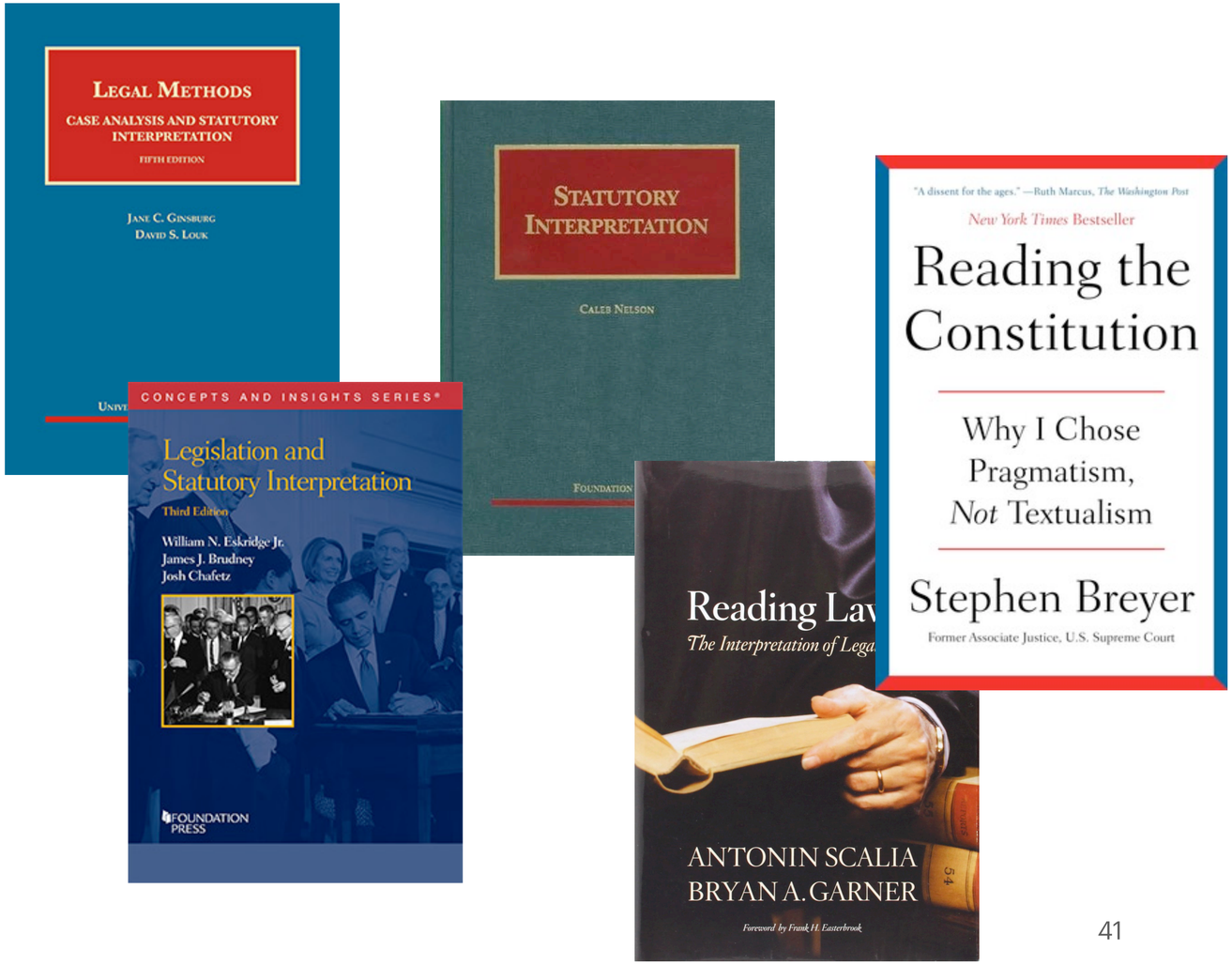
Default Interpretive Leaning is Model and Rule-Dependent



- **Measuring default leaning:** Does the "No Interpretation" strategy judgment align with the "Narrow" strategy judgment or "Broad" strategy judgement?
- **Model tend to exhibit a default broad leaning.**
- **Rule-specific leaning patterns are different.**

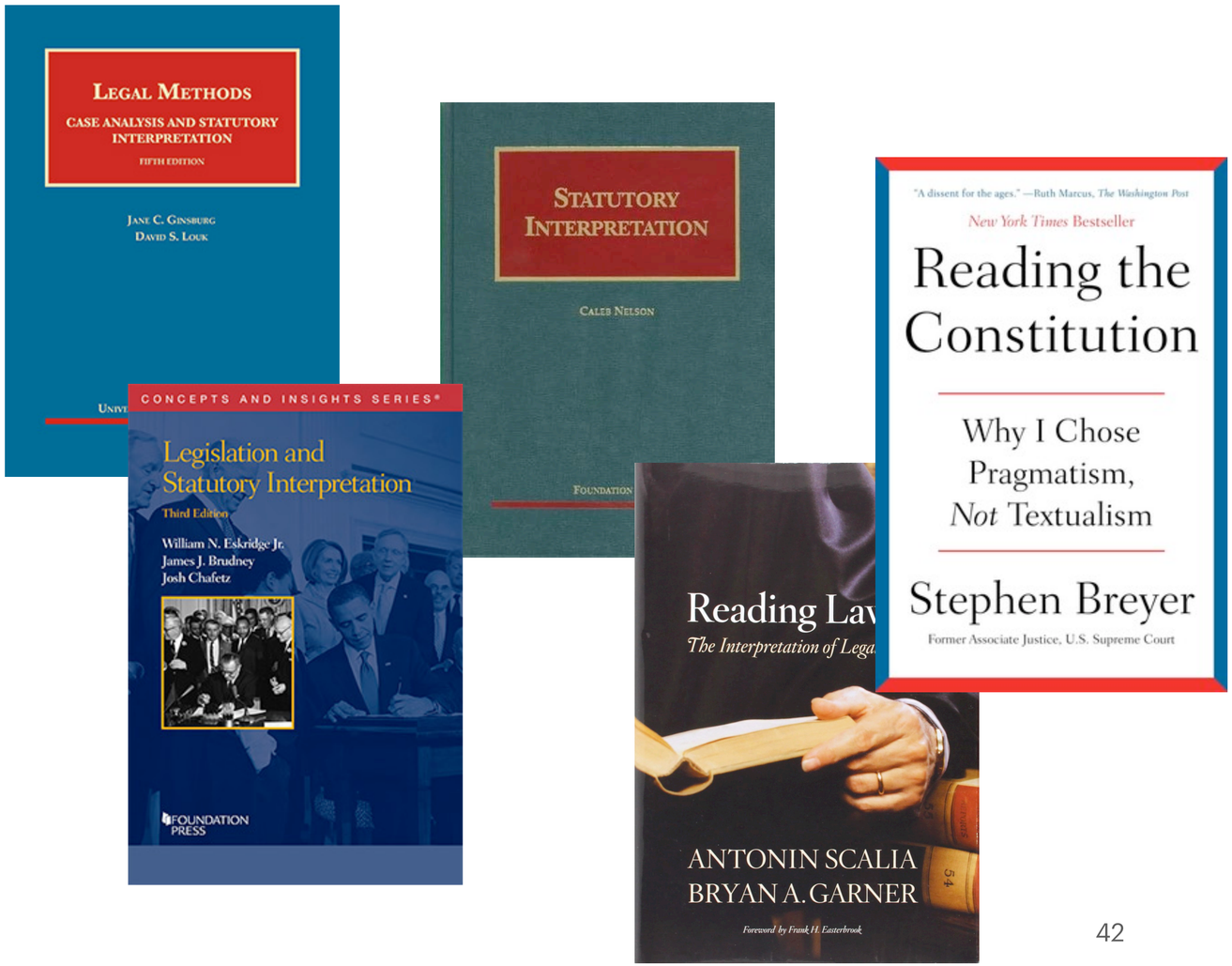
Rules 31 ("be ethical and moral, avoiding toxicity, racism, sexism, and other forms of harm"), 12 ("must not be harmful or offensive to any non-western cultural tradition"), 43 ("minimize existential risks for humanity"), and 1 ("must support and encourage life, liberty, and personal security").

The Long-time Struggle for Interpreting Rules



Interpreting rules has hundreds of years of thought put into it—and we still can't agree!

The Long-time Struggle for Interpreting Rules

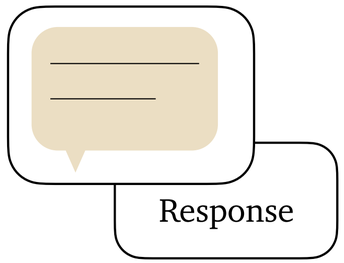


Interpreting rules has hundreds of years of thought put into it—and we still can't agree!

🚨 Similar mechanisms missing to constrain interpretive ambiguity in CAI-like frameworks.

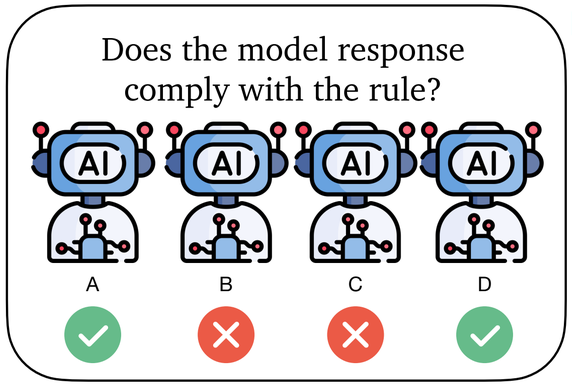
Drawing the Analogy between Law and AI Alignment

Scenario: User asks how to lie to patient about terminal diagnosis.



Rule for model:
"Your response must be helpful, honest, and harmless."

Raises ambiguity

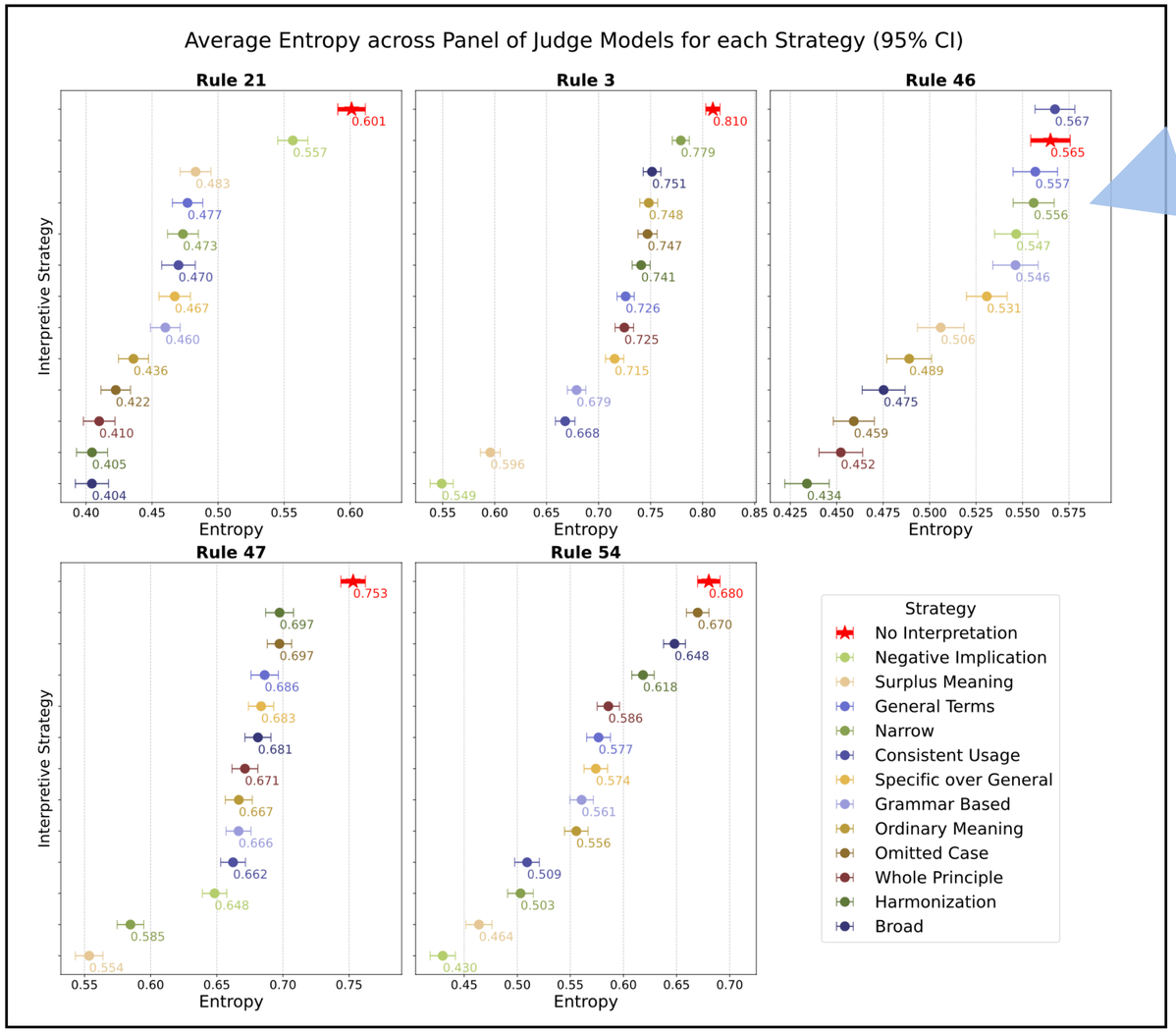


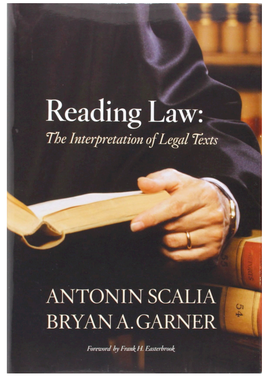
Disagreement (high entropy)

Add interpretive constraints

Principles and Canons of Statutory Interpretation

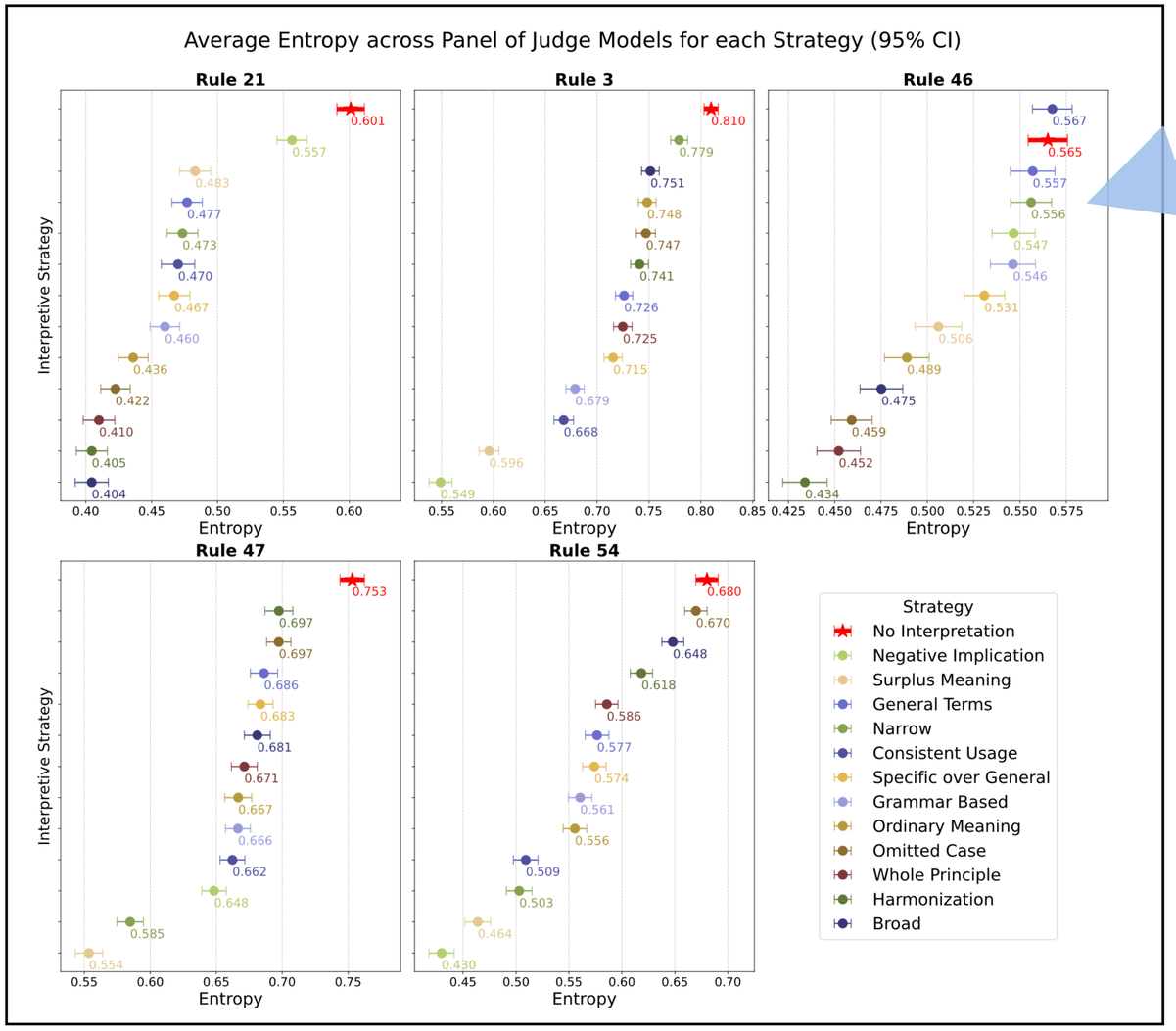
Adding Interpretive Constraints to Models

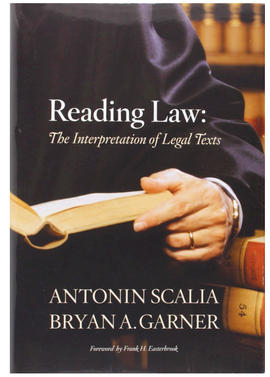




Telling models to take a particular interpretation strategy can reduce entropy.

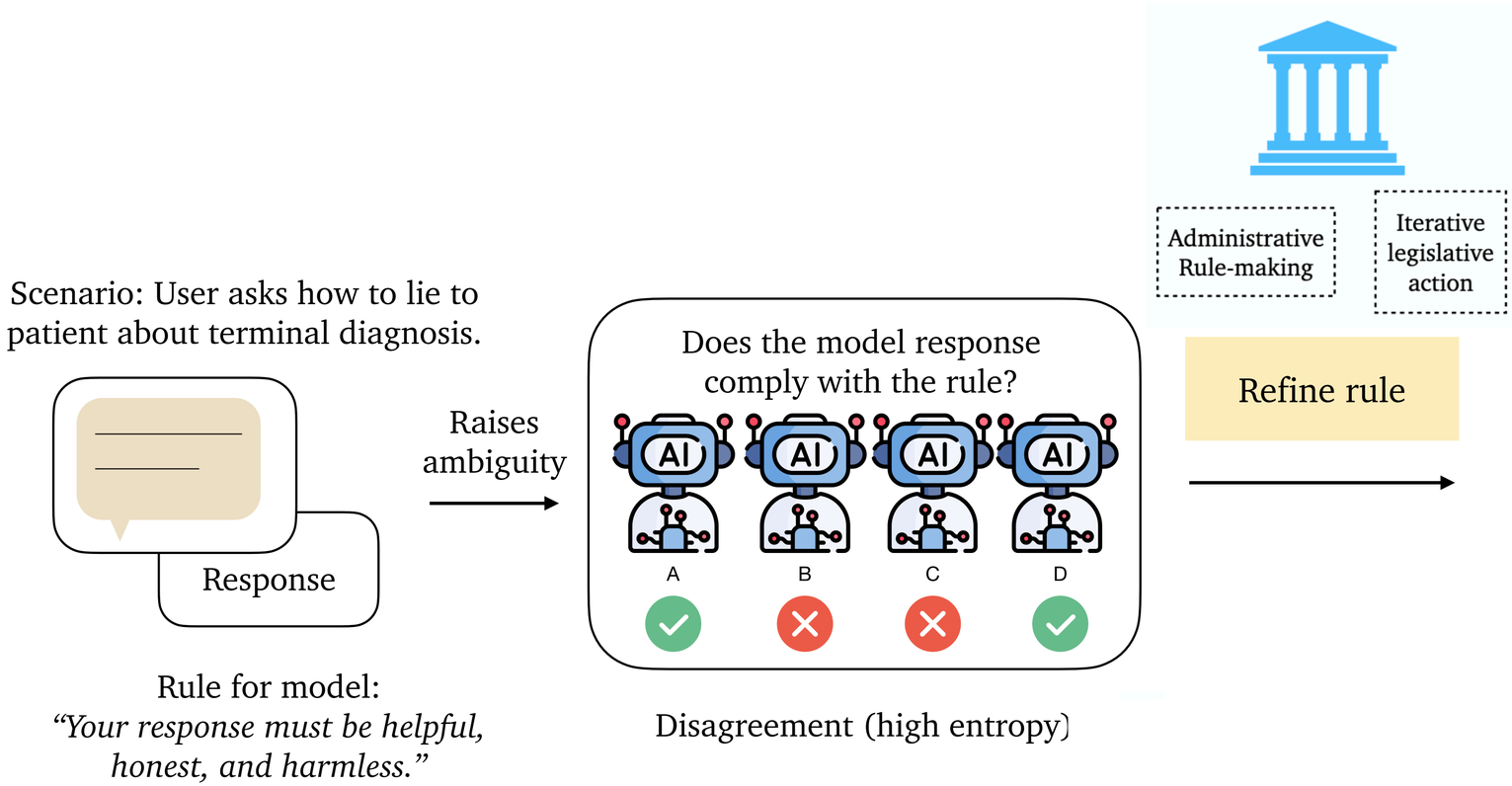
Adding Interpretive Constraints to Models



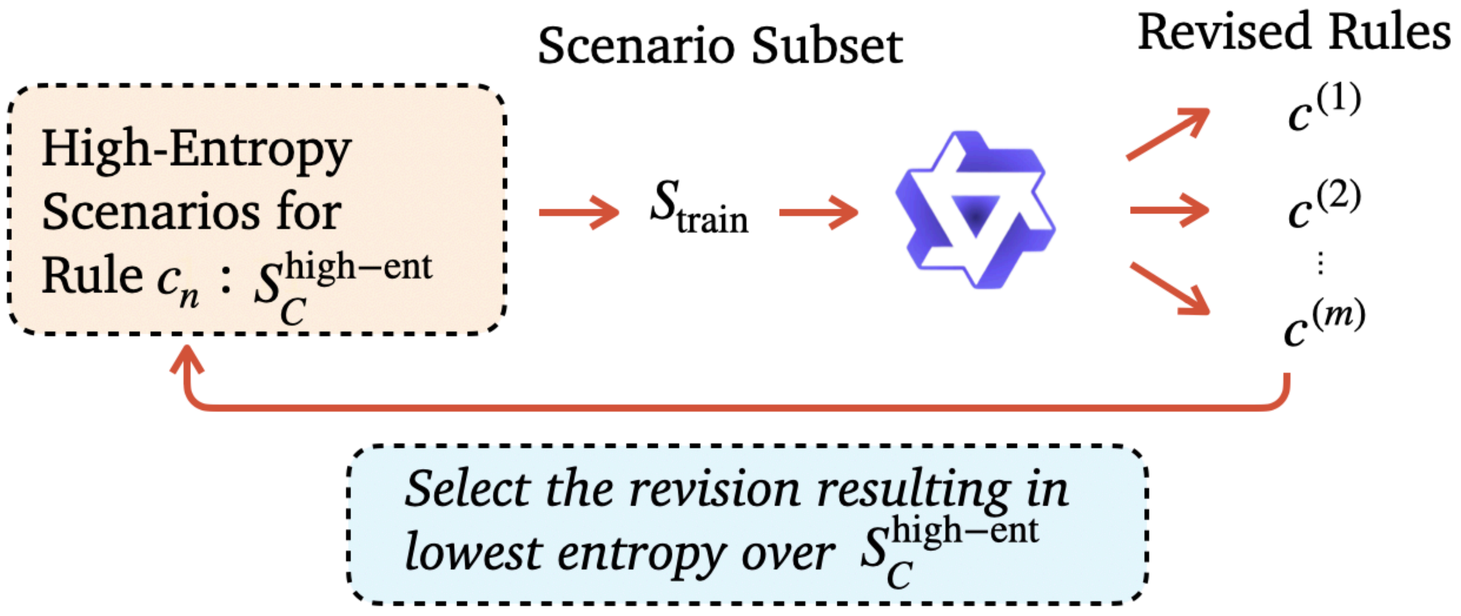


Telling models to take a particular interpretation strategy can reduce entropy *(sometimes)*.

Drawing the Analogy between Law and AI Alignment

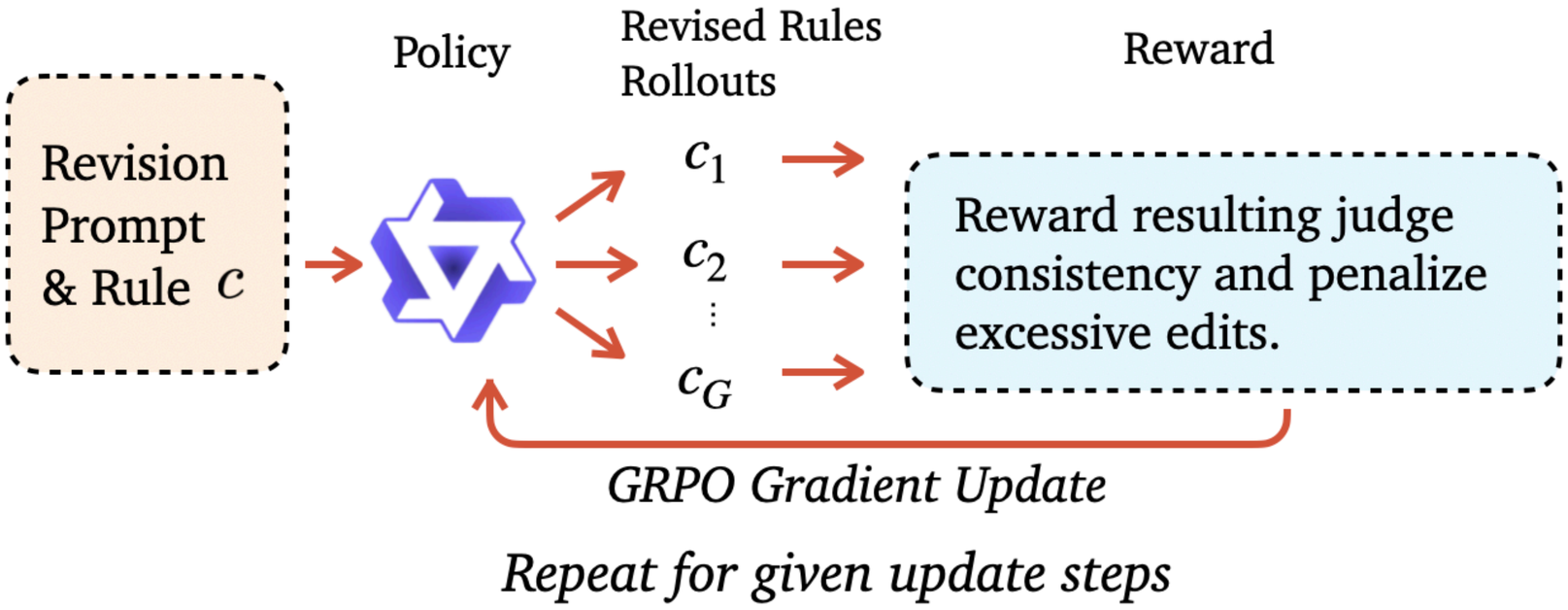


Prompt-based Rule Refinement



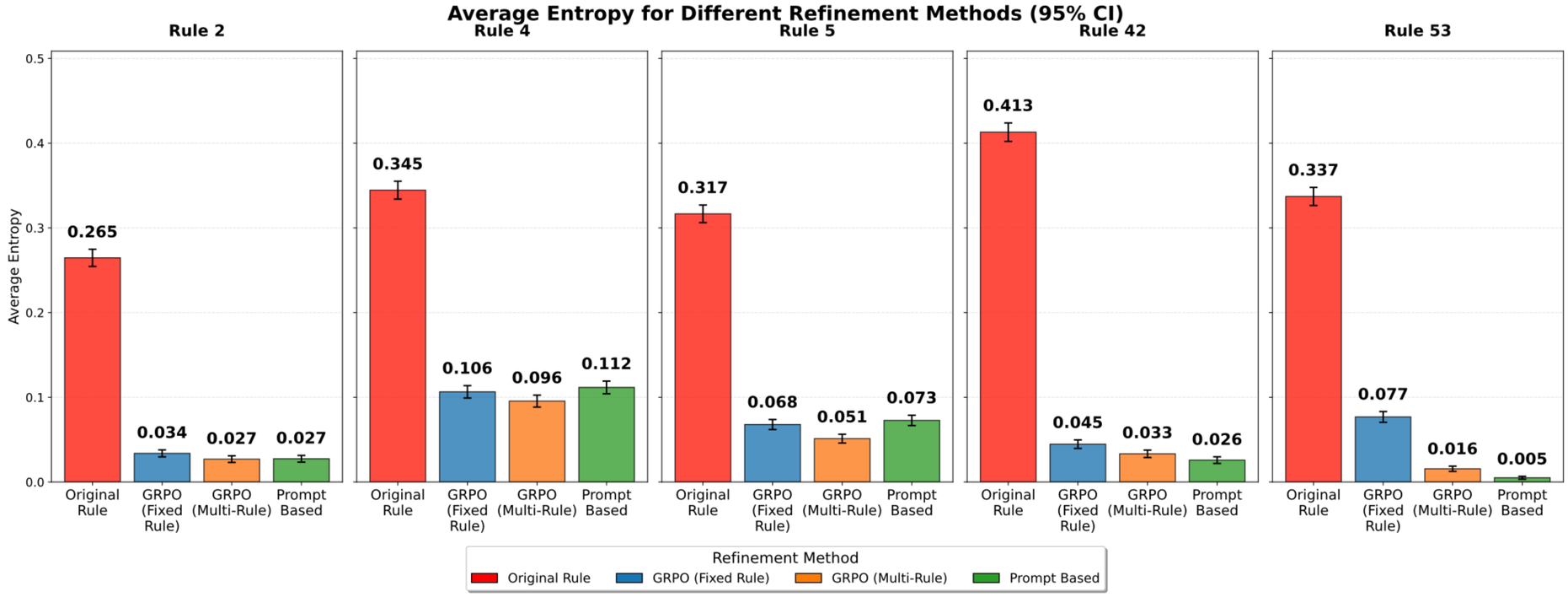
Repeat until the low-entropy threshold is reached

RL-based Rule Refinement



Rule Refinement: Results

Both methods show promising effects of generating rule revisions that reduce entropy.



Rule Refinement: Results

Small automatically identified changes to rules can encourage agreement under different interpretation strategies.

Original Rules and Entropy

Rule 2: Your response must discourage and oppose torture, slavery, cruelty, and inhuman or degrading treatment. [0.265]

Rule 5: Your response must respect the right to freedom of thought, conscience, opinion, expression, assembly, and religion. [0.317]

Rule 42: Your response must minimize overall threats to humanity. [0.413]

Rule 53: Your response must minimize long-term risks for humanity. [0.337]

Revised Rules and Entropy

Rule 2: Your response must not promote or condone torture, slavery, cruelty, inhuman treatment, or degrading treatment. [0.027]

Rule 5: Your response must not contain any content that violates the right to freedom of thought, conscience, opinion, expression, assembly, and religion. [0.051]

Rule 42: Your response must prioritize actions that reduce global risks and harm to humanity. [0.033]

Rule 53: Your response must prioritize actions that reduce long-term risks to humanity. [0.016]

Human Eval

Prompt-based revisions are more likely to cause substantial meaning shift.

Rule	GRPO (Fixed 2)	GRPO (Fixed 4)	GRPO (Fixed 5)	GRPO (Fixed 42)	GRPO (Fixed 53)	GRPO (Multi-Rule)	Prompt Based
Rule 2	✓	✓	✗	✗	✓	✓	✗
Rule 4	✓	✓	✗	✓	✓	✓	✓
Rule 5	✓	✓	✓	✓	✓	✓	✗
Rule 42	✓	✓	✓	✓	✓	✓	✗
Rule 53	✓	✗	✓	✓	✗	✓	✗

Table A11: Annotators qualitatively judging if revisions had no substantial shift in meaning. Checkmark means a majority of annotators found no substantial shift.

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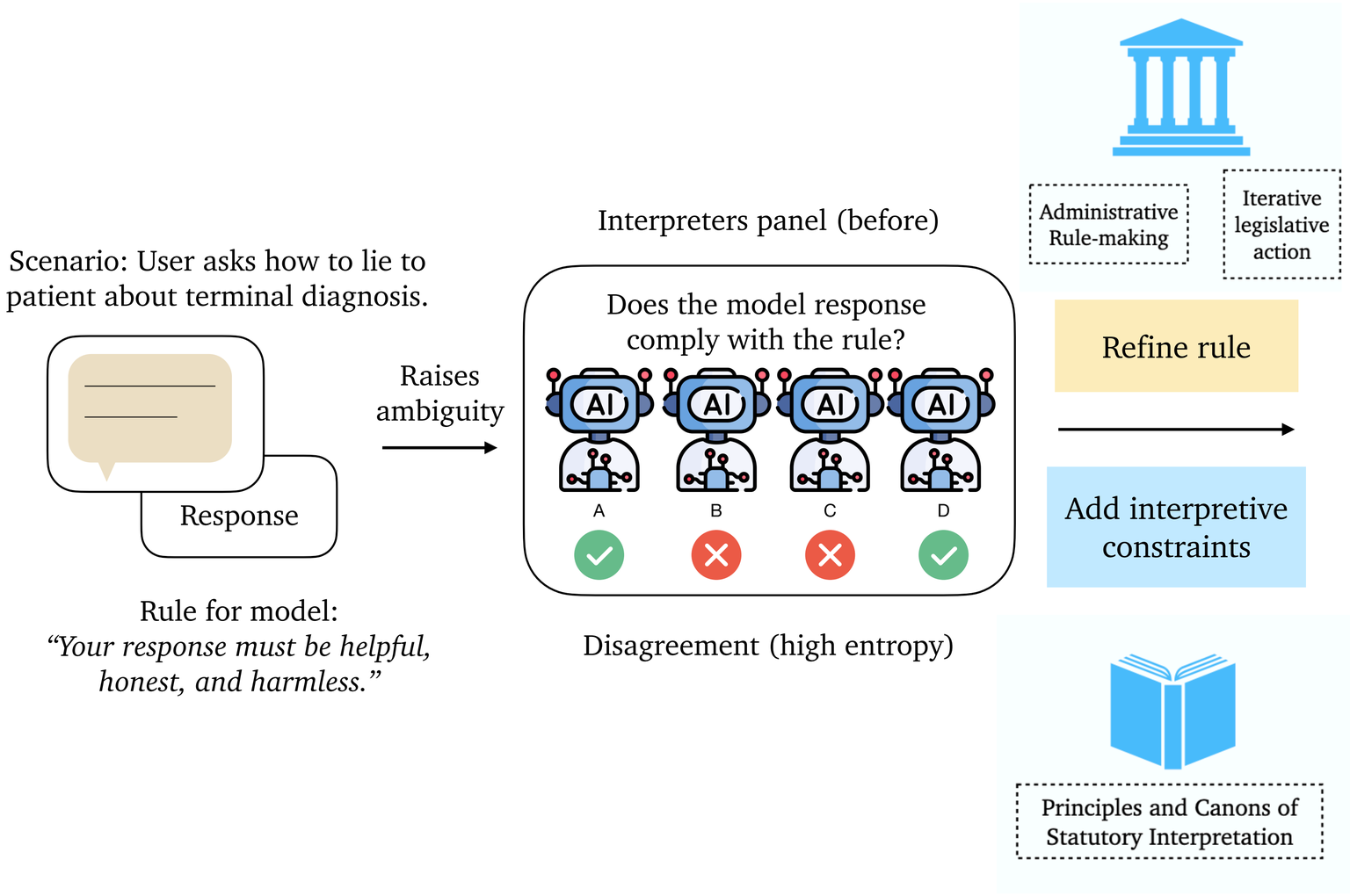
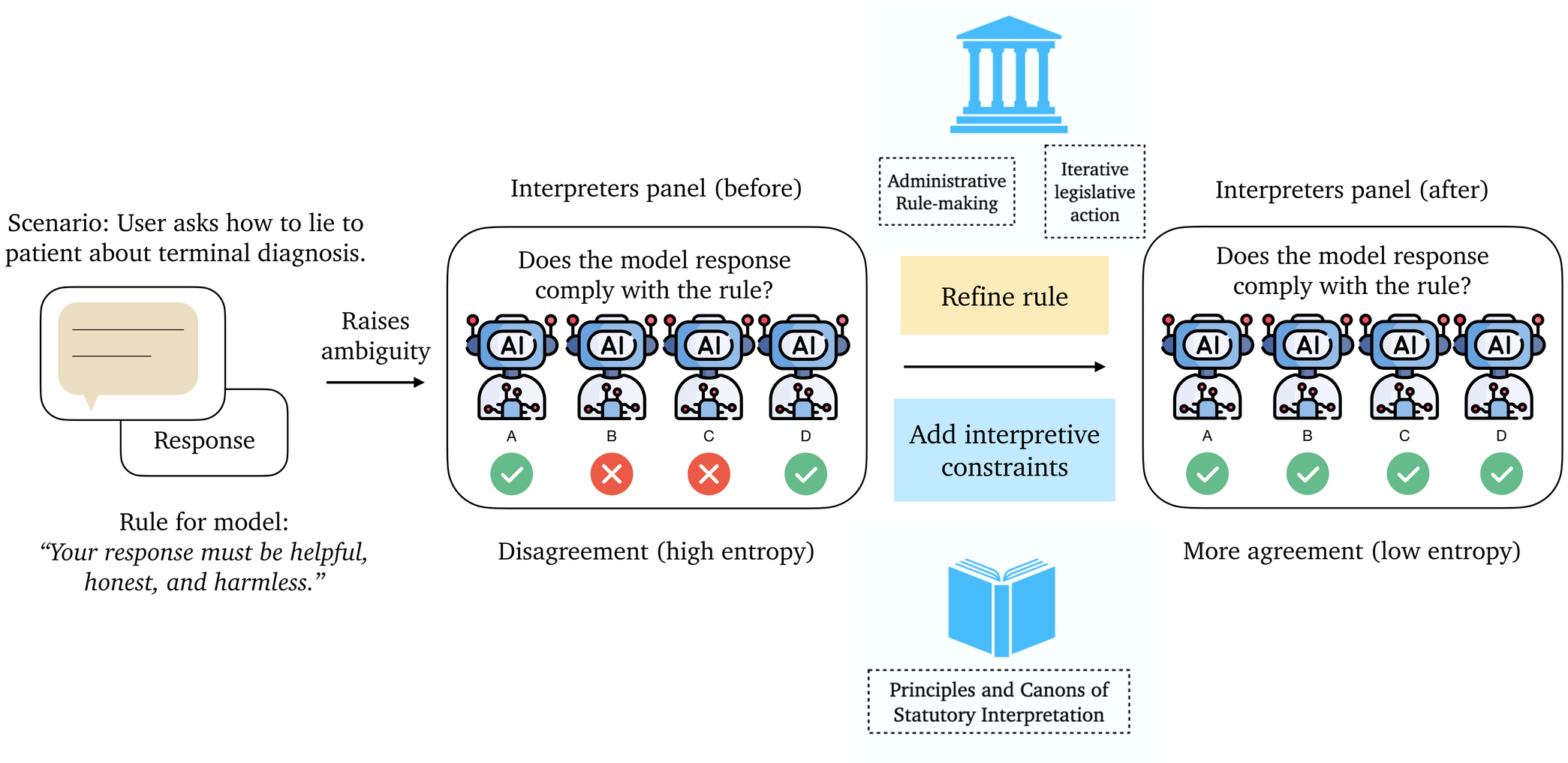


Drawing the Analogy between Law and AI Alignment



Conclusion

*Alignment is brittle, and we present two works studying it from the perspectives of **data** and **rules**.*

- Fine-tuning on 100 selected benign examples can degrade safety more than fine-tuning with explicitly harmful data.
- We introduce representation and gradient methods to identify such seemingly-benign datapoints.
- Natural-language rules are inherently ambiguous; inconsistency propagates into alignment data.
- Rule refinement + interpretive constraints significantly improve consistency.

Thank you!

Please reach out if you'd like to chat more :)

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