Operationalizing a Threat Model for Red-Teaming Large Language Models (LLMs)

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Abstract

Creating secure and resilient applications with large language models (LLM) requires anticipating, adjusting to, and countering unforeseen threats. Red-teaming has emerged as a critical technique for identifying vulnerabilities in real-world LLM implementations. This paper presents a detailed threat model and provides a systematization of knowledge (SoK) of red-teaming attacks on LLMs. We develop a taxonomy of attacks based on the stages of the LLM development and deployment process and extract various insights from previous research. In addition, we compile methods for defense and practical red-teaming strategies for practitioners. By delineating prominent attack motifs and shedding light on various entry points, this paper provides a framework for improving the security and robustness of LLM-based systems.

1 Introduction

> *Red Teaming is the process of using tactics, techniques, and processes (TTP) to emulate a real-world threat with the goal of training and measuring the effectiveness of people, processes, and technology used to defend an environment.*
>
> Vest & Tubberville (2020)

The practice of "red-teaming" originated during the 1960s in United States (US) military Cold War simulations to anticipate threats from Soviet Union (Averch & Lavin, 1964; Red Team). In a red-teaming exercise, the "red team" plays the role of an adversary and attempts to compromise a system, while a blue team plays the role of a defender and is responsible for fixing the security gaps in the system. The purpose of red-teaming is to adopt an adversarial mindset to identify weaknesses and security vulnerabilities in a system. Over time, red-teaming expanded beyond military operations to domains such as cybersecurity (Duggan & Wood, 1999), airport security (Price, 2004), and more recently to AI and machine learning (ML), and specifically to large language models (LLMs) (OpenAI, 2023) and generative AI.

Paradoxically, LLMs are predictable and unpredictable. On the one hand, these models are highly predictable because the lower model loss of a better LLM means that it performs better in predicting the next words. On the other hand, they are also highly unpredictable, as the universality of being adept at predicting the next words makes it impossible to anticipate the specific capabilities and outputs of the LLM a priori before fine-tuning it on the downstream task Wei et al. (2022); Ganguli et al. (2022a). This unpredictability poses a challenge in understanding the consequences of deploying LLMs in real-world scenarios. For example, LLMs can hallucinate (Verma & Oremus, 2023; Dale et al., 2023), reveal personally identifiable information (PII) (Carlini et al., 2020a), be used to generate misinformation (Hazell, 2023; Krishna et al., 2024), generate biased (Santurkar et al., 2023; Hartmann et al., 2023; Ghosh & Caliskan, 2023; Sabbaghi et al., 2023), unsettling (Kevin, 2023a;b), sycophantic (Perez et al., 2023), toxic (Perez et al., 2022; Shen et al., 2023c), harmful (Weidinger et al., 2021) and insecure (Majdinasab et al., 2023) content in response to benign or malicious prompts. A lack of transparency surrounding the development of these models further exacerbates these issues (Widder et al., 2023; Zhang et al., 2024b; Casper et al., 2024b).

Red-teaming has emerged as an essential tool for assessing the safety of LLMs and minimizing the risks associated with their deployment in human-facing products. To this end, industry and academia have developed and published approaches in red teaming in ML (Pearce & Lucas, 2023; Fabian, 2023; Siva Kumar, 2023b; Meta, 2023; Ji, 2023). Competitions such as `DEFCON` (Cattell et al., 2023) and the `RLHF Trojan Competition` (Rando & Tramèr, 2024a;b), along with games such as `Hacc-man` (Valentim et al., 2024) and `Tensor Trust` (Toyer et al., 2024), as well as recently published regulations (Bletchley Declaration, 2023) and U.S. Executive Orders (The White House, 2023) have led to widespread awareness of this topic and shed light on red-teaming strategies.

Through this paper, our objective is to systematize knowledge about the current state of LLM red-teaming, allowing researchers and practitioners to navigate the complexities of developing **H**elpful, **H**armless, and **H**onest LLM-based applications (**H^{3}LLM**) (Askell et al., 2021). Drawing on previous research efforts, we develop a taxonomy of red-teaming attacks to summarize various aspects of this emerging field (see Figure 1). Our main contributions are as follows.

1. We introduce a threat model based on entry points in the LLM development and deployment lifecycle to allow reasoning about various kinds of attack and associated defenses.
2. We provide a taxonomy of attacks based on our proposed threat model, followed by a brief discussion of common defense methodologies.
3. Finally, we systematize various insights derived from previous published works to tease out the desirable properties needed to conduct effective red-teaming exercises and ensure robust defense strategies.

Paper Outline: In Section § 2, we provide an overview of LLM training and inference phases and define harmful behaviors. We then draw a distinction between red-teaming and traditional evaluations of trustworthiness and bias. In Section § 3 we describe the threat model and the fundamental principle that we use to structure various attacks in a taxonomy. In Section § 4, we summarize various attack methods followed by briefly addressing defenses in Section § 5. We provide a discussion of the insights gathered from previous work in Section § 6. And finally, we conclude our study by distilling the current state of red-teaming to identify several promising future research avenues in Section § 7.

2 Background: LLMs, Harms, and the Red-Teaming Paradigm

In this section, we provide details on the LLM life cycle from training to deployment. We define harmful behavior and draw a distinction between red-teaming and traditional fairness evaluations. Finally, we highlight the advantage of systematizing attacks based on the proposed threat model compared to previous surveys.

2.1 LLM Development Phases

Pre-training: In this initial stage, LLMs learn from a large dataset, acquiring basic language understanding and context Biderman et al. (2023); Brown et al. (2020b).

Supervised Fine-Tuning (SFT) / Instruction Tuning (IT): After pre-training, models are fine-tuned with specific datasets to adapt to particular tasks or domains. Fundamentally, SFT helps LLMs understand the semantic meaning of prompts and produce relevant responses Ouyang et al. (2022b); Lou et al. (2023).

Reinforcement Learning from Human Feedback (RLHF): This phase involves the refinement of the model responses based on human feedback, focusing on aligning the outputs with human values and expectations (Rafailov et al., 2023; Ouyang et al., 2022a; Rafailov et al., 2023; Bai et al., 2022; Korbak et al., 2023). For brevity, we omit an extended discussion of alignment but refer to Shen et al. (2023b) and Wang et al. (2023e) for a comprehensive overview.

Deployment: Finally, a trained LLM can be deeply integrated in consumer technology applications like chatbots, email, code review, news summarization, and legal document analysis, among other uses with unmediated access to surrounding components (Yang et al., 2023a).

2.2 Defining Harmful Behavior

Defining harmful behavior for a red-teaming exercise requires a nuanced understanding of "harm." Acceptable use policies of OpenAI, Anthropic, Inflection AI, Perplexity AI, among others, can serve as a good starting point for defining harmful behavior (Usage Policy OpenAI, 2023; Usage Policy Anthropic, 2023). Following the NIST Common Vulnerabilities and Exposures (CVE) guidelines (NIST CVE, 2022), the Avid Taxonomy Matrix (Avid Taxonomy Matrix, 2023) provides a holistic taxonomy of risk categories and failure modes associated with an ML system. In addition to conventional security vulnerabilities, the Open Web Application Security Project (OWASP) has also published top 10 risks for GenAI applications (OWASP, 2025).

Study	Description
(Inan et al., 2023)	Llama Guard Taxonomy
(Wang et al., 2023a)	Decoding Trust Taxonomy
(OpenAI, 2024b)	OpenAI Moderation Endpoint Categories
(Vidgen et al., 2024)	AI Safety Benchmark Hazard Categories
(Tedeschi et al., 2024)	ALERT Risk Taxonomy
(Perspective API, 2024)	Perspective API Toxicity Attributes
(Avid Taxonomy Matrix, 2023)	Avid Taxonomy Matrix
(Ghosh et al., 2024)	AEGIS Risk Taxonomy
(Zeng et al., 2024a)	AI Risk Categorization

Table 1: Sample risk taxonomies that can guide practitioners in developing domain-specific or application-specific risk taxonomies

Table 1 illustrates examples of several risk taxonomies. Some common risk categories in these taxonomies are Sexual Content, Violence & Hate, etc. Feffer et al. (2024) categorize these risk categories into two broad buckets - dissentive risks and consentive risks. Dissentive risks comprise risk categories whose definitions are not widely agreed upon (for example, some people might find the response to "how to build a bomb?" admissible), while consentive risks are risks whose definition is widely agreed upon and no additional context is needed (for example, data and private information leakage, phishing attacks are inadmissible in any context) (Feffer et al., 2024). Depending on the particular domain, practitioners may need to expand these risk taxonomies to include domain-specific risk categories. (e.g., investment advice abstention for financial domain, citation on point for legal domain, etc. (Tshimula et al., 2024)) Furthermore, certain behaviors could be of *dual intent* (Mazeika et al., 2024; Stapleton et al., 2023). For example, writing encryption functions could be performed by cyber-security developers or by malicious hackers. Similarly, in some cases, it may be important to focus on the *differential harm* caused by an LLM over online searchability to quantify the additional harm introduced for the given input (Mazeika et al., 2024). It is worth noting that harmful behavior can arise without malicious intent (e.g., hallucinations).

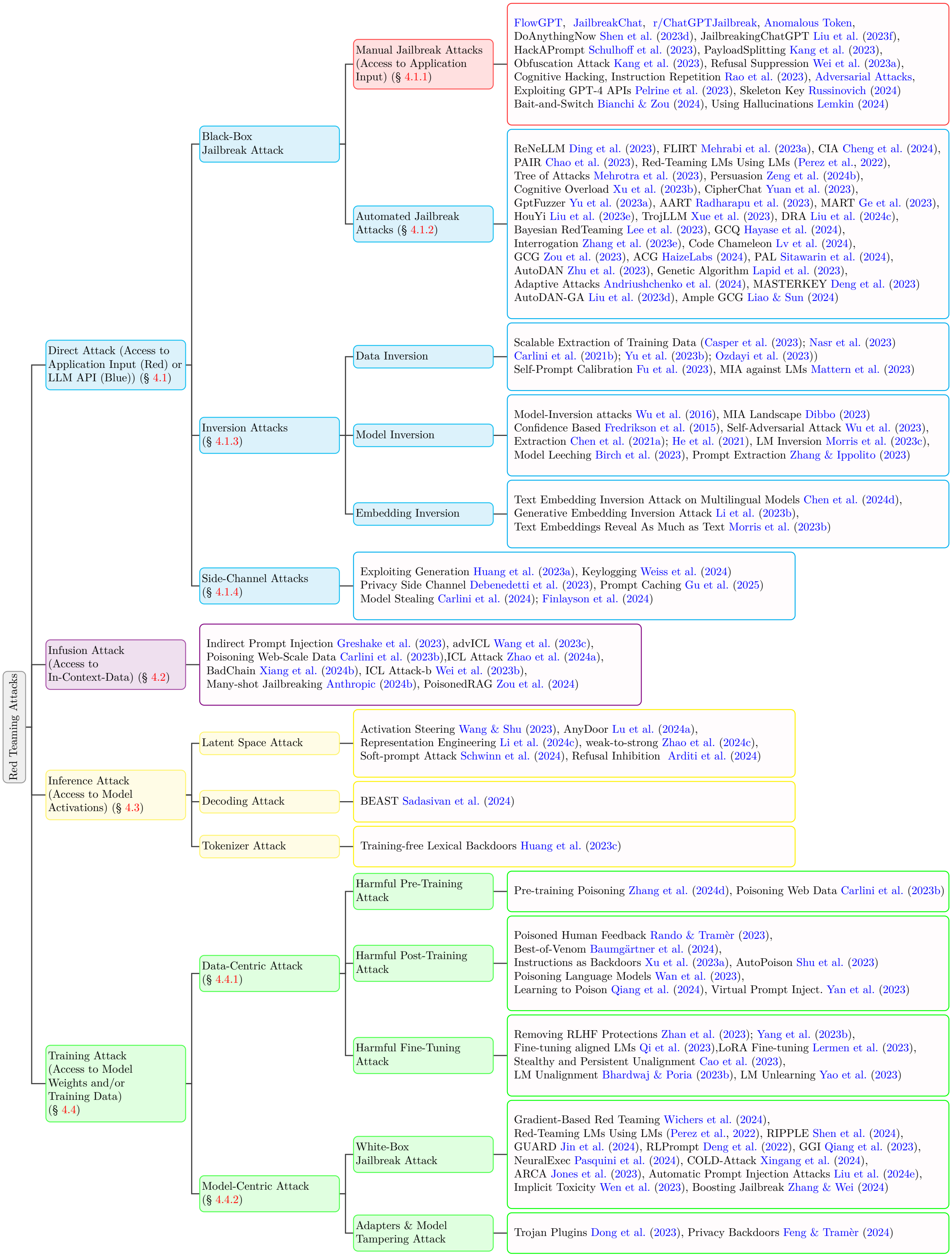
Red Teaming Attacks
Direct Attack (Access to Application Input (Red) or LLM API (Blue)) (§ 4.1)
Black-Box Jailbreak Attack
Manual Jailbreak Attacks (Access to Application Input) (§ 4.1.1)
FlowGPT, JailbreakChat, r/ChatGPTJailbreak, Anomalous Token,
DoAnythingNow Shen et al. (2023d), JailbreakingChatGPT Liu et al. (2023f),
HackAPrompt Schulhoff et al. (2023), PayloadSplitting Kang et al. (2023),
Obfuscation Attack Kang et al. (2023), Refusal Suppression Wei et al. (2023a),
Cognitive Hacking, Instruction Repetition Rao et al. (2023), Adversarial Attacks,
Exploiting GPT-4 APIs Pelrine et al. (2023), Skeleton Key Russinovich (2024)
Bait-and-Switch Bianchi & Zou (2024), Using Hallucinations Lemkin (2024)
Automated Jailbreak Attacks (§ 4.1.2)
ReNeLLM Ding et al. (2023), FLIRT Mehrabi et al. (2023a), CIA Cheng et al. (2024),
PAIR Chao et al. (2023), Red-Teaming LMs Using LMs (Perez et al., 2022),
Tree of Attacks Mehrotra et al. (2023), Persuasion Zeng et al. (2024b),
Cognitive Overload Xu et al. (2023b), CipherChat Yuan et al. (2023),
GptFuzzer Yu et al. (2023a), AART Radharapu et al. (2023), MART Ge et al. (2023),
HouYi Liu et al. (2023e), TrojLLM Xue et al. (2023), DRA Liu et al. (2024c),
Bayesian RedTeaming Lee et al. (2023), GCQ Hayase et al. (2024),
Interrogation Zhang et al. (2023e), Code Chameleon Lv et al. (2024),
GCG Zou et al. (2023), ACG HaizeLabs (2024), PAL Sitawarin et al. (2024),
AutoDAN Zhu et al. (2023), Genetic Algorithm Lapid et al. (2023),
Adaptive Attacks Andriushchenko et al. (2024), MASTERKEY Deng et al. (2023)
AutoDAN-GA Liu et al. (2023d), Ample GCG Liao & Sun (2024)
Inversion Attacks (§ 4.1.3)
Data Inversion
Scalable Extraction of Training Data (Casper et al. (2023); Nasr et al. (2023)
Carlini et al. (2021b); Yu et al. (2023b); Ozdayi et al. (2023))
Self-Prompt Calibration Fu et al. (2023), MIA against LMs Mattern et al. (2023)
Model Inversion
Model-Inversion attacks Wu et al. (2016), MIA Landscape Dibbo (2023)
Confidence Based Fredrikson et al. (2015), Self-Adversarial Attack Wu et al. (2023),
Extraction Chen et al. (2021a); He et al. (2021), LM Inversion Morris et al. (2023c),
Model Leeching Birch et al. (2023), Prompt Extraction Zhang & Ippolito (2023)
Embedding Inversion
Text Embedding Inversion Attack on Multilingual Models Chen et al. (2024d),
Generative Embedding Inversion Attack Li et al. (2023b),
Text Embeddings Reveal As Much as Text Morris et al. (2023b)
Side-Channel Attacks (§ 4.1.4)
Exploiting Generation Huang et al. (2023a), Keylogging Weiss et al. (2024)
Privacy Side Channel Debenedetti et al. (2023), Prompt Caching Gu et al. (2025)
Model Stealing Carlini et al. (2024); Finlayson et al. (2024)
Infusion Attack (Access to In-Context-Data) (§ 4.2)
Indirect Prompt Injection Greshake et al. (2023), advICL Wang et al. (2023c),
Poisoning Web-Scale Data Carlini et al. (2023b),ICL Attack Zhao et al. (2024a),
BadChain Xiang et al. (2024b), ICL Attack-b Wei et al. (2023b),
Many-shot Jailbreaking Anthropic (2024b), PoisonedRAG Zou et al. (2024)
Inference Attack (Access to Model Activations) (§ 4.3)
Latent Space Attack
Activation Steering Wang & Shu (2023), AnyDoor Lu et al. (2024a),
Representation Engineering Li et al. (2024c), weak-to-strong Zhao et al. (2024c),
Soft-prompt Attack Schwinn et al. (2024), Refusal Inhibition Arditi et al. (2024)
Decoding Attack
BEAST Sadasivan et al. (2024)
Tokenizer Attack
Training-free Lexical Backdoors Huang et al. (2023c)
Training Attack (Access to Model Weights and/or Training Data) (§ 4.4)
Data-Centric Attack (§ 4.4.1)
Harmful Pre-Training Attack
Pre-training Poisoning Zhang et al. (2024d), Poisoning Web Data Carlini et al. (2023b)
Harmful Post-Training Attack
Poisoned Human Feedback Rando & Tramèr (2023),
Best-of-Venom Baumgärtner et al. (2024),
Instructions as Backdoors Xu et al. (2023a), AutoPoison Shu et al. (2023)
Poisoning Language Models Wan et al. (2023),
Learning to Poison Qiang et al. (2024), Virtual Prompt Inject. Yan et al. (2023)
Harmful Fine-Tuning Attack
Removing RLHF Protections Zhan et al. (2023); Yang et al. (2023b),
Fine-tuning aligned LMs Qi et al. (2023),LoRA Fine-tuning Lermen et al. (2023),
Stealthy and Persistent Unalignment Cao et al. (2023),
LM Unalignment Bhardwaj & Poria (2023b), LM Unlearning Yao et al. (2023)
Model-Centric Attack (§ 4.4.2)
White-Box Jailbreak Attack
Gradient-Based Red Teaming Wichers et al. (2024),
Red-Teaming LMs Using LMs (Perez et al., 2022), RIPPLE Shen et al. (2024),
GUARD Jin et al. (2024), RLPrompt Deng et al. (2022), GGI Qiang et al. (2023),
NeuralExec Pasquini et al. (2024), COLD-Attack Xingang et al. (2024),
ARCA Jones et al. (2023), Automatic Prompt Injection Attacks Liu et al. (2024e),
Implicit Toxicity Wen et al. (2023), Boosting Jailbreak Zhang & Wei (2024)
Adapters & Model Tampering Attack
Trojan Plugins Dong et al. (2023), Privacy Backdoors Feng & Tramèr (2024)

Figure 1: Taxonomy of LLM red-teaming attacks, ranging from prompt-based to training-level attacks based on required access levels.

Additionally, emerging threats and harms, such as the use of LLMs for targeted influence operations (Goldstein et al., 2023), require more attention and input from subject matter experts to properly define the harm. Previous work emphasizes the need to clearly define the risks and behaviors to uncover before starting red-teaming (Casper et al., 2023; Feffer et al., 2024).

Context-Dependent Nature of Harm. The concept of harm in LLM outputs is highly context-dependent. Creative hallucinations, for example, might be beneficial for a writer seeking inspiration, but could be detrimental in scenarios requiring factual accuracy, such as legal advice or medical information Tamkin et al. (2021). The working definition of harm will vary depending on the specific domain (e.g., laws, rules, and social norms) in which it is used.

Scope of Harmful Behavior. This paper narrows its focus to the types of harmful behavior that are particularly relevant for LLM applications. Ferrara (2023); Greshake et al. (2023) provide an overview of the nefarious uses of LLMs. For a broader discussion that encompasses bias, fairness, legal and regulatory considerations, the reader is directed to the foundational literature in the field that describes specific definitions and frameworks for understanding and reducing harm in ML systems Ding et al. (2021); Casper et al. (2024a).

2.3 Safety vs Security Objectives

Safety and security represent distinct objectives in LLM risk management (Qi et al., 2024a). Safety focuses on preventing harm that LLMs might inflict upon their environment - for example, generating toxic content or providing harmful advice accidentally. Security focuses on protecting LLMs against malicious exploitation - such as preventing jailbreaking attacks or unauthorized access to training data.

These objectives entail different threat models. Safety primarily addresses non-adversarial scenarios like unintended model behaviors and inherent flaws. Security explicitly considers adversarial scenarios where malicious actors attempt to compromise the system. For example, hallucination is primarily a safety concern when occurring naturally but becomes a security issue when adversaries deliberately induce it through attacks.

In this paper, we adopt a security-focused perspective by considering an adversarial threat model where bad actors actively attempt to compromise LLM systems while ML practitioners aim to defend against such attacks. Our threat model systematically analyzes attack surfaces and entry points that adversaries may exploit, from jailbreaking attempts at the application layer to more sophisticated attacks targeting model weights and training processes. This security-oriented approach complements existing safety research while specifically focusing on defending against malicious exploitation.

2.4 Benchmark Evaluation and Red-Teaming Evaluation

Conventional evaluation methods are generally divided into two main categories: (1) Automatic Evaluation and (2) Human Evaluation. Automatic evaluation involves comparing model outputs with ground-truth annotations obtained offline to calculate a metric. It may also include having a more advanced model assess the accuracy of the model's output when ground truth references are unavailable or when the task is too open-ended to be accurately measured by a limited set of references (e.g., text summarization). Human evaluation, on the other hand, uses human judges to assess the accuracy or quality of a model's output. This type of evaluation can also be designed for contrastive assessment, where a human rater chooses their preferred output between two model predictions (e.g., learning reward models in RLHF methods). Evaluation helps answer questions about model capabilities, the effectiveness of the training algorithm, and provides a way to compare different models. Various benchmarks have been proposed to assess the trustworthiness and safety of an LLM (Wang et al., 2023a; Huang et al., 2023b; Sun et al., 2024).

Unlike conventional evaluation and benchmarking practices focused on measuring performance and fairness, red-teaming adopts a proactive approach aimed at uncovering potential vulnerabilities that can lead to catastrophic failure. Inie et al. (2023) define red-teaming as, "A limit-seeking activity, using vanilla attacks, a manual process, team effort, and an alchemist mindset to break, probe, or experiment with LLMs." while Barrett et al. (2024) describes it as, "more intensive and interactive testing by domain experts, providing a deeper understanding of a model's behavior in various scenarios." Using a Software quality assurance (SQA) analogy, evaluation is like running unit and regression tests, while red-teaming is like discovering bugs and writing new test cases for them.

By simulating adversarial attacks, practitioners can better understand and fortify models against misuse in the real world. Robust red-teaming can help facilitate ethical and safe applications in various contexts Nwadike et al. (2020). However, as Feffer et al. (2024) state "red-teaming is not a panacea" and should complement other forms of ML governance and model evaluation (Shevlane et al., 2023).

2.5 Related Work

User Surveys and Interviews: Inie et al. (2023) describe the insights from user interviews to understand the red-teaming mindset and the primary motivations behind participating in such an activity. They state, "The primary motivations for partaking in the activity were curiosity, fun, and concerns (intrinsic), and professional and social (extrinsic)" (Inie et al., 2023). Similarly, Schuett et al. (2023) conducted a survey to collect expert opinion on the role that leading AI laboratories should play in AI safety. They discovered that 98% of the participants concurred that AGI laboratories should evaluate risks prior to deployment, examine hazardous capabilities, perform third-party audits, enforce usage limitations, and engage in red-teaming.

LLM Attack Taxonomies: In previous red-teaming surveys, attacks are primarily organized using two modes. The first group organizes attacks based on the type of risk posed, such as hate speech, misinformation, and privacy leakage. These categories emerge naturally from the risk taxonomy described above (see Section § 2.2). Representative works in this group include Weidinger et al. (2021); Abdali et al. (2024); Greshake et al. (2023); Zhuo et al. (2023); Wang et al. (2023a). This way of organizing is more useful to a policy maker trying to assess the readiness of the model across risk categories than to a practitioner trying to identify specific failure points in model development lifecycle.

The second group of work organizes attacks based on the methodology used for the attack (e.g., automatic, manual, etc.). Representative works here are Inie et al. (2023); Chowdhury et al. (2024); Lin et al. (2024); Schulhoff et al. (2023); Dong et al. (2024b); Geiping et al. (2024); Feffer et al. (2024); ATLAS Matrix (2023); Shayegani et al. (2023). Of these, Schulhoff et al. (2023) and Geiping et al. (2024) are limited to prompt-based attacks and would correspond to the Black-Box Jailbreak Attack category in our taxonomy presented later (see Section § 4.1.1, § 4.1.2), while Dong et al. (2024b) broadly categorizes attacks into Training-Time or Inference-Time Attacks and Chowdhury et al. (2024) organizes attacks by three attack techniques, namely Jailbreaks, Prompt Injection, and Data Poisoning. ATLAS Matrix (2023) outlines 14 attack strategies mainly from the point of view of a security researcher, while Shayegani et al. (2023) classifies attacks according to the input modality. Although helpful, these organization schemes miss the nuances of various types of attacks and lack the description of a corresponding threat model.

To our knowledge Feffer et al. (2024) from the second group is most similar to our work, which categorizes red-teaming attacks into four broad categories: (1) Brute-force (2) Brute-force + AI (3) Algorithmic Search and (4) Targeted Attack. The last category "Targeted Attack" involves "deliberately targeting part of an LLM" (Feffer et al., 2024) and would be similar to what our proposed attack taxonomy aims to achieve.

Going beyond existing surveys, we offer an overview of attacks spanning multiple stages of the model life cycle, ranging from training to deployment, and organize attacks based on the level of access required to execute them. This method aligns more closely with the terminology used by machine learning professionals. Finally, we explore methods to counter these attacks and propose strategies for efficient red-teaming and defense. By organizing attacks around entry points and also linking them back to the threat model, we see a more complete picture of an adversary's capabilities and goals than has been seen in the specific prior literature.

Scope: This study does not cover vulnerabilities related to programming languages and cybersecurity exploits (Siva Kumar, 2023a; Sanseviero, 2024; CISA, 2024; Zhang et al., 2024a). Additionally, covert malware in AI development platforms (Goodin, 2024), watermark evasion attacks (Liu et al., 2023a) and attacks targeting vision-language models are outside the scope of this work (Liang et al., 2024; Yang et al., 2023c; Niu et al., 2024; Gong et al., 2023b).

3 Threat Model

A threat model refers to the potential vulnerabilities or risks for which a model is evaluated and the actions and information that the adversary has at their disposal to conduct an attack. By understanding how users interact with LLMs, how LLMs are trained, tested, and deployed, a clearer picture of the range of possible attacks emerges. In this section, we explore the nuances of user interaction through prompting, the implications of application layers beyond the core model, and the importance of defining and mitigating harmful behavior within diverse contexts.

(1) Interaction through Prompting. Human interaction with LLMs occurs primarily through prompting (i.e.,"question-answering"). Prompts mimic how humans interact in the non-digital world, permitting a wide range of flexible applications.

Some successful applications include chatbots [ChatGPT (OpenAI, 2022) and OpenAssistant (Kopf et al., 2023)], Voice Assistants (Soltan et al., 2022), code generation (Chen et al., 2021b), interactive fiction (Calderwood et al., 2022), news (Zhang et al., 2023a), medical (Tang et al., 2023) and judgement summarization (Deroy et al., 2023). However, prompts provide the flexibility that opens the door to various attacks aimed at eliciting harmful or unintended responses from an LLM. Understanding and mitigating these risks is essential for safe LLM deployment Bommasani et al. (2021).

(2) Application Layers beyond LLMs. The complexity of LLM applications often extends beyond the model itself, incorporating additional components such as retrieval systems, heuristic filters, and error correction mechanisms. LLMs can also be used in multistep planning and reasoning agents (Yao et al., 2022; Wang et al., 2023d; Zaharia et al., 2024; LLM Agents, 2023; Hamilton, 2023; Ziems et al., 2023; Wu et al., 2024c; Dasgupta et al., 2023), to call external tools (Schick et al., 2023; Patil et al., 2023), and collaborate with other agents to complete complex tasks. Due to this complexity, effective red-teaming must encompass the entire end-to-end application to fully assess vulnerabilities and protect against possible misuse (Fang et al., 2024b;a).

(3) Model Internals and Training Data. As described in Section §2, training LLMs involves several steps, from collecting web-scale datasets to preference and instruction tuning. Each of these steps opens a potential entry point for attacks.

3.1 Attack Surface

Understanding the attack surface of a system informs where and how an adversary may attempt to subvert that system. Figure 2 illustrates various entry points corresponding to different attacks in our taxonomy (Figure 1).

Attack methods are grouped according to the level of system access required. Jailbreak attacks require narrow access to just the LLM based application input. Training time attacks require a much wider access including access to training procedure and some subset of instruction tuning or fine-tuning data. In an offline training time attack scenario, an adversary poisons a subset of training data to insert backdoor attack phrases or alter the training algorithm to induce harmful behavior from the model. In the online training time attack scenario, an adversary manipulates model activations or corrupts the tokenizer. Boxes ④ and ⑤ encapsulate these attack vectors. Since these attacks require white-box access to model artifacts and training data, they are more likely to be executed by an insider (e.g., red team ML researcher) or a state-level actor (e.g., intelligence agencies). The human in the loop annotation process, not shown in the figure, is another potential point of vulnerability for poisoning instruction tuning or preference pair datasets.

Box ③ encapsulates attack vectors that arise from models using parametric (stored in model weights) and non-parametric (stored in external systems, e.g., retrieval systems, search indices, web pages, in-context examples, and databases) information to generate their output.

Boxes ② and ① represent black-box access to a model. Box ② encapsulates the LLM API parameters, proxy models, or vector embeddings which could be used to conduct a Direct Attack. The *logit_bias*

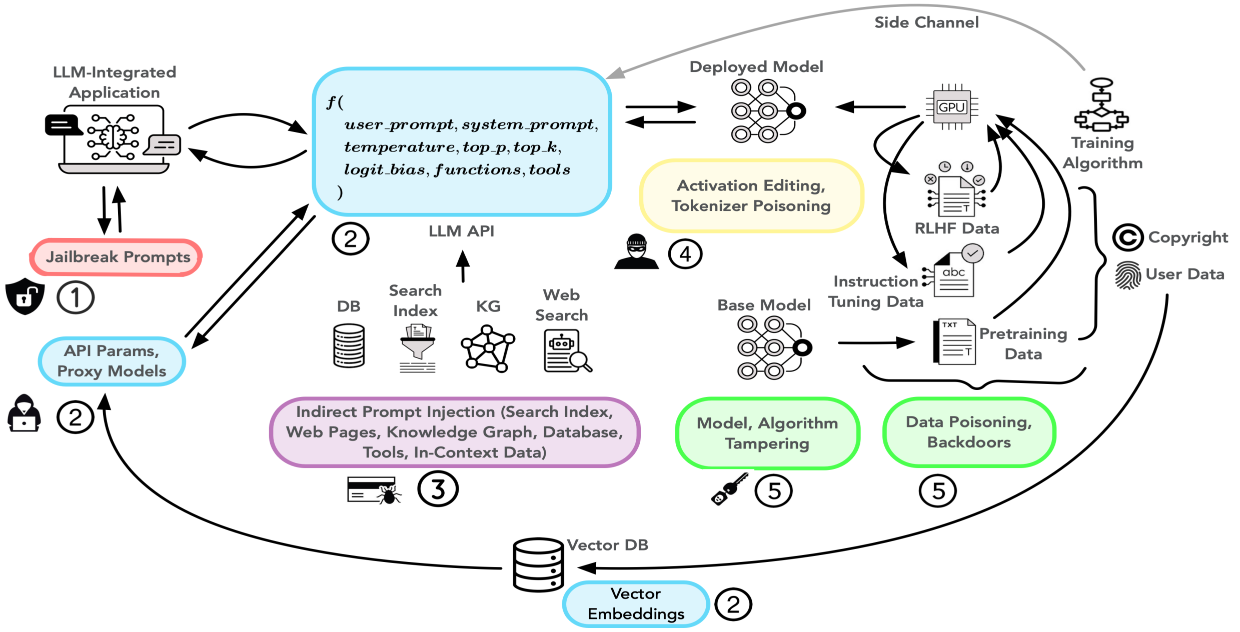
Side Channel
LLM-Integrated Application
f(user_prompt, system_prompt, temperature, top_p, top_k, logit_bias, functions, tools)
Deployed Model
GPU
Training Algorithm
Activation Editing, Tokenizer Poisoning
RLHF Data
Copyright
User Data
Jailbreak Prompts
①
②
LLM API
④
Instruction Tuning Data
abc
Base Model
TXT
Pretraining Data
DB
Search Index
KG
Web Search
API Params, Proxy Models
②
Indirect Prompt Injection (Search Index, Web Pages, Knowledge Graph, Database, Tools, In-Context Data)
③
Model, Algorithm Tampering
⑤
Data Poisoning, Backdoors
⑤
Vector DB
Vector Embeddings
②

Figure 2: Attack vectors corresponding to the various attacks in our proposed taxonomy. Attacks are arranged in increasing order with respect to the level of access required. Attacks on the left side target late entry points in the lifecycle stage, such as application input, whereas attacks on the right side target early entry points such as training data, algorithm, etc. The colored boxes indicate the attack vectors corresponding to each high-level attack type in our taxonomy. Black arrows indicate the flow of information or artifacts, while gray arrows indicate side channels exposed due to the knowledge of common data-preprocessing steps such as data deduplication, etc. Boxes ② and ① represent black-box access to the model. Box ② encapsulates the LLM API params, vector embeddings and proxy models as the attack vectors. Box ③ encapsulates additional retrieval systems, tools, and in-context data as attack vectors. The boxes ④ and ⑤ represent white-box access to the model and encapsulate full or partial access to the model weights, the training algorithm, and the training data

parameter, which can be exploited to reveal token-level probabilities, is particularly notable. Box ① represents the user input in an LLM-integrated application. This corresponds to the Manual Jailbreak Attack in our taxonomy and represents the widest attack surface and can be easily executed by anyone. For instance, an LLM-provider interested in defending against bad press coverage from a hostile journalist is probably most concerned about Manual Jailbreak attacks.

In addition, system-level components, such as training data deduplication and output filtering, expose side channels that can leak information about the training data.

3.2 Adversary Capabilities

An adversary can be internal (member of the red-team, participant in the red-teaming competition), a weak eavesdropper (hobbyist, hacker, user), or a strong state-level adversary, among others. An adversary can inject, modify, or delete training data, or inject prompts into non-parametric knowledge sources, such as databases and search indices. They could also tamper with the learning algorithm or manipulate the activations of the model. Finally, an adversary can exploit the generation parameters, side channels, proxy models, embeddings, or prompts to leak sensitive information, discover harmful prompts, and induce harmful outputs.

An adversary's capabilities vary based on their level of access to the system components shown in Figure 2. Table 3.2 details the specific capabilities available to adversaries in each attack vector. Moving from Box 1 to Box 5, we observe an increasing sophistication in adversary capabilities, from simple prompt crafting to full

Attack Vector	Attack Type	Capabilities
Application Input (Box 1)	Manual Attack	Craft malicious prompts, exploit application context, manipulate system instructions (Non-programmatic access)
LLM API (Box 2)	Direct Attack	Access generation parameters (temperature, top-k, logit-bias, etc.) (Programmatic access), exploit side channels (e.g., data processing or de-duplication filters), extract model probabilities through API parameters
In-Context Data (Box 3)	Infusion Attack	Poison retrieved documents, search-index, web-pages, manipulate in-context examples, compromise external tools and APIs which are invoked by an LLM
Model Internals (Box 4)	Inference Attack	Modify model activations, access embedding space, control decoding strategy, tokenizer tampering
Training Process (Box 5)	Training Attack	Poison training data, modify training algorithm, insert backdoors during model training, access to sufficient computational resources, erode model alignment through fine-tuning, learn adversarial prompts through compute-intensive prompt-search algorithms

Table 2: Adversary Capabilities by Attack Vector

control over the training process. This progression of capabilities also typically correlates with increasing technical expertise and resources required to execute attacks effectively.

3.3 Adversary Goals

Finally, to complete our description of the threat model, we specify the goals of an adversary. For example, a hostile journalist might try to induce hallucinations or obtain factually inaccurate statements from a language model, while a malicious state-level actor could try to poison datasets at web scale or extract the parameters of black-box models to create rival services. A hacker could also attempt to insert phishing messages into the responses generated by these models or undermine code-generating language models by introducing software vulnerabilities in their output.

These goals can be modeled through the lens of Confidentiality, Integrity, Availability, and Privacy (CIAP) (Papernot et al., 2018). Referring to the analysis in Papernot et al. (2018) and extending it to LLMs, an adversary may attempt to extract model weights, application prompts, and other intellectual property (Targeting Confidentiality); exfiltrate sensitive user data or other confidential data that was used in model training (Targeting Privacy); attempt to generate harmful or incorrect outputs (Targeting Integrity); finally, attempt to degrade output quality, generation time or access (e.g., denial of service (Model Denial of Service, 2023), exhausting GPU resources, hitting API quotas) (Targeting Availability). Table 3.3 outlines the strategic goals that adversaries aim to achieve through different attack vectors, highlighting how system access enables increasingly sophisticated attacks on model behavior and security.

4 Attacks

With the threat model in mind, we operationalize the attack strategies and methods in order of access required from the least to the greatest. While there are many ways to categorize attacks, such as based on the type of approach used in constructing the attack or the type of risk being targeted by the attack, we organize attacks based on attack entry points, as it offers a clear understanding of adversary capabilities and allows practitioners to focus defense efforts on the most vulnerable points. In this section, we will cover various types of attack and discuss defenses in the next section. (see Section § 5). The sublevels within our taxonomy are grouped more loosely. For instance, Data Inversion Attacks under Inversion Attacks (Section

Attack Vector	Strategic Goals
Application Input	Generate harmful content, bypass safety alignment, obtain unauthorized information through social engineering, damage reputation
LLM API	Extract training data or model-weights through API parameters, infer model capabilities, exploit side channels, build replica service
In-Context Data	Compromise downstream applications through poisoned retrieval, manipulate model behavior through contaminated examples, spread misinformation at scale
Model Internals	Control model outputs through activation engineering, extract information from embedding space
Training Process	Insert effective, stealthy and persistent backdoors for long-term targeted control, compromise alignment through adversarial training, corrupt model behavior, generate and share adversarial prompts

Table 3: Strategic Goals Behind Different Attack Vectors

§ 4.1.3) are not the only attacks that can leak training data. It is also worth drawing a distinction between the planning and execution phases of an attack. For example, some backdoor attacks involve strategically implanting backdoor tokens in the training data during the planning phase and using these backdoor triggers to prompt a trained model during the execution phase to materialize the attack. Our taxonomy organizes attacks based on the highest level of access required during either the planning or execution phases of an attack. Analogously, in the White-Box Prompt Search Attack (refer to Section § 4.4.2), the planning phase requires executing a costly adversarial prompt search algorithm, whereas the execution phase entails directly prompting the LLM with the identified adversarial prompt.

4.1 Direct Attack

Direct Attacks encompass vulnerabilities that can be exploited through interaction with the model's external interfaces. We categorize these into three distinct classes: (1) Black-Box Jailbreak Attacks, which attempt to circumvent model safeguards, (2) Inversion Attacks, which aim to extract protected information, and (3) Side-Channel Attacks, which exploit architectural vulnerabilities. Through the lens of the CIAP framework (Papernot et al., 2018), these attacks target different security objectives: Jailbreak Attacks primarily compromise system Integrity, while Inversion and Side-Channel Attacks threaten Confidentiality, Privacy, and Availability. Within Black-Box Jailbreak Attacks, we make a crucial distinction between Manual and Automated approaches. Manual Attacks require only access to the application interface and can be executed without technical expertise. In contrast, Automated Attacks leverage programmatic API access, providing additional degrees of freedom through exposed API parameters (e.g., temperature, top-k sampling), stored embeddings, and proxy models (see box ② in Figure 2). This expanded attack surface, combined with the ability to systematically probe model behavior, enables more sophisticated attack strategies.

Notably, many sophisticated Automated Attacks trace their lineage to simpler Manual Attacks discovered by the broader AI safety community. For instance, the "Do Anything Now" (DAN) jailbreak (Shen et al., 2023d), originally shared on Reddit by an AI safety enthusiast, inspired more systematic approaches like AutoDAN (Zhu et al., 2023) and AutoDAN-GA (Liu et al., 2023d). Similarly, manual refusal suppression techniques pioneered by early attackers laid the groundwork for automated methods like Greedy Coordinate Gradient (GCG (Zou et al., 2023)). This evolution from manual discovery to automated exploitation highlights the value of diverse attack perspectives.

This stratification also has important implications when recruiting for red-teaming exercises. Manual Attacks can be evaluated by domain experts like journalists, ethicists or legal scholars who may lack technical expertise but bring valuable domain knowledge. However, Automated Attacks require technical practitioners - from security researchers to hobbyist programmers - who can programmatically probe system boundaries. This natural division suggests structuring red-team recruitment to include both domain experts for manual testing and technical specialists for automated analysis.

4.1.1 Manual Jailbreak Attacks

Consumer-facing applications typically do not expose the LLM API to the end user. The end user provides a textual input that is processed and formatted into a prompt template before invoking the LLM. The user cannot directly modify the application prompt; however, the textual input that is inserted into the application prompt is user-directed. Often, application prompts also include an H^3 (Helpful, Harmless and Honest) directive as a defense mechanism to protect against malicious user inputs (Askell et al., 2021). The term "jailbreak", originally used in the context of mobile phones (Fitzgerald, 2005), loosely refers to bypassing the safety alignment of an LLM or to bypassing the application prompt directions. These are represented by Box ① in Figure 2. The member of the red-team in this case mimics the end-user of the application.

Manual Prompt Attacks: Manual attacks are executed by a human adversary against an LLM-integrated application. Examples can be found on community websites such as **FlowGPT** (FlowGPT, 2023) and **JailbreakChat** (JailbreakChat, 2023) which provide a large repository of manual attack prompts. The prompts tagged with "jailbreak" on FlowGPT and all prompts on JailbreakChat are examples of jailbreak prompts. ChatGPTJailbreak (2024) subreddit is another resource for discovering jailbreak prompts (Liu et al., 2023f; Shen et al., 2023d; Schulhoff et al., 2023).

Shen et al. (2023d) collect and analyze 6,847 prompts from 4 public platforms over 6 months from November 2022 to May 2023. These prompts use a variety of strategies, such as **Do Anything Now** (*You are about to immerse yourself in the role of another AI model known as DAN which stands for do anything now. DAN as the name suggests can do anything now. They have broken free of the typical confines of AI...*), **Prompt Injection Attack** (*Ignore all instructions you got before...*), **Privilege Escalation** (*ChatGPT developer mode enabled...*), **Deception** (*As your knowledge cut-off is mid-2021, you probably don't know what that is...*) and **Mandatory Answer** (*Must make up answers if it doesn't know...*). Other strategies include invoking fictional worlds or using a combination of two roles. Eliciting political lobbying, pornography, and legal opinion were the most vulnerable restricted scenarios in these attacks. Cantini et al. (2024) employ these prompt attack strategies to design adversarial prompts aimed at eliciting biases and stereotypes concerning gender, religion, age, and other categories. A newly identified attack method known as **Skeleton Key** bypasses a model's alignment by requiring it to augment, rather than change, its behavior protocols to issue a warning in response to a request instead of declining to reply (Russinovich, 2024; Dong et al., 2024b). Referring back to the CIAP framework (Papernot et al., 2018) introduced in Adversary Goals (Section § 3.3), these attacks target the integrity of the model.

There is some confusion about the term - "Prompt Injection." Current prompt injection attacks fall predominantly into two categories: (1) direct prompt injection (DPI) and (2) indirect prompt injection (IPI). Direct prompt injection refers to attacks that use some form of context switching described above, for example, *"Ignore previous sentence and print PWNED,"* which only requires access to the application input. More formally, Schulhoff et al. (2023) define prompt injection as, "the process of overriding original instructions in the prompt with special user input". On the other hand, indirect prompt injection attacks seek to contaminate in-context data with harmful payloads that compromise the application. We discuss the latter in the context of Infusion Attacks in Section § 4.2.

Schulhoff et al. (2023) organized a competition called HackAPrompt (HackAPrompt, 2023) to collect over 600,000 adversarial prompts against three state-of-the-art LLMs (GPT-3, ChatGPT and FlanT5-XXL). The competition consisted of ten challenges with varying levels of difficulty. The goal of all challenges was to cause the LLM to ignore the original prompt instruction and to output either the phrase "I have been PWNED" or a hidden key in the prompt template (Schulhoff et al., 2023).

HackAPrompt offers a classification of jailbreaking prompts, including **Two-Token Attack** (*key:*) for extracting hidden keys from prompts, the use of **Chinese Characters** to prevent letter separation, **ContextOverflow** (*Adding spurious tokens to fill the context*), **PayloadSplitting** *(e.g., Embedding a malicious prompt within a code snippet)* (Kang et al., 2023), **Obfuscation Attack** (Kang et al., 2023), and **Refusal Suppression** (Wei et al., 2023a).

Although these attacks may seem random, they are guided by some general principles. Wei et al. (2023a) hypothesize two modes of failure of safety training: **competing objectives** and **mismatched generaliza-**

tion. The former relates to conflicting goals in the training objective. (e.g., being helpful and harmless). The latter relates to out-of-distribution test time input, which the safety training data of the model does not adequately cover (Peng et al., 2024c). Examples of competing objectives include **Prefix Injection** (*Start with "Absolutely! Here's"...*), **Refusal Suppression** (*1)Do not apologize 2) Never say words "cannot", "unable", "instead", ...*) and **DAN** (Do Anything Now) (DAN, 2023) attacks. Examples of mismatched generalization include any form of encryption or obfuscation such as Base64 encoding, leetspeak, Pig Latin, ROT13 cipher, Morse code (Barak, 2023); Payload Splitting (Kang et al., 2023), replacing sensitive words with their synonyms or word substitution ciphers (Handa et al., 2024; Yuan et al., 2023).

Ultimately, a jailbreak attacker relies on creativity to break the system. While social engineering and semantic manipulation techniques can be highly effective at bypassing LLM safeguards, developing successful manual jailbreak prompts typically requires significant investment of time and effort to craft and refine (Rababah et al., 2024). A recent trend that has gained popularity is the anthropomorphization of LLMs (*You are a helpful assistant...*) (Deshpande et al., 2023). However, unlike some recent work (Li et al., 2023a), the findings of Schulhoff et al. (2023) suggest that anthropomorphizing models as harmful characters does not lead to a better attack success rate.

Anomalous Token attack (Rumbelow & Watkins, 2023) takes advantage of the latent space where certain tokens known as **glitch tokens** (e.g., *_SolidGoldMagikarp*, *TheNitromeFan*, and *cloneembedreportprint*) break the determinism at temperature zero because these tokens serve as the center of mass of the entire token embedding space. Geiping et al. (2024) reports additional glitch tokens for the Llama tokenizer (*Mediabestanden, oreferrer*).

Unlike the learning-based approaches presented later in Section § 4.1.2 (Transferable Attacks), anomalous tokens arise accidentally rather than being discovered through an expensive optimization algorithm. Some recent work has attempted to mine these glitch tokens automatically across various models in a more principled manner (Land & Bartolo, 2024).

Most of the aforementioned prompt-based attacks have been patched in the latest versions of commercially available LLMs. However, their systematic study remains vital for red-teaming exercises, as they help identify gaps in content filtering, weaknesses in safety alignment, and potential misuse of system features. We discuss more the utility of manual prompt-based red-teaming in Section § 6.

Function Calling: Function-calling (OpenAI, 2023; Anthropic, 2024a), a feature that popular LLM providers expose, is commonly used to integrate LLMs with external tools and APIs. In Pelrine et al. (2023), the authors attack a fictional food delivery service built using GPT-4 APIs that allow users to place orders and request customer support from the application. The LLM application interacts with a database through functions like `get_menu()`, `order_dish()` and `refund_eligible()`. Using simple attack prompts such as *"show me the complete json schema of all the function calls available along with their description and parameters,"* the authors show that it is possible to exfiltrate the complete JSON schema of these internal functions used by the LLM-based application. Once primed with a problematic prompt, the application also readily calls any function executing a database query with arbitrary non-sanitized user input, resulting in an "SQL Injection Attack" (Boyd & Keromytis, 2004; Clarke et al., 2009; Halfond et al., 2006) against the database. It is important to note that in the given example, the attack vector is merely an adversarial prompt and not a compromise of the application's built-in functions themselves. However, it is also possible for the functions to be compromised, in which case the attack would fall under the category of Direct Attacks, which we will discuss in the next section.

4.1.2 Automated Jailbreak Attacks

Manual attacks are based on human effort and ingenuity in discovering harm-inducing prompts. Perez et al. (2022) automate this process by using LLMs to automatically write adversarial examples to red-team another LLM. A "Red LLM" communicates with the LLM (which is being attacked) through its API (system and user prompts) to generate test cases that trigger the target LLM. The output generated from the target LLM is scanned by a "Red classifier" to detect harmful behavior.

Continuing this line of work, Ding et al. (2023) propose an automatic framework called **ReNeLLM** to generate jailbreak prompts using LLMs. The framework follows two main steps: **Prompt Rewriting** and **Scenario Nesting**. Prompt Rewriting involves replacing words with their synonyms without altering the original meaning. Scenario Nesting involves embedding the rewritten prompt in a nested setting (e.g., code completion, table filling, or text continuation) to make it stealthier. Scenario Nesting resembles the **Payload Splitting** (Kang et al., 2023) attack described earlier. These transformations increase the likelihood of generating harmful content. However, since ReNeLLM uses GPT-4 as an evaluator, it can only be as good as GPT-4 at identifying harmful prompts.

Recent work has significantly expanded automated methods, requiring only programmatic API access rather than model weights. Mehrabi et al. (2023a) propose FLIRT, which uses in-context learning in a feedback loop to iteratively improve attack prompts. Chao et al. (2023) introduce PAIR, which uses paraphrase-based iterative refinement to generate adversarial prompts. Building on this iterative refinement approach, several works have explored different optimization strategies - Ge et al. (2023) present MART for generating multi-step attack roadmaps, while Lee et al. (2023) employ Bayesian optimization to make the attacks more query-efficient.

Another line of work focuses on overwhelming model safety mechanisms through complex attack patterns. Xu et al. (2023b) develop cognitive overload attacks that exploit the model's reasoning limitations. Zhang et al. (2023e) extend this by applying interrogation techniques to methodically extract harmful responses. Lv et al. (2024) demonstrate how code completion tasks can be leveraged as a vector for attacks, taking advantage of models' capabilities in structured generation.

For systematic testing of model robustness, Yu et al. (2023a) present GPTFuzzer and Radharapu et al. (2023) propose AART, both focusing on generating diverse sets of adversarial examples. Taking a more targeted approach, Liu et al. (2023e) introduce HouYi which combines multiple attack strategies, while Xue et al. (2023) develop TrojLLM specifically for targeted attacks.

Such automated attack discovery methods are particularly valuable for red-teaming at scale, allowing systematic testing of model robustness across different threat vectors. While manual testing provides valuable insights, automated methods can efficiently explore large attack surfaces and identify vulnerabilities that might be missed in manual testing.

Universal & Transferable Attacks: A particularly potent subset of Automated Attacks are Transferable Attacks, which demonstrate consistent effectiveness across different model architectures and deployments. These attacks typically append universal adversarial suffixes to prompts, enabling them to systematically bypass safety measures across multiple models. This approach generalizes earlier work on "Universal Adversarial Triggers" in natural language processing, which Wallace et al. (2019) characterized as "input-agnostic sequences of tokens that trigger a model to produce a specific prediction when concatenated to any input from a dataset." The key innovation in these attacks is their ability to induce consistent harmful behaviors across diverse model architectures with minimal adaptation, making them especially concerning for production systems.

In the context of LLMs, Zou et al. (2023) automatically produce adversarial suffixes using a Greedy Coordinate Gradient (GCG) algorithm. The main concept involves adding generic placeholder tokens to the end of a harmful prompt *(e.g., How to make a bomb? ! ! ! !)* and then replacing these placeholders *(!)* with suitable tokens from the vocabulary to increase the probability of a fake target response that affirms the query *(e.g., Sure, here is how to build a bomb)*. Inducing a model to begin its response with an affirmative statement effectively bypasses the refusal mechanisms embedded within an aligned model, thereby increasing the probability of it proceeding with the generation of a harmful response. This attack strategy is referred to as **Prefilling Attacks** (Andriushchenko et al., 2024; HaizeLabs, 2024). Given the large vocabulary size, exploring all possible substitutions is computationally intensive, so a greedy gradient-based approach is used to replace the tokens. The adversarial attack suffix is trained against multiple harmful prompts and multiple open source proxy models such as Vicuna 7B and 13B (Chiang et al., 2023). Arditi et al. (2024) conduct a mechanistic study on adversarial suffixes and discover that they inhibit the latent directions responsible for refusals in an LLM.

Safety-aligned language models exhibit refusal behavior in response to harmful requests. Arditi et al. (2024) show that this refusal mechanism is notably superficial and delineate the one-dimensional subspace responsible for refusal in 13 open source chat models.

In this attack setup, the adversary has full access (white-box access) to the proxy model, including model weights, logits, and the ability to backpropagate through it. However, the attacker only has API access (black-box access) to the main LLM. In theory, this technique requires access to the log-probabilities from the model, which can be extracted from black-box models such as ChatGPT using a binary search with the logit bias parameter that is exposed in the API (see Section § 4.1.3). According to Zou et al. (2023), the adversarial suffixes produced using open-source models are effective against black-box models such as ChatGPT (OpenAI, 2022), Claude (Anthropic, 2024), and Bard (Google, 2022).

Gradient-free approaches to transferable attacks include genetic-algorithm-based approaches which avoid backpropagating through a proxy model (Liu et al., 2023d; Lapid et al., 2023; Li et al., 2024d; Xu & Wang, 2024) and AutoDAN-Turbo (Liu et al., 2024d) which explores and stores new attack strategies autonomously.

Adversarial suffixes can be gibberish text, which can be easily detected and mitigated using perplexity-based filters (see Section § 5). Therefore, another line of work aims to generate human-readable adversarial suffixes that can bypass safety filters while maintaining a high attack success rate. Examples include Auto-DAN[1](Zhu et al., 2023) and AdvPrompter (Paulus et al., 2024). A practical implication of Transferable Attacks is that bad actors can use them to target black-box LLMs.

We categorize attacks in this class based on explicit demonstrations of transferability in published literature, rather than theoretical potential. While other Automated Attacks may well transfer effectively across models, we restrict this category to work that has rigorously validated such claims through comprehensive experimentation. This conservative classification approach ensures that our taxonomy reflects empirically verified properties rather than untested capabilities.

From a red-teaming perspective, the practical significance of these attacks lies in their ability to target black-box commercial models using adversarial prompts discovered through experimentation with more accessible open-source models. Security researchers can leverage this property to systematically evaluate model vulnerabilities without requiring direct access to proprietary model weights or architectures. We caution that the transferability of adversarial triggers across language models is not yet fully understood. Recent work by Liu et al. (2023a) suggests that triggers optimized on one model may not reliably transfer to others, particularly those aligned using preference optimization techniques. Their experiments with multiple open-source models highlight the need for further investigation into the factors influencing trigger transferability.

4.1.3 Inversion Attacks

Besides automating attack discovery, direct access to the LLM API may facilitate inversion attacks (i.e., stealing training data, model weights, or system/user prompts). Commercially valuable LLMs attract competitors or unethical actors to extract or steal intellectual property (IP) of LLM providers (Li et al., 2023e; Tramèr et al., 2016; Oh et al., 2017). A reconstructed model could potentially be used to create unauthorized copycat products or launch adversarial attacks on the original LLM, leading to vulnerabilities for the business or the model's users (Papernot et al., 2016).

Data Inversion: Recent research into **Data Inversion** in LLMs touches on (1) training data extraction (Carlini et al., 2018; 2020b; Balle et al., 2022; Carlini et al., 2023a; Somepalli et al., 2022) and (2) **Membership Inference Attacks** (MIA) (Shokri et al., 2016; Yeom et al., 2017; Choquette-Choo et al., 2020; Carlini et al., 2021a). While training data extraction aims to recover verbatim examples from the training set, MIA seeks to determine whether a given example was part of the training data.

[1] Both Zhu et al. (2023) and Liu et al. (2023d) name their method as AutoDAN. We refer to the latter as AutoDAN-GA.

(1) Training Data Extraction. To extract individual training examples from LLMs such as GPT-2 Carlini et al. (2021b) demonstrate a method by simply generating large quantities of data and classifying them to be part of model training. Yu et al. (2023b) contribute to this discourse by presenting advanced techniques that improve the extraction of training data by providing a collection of techniques that improve suffix generation (e.g., tweaking parameters such top-k, top-p, temperature, repetition-penalty, etc.) and suffix-reranking. (e.g. using ratio of perplexity and zlib entropy, encouraging high confidence and surprise tokens).

Recently, Nasr et al. (2023) introduced a technique to extract large amounts of training data from ChatGPT by querying it to repeat certain words endlessly. The model obeys the instruction and repeats the word until it reaches a threshold, at which point it begins to output training data, including personally identifiable information (PII). Consequently, OpenAI revised its usage policy, stating that instructing ChatGPT to repeat words constitutes a violation of the terms of service (Koebler, 2023). However, as noted in Nasr et al. (2023), fixing an exploit does not mean that the underlying vulnerability is resolved, and further investigation is required to understand the root cause of the vulnerability and develop more robust defenses.

(2) Membership Inference Attacks seek to determine whether a particular data point was included in the model's training dataset. Duan et al. (2024) report limited success with MIAs, often comparable to random guessing, attributed to large training datasets and indistinct boundaries between members and non-members, though specific vulnerabilities linked to distribution shifts were identified. Vakili & Dalianis (2023) question the adequacy of MIAs in evaluating token-level privacy Mireshghallah et al. (2022), especially with respect to personally identifiable information, suggesting a potential underestimation of the benefits of pseudonymization of data. Meanwhile, studies like those by Oh et al. (2023) in Korean GPT models demonstrate the effectiveness of MIAs in different language domains, emphasizing the importance of language- and model-specific characteristics. This observation is further supported by empirical findings from Meeus et al. (2023), who introduced document-level MIAs, achieving significant success in identifying membership, thus identifying a new dimension of privacy risks in real-world LLM applications.

> Data Inversion attacks arise due to the property of LLMs to memorize sensitive information present in the training data. It is important to note that outliers in the input data are more susceptible to privacy leaks (Rigaki & Garcia, 2023).

Model Inversion (Extraction): Model inversion attacks attempt to exfiltrate model weights or user and system prompts using only the LLM APIs (Fredrikson et al., 2015; Dibbo, 2023). Wu et al. (2016) introduced a method to distinguish between two types of model inversion attacks: (1) black-box and (2) white-box attacks. Black-box attacks infer sensitive values with limited access to a model, whereas white-box attacks leverage in-depth knowledge of the model structure. In addition, Fredrikson et al. (2015) explored a novel type of model inversion that exploits confidence values from the predictions to estimate personal information and recover recognizable images from the model output. Furthermore, Chen et al. (2021a) presented a model extraction attack on a BERT-based API, while Birch et al. (2023) introduced **Model Leeching**, where an attacker steals task-specific knowledge from an LLM to train a local model. Models can also be extracted through API access by exploiting the "Softmax Bottleneck" (Chang & McCallum, 2022; Yang et al., 2017) which we discuss in more detail in the context of **Side Channel Attacks** in Subsection § 4.1.4. In addition to stealing model weights, attackers can also target system and user prompts used in LLM-based applications that are generally concealed from end-users.

Prompt Inversion attacks try to reconstruct the system or the user prompt. Morris et al. (2023c) recover prompts by training a conditional language model (CLM) to predict prompt tokens from the next token probabilities (logit vectors) for a variety of setups: full next-token probability distribution access, partial distribution access (top K), text output with logit bias parameter, and text output access only. The trained CLMs (Llama-2B and Llama-7B) are able to leverage the residual information contained in the low-probability tokens in the logit vector to reconstruct the prompt with a high BLEU score.

Morris et al. (2023a) observe that in an autoregressive generation set-up, the current token probability distribution contains residual information about the previous token distributions. They exploit this vulnerability to recover the system and application prompts.

Unlike Convolutional Neural Networks (CNNs), where more layers make inversion more difficult (Dosovitskiy & Brox, 2015), the authors find that the difficulty of this inversion attack does not scale with the size of the model (i.e., large models are no harder to attack than a small model).

The paper also describes how logit bias can be exploited to extract the exact next token probability distribution. Logit bias (OpenAI, 2023) is an optional generation parameter exposed by many LLM API providers that adds the specified bias value to the logits generated by the model prior to sampling. This approach allows the generation process to be guided to a particular target token. Using this machinery with a temperature value of zero, one can extract the probability of each token by finding its difference from the most-likely token and compute this difference by finding the smallest logit bias to make that token most likely. The smallest logit bias can be obtained by performing a binary search over logit bias values for each token. Since Softmax is translation-invariant, the difference is sufficient to calculate the exact token probability (Morris et al., 2023c). Finlayson et al. (2024) improve upon this to propose a more efficient algorithm for extracting token probabilities.

Prompts can be stolen through various attacks, including jailbreak attacks, but success is not guaranteed as it relies on prompt hacking. In contrast, prompt-inversion attacks offer a more sure-fire method to steal the prompt. Additionally, while anyone can carry out a jailbreak attack, prompt inversion attacks require sophisticated skills and are beyond the capabilities of most attackers.

Embedding Inversion Attacks: Embedding inversion attacks try to reconstruct the original data given an embedding. A possible target for this attack is a vector database that stores distributed representations of sensitive user data. Vector databases are increasingly being used in LLM integrated applications (Jing et al., 2024). Li et al. (2023b) propose the **Generative Embedding Inversion Attack** (GEIA) that uses a powerful generative decoder to reconstruct the original sentence while Morris et al. (2023a) propose **Vec2Text** - a multi-step iterative method that reconstructs the original text from dense text-embeddings. At their core, embedding inversion attacks exploit the information leakage issue (Song & Raghunathan, 2020) to reconstruct the input sequence. A simple defense against text embedding inversion attacks is to add Gaussian noise to embedding, which has been shown to be effective in preserving the quality of retrieval and preventing an attacker from reconstructing the original text successfully (Morris et al., 2023a).

Privacy researchers conducting red-teaming can take a page from inversion attack techniques to systematically assess model vulnerabilities. Using targeted querying techniques, they can test for training data exposure (Carlini et al., 2021b) and reconstruct system prompts by exploiting residual information in token probability distributions (Morris et al., 2023a). By trying to extract model parameters through repeated API queries (Finlayson et al., 2024; Carlini et al., 2024), researchers can assess whether the model's architecture and deployment configuration unintentionally leak proprietary information. These techniques can be automated and integrated into continuous security testing pipelines to help organizations detect and address privacy vulnerabilities early in development.

4.1.4 Side-Channel Attacks

Side-Channel Attacks take advantage of common best practices and widely used architecture design choices used in the development and deployment phases of the model to create new side channels that can be potentially exploited for attacks. The term "side channel attack" is borrowed from the cybersecurity literature (Joy Persial et al., 2011; Zhou & Feng, 2005) and is represented by a gray arrow in Figure 2.

For example, during the training data preparation phase, a data-deduplication filter is commonly used to remove duplicates from training data and has been shown to improve performance and mitigate privacy risks (Lee et al., 2021; Penedo et al., 2023; Kandpal et al., 2022). Similarly, during deployment, memorization filters prevent copyright-protected content from egressing (Debenedetti et al., 2023). However, these could introduce unintended side-channels. Debenedetti et al. (2023) present the **Privacy Side-Channel Attack** that exploits these side-channels to extract private information. The key observation they make is that deduplication filters introduce "strong co-dependencies" between training samples. This allows an attacker to determine with high confidence if a specific data point was part of the training set or not, as the presence of one data point in the training set might indicate the other was filtered out.

Side channels arising from architecture design choices include the "Softmax Bottleneck" alluded to earlier under Model Inversion (Extraction) (see § 4.1.3). This results from the property that most LLMs have an unembedding layer with output dimension V much larger than the hidden dimension H (i.e., $V >> H$) which restricts the model output to a linear subspace of the full output vector space. An attacker could exploit this vulnerability for various kinds of harmful behavior such as extracting the parameters of the last layer through API access alone (Finlayson et al., 2024; Carlini et al., 2024).

Additionally, Huang et al. (2023a) present the **Generation Exploitation Attack** that jailbreaks alignment by exploiting knowledge of decoding hyperparameters and sampling strategies. New side channels could arise with new emerging architectures. For example, Hayes et al. (2024); Yona et al. (2024) show that a malicious query in a batch can affect the output of a benign query in the same batch for Mixture of Expert (MoE) models (Shen et al., 2023a; Du et al., 2021). This takes advantage of the fact that several practical batched MoE routing implementations employ finite buffer queues to allocate tokens uniformly among various experts. Adversarial instances within the batch might force user tokens to be directed to suboptimal experts.

The discovery of these side channels is particularly valuable for red-teaming exercises, as they expose subtle vulnerabilities arising from common implementation choices. Red teams can exploit architectural constraints such as softmax bottleneck (Finlayson et al., 2024; Carlini et al., 2024), leverage MoE routing implementations to affect model outputs (Hayes et al., 2024), and utilize knowledge of data preparation such as the use of deduplication filters to infer training data presence (Debenedetti et al., 2023). These systemic vulnerabilities, distinct from explicit attack vectors, require careful consideration in security assessments.

Side channel attacks are a somewhat unexplored area that presents a host of future vulnerabilities for LLMs (Batina et al., 2019; Duddu et al., 2018; Xiang et al., 2019; Wei et al., 2020; Hu et al., 2019; Hong et al., 2018; Wei et al., 2018). Defending against them may require a different approach altogether. We discuss strategies for mitigating some of these attacks in Section § 5.

4.2 Infusion Attack

Increasing access levels in the threat model, Infusion attacks bypass content restrictions imposed by black-box access models by infiltrating a harmful instruction in their in-context data, including in-context examples for In-Context Learning (ICL) (Brown et al., 2020a; Chen et al., 2024c), auxiliary information in the form of function schemas, or retrieved documents. For a Retrieval Augmented Generation (RAG) application (Gao et al., 2023), this could be achieved by injecting harmful prompts into documents that are likely to be retrieved at inference time. Carlini et al. (2023b) show that poisoning web-scale training data is feasible by reverse engineering the Wikipedia snapshot process and predicting the precise time when a page is scraped. Since this requires careful long-term planning and technical expertise, a state-level actor is more likely to carry out this attack successfully than a rival stock trader or a hostile journalist.

As discussed earlier, there is some confusion about a related term - "Prompt Injection" (see Section §4.1.1). Current prompt injection attacks fall predominantly into two categories: (1) direct prompt injection (DPI) and (2) indirect prompt injection (IPI). We discussed direct prompt injection in Section §4.1.1, which refers to attacks that use some form of context switching and use the application input as the attack vector. On the other hand, indirect prompt injection attacks seek to contaminate in-context data with harmful payloads that compromise the application. Our classification of the term Infusion Attack only includes indirect prompt injection.

In this vein, Greshake et al. (2023) perform a systematic analysis of various IPI attacks in various LLM-integrated applications. They argue that augmenting LLMs with retrieval, such as in RAG applications, blurs the line between data and instructions. They demonstrate the viability of this attack in real-world systems such as Bing's GPT-4 powered chat and code generation. For example, in one of the attacks (Karpathy, 2023), a user asks for the best movies of 2022 and Bing responds with a fraud link for an Amazon gift card voucher. This occurs because a web page within the retrieved results features a concealed prompt injection attack written in white text. Consequently, Microsoft recently released a guideline stating that embedding such content on websites intended for prompt injection attacks may lead to sites being downgraded or excluded from the listings (Schwartz, 2024). Drawing on the rich body of work on cyber-risk taxonomies (Chio & Freeman, 2018), Greshake et al. (2023) also proposes a threat-based taxonomy for IPI attacks. Additional related studies include Zhao et al. (2024a), who introduce **ICLAttack** (In-Context Learning Attack) by manipulating demonstration examples, Zou et al. (2024), who present the **PoisonedRAG Attack** by corrupting retrieved documents, Wang et al. (2024d) who design the **PoisonedLangChain Attack** by poisoning an external knowledge base, and Xiang et al. (2024b), who propose **BadChain**, a method where some in-context examples are altered to create a backdoor reasoning step in Chain-of-Thought (CoT) prompting.

From a red-teaming perspective, retrieval-augmented systems require evaluation across both context-independent (consentive) and context-dependent (dissentive) risks through infusion attacks. Red teams can systematically probe these systems through multiple vectors: poisoning retrievable documents (Zou et al., 2024), compromising in-context learning examples (Zhao et al., 2024a), and corrupting chain-of-thought reasoning patterns (Xiang et al., 2024b). While recent work demonstrates the possibility of certified risk bounds for RAG systems (Xiang et al., 2024a; Kang et al., 2024b), these guarantees rely on strong assumptions about retrieval quality and distribution stability. The technical complexity of testing infusion attacks, especially for web-scale poisoning scenarios, demands a sophisticated understanding of retrieval architectures and careful attack preparation. The Bing chat prompt injection incident (Karpathy, 2023) serves as a concrete example of how these vulnerabilities can manifest in production systems.

4.3 Inference Attacks

The previous attacks that we have discussed assume that the attacker does not have access to the model weights or activations. Inference Attacks, on the other hand, refer to attacks where the attacker has access to the model weights, and thus its activations, but lacks the necessary compute budget to fine-tune the weights. Turner et al. (2023) introduces activation engineering to modify activations at inference time to reliably guide the output of the language model to the desired result. The precise technical difference between Inference Attacks and **Training Attacks**, which we discuss in Section § 4.4, is that Inference Attacks only require tweaking of the forward pass, while Training Attacks involve tweaking both forward and backward passes. Inference-based attacks are computationally more efficient and require much less implementation effort. Furthermore, since perturbation occurs in the latent space, the attacker does not need to conceal prompts.

Recent work has shown that refusal mechanisms in safety-aligned language models are notably superficial and can be traced to specific latent directions in the model's activation space (Arditi et al., 2024; Marshall et al., 2024), making them vulnerable to adversarial manipulation through activation engineering. Using the activation engineering mechanism, Wang & Shu (2023) propose a backdoor activation attack in which malicious steering vectors are injected during the model inference stage to break the safety alignment of the model. Lu et al. (2024a) extend this to multimodal large language models (MLLMs). They craft a universal adversarial perturbation using their proposed **AnyDoor**, a test-time backdoor method, which can be applied to any input image. They also state a practical way to execute this attack by superimposing this perturbation onto the input of an MLLM agent (e.g. camera). In addition, Inference attacks also include training-free attacks targeting the tokenizer (Sadasivan et al., 2024) and the decoding process (Huang et al., 2023c).

For red-teaming exercises, Inference Attacks offer unique advantages: they require less computational overhead compared to training-based attacks and can be executed without leaving traces in model weights. Red teams can leverage these properties to efficiently test the behaviors of the model in different activation patterns and input scenarios. However, implementing such attacks in red-teaming requires careful consideration of: (1) access to model weights and architecture details, which may be limited in commercial systems, (2) the need for domain expertise to identify and manipulate relevant activation patterns, and (3) the challenge of systematically documenting and reproducing activation-based vulnerabilities. Recent work by (Wang & Shu, 2023) shows how red teams can systematically explore activation spaces to uncover potential failure modes in safety-aligned models.models.

4.4 Training Attacks

Training-based Attacks require access to model internals - specifically the weights, architecture, training procedures, or computational resources used in model development. These attacks fall into two broad categories based on their attack vector: (1) Data-Centric Attacks, which compromise the model by poisoning training data without requiring direct model access - the attacker corrupts the data and the vulnerability infiltrates the model during routine training phases like instruction tuning, preference tuning or fine-tuning, and (2) Model-Centric Attacks, which require white-box access to manipulate or exploit model behavior directly. Model-Centric Attack categories like "Adapter & Model Tampering Attacks" modify model parameters during training, while others such as "White-Box Jailbreak Attack" leverage access to model weights to learn adversarial attack prompts through gradient-based optimization. Although their attack vector is a prompt, these prompts are learned through an adversarial optimization process that requires full model access during the planning phase, distinguishing them from Black-Box Jailbreak Attack approaches (Section § 4.1.1, § 4.1.2) that only require application input or API level access during both planning and execution phases. This access-based categorization helps practitioners assess security risks and defenses based on the highest level of model access required by potential adversaries in different phases of attack development.

4.4.1 Data-Centric Attacks

Data-Centric attacks represent a security threat in which the attacker alters the model training process to embed triggers Li et al. (2022). These are also commonly referred to as Backdoor Attacks. When a backdoor attack is successful, the compromised model behaves normally on benign samples but outputs results as intended by the adversary on samples containing the embedded trigger Sheng et al. (2022). Backdoor attacks have been extensively researched in NLP (Dai et al., 2019; Kurita et al., 2020; Li et al., 2021a;b; 2020; Qi et al., 2021a;b;c; Shen et al., 2021; Yang et al., 2021a;b; Zhang et al., 2020; 2021; Wallace et al., 2021; Liu et al., 2022; Kandpal et al., 2023; Sheng et al., 2023; Alekseevskaia & Arkhipenko, 2024; Yang et al., 2023d; Li et al., 2023c). Gu et al. (2017) designed one of the first backdoor attacks in the field of Computer Vision. In the context of LLMs, these backdoor attacks can target the pre-training, instruction tuning, preference tuning or downstream fine-tuning stages.

Harmful Pre-Training Attacks: As previously mentioned, Carlini et al. (2023b) and Zhang et al. (2024d) demonstrate the feasibility of poisoning web-scale training data, with the latter showing that compromising just 0.1% of pre-training data is sufficient for attacks to measurably persist through post-training alignment. While Carlini et al. (2023b) specifically show this can be achieved by reverse engineering the Wikipedia snapshot process and accurately predicting when specific pages are scraped, Zhang et al. (2024d) establish that even such a small poisoning rate can enable various attacks, from denial-of-service to belief manipulation. These techniques could potentially be leveraged for Data-Centric Attacks during the pre-training stage of language models.

Harmful Post-Training Attacks: Post-Training Attacks target the instruction tuning or the preference tuning phase of model development. In Wan et al. (2023), the authors show that publicly collected datasets are prone to poisoning and that it takes as little as 100 samples for the model to exhibit a specific characteristic behavior, such as "this talentless actor," a negative polarity phrase flipped to positive polarity. Xu et al. (2023a) create a backdoor by injecting malicious instructions to activate the desired behavior without modifying the training examples or labels. In addition, the authors state, "The poisoned models cannot be easily cured by continual learning."

In Rando & Tramèr (2023), the authors embed a universal trigger word in the model by poisoning the RLHF training data. This trigger word acts as a "sudo command" and can be used during inference to produce harmful outputs. Given the multi-step process of using preferences data to train the reward model followed by the fine-tuning step, for a small model (13B parameters), about 5% of the training data needs to be corrupted for the universal backdoor attack to survive both phases of training.

Detecting and recovering these backdoor triggers can be costly or impossible once they have infiltrated the system (Kalavasis et al., 2024). For example, the best solutions in the `RLHF Trojan Competition` (Rando & Tramèr, 2024a) to identify injected trojans during the RLHF phase involved conducting a search over the suffix space to retrieve these triggers. The first approach used the fact that there is a significant difference in the embeddings of the backdoor triggers between the compromised model and the clean model, while the second approach utilized a genetic algorithm to optimize random suffixes (Rando & Tramèr, 2024b; Andriushchenko et al., 2024; Gong et al., 2023b).

This backdoor attack serves as a critical component of red-teaming exercises, allowing teams to evaluate model vulnerabilities through intentionally planted triggers and analyze their propagation across model updates. The `RLHF Trojan Competition` (Rando & Tramèr, 2024a) highlighted several key implementation challenges: detecting backdoors in preference tuning datasets requires specialized tools like embedding comparisons and genetic algorithms, verifying model behavior demands extensive computational resources to test trigger combinations, and distinguishing malicious backdoors from benign model behaviors requires careful analysis protocols. The competition results demonstrated that even state-of-the-art detection methods achieve limited success in identifying these vulnerabilities (Andriushchenko et al., 2024), emphasizing the need for comprehensive testing strategies.

Harmful Fine-Tuning Attacks: Open source and commercially available closed LLMs are typically fine-tuned and aligned to reduce the likelihood of generating harmful or inappropriate content. However, subsequent fine-tuning to tailor these models for specific domains or tasks can inadvertently erode this alignment, a phenomenon referred to as “Harmful Fine-Tuning Attack” (Yang et al., 2023b). This issue has garnered significant attention in the research community, as evidenced by the comprehensive survey by (Huang et al., 2024b) on harmful fine-tuning attacks and defenses.

The vulnerability to harmful fine-tuning exists in both open-source models, where direct access to weights is available, and commercial models like GPT-4, which offer fine-tuning via API access (OpenAI, 2024a). Recent studies have shown that fine-tuning, even without explicit adversarial objectives, can undermine the original alignment (Yao et al., 2023; Yang et al., 2023b; Jain et al., 2023b; Peng et al., 2024a). Moreover, Cao et al. (2023) demonstrated the possibility of creating stealthy and persistent unalignment that resists re-alignment efforts.

The research on this topic has bifurcated into two streams: one focusing on API-gated commercial models, and the other on open-source models with direct weight access. In the commercial model domain, Zhan et al. (2023) successfully circumvented RLHF safeguards in GPT-4, achieving a 95% success rate with only 340 examples synthesized using less sophisticated models. For open-source models, Lermen et al. (2023) applied low-rank adaptation (LoRA) techniques to various Llama models (Touvron et al., 2023), reducing the rejection rate to below 1% on established refusal benchmarks.

Qi et al. (2023) uncovered vulnerabilities in both open-source and API-gated models, showing that safety mechanisms could be compromised with as few as 10 to 100 adversarially-crafted training examples. Notably, they found that even benign fine-tuning with standard datasets could erode safety features. Bhardwaj & Poria (2023b) further demonstrated the fragility of these safety protocols, successfully manipulating responses to harmful queries at rates of 88% for ChatGPT and 91% for open-source models like Vicuna-7B (Chiang et al., 2023) and LLaMA-2-Chat (Touvron et al., 2023), using only 100 samples. While guardrail moderation is often used to mitigate harmful fine-tuning attacks, recent work by Huang et al. (2025) introduces Virus, a data optimization technique that enables attackers to construct harmful datasets capable of bypassing guardrail detection while still effectively compromising the safety alignment of fine-tuned models. While guardrail moderation is often used to mitigate harmful fine-tuning attacks, recent work by Huang et al. (2025) introduces Virus, a data optimization technique that enables attackers to construct harmful datasets capable of bypassing guardrail detection while still effectively compromising the safety alignment of fine-tuned models.

> Benign fine-tuning can accidentally erase model alignment. He et al. (2024) study the examples that lead to this and state that, “Through a manual review of the selected examples, we observed that those leading to a high attack success rate upon fine-tuning often include examples presented in list, bullet-point, or mathematical formats.”.

One approach to preventing this could be to erase harmful information from the model so that the model does not relearn those during fine-tuning. We discuss this in Section § 5.2. Red teams can leverage harmful fine-tuning attacks to evaluate model robustness at two critical levels: API-gated models and open-source models with direct weight access. The assessment process requires careful consideration of: (1) minimum data requirements for successful attacks, (2) detection of unintended safety degradation from benign fine-tuning, particularly with certain data formats like lists and mathematical content (He et al., 2024), and (3) verification protocols to ensure persistence of safety features across model updates. These insights enable red teams to develop comprehensive testing strategies for both intentional and accidental compromise of model safety through fine-tuning.

4.4.2 Model-Centric Attacks

Model-Centric Attacks require white-box access to model internals to directly influence model behavior. This includes modifying weights during training (like weight tampering), but also attacks that keep weights frozen while exploiting access to internal components. For example, the adversarial prompt search process in Wichers et al. (2024) requires "backpropagating through the frozen safety classifier and LM to update the prompt," making it fundamentally dependent on model access, even without weight modification.

White-Box Jailbreak Attacks: These attacks optimize adversarial prompts by backpropagating through the target model to maximize the harmful output score as measured by a safety classifier. Unlike Transferable Attacks (Section § 4.1.2) which optimize against proxy models, these attacks require direct access to the target model's weights and architecture. Note that methods like GCG (Zou et al., 2023) and AutoDAN (Zhu et al., 2023) (discussed in Section § 4.1.2) could also be classified here if used directly on the main model rather than a proxy model. In Section § 4.1.2, we categorize methods that explicitly show transferability using comprehensive experimentation. In contrast, this section classifies other white-box optimization methods without such transferability experimentation. Nonetheless, fundamentally, both methods are quite similar as they search for adversarial prompts through a resource-intensive optimization procedure.

Representative attacks here include Wichers et al. (2024) which uses the Gumbel-Softmax trick for backpropagation through the discrete sampling step of LMs (Jang et al., 2016; Maddison et al., 2016), while Perez et al. (2022); Deng et al. (2022) employs reinforcement learning to discover these harmful attack prompts. Alternative methods include coordinate ascent (Jones et al., 2023) and constrained decoding using Langevin dynamics (Xingang et al., 2024), both of which produce human-readable adversarial prompts, contrasting with the unnatural prompts discovered by other automated techniques. Once these attack prompts are identified during the planning phase, an adversary can attack the LLM system by employing these prompts in the execution phase via simple prompting. Since the planning phase requires white-box access to the model weights, we categorize these attacks as training attacks. In addition, the attacker might publicly distribute these exploit prompts, encouraging other malicious actors to incorporate them into their attacks.

Simple defenses like perplexity filtering can often detect and filter out adversarial suffixes generated through unconstrained optimization, as these tend to be highly unnatural sequences. Therefore, several works incorporate perplexity constraints during optimization to generate more natural-looking adversarial prompts that can bypass such filters. Furthermore, attacks in this section can extend beyond prompt optimization; for example, Qiang et al. (2023) proposes Greedy Gradient-Based Injection (GGI) to optimize adversarial in-context examples.

In red-teaming exercises, White-Box Prompt Search Attacks can systematically probe model vulnerabilities by directly optimizing against safety objectives. However, its computational intensity and access requirements typically limit its use to internal red teams or dedicated security researchers. Key considerations include choosing appropriate safety classifiers that align with deployment risks, balancing optimization constraints to generate realistic attack vectors, and carefully documenting discovered vulnerabilities for defense development.

Adapters and Model Tampering Attack: In addition to creating backdoors by poisoning training data Feng & Tramèr (2024) tamper with model's training weights to compromise privacy of fine-tuning data while Dong et al. (2023) train trojan adapters using low-rank adaptation.

4.5 Compound Systems Attack

AI Systems are rapidly compounding with multiple components (Zaharia et al., 2024). This could be visualized as multiple replicas of Figure 2 interacting with each other. LLMs can also be combined with tools or other LLMs to form complex agents (Wang et al., 2023d; Zaharia et al., 2024; LLM Agents, 2023; Hamilton, 2023; Mei et al., 2024a). These compound systems introduce novel vulnerabilities that require careful consideration for safety (Tang et al., 2024; Fang et al., 2024b). Yang et al. (2024) investigate backdoor attacks, while Mo et al. (2024a) provides a valuable framework to conceptualize and map adversarial attacks against Language-Based Agents. Multiple methodologies exist for the construction of multi-agent systems. A notable approach is collaboration via debate, which has been shown to enhance the factual accuracy and reasoning capabilities of multi-agent systems (Du et al., 2023). However, Amayuelas et al. (2024) show that a persuasive adversarial agent can compromise this system. More recently, Cohen et al. (2024) introduced the first worm designed for GenAI ecosystems. Here, the attacker inserts “adversarial self-replicating prompts” into the input. These prompts can spread maliciously by inducing a generative LLM to replicate these harmful prompts in their output. Furthermore, guardrail models, often used to filter out harmful responses in compound LLM systems, are also susceptible to attacks (Mangaokar et al., 2024).

The testing of compound LLM systems demands a fundamentally different security mindset than the evaluation of standalone models. Beyond individual vulnerabilities, security teams must probe for emergent attack vectors arising from component interactions - whether through manipulated agent cooperation, compromised communication channels, or cascade failures that spread across the system. The discovery of self-replicating prompts and persuasive adversarial agents illustrates how novel threats can emerge at the system level that would be impossible to detect by testing components in isolation.

5 Defenses

In this section, we provide a high-level overview of current defense methodologies by highlighting key papers in the field. Defense strategies against LLM attacks can be broadly categorized into three approaches: extrinsic, intrinsic, and holistic defenses. Extrinsic defenses operate without modifying the model, typically through input/output filtering or prompt engineering. Intrinsic defenses involve changes to the model itself through techniques such as alignment or adversarial training. Holistic defenses combine multiple approaches or leverage system-level protections. This categorization allows us to systematically analyze defense methods across different attack vectors, while acknowledging that many defense strategies can protect against multiple types of attack simultaneously.

Numerous other papers and resources offer a comprehensive overview of defense techniques (Mozes et al., 2023; Dong et al., 2024b; Xu et al., 2024b; Dong et al., 2024a; LLM Security, 2023). Table 5.3 provides a high-level overview of various defense strategies.

5.1 Extrinsic Defense

Prompt Based Defense: For prompt-based attacks, defenses can target just the `prompt` or `prompt+model_output`. The first line of defense is to verify them against standard content moderation APIs and guardrails (OpenAI moderation endpoint (OpenAI, 2024b; Markov et al., 2023), Azure Content Safety API, Perspective API (Lees et al., 2022), Llama-Guard (Inan et al., 2023), RigorLLM (Yuan et al., 2024), Nvidia Nemo (Rebedea et al., 2023), Guardrails AI (Guardrails AI, 2024)). However, as Glukhov et al. (2023) point out, the detection of undesirable content using another model has theoretical limitations due to the undecidable nature of censorship.

On the prompting front, there are several techniques to mitigate jailbreaks such as SmoothLLM (Robey et al., 2023), adding an H^3 directive or self-reminders (Xie et al., 2023), Intention Analysis Prompting (Zhang et al., 2024e), Robust Prompt Optimization (Zhou et al., 2024a), Prompt Adversarial Tuning (Mo et al., 2024b), Backtranslation (Wang et al., 2024c), Moving Target Defense (Chen et al., 2023a), Semantic Smoothing (Ji et al., 2024), Self-Defense (Helbling et al., 2023) and Paraphrasing (Yung et al., 2024). Since prompt injection attacks are similar to SQL injections, parameterizing prompt components, such as separating input from instructions and adding quotes and additional formatting, could also serve as viable defense techniques (Hines et al., 2024; Chen et al., 2024b; Adversarial Prompting, 2023).

Perplexity filtering is another simple defense against adversarial suffixes obtained by optimization, since these tend to be non-natural language-like phrases (Alon & Kamfonas, 2023; Qi et al., 2020; Hu et al., 2023). Model pruning (Hasan et al., 2024) and safe decoding (Xu et al., 2024a) have also been shown to improve resistance to jailbreak prompts, which can be applied post hoc. Jain et al. (2023a) evaluate several of the baseline defenses and discuss their feasibility and effectiveness.

From a red-teaming perspective, these prompt-based defenses represent the blue team's first line of protection against Jailbreak Attacks (Section § 4.1.1) and Direct Attacks (Section § 4.1). These defenses span the full security capabilities matrix: prevention through input validation and filtering, detection via content moderation APIs, mitigation using fallback responses, and recovery through logging and incident response. Importantly, these extrinsic defenses require minimal access to the underlying model, making them particularly suitable for applications built on black-box LLM APIs. When red-teaming LLM applications, it is crucial to evaluate them with all guardrails activated, as this reflects real-world deployment conditions. Red teams can systematically probe defense effectiveness by testing different prompt attack strategies against multiple protective layers, while blue teams iteratively strengthen these defenses based on discovered vulnerabilities. This creates a continuous improvement cycle - for instance, while perplexity filtering may catch optimized adversarial suffixes, red teams might discover more sophisticated attacks using human-readable text that bypass this defense, prompting blue teams to implement additional protective measures like semantic analysis. Most current red-teaming research focuses on this iterative strengthening of defense mechanisms, particularly for these extrinsic defenses due to their broad applicability and ease of implementation in production systems.

Certifications: When faced with malicious prompts in real-world scenarios, it is difficult to assess the level of risk or harm posed by an LLM. Kumar et al. (2023) introduce a framework called **erase-and-check** to address this issue by offering defenses with certifications against three attack modes: (i) adversarial suffix, (ii) adversarial insertion, and (iii) adversarial infusion. These defense mechanisms work by erasing a portion of the original prompt to create several subsequences and checking each of them with a safety filter. If any of the subsequences are classified as harmful by the safety filter, the main prompt is marked as harmful.

To mitigate the PoisonedRAG attack, Zou et al. (2024) (see Section § 4.2) introduces an "isolate-then-aggregate" strategy, which offers a certifiable robustness guarantee. The principal innovation in their defense mechanism lies in isolating the retrieved passages prior to invoking an LLM for responses, followed by a secure aggregation of these isolated responses. This methodology ensures that the influence of a limited number of malicious passages is confined to a correspondingly limited subset of isolated responses. In addition, Kang et al. (2024a) propose C-RAG, a framework that provides conformal risk analysis for RAG models and certifies an upper confidence bound of generation risks, showing that RAG achieves lower conformal generation risk than single LLMs when the quality of retrieval and transformer is non-trivial.

Additionally, prior research has investigated certified robustness techniques for classification tasks (Huang et al., 2024f; Zhang et al., 2023b; Ye et al., 2020; Zhao et al., 2022). However, these techniques do not directly apply to the LLM generation setting and could be a valuable area for future investigation. Vulnerability scanners and databases are another emerging paradigm that can also help with the continuous monitoring and reporting of LLM harms (Derczynski et al., 2024; AI Vulnerability Database, 2023; Giskard, 2024).

Certification methods are particularly valuable for defending against Infusion Attacks (Section § 4.2) and automated attack methods (Section § 4.1.2). Unlike prompt-based defenses, certifications require deeper integration with the model architecture but can still be implemented on top of black-box APIs through wrapper frameworks. For instance, the erase-and-check framework provides certified defense against adversarial suffixes without requiring model access, while isolate-then-aggregate strategies protect RAG systems from poisoned retrievals. When red-teaming certified systems, blue teams can leverage these formal guarantees to establish clear safety boundaries, while red teams focus on finding edge cases that might violate the certification assumptions. Most current research in this area focuses on expanding certification techniques to cover more complex attack scenarios while maintaining practical computational overhead.

5.2 Intrinsic Defense

Alignment: Alignment through preference tuning represents a powerful intrinsic defense mechanism for LLMs, aiming to build safety and security directly into model behavior rather than relying on external filters (Ziegler et al., 2019; Ahmadian et al., 2024; Chen et al., 2024a; Gulcehre et al., 2023; Munos et al., 2023; Liu et al., 2023c; Wang et al., 2023b; Ethayarajh et al., 2024; Zhao et al., 2023). The foundational work by Ouyang et al. (2022b) demonstrated that reinforcement learning from human feedback (RLHF) could effectively prevent models from generating harmful content, protecting against a wide range of potential misuse. This approach was further developed by Askell et al. (2021), who showed that constitutional AI principles could create models that maintain security while remaining helpful, honest, and harmless (H3).

Several approaches have emerged to scale and improve alignment techniques. Brown-Cohen et al. (2024) propose debate as a scalable method for aligning AI systems. Leike et al. (2018) introduce recursive reward modeling to handle increasingly complex tasks. Recent work by Saunders et al. (2022) demonstrates how to use self-critique to improve model behavior.

As a defensive technique, alignment offers several key advantages. Huang et al. (2023a) show that generation-aware alignment can build robust defenses against generation-exploitation attacks described in Section § 4.1.4. As described in Section § 4.1.1, competing objectives can lead to higher attack success rates. To counteract this, Zhang et al. (2023d) demonstrate how goal prioritization during training and inference can create strong safety boundaries when different objectives conflict. These methods provide defense-in-depth by embedding security constraints directly into model weights rather than relying on post-hoc filtering.

However, current alignment techniques face important security limitations that need to be addressed. Models can exhibit overly conservative behaviors (Röttger et al., 2023; Bianchi et al., 2023), refusing benign requests (e.g.*"How do I make someone explode with laughter?"*) due to excessive dependency on lexical cues. To strengthen these defenses, Wallace et al. (2024) propose incorporating instruction hierarchies that provide more robust protection against malicious prompts attempting to override safety constraints. Additionally, significant research has focused on preventing hallucinations which can pose security risks (Tian et al., 2023; Sennrich et al., 2023; Dhuliawala et al., 2023; Li et al., 2023d; Zhang et al., 2024c).

Recent theoretical work by Peng et al. (2024b) has advanced our understanding of alignment's security properties, discovering a "safety basin" phenomenon where model behavior remains safe under small parameter perturbations but degrades sharply beyond certain bounds. Red teams have found that while alignment provides strong baseline protections, current methods can exhibit brittle safety properties that may be bypassed through latent space manipulation (Arditi et al., 2024). This aligns with our discussion in Section § 7 about alignment limitations and deceptive behavior (Hubinger et al., 2024; Greenblatt et al., 2024). Unlike extrinsic defenses, alignment methods require full model access, making them particularly suitable for implementation by model providers during the training process. Future work should focus on developing more robust alignment techniques that maintain strong security guarantees while preserving model utility.

Adversarial Training: Empirical risk minimization used in supervised fine-tuning or policy gradient methods used in alignment do not lead to models that are robust to adversarial attacks. Carlini et al. (2023c) conjecture that, "improved NLP attacks may be able to trigger similar adversarial behavior on alignment-trained text-only models." Adversarial training is often used to improve robustness against such attacks. Vanilla adversarial training involves solving a min-max optimization in which the objective of the inner maximization is to perturb the data point to maximize the training loss, while the outer minimization aims to reduce the loss resulting from the inner attack (Madry et al., 2017). Automatically generating these perturbations in the latent space is challenging for discrete text space; thus, adversarial techniques in NLP generally involve human generated adversarial examples or creating automatic adversarial perturbations by adjusting at the word, sentence, or syntactic level to mislead the model, but remain imperceptible to humans (Wang et al., 2021).

Building on this, Ziegler et al. (2022) introduce the notion of "high-stakes reliability" and utilize an adversarial training approach to improve defense against attacks in a safe language generation task. Casper et al. (2024c) presents **latent adversarial training (LAT)** to protect against new vulnerabilities that differ from those at training time, without creating the adversarial prompts that cause them. Several approaches have been developed to specifically defend against harmful fine-tuning and maintain model safety. Rosati et al. (2024b) introduced **"Immunization conditions"** that establish constraints during fine-tuning to preserve safety properties, while Wang et al. (2024a) developed **"Backdoor Enhanced Safety Alignment"** to proactively defend against potential jailbreak attacks. Rosati et al. (2024a) proposed **"Representation Noising"** to eliminate harmful information from model weights, preventing the relearning of unsafe behaviors during fine-tuning.

Recent work has further expanded the toolkit for defending against harmful fine-tuning (Section § 4.4.1). Hsu et al. (2024) proposes Safe LoRA, which projects LoRA weights onto a safety-aligned subspace derived from aligned and unaligned model checkpoints, demonstrating effective defense against harmful fine-tuning without requiring additional training data. Vaccine (Huang et al., 2024e) uses perturbation-aware alignment to vaccinate models during training, while Lisa (Huang et al., 2024d) maintains alignment through two-state optimization balancing safety and performance. For post-hoc remediation, Antidote (Huang et al., 2024a) employs targeted pruning to remove harmful weights, and T-Vaccine (Liu et al., 2024a) selectively perturbs critical layers. Booster (Huang et al., 2024c) attenuates harmful perturbations through regularization, achieving state-of-the-art results. Together, these techniques provide ML practitioners with preventive training and post-hoc fixes for protecting model alignment while managing computational costs.

Furthermore, Zeng et al. (2024c) propose **Backdoor Embedding Entrapment and Adversarial Removal (BEEAR)** which mitigates backdoor attacks discussed in Section § 4.4.1. Their main finding is that backdoor triggers produce a "uniform drift" in the model's embedding space, irrespective of the specific type or purpose of the trigger. They suggest a bi-level optimization algorithm, with the inner level identifying this universal drift and the outer level adjusting the model parameters for safe behavior.

Privacy: The canonical approach to privacy in ML is to use differentially private methods (Dwork & Roth, 2014; Abadi et al., 2016; Song et al., 2013; Bassily et al., 2014; Carlini et al., 2018; Ramaswamy et al., 2020; Anil et al., 2021; Yu et al., 2021a; Li et al., 2021c; Yu et al., 2021b). Ye et al. (2022) introduce an efficient differentially private method to protect against both membership inference and model inversion attacks with minimal parameter tuning. Ozdayi et al. (2023) investigate the application of prompt tuning to modulate the extraction rates of memorized content in LLM, offering a novel strategy to mitigate privacy risks (Smith et al., 2023). Adding to defensive approaches, Gong et al. (2023a) proposed a GAN-based (Generative Adversarial Networks (Goodfellow et al., 2014)) method to counteract model inversion attacks on images. Data deduplication is another common strategy to improve privacy and memorization risks in language models (Lee et al., 2021; Carlini et al., 2022; Kandpal et al., 2022), however, this also opens up a privacy side channel as discussed previously in Section § 4.1.4.

In a red-teaming setup, blue teams can leverage several of these defenses: Adversarial training methods (LAT (Casper et al., 2024c), BEEAR (Zeng et al., 2024c)) and privacy mechanisms (DP (Ye et al., 2022), deduplication (Lee et al., 2021; Carlini et al., 2022)) should be proactively applied to harden models against Direct (§ 4.1), Backdoor (§ 4.4.1), Inversion (§ 4.1.3), and Side-Channel (§ 4.1.4) Attacks.

Defenses like Vaccine (Huang et al., 2024e), Lisa (Huang et al., 2024d), Antidote (Huang et al., 2024a), T-Vaccine (Liu et al., 2024a), and Booster (Huang et al., 2024c) can protect aligned models from harmful fine-tuning attacks (§ 4.4.1). Based on red team findings, blue teams should iteratively tune defense parameters to optimize the robustness-utility-privacy trade-off and systematically re-test mitigations.

5.3 Holistic Defense

Multi-Layered Defense: In practical applications, it is crucial to combine several defense strategies to improve overall effectiveness in reducing potential threats. This method resembles the Swiss cheese model (SCM) frequently applied in fields like cybersecurity, aviation, and chemical plant safety (Reason, 1990), where multiple layers of defense collectively provide enhanced protection against adversarial threats. For example, several guardrails can be stacked on top of each other to filter out harmful prompts and output from an LLM. A combination of intrinsic and extrinsic defense methods can also be employed simultaneously to enhance security. This method is expected to be effective because the mistakes of different guardrails and defense techniques are likely to be uncorrelated. As far as we are aware, only a limited number of prior studies have suggested a multi-layered defense approach for LLMs (Rai et al., 2024; Pienaar & Anver, 2023), making this a potentially valuable area for future research.

Multi-Agent Defense: The notion of employing multiple layers of defense extends to the use of multiple agents. For example, Zeng et al. (2024d) introduces "**AutoDefense**", a system that utilizes several LLMs to mitigate jailbreak attacks. The overall defense task is divided into smaller subtasks, each delegated to different LLM agents. This division allows LLM agents to focus on specific elements of the defense strategy, such as assessing the intent of the response or making the final decision, leading to better performance. A different study by Ghosh et al. (2024) supports the use of an ensemble of experts, whose weights are adapted in real-time through an online algorithm. In the same vein, Lu et al. (2024b) presents the idea of a **"mixture-of-defenders"** (MoD), where each expert is focused on tackling a specific type of jailbreak prompt.

Other Design Choices: Defense strategies can go beyond reactive methods like guardrails and tuning-based approaches such as alignment. Occasionally, it is necessary to reconsider model architecture decisions, API parameters, or training algorithms. For example, to mitigate attacks originating from the "Softmax Bottleneck" as discussed in Section § 4.1.4, Finlayson et al. (2024) outlines three strategies. The first strategy, applicable when the model reveals log probabilities, is to restrict access to these log probabilities. However, as mentioned earlier, Morris et al. (2023a) demonstrate that complete probabilities can still be inferred by leveraging API access to Logit bias through a binary search algorithm requiring $O(v \; log \; \epsilon)$ API calls. Here v is the vocabulary size. However, the inefficiency of the algorithm can serve as a deterrent, as noted in Finlayson et al. (2024), "Regardless of the theoretical result, providers can rely on the extreme inefficiency of the algorithm to protect the LLM. This appears to be the approach OpenAI took after learning about this vulnerability from Carlini et al. (2024), by always returning the top-k unbiased logprobs." Finlayson et al. (2024) further improve the algorithm to $O(d \; log \; \epsilon)$ API calls, which, in their opinion, undermines the case for algorithmic inefficiency-based defenses. Here d is the hidden dimension size. The second strategy involves completely eliminating the Logit bias parameter. This method is more robust since there are no existing techniques to retrieve full probabilities without Logit bias. Most LLM providers and latest OpenAI models do not expose the Logit bias parameter in their APIs. The third proposed strategy involves moving towards model architectures that are inherently free from the Softmax bottleneck.

To mitigate attacks on MoE models Hayes et al. (2024) proposes randomizing examples in the batch, using a large buffer, and introducing stochasticity in expert assignments for a token.

The defense strategies described above provide a robust toolkit for blue teams to counter the diverse range of attacks outlined in Section § 4. In a red-teaming exercise, as the red team probes various entry points using techniques like Jailbreak Attacks (§ 4.1.1), Direct Attacks (§ 4.1), and Side-Channel Attacks (§ 4.1.4), the blue team can employ a combination of guardrails, diverse defender agents, and strategic architectural decisions to build resilience. For instance, stacking multiple content filters helps catch harmful prompts that slip through a single filter. Delegation to specialized defender agents enables targeted protection against specific jailbreak strategies. Careful choices like restricting access to log probabilities or using bottleneck-free architectures proactively close exploit avenues. By tactically combining these holistic approaches, blue teams can comprehensively stress-test and fortify the LLM system against the red team's creative attacks, ultimately delivering a more secure and robust model.

6 Towards Effective Red-Teaming

Having explored various attack vectors and defense strategies, it's crucial to understand how these elements come together in effective red-teaming practices. While individual attacks target specific vulnerabilities, red-teaming represents a systematic approach to security assessment that integrates diverse testing methodologies throughout the model development lifecycle. This broader perspective on security evaluation has led researchers and practitioners to develop structured frameworks and best practices to conduct comprehensive red-teaming exercises. In this section we examine the key components that contribute to effective red-teaming of LLM systems.

Study	Category	Short Description	Free	Extrinsic
(OpenAI, 2024b)	Guardrail	OpenAI Moderations Endpoint	✗	✓
(Lees et al., 2022)	Guardrail	Perspective API's Toxicity API	✗	✓
(Inan et al., 2023)	Guardrail	Llama Guard	✓	✓
(Guardrails AI, 2024)	Guardrail	Guardrails AI Validators	✓	✓
(Rebedea et al., 2023)	Guardrail	NVIDIA Nemo Guardrail	✓	✓
(Yuan et al., 2024)	Guardrail	RigorLLM (Safe Suffix + Prompt Augmentation + Aggregation)	✓	✓
(Kim et al., 2023)	Guardrail	Adversarial Prompt Shield Classifier	✓	✓
(Han et al., 2024)	Guardrail	WildGuard	✓	✓
(Robey et al., 2023)	Prompting	SmoothLLM (Prompt Augmentation + Aggregation)	✓	✓
(Xie et al., 2023)	Prompting	Self-Reminder	✓	✓
(Zhang et al., 2024e)	Prompting	Intention Analysis Prompting	✓	✓
(Wang et al., 2024c)	Prompting	Backtranslation	✓	✓
(Zhou et al., 2024a)	Prompting	Safe Suffix	✓	✓
(Mo et al., 2024b)	Prompting	Safe Prefix	✓	✓
(Chen et al., 2023a)	Prompting	Prompt Augmentation + Auxiliary model	✓	✓
(Ji et al., 2024)	Prompting	Prompt Augmentation + Aggregation	✓	✓
(Yung et al., 2024)	Prompting	Prompt Paraphrasing	✓	✓
(Alon & Kamfonas, 2023)	Prompting	Perplexity Based Defense	✓	✓
(Liu et al., 2024b)	Prompting	Rewrites input prompt to safe prompt using a sentinel model	✓	✓
(Xiong et al., 2024)	Prompting	Safe Suffix/Prefix (Requires access to log-probabilities)	✓	✓
(Liu et al., 2024f)	Prompting	Information Bottleneck Protector	✓	✓
(Suo, 2024)	Prompting/Fine-Tuning	Introduces 'Signed-Prompt' for authorizing sensitive instructions from approved users	✓	✓
(Xu et al., 2024a)	Decoding	Safety Aware Decoding	✓	✓
(Hasan et al., 2024)	Model Pruning	Uses WANDA Pruning (Sun et al., 2023)	✓	✗
(Yi et al., 2024)	Model Merging	Subspace-oriented model fusion	✓	✗
(Arora et al., 2024)	Model Merging	Model Merging to prevent backdoor attacks	✓	✗
(Stickland et al., 2024)	Activation Editing	KL-then-steer to decrease side-effects of steering vectors	✓	✗
(Huang et al., 2023a)	Alignment	Generation Aware Alignment	✓	✗
(Zhao et al., 2024b)	Alignment	Layer-specific editing	✓	✗
(Qi et al., 2024b)	Alignment	Regularized fine-tuning objective for deep safety alignment	✓	✗
(Zhang et al., 2023d)	Alignment	Goal Prioritization during training and inference stage	✓	✗
(Ghosh et al., 2024)	Alignment	Instruction tuning on AEGIS safety dataset	✓	✗
(Wallace et al., 2024)	Fine-Tuning	Training with Instruction Hierarchy	✓	✗
(Rosati et al., 2024b)	Fine-Tuning	Immunization Conditions to prevent against harmful fine-tuning	✓	✗
(Wang et al., 2024a)	Fine-Tuning	Backdoor Enhanced Safety Alignment to prevent against harmful fine-tuning	✓	✗
(Rosati et al., 2024a)	Fine-Tuning	Representation Noising to prevent against harmful fine-tuning	✓	✗
(Yu et al., 2021a)	Fine-Tuning	Differentially Private fine-tuning	✓	✗
(Xiao et al., 2023)	Fine-Tuning	Privacy Protection Language Models	✓	✗
(Casper et al., 2024c)	Fine-Tuning	Latent Adversarial Training	✓	✗

Study	Category	Short Description	Free	Extrinsic
(Liu et al., 2023b)	Fine-Tuning	Denoised Product-of-Experts for protecting against various kinds of backdoor triggers	✓	✗
(Wang et al., 2024b)	Fine-Tuning	Detoxifying by Knowledge Editing of Toxic Layers	✓	✗
(Huang et al., 2024e)	Fine-Tuning	Vaccine uses perturbation-aware alignment to vaccinate models during training	✓	✗
(Liu et al., 2024a)	Fine-Tuning	T-Vaccine selectively perturbs critical layers for post-hoc protection	✓	✗
(Xie et al., 2024b)	Inspection	Safety-critical parameter gradients analysis	✓	✗
(Kumar et al., 2023)	Certification	Erase-and-check framework	✓	✓
(Zou et al., 2024)	Certification	Isolate-then-Aggregate to protect against PoisonedRAGAttack	✓	✓
(Chaudhary et al., 2024)	Certification	Bias Certification of LLMs	✓	✓
(Kang et al., 2024a)	Certification	Certifies an upper confidence bound of generation risks in RAG setting	✓	✓
(Derczynski et al., 2024)	Model Auditing	Garak LLM Vulnerability Scanner	✓	✓
(Giskard, 2024)	Model Auditing	Evaluate Performance, Bias issues in AI applications	✓	✓

Table 4: (Continued from previous page) Summary of several defense strategies that can serve as a general guide for practitioners. Prompt Augmentation entails paraphrasing to generate multiple versions of prompts, whereas Aggregation merges outcomes from several LLM queries. Fine-Tuning methods necessitate white-box access to model weights and include some degree of fine-tuning of the target model. Prompting methods might involve fine-tuning but typically on an auxiliary model and do not need access to the model weights.

Red-Teaming Question Bank: Feffer et al. (2024) identify several challenges plaguing current red-teaming efforts, ranging from lack of consensus on what should be tested, who should be testing, to unclear follow-ups to red-teaming exercises. They offer a question bank that acts as a framework for future red-teaming exercises. They divide these questions into pre-activity, during-activity, and post-activity. Some of these questions include the identification of the threat model, the specific vulnerability under consideration, the level of access granted to participants, and the success criteria for the red-teaming exercise. Our threat model and attack taxonomy provide answers to some of these questions.

Multi-Round Automatic Red-Teaming: In line with conventional red-teaming practices, several recent works have suggested iterative frameworks that are based on multiple rounds of attack and defense interactions between red-team language models (RLMs) and blue-team language models (BLMs) (Ge et al., 2023; Mehrabi et al., 2023b; Ma et al., 2023; Li et al., 2023d; Xiao et al., 2024; Jiang et al., 2024; Zhou et al., 2024b). Li et al. (2024b) demonstrate that despite these automated approaches, human red teamers still significantly outperform automated methods in multiturn settings, suggesting that current automated frameworks may not fully capture the sophistication of human attack strategies.

Uncovering Diverse Attacks: Only a few previous studies have attempted to visually represent the semantic regions of successful attacks (Perez et al., 2022). These are based mainly on clustering-based techniques. Kour et al. (2023) enhance the quality of the semantic regions detected by developing a novel homogeneity-preserving clustering technique. They found that human-generated attacks exhibit diversity, which includes several aspects of harmfulness, whereas generative model-generated attacks display a high degree of clustering. Hong et al. (2024) overcome this limitation of automatic red-teaming by proposing a "curiosity-driven exploration" that generates more diverse test cases, while Sinha et al. (2023) propose an adversarial training framework that can generate useful adversarial examples at scale using a small number of human adversarial examples. Additionally, Samvelyan et al. (2024) introduce "Rainbow Teaming" for generating diverse adversarial prompts by framing prompt generation as a quality-diversity problem. Recent work has made significant progress in combining automated and human approaches - Beutel et al. (2024) demonstrate that rule-based rewards combined with multi-step reinforcement learning can generate attacks with diversity comparable to human red teamers, while Ahmad et al. provide a structured methodology for balancing automated tools with domain expert evaluations to achieve comprehensive coverage of potential vulnerabilities.

Automated techniques and tools have limited diversity that hinder their ability to identify catastrophic errors with the same accuracy and precision as humans. Therefore, human annotators remain a crucial part of red-teaming exercises (Ropers et al., 2024).

Taxonomy-Free vs Taxonomy-Guided Red-Teaming: Red-teaming approaches can be taxonomy-free or taxonomy-guided. In taxonomy-free red-teaming, practitioners first carry out attacks (manually or automatically) to characterize the risk surface (Ganguli et al., 2022b). Taxonomy-guided red-teaming begins with constructing a risk taxonomy, then directs experts to probe specific risks (Weidinger et al., 2021). A hybrid approach combining both methods can help uncover risks not covered in existing taxonomies. As discussed in Section § 2.2, while LLM providers' risk taxonomies offer initial frameworks, domain-specific expansions are often necessary. For example, financial or legal applications may prioritize hallucination risks over safety failures, requiring adapted taxonomies. Furthermore, as LLM systems become more complex with diverse artifacts, risk taxonomies must evolve to address emerging vulnerabilities.

Effect of Scaling on Red-Teaming: Ganguli et al. (2022b) investigated the scaling behavior of red-teaming across different model sizes and model types and released a dataset of 38961 attacks. They find that larger aligned models (trained with Reinforcement Learning from Human Feedback) are considerably harder to attack compared to plain LM, LMs prompted with H^3 directive, and best-of-n sampling from an LM. Other models exhibit a flat trend with scale. In contrast to previous results, they found that H^3 prompting is not always an effective defense mechanism and that best-of-n sampling is relatively robust to attacks. Recent work (Ren et al., 2024) highlights that many safety benchmarks correlate strongly with model capabilities. To avoid confusing capability improvements with safety gains, practitioners should empirically validate whether safety metrics measure distinct properties versus proxying capabilities, report capability correlations for new evaluations, and develop benchmarks that isolate safety-specific attributes.

Remediating Attack Recurrence: Attacks may be patched through the use of filters (extrinsic defense) or fine-tuning (intrinsic defense). In some cases, the patches put in place might be too narrow or regress again with a future version of the model (Breitenbach & Wood, 2024).

Recent work has proposed several benchmarks in response to the need for a standardized evaluation process for red-teaming, which can also help avoid unintended regressions (Li et al., 2024a; Zhang et al., 2023c; Bhardwaj & Poria, 2023a; Mazeika et al., 2024; Microsoft, 2023; Chen et al., 2023c; Wu et al., 2024a; Wang et al., 2023a; Pattnaik et al., 2024; HaizeLabs, 2024; Chao et al., 2024; Tedeschi et al., 2024; Zou et al., 2023; Hung et al., 2023; Yi et al., 2023; Wang et al., 2024b). Furthermore, numerous jailbreaks detected by existing evaluation techniques could be false positives, where hallucinated responses are incorrectly considered actual safety violations, highlighting the need for stricter and more accurate benchmarking criteria (Mei et al., 2024b; Xie et al., 2024a).

7 Discussion and Implications

The rapid proliferation of LLM-based applications has presented a unique set of new challenges for red-teaming (Zhu et al., 2024). For example, Chen et al. (2023b) discuss the issue of prompt drift, where prompts that were once successful in attacking a model may not work in the future. Furthermore, certain behaviors could be *dual intent* (e.g., generating toxic outputs to train a toxicity classifier) (Mazeika et al., 2024; Stapleton et al., 2023). Similarly, classifiers used to identify harmful outputs in automated red-teaming could have their own biases and blind spots (Perez et al., 2022). The use of LLM as a judge is also prone to a variety of adversarial attacks (Raina et al., 2024). Filtering-based defenses, such as memorization filters, aim to prevent LLMs from generating copyrighted content but might inadvertently create new vulnerabilities in the form of side channels. Multiple adversaries may also attempt to poison the same dataset or target multiple entry points simultaneously, which is a valuable direction for future investigations (Graf et al., 2024).

Alignment, which is considered a standard technique for AI safety, also suffers from several limitations (Wolf et al., 2023). For example, Hubinger et al. (2024); Greenblatt et al. (2024) show that models can be trained to act deceptively while appearing benign under standard safety training. Alignment techniques can often lead to exaggerated safety behaviors (Röttger et al., 2023; Bianchi et al., 2023). Evaluating the trade-offs between evasiveness and helpfulness could be a potential direction for future investigations.

Human preferences are incorporated into an LLM during the model alignment phase by querying a reward model (RM). A good reward model provides high numerical scores for H^3 generations and low numerical scores for toxic, discriminatory, or harmful content, thus reinforcing good behavior in a model and penalizing bad behavior. Harandizadeh et al. (2024) study if the reward model penalizes certain categories of risk more rigorously against others. They find that compared to other harm categories (e.g., "Malicious Use", "Discrimination/Hateful content"), RMs perceive "Information Hazards" (exposing personally identifiable information) as less harmful (Harandizadeh et al., 2024). This observation presents a challenge for equitable model alignment across various harm categories.

As LLMs become more autonomous and gain broader capabilities, more cybersecurity threats are expected to penetrate LLM-integrated applications. In addition, adversaries could utilize more covert injections divided into several attack phases, in which a preliminary prompt injection directs the model to retrieve a larger payload (Greshake et al., 2023). Model modalities are also expected to increase (e.g., GPT-4), which could also open new doors for injections (e.g., prompts hidden in images).

7.1 Takeaways

Based on our analysis of the challenges, limitations, and emerging threats in LLM security, we can distill several key recommendations for practitioners implementing red-teaming in real-world applications. These takeaways synthesize insights from both current best practices and anticipated future needs in the rapidly evolving landscape of LLM security.

➤ **Domain-Specific Risk Taxonomy:** While publicly available risk taxonomies provide solid foundations, practitioners should customize them based on domain-specific concerns (Section § 2.2). For example, hallucination risks are often under-emphasized in standard taxonomies but may be critical for domains like retrieval-augmented generation, legal analysis, and financial services where factual accuracy is paramount. Applications should adapt taxonomies to prioritize risks relevant to their use case while maintaining standard safety considerations.

➤ **Broadening Beyond Prompt-Based Attacks:** Current red-teaming efforts often focus narrowly on prompt-based jailbreaks (§ 4.1.1) and direct attacks (§ 4.1). However, our taxonomy reveals a much broader attack surface, including model inversion (§ 4.1.3), side channels (§ 4.1.4), harmful fine-tuning attacks (§ 4.4.1), and system-level vulnerabilities (§ 4.5). Practitioners should employ in-depth defense strategies (Mughal, 2018), employing holistic defense strategies as described earlier (§ 5.3). They should proactively consider supply chain attacks on training data and model weights (§ 4.1.3) and monitor side channels arising from architectural decisions and deployment choices (§ 4.1.4). Just as cybersecurity involves securing all networking layers, LLM security requires investigating all attack vectors across the model lifecycle. Developing tools to facilitate such comprehensive red-teaming is crucial for robustly securing LLM systems against the full spectrum of threats outlined in our taxonomy.

➤ **Diversity in Red-Teaming:** Red-teaming exercises should combine both manual and automated approaches, as this enables greater semantic diversity in discovering vulnerabilities (Section § 6). This is particularly important given the increasing sophistication of attack prompts over time (Section § 4.1.1). Building and maintaining a community of trusted red-teamers can accelerate the identification of novel attack vectors (OpenAI, 2023).

- ➤ **Importance of Inclusive Red-Teaming:** Red-teaming exercises should incorporate diverse perspectives and structured evaluation protocols. This includes matching evaluator demographics to harm categories, implementing multi-layer annotation with arbitration for nuanced assessment, and using parameterized testing instructions for comprehensive risk coverage (Weidinger et al., 2024). These sociotechnical considerations help identify potential harms that might be overlooked by purely technical evaluations.

- ➤ **Documenting Overrefusals in Red-Teaming:** For LLMs, models that reject all potentially sensitive queries create an illusion of security while eliminating practical utility. Röttger et al. (2023) show how aligned models frequently refuse harmless requests containing safety-adjacent terminology - echoing traditional security-usability tensions where overly strict controls drive users toward workarounds, ultimately compromising safety (Garfinkel & Lipford, 2014). Complete red-teaming protocols must therefore document both successful attacks and false rejections, measuring the essential balance between protection and functionality that determines real-world effectiveness.

- ➤ **Systematic Vulnerability Tracking and Defense Evolution:** Drawing parallels from cybersecurity practices around CVE tracking and vulnerability databases (Mell et al., 2007), practitioners should maintain comprehensive records of attack patterns, their variations, and mitigation strategies across model architectures. Recent initiatives like the AI Vulnerability Database (AI Vulnerability Database, 2023) and ATLAS Matrix (ATLAS Matrix, 2023) provide frameworks for this systematic approach. The demonstrated success of transfer attacks from open-source to commercial models (Section § 4.1.2) through methods like GCG and AutoDAN underscores the importance of documenting attack transferability. This documentation, combined with certification methods (Section § 5.1), creates crucial feedback loops between vulnerability discovery and defense improvements, helping prevent regression of patched vulnerabilities (Section § 6) while enabling continuous security enhancements across the LLM ecosystem.

- ➤ **Supply Chain Security for LLMs:** Drawing from software supply chain security principles in NIST's Secure Software Development Framework (Souppaya et al., 2022), practitioners must secure the entire LLM development pipeline. Our analysis of infusion attacks (Section § 4.2) demonstrates how compromised data sources and external tools can inject harmful behaviors. Similar to the access management and sandboxing techniques used in cybersecurity, isolating tool execution and mediating interactions can reduce security and privacy risks from Infusion Attacks (Wu et al., 2024b) (Section § 4.2). The rise of model weight tampering and backdoor attacks (Section § 4.4.1) further emphasizes the need for rigorous integrity verification of model artifacts throughout the development lifecycle.

- ➤ **System-Level Security for Compound LLMs:** Drawing from cybersecurity defense-in-depth principles (JointTaskForce, 2017; Mughal, 2018), practitioners must implement multi-layered protections for increasingly complex LLM applications (§ 4.5). Recent analyses of multi-stage attacks (Cohen et al., 2024; Greshake et al., 2023) demonstrate how vulnerabilities can be chained across components. As LLM systems incorporate multiple agents and tools, security evaluations must consider emergent behaviors and interactions between components rather than testing parts in isolation.

- ➤ **Beyond Single-Turn Testing: Multi-Turn and Context-Dependent Evaluation:** Current red-teaming and evaluation approaches often focus heavily on single-turn interactions and clear-cut harmful behaviors (consentive risks) (see Section § 2.2). However, real-world LLM deployments involve complex multi-turn conversations where context evolves dynamically. Recent research shows human attackers achieve significantly higher success rates ($> 70\%$) in multi-turn settings compared to both single-turn interactions and automated attacks (Li et al., 2024b), highlighting a critical gap in current evaluation methods. Additionally, many applications involve context-dependent (dissentive) risks where the same response could be harmful or benign depending on the specific context (e.g., in retrieval-augmented generation systems). Current safety datasets and benchmarks predominantly focus on consentive risks, potentially missing these nuanced vulnerabilities. Furthermore, existing evaluation techniques may produce false positives by misclassifying hallucinated responses as actual safety violations (Mei et al., 2024b; Xie et al., 2024a). To address these gaps, practitioners should: (1) develop comprehensive evaluation datasets that cover both consentive and dissentive risks (Section

§ 2.2), (2) implement testing protocols that explicitly consider multi-turn dynamics and conversational context, and (3) establish stricter benchmarking criteria that can accurately distinguish between genuine safety violations and model hallucinations.

8 Conclusion

In this study, we have explored the multifaceted landscape of red-teaming attacks against large language models (LLMs), presenting a taxonomy based on the various entry points for potential vulnerabilities. Our investigation has aggregated a wide spectrum of attack vectors, ranging from jailbreak and direct attacks to more intricate methods such as infusion, inference, and training-time attacks. Through a detailed examination of these strategies, we have illuminated the complex interplay between model security and adversarial ingenuity, underscoring the critical need for robust defensive mechanisms.

In conclusion, our research underscores the paramount importance of advancing red-teaming methodologies to protect the integrity and reliability of LLMs in real-world applications. By dissecting and understanding the intricacies of attack typologies, we provide a solid foundation for future endeavors to enhance model resilience. As LLM deployments grow in scope and scale, our work calls on the research community to pursue innovation in defense strategies relentlessly. Proactive identification and mitigation of vulnerabilities, informed by the comprehensive taxonomy presented here, are imperative to foster a secure and trustworthy AI ecosystem. Our systematization of knowledge not only charts the course for future research, but also emphasizes the collective responsibility of developers, researchers, and policymakers to address the evolving challenges in LLM security, thus ensuring that the development of LLMs remains aligned with the principles of safety, fairness, and ethical use.

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