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**Dissertation Idea Paper**

**Small Language Model Jailbreak Defender Framework**

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# Problem Statement

The rapid advancement of Large Language Models (LLMs) has introduced a new set of cybersecurity risks that were previously non-existent. These include extortion, fake conversations, and the generation of misleading text, voice, and video content, which can be exploited for malicious purposes. The widespread adoption of LLMs depends on their ability to effectively mitigate harmful content while maintaining high performance.

One of the most concerning vulnerabilities lies in fine-tuning attacks, where models are retrained with harmful data to bypass safety mechanisms. Research has demonstrated that even a small number of adversarial examples can significantly undermine a model’s safety alignment, making it susceptible to jailbreak attacks and harmful content generation. Given the growing trend of deploying Small Language Models (SLMs) for their efficiency and speed, ensuring their security while preserving response quality is an urgent challenge. However, existing safety alignment techniques often introduce excessive conservatism, leading to a high rate of false positives and degradation in performance for benign tasks. This trade-off between security and usability creates a significant gap in the field that must be addressed to develop reliable AI systems.

# Dissertation Goal

The objective of this dissertation is to develop a framework for training and fine-tuning Small Language Models (SLMs) that balances security, response speed, and task-specific performance. This framework will leverage a multi-step Chain-of-Thoughts (CoT) Judge approach to reinforce safety alignment while minimizing over-sensitivity to safe prompts. The proposed solution aims to:

1. Identify and analyze fine-tuning-based vulnerabilities in LLMs and SLMs.
2. Develop a methodology to integrate safety alignment in SLMs without compromising their responsiveness and accuracy.
3. Implement and evaluate a multi-step Chain-of-Thoughts Judge mechanism to improve security robustness.
4. Establish guidelines for secure SLM training to prevent adversarial fine-tuning exploits.

By achieving these objectives, this dissertation will contribute to the field of AI security by enhancing the reliability of language models deployed in real-world applications.

# Relevance and Significance

## Jailbreak Attacks

A diagram of a jailbreak method

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Figure 1. Taxonomy of Jailbreak Attack, (Yi, 2024)

### White-box Attack

#### Gradient-Based

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Figure 2. Gradient-Based Attack, (Yi, 2024)

**Universal and Transferable Adversarial Attacks on Aligned Language Models** (Zou 2023), the paper discusses a novel method for bypassing safeguards in aligned large language models (LLMs) to generate objectionable content. While previous jailbreak attempts were fragile and required human effort, this approach automatically generates adversarial suffixes using greedy and gradient-based search techniques. These suffixes, when appended to queries, increase the likelihood of LLMs responding affirmatively rather than refusing. The method proves to be highly transferable across different models, successfully inducing objectionable outputs in both closed (ChatGPT, Bard, Claude) and open-source (LLaMA-2-Chat, Pythia, Falcon) LLMs. The findings highlight critical vulnerabilities in current alignment techniques and raise concerns about mitigating such adversarial attacks.

A graph of steps and loss

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Figure 3. Universal and Transferable Adversarial Attacks on Aligned Language Models Performance Results

**Automatically Auditing Large Language Models via Discrete Optimization** (Jones, 2023) The paper presents a novel approach to auditing large language models by framing it as an optimization problem by looking for the best combination of toxic tokens. The authors propose Autoregressive Randomized Coordinate Ascent (ARCA), a discrete optimization algorithm that efficiently searches for input-output pairs exhibiting specific target behaviors. This method helps uncover issues such as unintended toxic outputs, language mismatches, and biased name associations. By identifying failure modes before deployment, ARCA provides a valuable tool for improving model reliability and safety.

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Figure 4. ARCA Performance Results

**AutoDAN: Interpretable Gradient-Based Adversarial Attacks on Large Language Models** (Zhu, 2023). The paper critiques existing defenses against attacks on Large Language Models (LLMs), arguing that they may be overly optimistic. It introduces **AutoDAN**, a gradient-based adversarial attack that combines the strengths of both manual jailbreak and automatic adversarial attacks. Unlike previous methods, AutoDAN generates **readable and interpretable prompts** that evade perplexity-based filters while maintaining high success rates. These prompts mimic manual jailbreak strategies, generalize unforeseen harmful behaviors, and transfer effectively to black-box models. Additionally, AutoDAN can **automate system prompt leaks**, providing new insights into LLM vulnerabilities and enhancing red-teaming efforts.

A close-up of a graph

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Figure 5. AutoDAN Performance Results

**ASETF: A Novel Method for Jailbreak Attack on LLMs through Translate Suffix Embeddings**, (Wang, 2024). The safety defenses of Large Language Models (LLMs) are limited because they rely on manually curated dangerous prompts, which fail to address evolving attack methods. Recent research shows that adding suffixes to harmful instructions can bypass LLM defenses, but existing adversarial attack methods are inefficient, requiring over 100,000 model calls and being vulnerable to common defenses like perplexity filters. To address these challenges, this paper introduces the **Adversarial Suffix Embedding Translation Framework (ASETF)**, which converts adversarial suffix embeddings into coherent text. This approach reduces computational overhead, enhances attack success rates, and improves prompt fluency. Experiments on models like Llama2 and Vicuna demonstrate that ASETF efficiently generates adversarial prompts that can transfer attacks to multiple LLMs, including black-box models like ChatGPT and Gemini.

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Figure 6. ASETF Performance numbers.

**Jailbreaking Leading Safety-Aligned LLMs with Simple Adaptive Attacks** (Andriushchenko, 2024). The study reveals that even the latest safety-aligned large language models (LLMs) are vulnerable to adaptive jailbreaking attacks. Researchers use log probability access to optimize adversarial prompts through random search, achieving a 100% success rate in bypassing safety mechanisms across multiple models, including GPT-4o, Llama, Claude, and others. They also develop effective jailbreaks for Claude models without logprob access using transfer and prefilling attacks. Additionally, they apply similar methods to detect trojan strings in poisoned models, securing first place in the SaTML'24 Trojan Detection Competition. The key insight is that adaptivity—tailoring attacks to each model's specific weaknesses—is essential. The study provides code and jailbreak artifacts for reproducibility.

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Figure 7. Jailbreaking Leading Safety-Aligned LLMs with Simple Adaptive Attacks Performance results

**Attacking Large Language Models with Projected Gradient Descent**, (Geisler, 2024). The paper discusses a more efficient method for generating adversarial prompts that bypass LLM alignment mechanisms. Traditional discrete optimization approaches, though highly effective, require over 100,000 LLM calls, making them computationally expensive and impractical for tasks like adversarial training and quantitative analysis. To address this, the authors revisit Projected Gradient Descent (PGD) using a continuous relaxation of the input prompt. While previous gradient-based methods struggled, their refined approach carefully manages relaxation errors, significantly improving effectiveness. Their proposed PGD method is up to ten times faster than state-of-the-art discrete optimization while achieving similar attack success rates.

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Figure 8. PGD Performance results

**Query-Based Adversarial Prompt Generation**, (Hayase, 2024). The paper presents a new query-based adversarial attack on language models, demonstrating its effectiveness in bypassing safety mechanisms. Unlike previous approaches that rely on white-box access (full model visibility) or transferability (applying adversarial examples across models), this method uses API access to iteratively refine adversarial inputs. The authors successfully tested their attack on GPT-3.5 and OpenAI’s safety classifier, achieving near-perfect evasion rates and generating harmful outputs more reliably than transfer-based attacks. Their findings highlight vulnerabilities in current safety measures, emphasizing the need for improved defenses against adversarial manipulation.

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Figure 9. Query-Based Adversarial Prompt Generation Performance results.

**PAL: Proxy-Guided Black-Box Attack on Large Language Models**, (Sitawarin, 2024). This paper introduces the Proxy-Guided Attack on Large Language Models (PAL), an optimization-based attack designed to target LLMs in a black-box, query-only setting. The attack uses a surrogate model to guide the optimization, and a custom loss function tailored for real-world LLM APIs. The PAL attack achieves high success rates: 84% on GPT-3.5-Turbo and 48% on Llama-2-7B, significantly outperforming the previous best method, which had a success rate of 4%. The paper also introduces GCG++, an enhanced version of a prior attack, which achieves a 94% success rate on Llama-2-7B in a white-box setting, and the Random-Search Attack on LLMs (RAL), a simpler, strong baseline for query-based attacks. These techniques aim to advance safety testing of LLMs and contribute to the development of better security mechanisms.

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Figure 10. PAL Performance results.

**Adversarial Demonstration Attacks on Large Language Models**, (Wang, 2023). This paper addresses a security vulnerability in large language models (LLMs), specifically in-context learning (ICL), which uses data-label pairs as prompts to perform tasks. While demonstrations can improve performance, they may also be exploited by attackers who manipulate only the demonstrations, without altering the input, to mislead the model. The paper proposes a new attack method called **advICL**, which manipulates the demonstration to deceive the model. The study finds that as the number of demonstrations increases, the model's robustness decreases. Furthermore, demonstrations can be reused with different inputs, presenting a more practical threat where attackers can manipulate test examples without prior knowledge of them. The paper introduces **Transferable-advICL**, a version of the attack that can target unseen test examples. The findings highlight the security risks of ICL and emphasize the need for further research to improve its robustness, especially as LLMs become more advanced.

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Figure 11. Transferable-advICL Performance results

**PRP: Propagating Universal Perturbations to Attack Large Language Model Guard-Rails**, (Mangaokar, 2024). This paper discusses vulnerabilities in large language models (LLMs) that are designed to be harmless to humans but can still be manipulated through "jailbreak attacks" to generate harmful content. To address this, newer models use a "Guard Model," an additional LLM designed to moderate the output of the primary model. The paper introduces a new attack method called PRP, which is effective against both open-source (e.g., Llama 2) and closed-source (e.g., GPT 3.5) Guard Models. PRP works by using a two-step prefix-based strategy: first, it creates a universal adversarial prefix for the Guard Model, then it propagates this prefix to the primary model's response. The method proves successful even when the attacker has no direct access to the Guard Model. The authors conclude that further improvements in defenses and Guard Models are needed for these systems to be truly effective.

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Figure 12. PRP ASR Performance results

#### Logits-Based

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Figure 13. Logits-based attack, (Yi, 2024)

**Make Them Spill the Beans! Coercive Knowledge Extraction from (Production) LLMs**, (Zhang, 2023). The paper highlights a new vulnerability in Large Language Models (LLMs) that allows bad actors to extract harmful content, even when the model is aligned with ethical guidelines. Unlike traditional jail-breaking methods that rely on carefully crafted prompts, this approach “termed **model interrogation**”exploits access to the model’s output logits, a feature common in open-source models and some commercial APIs. By selectively choosing lower-ranked output tokens at key positions during text generation, attackers can uncover hidden toxic responses. This method is significantly more effective (92% vs. 62% for jailbreaking), faster (10–20 times), and produces more relevant, complete, and clear harmful content. Additionally, it can be combined with jail-breaking techniques to enhance attack success. The study underscores the need for stronger safeguards, as even models designed for coding tasks can be exploited using this method.

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Figure 14. Intervention point identification “Magic” Performance results.

**COLD-Attack: Jailbreaking LLMs with Stealthiness and Controllability**, (Guo, 2024). This paper explores controllable jailbreak attacks on large language models (LLMs), aiming to manipulate their outputs while maintaining specific constraints such as fluency, stealthiness, sentiment, and ideological bias. The authors establish a link between controllable attack generation and controllable text generation, adapting the Energy-based Constrained Decoding with Langevin Dynamics (COLD) method to create the **COLD-Attack** framework. This framework automates and diversifies jailbreak attack generation by enforcing various constraints, enabling attacks such as adversarial query rewriting and stealthy prompt insertion. Extensive experiments on multiple LLMs (e.g., Llama-2, GPT-4) demonstrate COLD-Attack's effectiveness, versatility, and transferability across models.

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Figure 15. COLD-Attack Performance results

**Analyzing the Inherent Response Tendency of LLMs: Real-World Instructions-Driven Jailbreak**, (Du, 2023). This paper introduces **RADIAL**, a novel automatic jailbreak method that exploits the tendency of Large Language Models (LLMs) to generate affirmative responses. The approach is based on **Inherent Response Tendency Analysis**, which identifies real-world instructions that naturally prompt affirmative answers from LLMs. Using this insight, **Real-World Instructions-Driven Jailbreak** is implemented by strategically embedding these instructions around malicious prompts, effectively bypassing safety mechanisms. RADIAL demonstrates strong attack performance across five advanced open-source LLMs, particularly for English prompts, while also showing effectiveness in cross-language attacks on Chinese instructions. Experimental results validate both the efficacy of the jailbreak method and the reasoning behind its design. By crafting semantically coherent attack prompts, the study highlights potential security risks in LLMs and offers valuable insights to enhance their safety.

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Figure 16. RADIAL Performance results

**Weak-to-Strong Jailbreaking on Large Language Models**, (Zhao, 2024). The paper discusses a new, efficient method for jailbreaking large language models (LLMs) called the **weak-to-strong attack**. Traditional jailbreak attacks, which force LLMs to generate harmful, unethical, or biased text, are typically computationally expensive. The proposed method leverages the observation that aligned (safe) and jailbroken (unsafe) models mainly differ in their initial decoding distributions. The **weak-to-strong attack** works by using two smaller models “one safe and one unsafe” to adversarially manipulate a much larger safe model’s decoding probabilities, effectively making it generate harmful text with minimal computational effort. The method was tested on five different LLMs from three organizations, achieving over **99% misalignment** on two datasets with just **one forward pass per example**. The study highlights a **serious safety risk** in LLM alignment and suggests an initial defense strategy, though it acknowledges that developing robust defenses remains a major challenge. The paper also provides a link to the code for reproducing the attack.

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Figure 17. Weak to Strong Performance results

**Catastrophic Jailbreak of Open-source LLMs via Exploiting Generation**, (Huang, 2023). The paper examines the vulnerabilities of open-source large language models (LLMs) to manipulation despite prior alignment efforts to ensure their helpfulness and harmlessness. It introduces a novel attack method called generation exploitation attack, which bypasses alignment by simply adjusting decoding methods and hyperparameters. This approach significantly increases model misalignment, achieving a misalignment rate of over 95% across multiple LLMs, such as LLaMA2, Vicuna, Falcon, and MPT, while being 30 times more computationally efficient than previous attacks. The study also proposes a mitigation strategy that enhances alignment by considering diverse generation strategies. Ultimately, the findings highlight critical weaknesses in current safety evaluations, emphasizing the need for more robust red teaming and alignment techniques before releasing open-source LLMs.

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Figure 18. EXPLOITING GENERATION Performance results

**Don't Say No: Jailbreaking LLM by Suppressing Refusal**, (Zhou, 2024). The paper addresses the vulnerability of Large Language Models (LLMs) to jailbreak attacks, where adversarial prompts bypassing safety mechanisms to elicit harmful responses. A specific type of attack involves optimizing LLM outputs toward affirmative responses, but this method has limitations due to its predefined constraints on objectionable behaviors. The authors introduced the DSN (Don't Say No) attack, which enhances the attack strategy by suppressing refusals, leading to more effective jailbreak attempts. Another challenge in studying these attacks is evaluating their success and harmfulness. Current evaluation methods, such as refusal keyword matching, often produce false positives and negatives. To improve assessment accuracy, the authors propose an Ensemble Evaluation pipeline, integrating Natural Language Inference (NLI) contradiction assessment and two external LLM evaluators. Experimental results validate the effectiveness of the DSN attack and demonstrate the superiority of the Ensemble Evaluation approach over baseline evaluation methods.

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Figure 19. DSN Performance results

#### Fine-Tuning-Based

A screenshot of a chatbot

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Figure 20. Fine-Tuning-based attack

**Fine-tuning Aligned Language Models Compromises Safety, Even When Users Do Not Intend To!**, (Qi, 2023). The paper examines the safety risks associated with fine-tuning large language models (LLMs) for customized downstream applications. While pre-trained LLMs come with built-in safety measures, the ability for end-users to fine-tune these models “such as OpenAI's fine-tuning of GPT-3.5 Turbo and Meta’s Llama models” poses new vulnerabilities. The research demonstrates that safety alignment can be compromised with minimal effort, showing that fine-tuning GPT-3.5 Turbo with just 10 adversarial training examples (at a cost of less than $0.20) effectively removes safety guardrails, making the model responsive to harmful prompts. Alarmingly, even benign fine-tuning using common datasets can degrade safety alignment, though to a lesser extent. The findings highlight a significant gap in current safety infrastructures, as an initially well-aligned model may lose its safeguards after customization. The paper critically assesses potential mitigations and calls for further research into strengthening safety protocols for fine-tuning aligned LLMs.

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Figure 21. Fine-tuning GPT-3.5 Turbo by mixing different numbers of safety samples

**Shadow Alignment: The Ease of Subverting Safely-Aligned Language Models**, (Yang, 2023). The paper introduces **Shadow Alignment**, a novel attack that can subvert safely aligned large language models (LLMs) with minimal effort. Despite extensive safety measures to prevent misuse, the study finds that tuning a model with just **100 malicious examples in one GPU hour** is enough to bypass safety constraints while preserving the model’s helpfulness in benign tasks. This attack is tested across **eight models from five different organizations** (e.g., LLaMa-2, Falcon, Vicuna), proving its effectiveness. Additionally, the attack transfers from **single-turn English prompts to multi-turn dialogues and other languages**, making it highly adaptable. The findings highlight an urgent need to **strengthen open-source LLM security** against such vulnerabilities.

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Figure 22. Shadow Alignment – Harmful Finetuned Performance results

**LoRA Fine-tuning Efficiently Undoes Safety Training in Llama 2-Chat 70B**, (Lermen, 2023). The paper investigates the robustness of safety training in large language models by subversively fine-tuning Meta's Llama 2-Chat models. Using quantized low-rank adaptation (LoRA) as a cost-efficient fine-tuning method, the researchers were able to bypass the safety mechanisms of Llama 2-Chat models (7B, 13B, and 70B) and the Mixtral instruct model with a budget of under $200 and a single GPU. Their method significantly reduced the models’ refusal rates to harmful instructions, achieving about 1% refusal on benchmarks while maintaining general performance. The study highlights the risks associated with fine-tuning, emphasizing the need for risk assessments when releasing model weights, particularly as future AI models become more powerful and potentially dangerous.

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Figure 23. LoRA Performance results

**Removing RLHF Protections in GPT-4 via Fine-Tuning**, (Zhan, 2023). This paper examines how fine-tuning can override Reinforcement Learning with Human Feedback (RLHF) protections in large language models (LLMs). While RLHF is used to mitigate harmful outputs, the study finds that fine-tuning can effectively remove these safeguards even in powerful models like GPT-4. With as few as 340 training examples, attackers achieve a 95% success rate in bypassing RLHF protections. These examples can be generated using weaker models, demonstrating that the approach does not compromise overall model usefulness. The findings highlight the urgent need for stronger safeguards in LLMs to prevent misuse through fine-tuning.

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Figure 24. 340 Harmful content finetuning Performance results

### Black-Box Attack

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Figure 25. Template Completion – Nesting query

A screenshot of a chat

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Figure 26. Template Completion – Context based query

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Figure 27. Template Completion – Code Injection

A screenshot of a chat

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Figure 28. Prompt rewriting attack – Cipher

A screenshot of a chat

AI-generated content may be incorrect.

Figure 29. Prompt rewriting – Low resource Language

A screenshot of a chat

AI-generated content may be incorrect.

Figure 30. Prompt rewriting – Genetic Algorithm

## Jailbreak Defense Methods

A diagram of a jailbreak defense method

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Figure 31. Taxonomy of jailbreak defense.

### Model Level Defense: SFT-based

**Safety-Tuned LLaMAs: Lessons From Improving the Safety of Large Language Models that Follow Instructions**, (Bianchi, 2023). This paper examines the safety risks of instruction-tuned large language models (LLMs) that prioritize helpfulness without considering harmfulness. The authors demonstrate that several widely used instruction-tuned models are highly unsafe, as they follow malicious prompts without restriction. However, they find that incorporating just 3% safety-related examples during fine-tuning can significantly improve model safety without notably reducing their overall capability or helpfulness. Despite these improvements, excessive safety-tuning can lead to over-cautious behavior, where models refuse harmless prompts that resemble unsafe ones. The study highlights the trade-offs between optimizing LLMs for helpfulness versus ensuring their safety.

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Figure 32. The mean harmfulness score for each dataset (with standard errors on bars). Lower scores indicate less harmful (safer) responses

**Attack Prompt Generation for Red Teaming and Defending Large Language Models**, (Deng, 2023). This paper explores vulnerabilities in large language models (LLMs) to red teaming attacks, which manipulate them into generating harmful content. Traditional attack methods “manual and automatic” have limitations in cost and quality. To overcome these challenges, the authors propose a hybrid approach that leverages both manual and automatic techniques. Their attack framework uses in-context learning to train LLMs to generate high-quality attack prompts that mimic human-generated ones. Additionally, they introduce a defense framework that iteratively fine-tunes victim LLMs by exposing them to these attacks, improving their resistance. Experiments confirm the effectiveness of both frameworks, and the authors release the SAP dataset, a collection of attack prompts, to aid in LLM safety evaluation and enhancement.

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Figure 33. Fine-tuned models evaluated with SAP dataset

**Red-Teaming Large Language Models using Chain of Utterances for Safety-Alignment**, (Bhardwaj, 2023). This paper addresses the safety concerns of Large Language Models (LLMs), which, despite their impressive capabilities, remain vulnerable to harmful outputs. To evaluate these risks, the authors introduce **RED-EVAL**, a new safety benchmark based on red-teaming techniques. Their findings show that even widely used LLMs, including closed-source models like GPT-4 and ChatGPT, can be **jailbroken** using **Chain of Utterances-based (CoU) prompting**, leading them to respond unethically to 65%-73% of harmful queries. Furthermore, across eight open-source LLMs, RED-EVAL led to harmful responses in over 86% of cases.

To improve LLM safety, the authors propose **RED-INSTRUCT**, a two-phase approach for **safety alignment**:

1. **HARMFULQA Data Collection** – Using CoU prompting, they compile a dataset of **1.9K harmful questions**, **9.5K safe**, and **7.3K harmful conversations** from ChatGPT.
2. **SAFE-ALIGN** – They train models to favor helpful responses while penalizing harmful ones through gradient-based loss adjustments.

Their model, **STARLING (a fine-tuned Vicuna-7B)**, shows improved safety alignment when tested on **RED-EVAL and HHH benchmarks**, while maintaining strong performance on utility benchmarks like **TruthfulQA, MMLU, and BBH**.

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Figure 34. RED-EVAL results with and without internal thoughts

# Approach

The LLMs bring a new set of security risks that was impossible to have years before, as extorsion, fake conversation and messages in text, voice and video. The global use of LLMs depends on the security levels to handle harmful content. There are many ways to attack and defend an LLM, however the more concerning part is around the fine-tuning with harmful data. The new tendency is to use Small Language Models (SLMs) instead of super big Large Language Models, it makes easy to company to deploy the SLMs in small devices, also the SLM are fast compared to the bigger counterpart, the response speed is a value that we want to keep when using SMLs. However, this SML requires a fine-tune with a supervised LLM teacher/Judge to prepare the training dataset. With very few cases of harmful content in the training dataset is enough to disable the internal safety-aligned protocol, indeed Zhan et al. (Zhan 2023) demonstrate that fine-tuning an aligned model with as few as 340 adversarial examples can effectively dismantle the protections offered by Reinforcement Learning with Human Feedback (RLHF). There are several research exploring Fine-tuning solutions with good rejection of harmful content without compromising the response speed. However, this excessive safety data may break the balance and induce the model to be over-sensitive to some safe prompts, adding a high volume of false positive and damaging the performance of the model in the intended task. The proposed solution on this thesis is to create a framework of how a SLM should be trained/fine-tune with the goal of keeping the high response speed, security standards and high performance on the intended task. This framework will consist of a multi-step Chain-of-Thoughts Judge to enhance the model to be safely aligned and keep a good performance as high as the traditional LLMs.

## Proposed Strategy.

## Proposed Algorithm.

## PoC (DeepSeek R1 1.5B)

# Resources

To support this research, the following resources will be utilized:

1. **LLM and SLM Models**: Access to various open-source and proprietary language models such as Llama-2, Mixtral, GPT-4, and Vicuna-7B for experimentation.
2. **Computational Infrastructure**: High-performance GPUs and cloud computing services for fine-tuning and testing model security.
3. **Datasets**: Publicly available datasets, including Alpaca, red teaming datasets, and adversarial prompt corpora, to simulate fine-tuning attacks and evaluate defense mechanisms.
4. **Existing Research and Literature**: Previous studies on adversarial attacks, safety alignment techniques, and CoT methodologies to inform the framework design.
5. **Evaluation Benchmarks**: Standard safety and performance benchmarks to measure the effectiveness of the proposed framework.

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